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Urbanization, landscape dynamics, and ecological vulnerability in Kisangani and its surrounding areas (Tshopo, DR Congo): spatial and prospective approaches

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Thèse de doctorat en cotutelle

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Dedication

In memory of my mother, **Scholastique MANGBELE NYATOLO,**
Who witnessed the beginning of this dream but passed away before seeing it brought to completion…Her unconditional love, quiet strength, and prayers shaped the path that I continue to follow today.

To my sister, **Lucie BALANDI,**
Whose support during my earliest steps at the university, and whose enduring kindness and courage, have remained a discreet compass guiding my choices.

To my twin brother, **Patrick BALANDI,**
Gone too soon, yet whose memory continues to accompany my every step...

This thesis stands as a tribute to their memory…

Epigraph

The earth does not belong to us; we belong to the earth.

Seattle, Native American Chief

Abstract

Over the past decades, demographic growth, economic transformations, and technological advances have profoundly reshaped global territorial dynamics. This evolution has led to accelerated urbanization, particularly pronounced in sub-Saharan Africa, where urban expansion often occurs outside established planning frameworks. This transition is characterized by diffuse spatial growth and increased landscape fragmentation. Intermediate cities, such as Kisangani in the Democratic Republic of Congo, offer a valuable setting for investigating the links between urban growth, environmental degradation, and territorial sustainability. This thesis addresses this issue by analyzing the spatial, ecological, and microclimatic transformations induced by urban expansion in Kisangani and evaluating planning scenarios to enhance its sustainability. To this end, an integrated approach combining remote sensing, landscape ecology, and prospective modeling was employed.

Analyses highlighted rapid, continuous urban and peri-urban expansion between 1987 and 2021, with the urban core increasing from 13.49 km² to 100.49 km², corresponding to an average annual growth rate of 8.2%. This growth results from a dual process of diffusion and coalescence and is accompanied by persistent densification. Notably, Kisangani diverges from the global tendency toward urban dedensification, despite the marked peri-urbanization observed between 2010 and 2021. Concurrently, the city lost nearly 47% of its mature forests, which were either converted to agricultural land or degraded, reflecting increasing pressure from human activities. Urban pressure also caused marked fragmentation of peripheral forest landscapes (Masako, Mbiye, Yoko, and Yangambi), particularly severe in Masako and Mbiye, where contiguous forest patches have almost disappeared. Since 2016, these landscapes have lost their core areas, with the interior/edge ratio approaching zero across all ecological distances used (50-200 m). The breakdown of ecological connectivity, especially in Masako and Mbiye, is reflected in the weak correlation between forest patch size and land surface temperature (LST), indicating advanced degradation of the remaining forest fragments. At the urban microclimatic level, landscape artificialization has intensified urban heat islands (UHIs) between 2000 and 2024: moderate UHIs more than doubled from 16 to 38 km², while high UHIs increased from 9 to 19 km². Finally, prospective modeling highlights differentiated trajectories: the business-as-usual scenario extends current dispersion; the sustainable scenario illustrates the potential for compact, ecological urbanization; and the hybrid sustainable scenario offers a realistic compromise between growth and environmental preservation. These results reveal the interdependence among urban dynamics, ecological degradation, and microclimatic alteration, underscoring the importance of integrated planning that effectively coordinates institutional, scientific, and community stakeholders.

Keywords: Urbanization, urban-rural gradient, forest landscape integrity, urban heat islands (UHI), remote sensing, spatial pattern, prospective scenarios.

Résumé

Urbanisation, dynamiques paysagères et vulnérabilité écologique dans la ville de Kisangani et ses périphéries (Tshopo, RD Congo) : approches spatiales et prospectives

Au cours des dernières décennies, la croissance démographique, les mutations économiques et les avancées technologiques ont profondément influencé les dynamiques territoriales mondiales. Cette évolution s'est traduite par une urbanisation accélérée, particulièrement marquée en Afrique subsaharienne, où l'essor des villes se déploie souvent hors des cadres de planification établis. Cette transition se caractérise par une expansion spatiale diffuse et une fragmentation accrue des paysages. Les villes intermédiaires, telles que Kisangani en République Démocratique du Congo, offrent un cadre privilégié pour étudier les liens entre la croissance urbaine, et la dégradation environnementale. C'est à cette problématique que s'est attachée la présente thèse, en analysant les transformations spatiales, écologiques et microclimatiques induites par la croissance urbaine de Kisangani et en évaluant les scénarios d'aménagement susceptibles d'en améliorer la durabilité. De ce fait, une approche intégrée combinant la télédétection, l'écologie du paysage et la modélisation prospective a été appliquée.

Les analyses ont mis en évidence une expansion urbaine et périurbaine rapide et continue entre 1987 et 2021, le noyau urbain passant de 13,49 km² à 100,49 km², soit un taux annuel moyen de 8,2 %. Cette croissance résulte d'un double processus de diffusion et de coalescence et s'accompagne d'une densification persistante, ce qui distingue Kisangani des tendances globales à la dédensification, malgré la forte périurbanisation observée entre 2010 et 2021. Parallèlement, la ville a perdu près de 47 % de ses forêts matures, converties en terres agricoles ou en formations dégradées, ce qui traduit l'emprise croissante des activités humaines. La pression urbaine a également provoqué une fragmentation marquée des paysages forestiers périphériques (Masako, Mbiye, Yoko et Yangambi), plus sévère à Masako et Mbiye, où les taches contiguës ont presque disparu. Depuis 2016, ces paysages ont perdu leurs zones d'intérieur, le ratio intérieur/lisière tendant vers zéro à toutes les distances (50-200 m). La rupture de la connectivité écologique, particulièrement à Masako et Mbiye, se traduit par une faible corrélation entre la taille des taches et la température de surface (LST), ce qui révèle une dégradation avancée des fragments résiduels. Sur le plan microclimatique, l'artificialisation du paysage a entraîné une intensification des îlots de chaleur urbains (Urban Heat Island, UHI) entre 2000 et 2024 : les UHI modérés ont doublé, passant de 16 à 38 km², tandis que les UHI élevés ont progressé de 9 à 19 km². Enfin, la modélisation prospective met en lumière des trajectoires différenciées : le scénario tendanciel prolonge la dispersion actuelle, le scénario durable illustre le potentiel d'une urbanisation compacte et écologique, tandis que le scénario hybride propose un compromis réaliste conciliant croissance et préservation de l'environnement. Ces résultats révèlent l'interdépendance entre la dynamique urbaine, la dégradation écologique et l'altération du microclimat, soulignant l'importance

d'une planification intégrée, fondée sur une coordination effective entre les acteurs institutionnels, scientifiques et communautaires.
Mots-clés : Urbanisation, gradient urbain-rural, intégrité des paysages forestiers, îlots de chaleur urbains (UHI), télédétection, structure spatiale, scénarios prospectifs.

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List of acronyms

- AGRINATURA: Association of European Universities and Research centres
- AGL: Agricultural and Grassland
- ANOVA : Analysis of Variance
- ANN : Artificial Neural Network
- BAU : Business As Usual
- BVD : Building Volume Density
- CA : Cellular Automata
- CEC : Centre Extra-Coutumier
- CNN : Convolutional Neural Network
- DTM : Digital Terrain Model
- DSM : Digital Surface Model
- EIC : Etat Indépendant du Congo
- ERAIFT : Ecole Régionale Post-universitaire d'Aménagement et de gestion Intégrés des Forêts et Territoires Tropicaux
- ETM : Enhanced Thematic Mapper
- FAO : Food and Agriculture Organization
- FoM: Figure of Merit
- GEE : Google Earth Engine
- GHSL : Global Human Settlement Layer
- GI : Green Infrastructure
- GPS : Global Positioning System
- IALE : International Association for Landscape Ecology
- ICD : Instrument de la Coopération au Développement
- INS : Institut National de la Statistique
- JRC : Joint Research Center
- LaSRC : Land Surface Reflectance Code
- LEDAPS : Landsat Ecosystem Disturbance Adaptive Processing System
- LPI : Largest Patch Index
- LST : Land Surface Temperature
- LUCC : Land Use and Land Cover Change
- MAB : Man and the Biosphere
- MEA : Millennium Ecosystem Assessment
- MEI : Magnitude of Edge Influence
- MF : Mature Forest
- MIR : Mid-Infrared

- ML : Machine Learning
- MODIS : Moderate Resolution Imaging Spectroradiometer
- MRAC: Musée Royal de l'Afrique Centrale
- MSS : Multispectral Scanner
- NbS : Nature Based Solution
- NDVI : Normalized Difference Vegetation Index
- NIR : Near-Infrared
- OA : Overall Accuracy
- OLI : Operational Land Imager
- OSM : OpenStreetMap
- PA : Producer Accuracy
- PLAND : Percentage of Landscape
- RDC : République Démocratique du Congo
- RBAC : Relative Built-up Change
- RFAC : Relative Forest Area Change
- RN : Route Nationale
- RP : Route Provinciale
- SE : Standard Error
- SF : Short Forest
- SIG : Systèmes d'Information Géographique
- SPOT : Système Probatoire d'Observation de la Terre ou Satellite Pour l'Observation de la Terre
- SR : Surface Reflectance
- SRTM: Shuttle Radar Topography Mission
- TM : Thematic Mapper
- TIRS: Thermal Infrared Sensor
- UA : User's Accuracy
- UHI : Urban Heat Island
- UN : United Nation
- UNESCO: United Nations Educational, Scientific and Cultural Organization
- UTM : Universal Transverse Mercator
- WGS : World Geodetic System

Chapter 1

General introduction

1.1. Problem statement and general context

Over the past century, demographic, economic, social, and technological dynamics have profoundly transformed both natural and human landscapes (Nancy et al., 2008; Schneider & Woodcock, 2008; Yahaya et al., 2024). Globally, this process has manifested as accelerated urbanization, characterized by rapid urban population growth (Cheng et al., 2013). While in 1950, nearly 70% of the world's population still resided in rural areas (United Nations, 2014), this trend reversed from 2007 onward, with the majority now concentrated in cities (Cheng et al., 2013; United Nations, 2014). Projections indicate that by 2050, nearly 70% of the global population, over 6.3 billion people, will reside in urban areas (United Nations, 2014). This dynamic, particularly pronounced in developing countries, especially in sub-Saharan Africa, poses new challenges for both territorial management and environmental sustainability.

In Africa, urbanization is progressing at an unprecedented rate. Although the continent remains the least urbanized globally (UN-Habitat, 2022), it records the highest urban growth rates in the world. The African urban population is expected to increase from 44% in 2022 to approximately 60% by 2050 (UN-Habitat, 2022), resulting in accelerated urban expansion. This urban growth most often manifests as dispersed, low-density, and poorly regulated expansions, commonly referred to as urban sprawl (European Environment Agency, 2006; Rubiera-Morollon & Garrido-Yserte, 2020). Initially observed in North American and European cities (Angel et al., 2010; Jacobs, 1961), such growth patterns now characterize African metropolises. They lead to inefficient land use, increased land artificialization, rising pressure on natural resources, and significant landscape degradation (Useni et al., 2017; Vermeiren et al., 2012).

Within this context, intermediate cities in Central Africa, such as Kisangani in the Democratic Republic of the Congo (DRC), are experiencing rapid demographic and spatial growth. Kisangani's population increased from 437,805 inhabitants in 1990 to over 2 million in 2021 (INS, 2022). This expansion, largely outside the framework and implementation of the urban plans successively developed in 1978, 2008, and 2010 (UN-Habitat, 2015) exerts increasing pressure on surrounding natural areas within a land governance framework characterized by a mix of formal regulations and informal practices, particularly in peri-urban and rural zones. Consequently, this less regulated urbanization transforms peripheral rural areas into hybrid spaces, where dispersed settlements, agriculture, and urban infrastructures coexist, known as peri-urban areas (André, 2017; Bogaert & Halleux, 2015; Sambieni, 2019). These dynamics generate pronounced fragmentation of natural ecosystems and increase the environmental vulnerability of these territories.

One of the major impacts of such unplanned urbanization dynamics concerns the degradation of green infrastructure, which provides essential ecosystem services: thermal regulation, carbon sequestration, hydrological regulation, biodiversity maintenance, and improvement of urban quality of life (Bixler et al., 2020; Useni et al., 2019; Zahoor et al., 2023). In Kisangani, the degradation of peri-urban forest reserves, such as Masako and Mbiye, illustrates the tensions between unsustainable urban growth and natural resource conservation. The conversion of forests into agricultural or built-up areas leads to habitat fragmentation, increased edge effects (Iyongo, 2013; Meniko et al., 2020), and microclimate alterations, thereby reducing the ecological integrity and resilience of forest ecosystems.

Another major issue concerns local warming and the formation of urban heat islands (UHI) (Dwivedi & Khire, 2018; Jato-espino, 2019). This phenomenon results from the thermal contrast between rural and urban areas, with urban areas exhibiting reduced diurnal temperature variation due to daytime solar energy absorption, which dissipates gradually at night (Kolokotroni et al., 2006). Changes in land use, intensified artificialization, and increased building verticality raise surface temperatures in urban areas (Arnfield, 2003; Liu et al., 2015; Oke, 2002; Stewart & Oke, 2012). These phenomena, still poorly documented for medium-sized African cities, pose significant social and economic challenges, including increased energy consumption, degraded air quality, higher health risks, and reduced water availability (Candra et al., 2016; Martínez et al., 2004; Stewart & Oke, 2012).

Finally, the absence of appropriate urban planning fuels contrasting development scenarios. Trend-based or Business-As-Usual (BAU) models, based on the continuation of historical growth (Morales et al., 2025; Tang et al., 2024; Thorne et al., 2013), exacerbate dispersion and consumption of natural spaces. In contrast, approaches inspired by the compact city model (Lehmann, 2016; Zapata Campos et al., 2022) and assumptions grounded in chorology, which emphasizes the importance of land as a limited and vulnerable resource (Bogaert et al., 2015) advocate responsible, rational urban space management, integrating land scarcity as a strategic and ecological pillar. Evaluating these growth models is crucial to anticipating possible trajectories and guiding governance choices toward more sustainable urban forms.

Thus, in the context of rapid urban growth and institutional fragility in the DRC, the city of Kisangani and its peripheries provide an ideal setting to analyze the impacts of urbanization on landscapes, urban green infrastructure, surrounding forest ecosystems, and local climatic dynamics. Understanding these processes is an essential step toward proposing more sustainable, context-specific urban and territorial planning strategies for intermediate tropical cities. However, to fully apprehend their complexity, it is necessary to situate them within a broader scientific perspective to grasp their foundations, mechanisms, and ecological implications. Examining the existing literature on urban sprawl, landscape spatial structure, green infrastructure, forest fragmentation, and urban heat islands is therefore essential to contextualize this thesis and identify the main gaps it seeks to address.

1.2. State of the art

The scientific literature on urbanization and its impacts highlights several major findings, while also revealing significant gaps, particularly in African contexts. In industrialized countries, the phenomenon known as urban sprawl (Rubiera-Morollon & Garrido-Yserte, 2020), a corollary of urban de-densification (Angel et al., 2010; Angel et al., 2011; Berry et al., 1963) has been extensively documented since the 1950s, both in terms of its formation mechanisms and its impacts on the environment, mobility, and land consumption. In contrast, research in cities in developing countries remains fragmented and limited, notably due to the scarcity of historical spatial data, weak monitoring systems, and a lack of operational tools.

As early as the 1960s, Jane Jacobs, in her seminal work *The Death and Life of Great American Cities* (Jacobs, 1961), already warned about the inefficiency of the dispersed city model in North America. This model was subsequently widely documented in Europe: cities were more compact in the 1950s than they are today, and urban sprawl has now become a generalized phenomenon (European Environment Agency, 2006). More recently, an analysis of a global sample of 120 cities between 1990 and 2000 showed a significant decline in densities, dropping on average from 144 inhabitants/ha in 1990 to 112 inhabitants/ha in 2000 (Angel et al., 2010). Spatially, these losses in urban density manifest as the formation of peri-urban areas, resulting from the expansion of the urban fringe into rural territories. However, it remains insufficiently demonstrated that this process of urban de-densification also affects cities in developing countries (Angel et al., 2010).

In many developing countries, the identification of this process remains constrained by a lack of reliable data that enable temporal and spatial monitoring of urban densities. The case of the Democratic Republic of the Congo (DRC) is particularly illustrative: the last scientific population census dates back to 1984, and since then, demographic statistics have relied largely on estimates and projections (INS, 2022). This absence of precise data constitutes a major obstacle to the systematic analysis of long-term urban density dynamics, which are nonetheless essential for understanding current spatial transformations. Consequently, this thesis addresses this gap by proposing the development of indices based on spatial characteristics and measurements to analyze and test the hypothesis of urban de-densification.

Building on these dynamics, another crucial dimension deserves attention: the impacts of urbanization on green infrastructure. Indeed, urban expansion not only alters densities and the morphology of cities; it also reconfigures landscapes by modifying their composition and configuration (Bogaert & Mahamane, 2005).

Green spaces in the Kisangani region, whether mature forests, degraded forests, agricultural areas, or grasslands, constitute key components of green infrastructure. Green infrastructure (GI) refers to a network of natural or semi-natural spaces and elements such as parks, wetlands, green areas, green roofs, and vegetated walls that provide ecosystem services and benefits to urban communities (Bixler et al., 2020; Zahoor et al., 2023). These benefits include the capacity to absorb, mitigate, and transform sudden or chronic urban stresses; improvements in air and water quality; reduction of the urban heat island effect; decreased flood risk; enhanced biodiversity; and the provision of recreational and cultural opportunities (Rogombe et al., 2022; Wellmann et al., 2020).

Numerous scientific studies focus on analyzing the spatiotemporal transformations of urban green infrastructure (Sambieni, 2019; Useni et al., 2017), understanding its typology and composition (Useni et al., 2019), and assessing the diversity of ecosystem services it provides (Chaoui, 2023; Cornet, 2020; Sirina et al., 2023). Studies conducted in the Kisangani region show that urbanization dynamics have a considerable impact. By analyzing the influence of road networks and population density on dense forest between 1986 and 2001, Bamba & Bogaert (2010) demonstrated significant correlations between demographic growth and ecological fragmentation. These findings highlight the central role of anthropogenic pressures in degrading green spaces. However, limiting the analysis of green infrastructure to dense forest alone appears reductive, as peri-urbanization also leads to the conversion of large areas of dense forest into degraded forest or agricultural zones, which likewise provide essential ecosystem services for urban life.

From a broader perspective, Kamunukamba & Koy (2014) mapped the evolution of green spaces in Kisangani between 1960 and 2010, quantifying changes in both number and surface area. However, the study did not thoroughly examine the configuration and composition of these spaces within the landscape, nor the mechanisms of conversion associated with urban expansion. Knowledge of how Kisangani's urban expansion modifies the composition and configuration of green spaces within the landscape, therefore, remains incomplete. These limitations underscore the importance of considering green infrastructure in its full diversity within a dynamic perspective. The analysis of the urban-rural gradient thus constitutes a particularly relevant framework for studying the spatial pattern of green spaces, accounting for processes of loss, fragmentation, and reconfiguration, as it captures both spatial contrasts and ecological transitions induced by urban expansion.

This thesis, therefore, aligns with ongoing research on urban dynamics by deepening the understanding of ecological transformations driven by urbanization and peri-urbanization. It seeks to fill a scientific gap by providing a spatial and temporal analysis of changes in green infrastructure, while accounting for the specificities and dynamic nature of the urban-rural gradient.

At a broader scale, several studies have examined the effects of urbanization and anthropogenic pressures on tropical forest landscapes and protected areas. While urbanization dynamics reshape the spatial pattern of green spaces within the urban-rural gradient, they also exert a significant influence on tropical forest habitats located near or farther from the city. These tropical forests play a fundamental role in maintaining biodiversity, ecological regulation, and the provision of ecosystem services (Eckehard et al., 2017; Edwards et al., 2019).

However, several studies highlight the increasing vulnerability of these ecosystems, threatened by agricultural expansion, logging, and urbanization (Lewis et al., 2015; Malhi et al., 2014). Between 2000 and 2012, tropical regions were the only climatic zones to exhibit a significant trend of fragmentation, with an estimated annual loss of approximately 2,101 km^2 of forest (Hansen, 2013). During the period 2010-2019, this trend intensified, particularly in Central Africa, where tropical forests recorded a loss of approximately 8.2% in cover (Vancutsem et al., 2021).

Fragmentation thus appears as a central indicator of forest landscape degradation (Bogaert et al., 2008). It leads to an increase in edge zones, which are particularly sensitive to ecological and microclimatic disturbances. Numerous studies have documented forest fragmentation and associated edge effects, particularly regarding their influence on species diversity, habitat affinity, and animal mobility (Dantas et al., 2016; Hending & Randrianarison, 2023; Iyongo, 2013; Laurance et al., 2007; Meniko et al., 2020). These studies have demonstrated significant modifications in community structure and ecological interactions within areas subject to edge effects. Additionally, other studies have emphasized the pivotal role of landscape metrics (spatial measures) in assessing the vulnerability of forests affected by edge influence (Bogaert et al., 1998; Bogaert et al., 1999; Ripple, 1991; Turner & Ruscher, 1988). While these works underscore the necessity of integrating such indicators to evaluate ecological integrity, others have highlighted the importance of simulation models to support the conservation of core forest patches and their ecological functions (Mladenoff et al., 1994; Zheng & Chen, 2000).

Despite the abundance of studies on forest fragmentation and edge effects, significant gaps remain, particularly in Central African forests. Two aspects, in particular, remain insufficiently explored: the precise quantification of the proportion or extent of forests affected by edge influence at different ecological distances, and the role of patch area in modulating the intensity of these effects.

To address this gap, it is necessary to integrate both a spatial approach and ecological indicators that connect the configuration of forest fragments to their functioning. In this perspective, the present thesis focuses on four representative forest landscapes in the Kisangani region: Yangambi, Yoko, Masako, and Mbiye. The study, therefore, evaluates fragmentation dynamics not only in terms of cover loss but also in terms of forest exposure to edge effects, accounting for patch size and local microclimatic conditions.

Understanding forest fragmentation dynamics and transformations in urban green infrastructure reveals a central point: changes in the composition and configuration of urban and peri-urban green spaces have direct consequences for ecological functions and ecosystem services. This observation aligns with the central hypothesis of landscape ecology, known as the “pattern/process paradigm.” (Bogaert & Mahamane, 2005). Among these consequences, thermal regulation in urban environments constitutes a major issue. As attractive spaces, cities are characterized by specific environmental conditions, and they can serve as relevant observatories for understanding the impacts of climatic modifications at both local and global scales (Bastin et al., 2019).

Studies conducted in various geographic contexts have shown that the intensity and distribution of urban heat islands (UHI) depend on factors such as building density, the reduction of green spaces, land conversion, and population growth (Arnfield, 2003; Liu et al., 2015; Oke, 2002; Stewart & Oke, 2012). In rapidly expanding tropical cities such as Shanghai and Kolkata, the reduction of green spaces and land-use changes has accentuated the intensity of urban heat islands (Mandal et al., 2022; Zhang et al., 2013).

Unlike densely populated megacities, Kisangani is a particular case in which urban growth occurs in a tropical context characterized by distinct climatic and land-use dynamics. Whereas most previous studies on urban heat islands have focused primarily on large, densely populated cities, emphasizing land-cover changes, vegetation loss, and surface temperature variations as key drivers of thermal dynamics, few have examined the role of urban morphology, particularly volumetric characteristics of built structures.

This thesis aims to address this gap by combining an analysis of the spatiotemporal dynamics of urban heat islands with an assessment of the interactions between land surface temperature (LST) and building volume density (BVD), which encompasses both building footprint and height. This approach allows for a better understanding of how urban morphology influences thermal dynamics. Moreover, spatial variations are examined along the urban-rural gradient to highlight the contributions of horizontal and vertical expansion to heat accumulation. This dual perspective provides a more comprehensive understanding of heat island formation in rapidly expanding tropical cities and helps identify key factors for urban planning and climate adaptation strategies.

Finally, the combination of these dynamics, de-densification and urban sprawl, transformations of green infrastructure along the urbanization gradient, forest fragmentation, and intensification of urban heat islands, highlights the necessity of extending the analysis toward a prospective dimension. This perspective is particularly relevant for African cities facing rapid urbanization in institutional contexts where planning and regulatory frameworks are often limited.

The literature shows that urban growth often leads to diffuse and weakly regulated expansion, generating environmental pressures and infrastructural inefficiencies (Angel et al., 2010; European Environment Agency, 2006; Jacobs, 1961). These effects are even more concerning in developing countries, where institutional weaknesses combined with demographic growth exert increased pressure on urban spaces (UN-Habitat, 2022). In this context, the continuation of unregulated growth models risks exacerbating the ecological and social impacts already observed. These findings underscore the importance of moving beyond retrospective analyses of urbanization to anticipate future developments. Research on land-use and land-cover change (LUCC) stresses the need to employ approaches capable of anticipating different scenarios and assessing various planning options (Houet et al., 2015; Mallampalli et al., 2016; Mas et al., 2011). However, studies systematically analyzing the influence of contrasting models of urban governance remain scarce, particularly in African cities, where institutional choices can determine urbanization trajectories.

This thesis adopts this perspective by employing prospective modeling to analyze three urban growth trajectories: a Business-As-Usual (BAU) scenario that extends historical dynamics without spatial constraints; a sustainable urbanization scenario that applies explicit spatial constraints to limit urban sprawl; and a hybrid scenario that combines sustainability principles with the local realities of Kisangani. This comparative approach not only addresses the scarcity of prospective studies on African cities but also enables the quantitative and spatial evaluation of the differentiated impacts of these trajectories.

Ultimately, this thesis distinguishes itself through an integrated approach that addresses multiple gaps identified in the literature on urban and landscape dynamics. It first develops spatial indicators to test the hypothesis of urban de-densification in a context marked by insufficient demographic data, then broadens the analysis of green infrastructure by incorporating multiple components and mobilizing the urban-rural gradient to characterize composition, configuration, and ecological transitions. It subsequently quantifies fragmentation and exposure to edge effects in four representative forest ecosystems (Yangambi, Yoko, Masako, and Mbiye), establishing an explicit link between patch area and local microclimatic conditions. Furthermore, it introduces an innovative climatic dimension by combining spatiotemporal analyses of land surface temperature (LST) and building volume density (BVD) to account for the combined roles of horizontal and vertical expansion in intensifying urban heat islands. Finally, integrating prospective modeling based on contrasting urban growth scenarios enables exploration of possible trajectories and their differentiated impacts on landscapes. Taken together, this thesis provides a systemic, multi-scalar, and forward-looking interpretation of the interactions between urbanization, spatial structure, and ecological dynamics, thereby offering an original contribution to the understanding and planning of cities in developing countries.

Considering these observations, it appears necessary to develop a scientific approach that articulates the urban, landscape, and ecological dynamics identified in the literature to deepen understanding within the specific context of Kisangani.

1.3. Scientific framework of the thesis

1.3.1. Research questions and hypotheses

The reviewed studies above highlight interconnected urban and ecological dynamics, ranging from dedensification and urban sprawl to transformations in urban and peri-urban green infrastructure, forest fragmentation, and the intensification of urban heat islands. While these phenomena have been extensively documented in industrialized countries, their understanding remains partial in the context of African cities, where rapid urban growth often unfolds under limited institutional and planning conditions (UN-Habitat, 2022).

Building on the identified observations and gaps, this thesis is structured around a central research question: *How does urban expansion in Kisangani relate to landscape transformation, natural and semi-natural ecological components, local climatic dynamics, as well as prospective scenarios for more sustainable urban development?*

To address this overarching question, the thesis is organized around five analytical axes, each explored through specific studies that have resulted in scientific publications.

Axis 1: Urban growth model

The study of urban growth is a fundamental step in understanding spatial transformations in cities. The literature shows that many cities experience a process of urban dedensification associated with spatial expansion (urban sprawl), with significant consequences for density and the spatial pattern of peri-urban and rural landscapes (Angel et al., 2010). In developing contexts, few studies have assessed whether these trends occur and, if so, how they manifest spatially. Accordingly, this axis addresses the following question: *How does the urban dedensification model observed elsewhere manifest in Kisangani, as reflected in the spatial patterns of urban, peri-urban, and rural areas?*

To answer this question, the thesis tests the hypothesis that the spatial growth of Kisangani follows a trend of urban dedensification, reflected in increases in the peri-urban fraction and the peri-urban/urban ratio. This mode of urban growth would produce differentiated effects on the spatial pattern of urban, peri-urban, and rural areas. In this framework, peri-urban areas are expected to expand, while the stability of rural zones is expected to decline as new urban and peri-urban areas develop.

Axis 2: Transformation of green infrastructure

Urban expansion modifies not only city density and morphology but also reshapes landscapes by affecting the composition and configuration of green spaces. In Kisangani, green spaces such as mature forests, degraded forests, and agricultural areas are key components of green infrastructure, providing services including thermal regulation, air and water quality, biodiversity, and recreational and cultural opportunities.

Previous research has quantified changes in the area and number of green spaces, but has rarely considered their composition and configuration dynamically along the urban-rural gradient. This axis, therefore, proposes a spatial and temporal analysis of green infrastructure changes, accounting for the specificities and dynamic nature of the urban-rural gradient. It addresses the following question: *How has urban expansion in Kisangani between 1986 and 2021 altered the composition and configuration of green spaces along the urban-rural gradient, as reflected in the spatial patterns of urban, peri-urban, and rural areas?*

The associated hypothesis posits that, at the landscape scale, urban expansion has reduced the proportion of mature and short forests while increasing the proportion of agricultural areas and grasslands. This expansion is expected to fragment the largest patches of mature and low forests, reduce their area, and consequently alter landscape configuration. Along the urban-rural gradient, urban areas would exhibit lower forest proportions and smaller residual forest patches than peri-urban and rural zones, reflecting more intense human activity, as reflected in lower values of the Largest Patch Index (LPI). Conversely, agricultural and grassland areas could form larger, more continuous fragments in peri-urban and rural areas. Given the dynamic nature of the urban-rural gradient between 1986 and 2021, the proportion of mature and short forests is expected to decline across all zones, accompanied by continued fragmentation, as reflected in decreasing LPI values. Agricultural and grassland surfaces should increase in peri-urban and rural areas, while in urban zones they may decrease and progressively fragment (low LPI values) as they are converted into built-up areas.

Axis 3: Forest fragmentation and edge effects

Surrounding tropical forests constitute a central component of the ecological infrastructure of cities, regulating biodiversity, local climate, and ecosystem services such as carbon storage and flood mitigation (Eckehard et al., 2017; Edwards et al., 2019). Urban and peri-urban expansion exerts increasing pressure on these ecosystems, leading to forest fragmentation and the proliferation of edge zones that are highly sensitive to ecological and microclimatic disturbances (Bogaert et al., 2008; Laurance et al., 2007).

While previous studies have documented forest fragmentation and its effects on species diversity and habitat structure, few have simultaneously quantified the proportion of forests affected by edge effects and the role of fragment size in modulating these effects, particularly in Central African forest landscapes. This axis, therefore, aims to assess forest fragmentation dynamics and exposure to edge effects across four forest complexes near Kisangani (Yangambi, Yoko, Masako, and Mbiye), integrating fragment size and microclimatic conditions. It explores the following question: *How do forest fragmentation and exposure to edge effects evolve in forest landscapes around Kisangani, and to what extent does patch size influence the intensity of these effects on surface temperature*?

The hypothesis posits that forest fragmentation should intensify over time in the four forest landscapes near Kisangani, each subjected to distinct anthropogenic pressures. This trend should manifest as declines in forest composition and configuration, as evidenced by negative trajectories in relative forest area change and reductions in the largest patch size. As fragmentation increases, the proportion of forest area exposed to edge effects is expected to rise, particularly at ecological distances of 50, 100, 150, and 200 m, where microclimatic disturbances are likely to be more pronounced. Moreover, a significant negative correlation is expected between forest patch area and the magnitude of edge effects on land surface temperature (LST), with smaller patches being more vulnerable to thermal disturbances due to their higher exposure and lower buffering capacity.

Axis 4: Urban Heat Islands (UHI)

The anticipated transformations of green infrastructure and the progressive degradation of surrounding forest ecosystems are expected to influence Kisangani's urban climate directly. The reduction of green spaces combined with increasing density and spatial expansion of buildings tends to favor heat accumulation in urban areas, contributing to intensified urban heat islands (Arnfield, 2003; Oke, 2002; Stewart & Oke, 2012).

Most UHI research has focused on large cities, primarily examining changes in land cover, vegetation, and surface temperatures, while the influence of urban morphology, particularly volumetric building characteristics, remains underexplored. Furthermore, variations along the urban-rural gradient have rarely been analyzed, even though they are essential for understanding how horizontal and vertical expansion shape heat accumulation. Within this context, this thesis addresses the following question: *To what extent does urban morphology, particularly building volume density, vegetation density, and spatial expansion, influence the spatiotemporal dynamics of surface temperature and UHI intensity along the urban-rural gradient in Kisangani?*

The associated hypothesis states that land surface temperature (LST) will vary significantly over time, accompanied by a progressive expansion of zones with moderate to high UHI intensity, driven by spatial transformations that alter the local thermal environment. Along the urban-rural gradient, LST and UHI intensity in 2024 are expected to differ markedly between zones, with higher values in urban areas likely linked to increased landscape artificialization. Analysis of the 2000-2024 period should reveal significant spatiotemporal differences, both between and within the three zones, in LST fluctuations and UHI intensity. Finally, building volume density (BVD) and vegetation density are expected to strongly modulate these dynamics, with BVD's influence intensifying over time, reflected in increasing R^2 values and regression slopes as Kisangani's built environment evolves toward denser, taller structures.

Axis 5: Prospective modeling of urban trajectories

The expected landscape dynamics, including dedensification, urban sprawl, green infrastructure transformation, forest fragmentation, and intensified urban heat islands, highlight the need to adopt a prospective approach to better anticipate spatial and ecological changes in Kisangani.

This thesis, therefore, adopts a forward-looking perspective using spatial modeling to analyze three possible urban growth trajectories in Kisangani: (i) a Business-As-Usual (BAU) scenario prolonging historical trends without spatial constraints (Morales et al., 2025; Tang et al., 2024; Thorne et al., 2013) (ii) a sustainable urbanization scenario integrating explicit spatial constraints to promote compact and controlled growth; and (iii) a hybrid urbanization scenario combining principles of sustainability with local realities. This approach fills a gap in prospective studies of intermediate African cities while quantitatively and spatially assessing how these scenarios shape landscape dynamics, the fragmentation of non-built spaces, and the preservation of ecological resources. It addresses the following question: *How do contrasting urban growth trajectories under BAU, sustainable, and hybrid scenarios affect the spatial pattern and landscape dynamics in Kisangani?*

The associated hypothesis proposes that, in the absence of effective planning mechanisms, the continuation of the current urban growth trajectory, represented by the business-as-usual (BAU) scenario, would lead to a faster increase in the total built-up area than in the expansion of the urban core, as measured by the Largest Patch Index (LPI). Built-up pixels are expected to grow more prominently along the urban fringe, where land availability is higher, indicating a predominance of outward expansion over infilling within the core. Conversely, implementing a functional green belt and limiting urban expansion to a maximum distance from existing built-up areas, while ensuring new developments are close to agricultural zones and the road network, is expected to generate more compact, ecologically protective, and spatially balanced urban configurations under the Sustainable Growth or Hybrid scenario. Furthermore, the two extreme planning trajectories, BAU and Sustainable Growth, are expected to exhibit distinct sensitivities to key modeling parameters that influence urban expansion. Variations in (i) demographic pressure, (ii) spatial growth rate, (iii) contiguity thresholds, (iv) minimum distance from existing built-up pixels, and (v) tolerance within the green belt are anticipated to produce contrasting effects on the simulated built-up area.

1.3.2. Research objectives

Drawing from the literature and the hypotheses established for each analytical axis, the thesis pursues a dual objective: on the one hand, to deepen the understanding of spatial, ecological, and climatic transformations induced by urban expansion in Kisangani; and on the other hand, to evaluate prospective scenarios that could support more sustainable urbanization.

The following objectives are structured according to an integrated logic that reflects the five analytical axes, to address the general research question and guide the scientific approach adopted.

Axis 1: Urban growth model

For this axis, the objective is to quantify and characterize Kisangani's spatial growth, determine whether the city follows a dedensification model, and assess its effects on the spatial pattern of urban, peri-urban, and rural areas.

Axis 2: Transformation of green infrastructure

The objective is to assess the impact of urban expansion (1986-2021) on the composition and configuration of green infrastructure along the urban-rural gradient and to identify differentiated effects across zones.

Axis 3: Forest fragmentation and edge effects

For this axis, the aim is to analyze the evolution of forest fragmentation and edge effects in four forest landscapes near Kisangani, quantifying the influence of patch size on microclimatic and thermal disturbances.

Axis 4: Urban Heat Islands (UHI)

The objective is to examine the spatiotemporal evolution of land surface temperature (LST) and UHI intensity in Kisangani, and to evaluate the roles of building volume density, vegetation density, and urban expansion along an urban-rural gradient.

Axis 5: Prospective modelling of urban trajectories

The objective is to analyse the potential impacts of three urban growth trajectories (BAU, sustainable, and hybrid) on spatial patterns and landscape dynamics to evaluate sustainable urban management options.

1.3.3. Systemic framework of the thesis

The literature shows that many studies have contributed to understanding the transformation of the physical landscape, the ecological components, and the climatic dynamics in urban environments. However, the complexity of the processes at hand in a context such as Kisangani requires an approach that can link these dimensions. This thesis takes this approach. It adopts a systemic and integrated perspective, viewing the city as a socio-ecological system in which natural, semi-natural, and built components constantly interact. Urban transformations are examined not only through spatial growth and land-use dynamics but also in relation to ecological regulations (fragmentation, edge effects, heat storage) and their consequences for local climatic dynamics.

Integration is also achieved through multi-scalar analysis along the urban-rural gradient, capturing ecological transitions and urban morphological types that modulate microclimates. The approach mobilizes complementary tools and indicators (remote sensing and landscape spatial pattern metrics) and combines spatial, ecological, and climatic approaches.

The systemic foundation also extends to a prospective and anticipatory dimension. Beyond describing ongoing transformations, the thesis examines possible future trajectories, interrogates urban growth pathways and their ecological implications, and proposes scenarios to inform planning choices.

This methodological and theoretical positioning helps move beyond fragmented interpretations of urbanization processes and clarifies the complex interrelations between urban growth, landscape configuration, and climatic regulation. The thesis, therefore, fits within a systemic, integrated framework designed to provide a comprehensive understanding of ongoing transformations and the socio-ecological challenges they entail. Figure 1.1 illustrates this systemic and integrated framework.

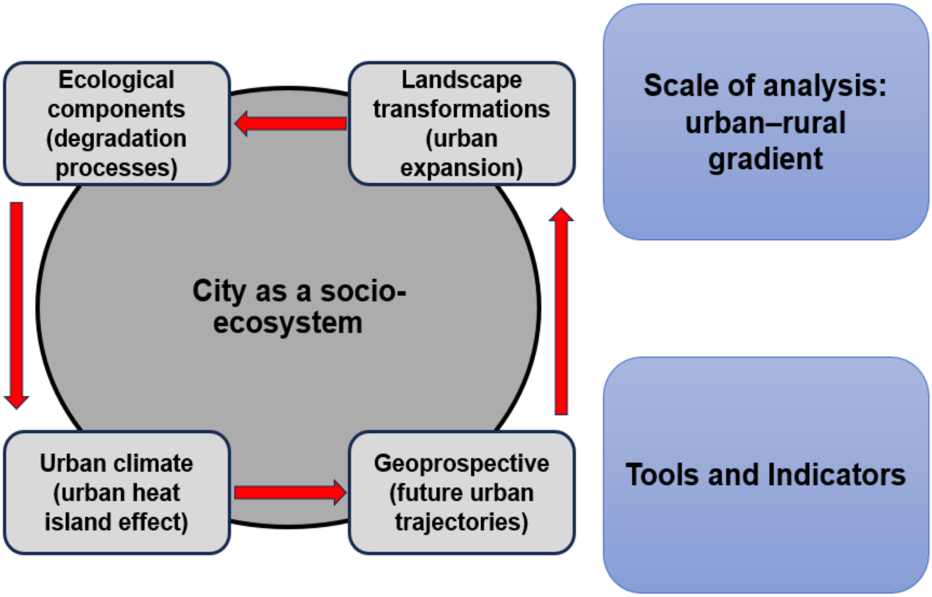


Figure 1.1. Systemic and integrated framework of the thesis. This diagram illustrates the systemic and integrated framework adopted in this thesis. The city is considered as a socio-ecosystem in which multiple interdependent dimensions interact. Urban expansion generates (dynamic) landscape transformations, leading to the degradation of ecological components. This degradation, in turn, affects the urban climate, notably by intensifying urban heat islands. Finally, geo-forecasting, by projecting future development trajectories, enables the identification of strategies to rethink urban expansion and mitigate its ecological and climatic impacts.

This cycle highlights interactions among the various components of the urban system and emphasizes the need for an integrated, interdisciplinary approach. Two cross-cutting dimensions structure this analytical framework: the urban-rural scale, which allows for capturing contrasts and transitions along the spatial gradient, and the tools and indicators, which provide the methodological basis for evaluating, measuring, and modeling these complex interactions.

1.3.4. Thesis structure

This thesis is organized into ten chapters that follow a progressive logic, moving from the general framing of the problem to a detailed analysis of the different research axes, culminating in a general discussion and conclusion.

Chapter 1 constitutes the general introduction. It situates the research problem within its global context, highlights the issues related to urban, ecological, and climatic dynamics, and provides a literature review structured around the five selected research axes. It then formulates the research questions and hypotheses and introduces the systemic and integrated framework, which serves as a guiding thread throughout the thesis.

Chapter 2 presents the theoretical and conceptual framework. This chapter compiles the fundamental knowledge used: urban expansion models and their implications, key concepts related to urbanization, and disciplinary foundations such as landscape ecology, urban ecology, and choralogy. It thus establishes the conceptual basis necessary to understand and interpret the analyses conducted.

Chapter 3 presents the research's methodological framework. It describes the data sources employed (satellite imagery, climatic and ecological data, field surveys, sociodemographic information) and the processing steps applied (image preprocessing, extraction of spatial, climatic, and ecological indicators). The analytical methods are then presented: change detection, calculation of spatial pattern indices, estimation of built density, extraction of land surface temperature, and statistical and spatial analyses. Finally, the chapter outlines the prospective approaches to modeling urban trajectories and demonstrates how these methods are integrated with the five research axes.

Chapters 4 to 8 develop the five thematic research axes successively:

- **Chapter 4** addresses Axis 1: the urban growth model. It analyzes the spatial dynamics of Kisangani's expansion and highlights the observed urban growth pattern.
- **Chapter 5** deals with Axis 2: the transformation of green infrastructure. It highlights the processes of loss, fragmentation, and recomposition of green spaces, considering the contrasts along the urban-rural gradient.
- **Chapter 6** is devoted to Axis 3: forest fragmentation and edge effects. It examines the extent of forest fragmentation, the proportion of forests affected by edge effects, and the resulting ecological implications.
- **Chapter 7** develops Axis 4: urban heat islands (UHI). It explores urban thermal dynamics, contrasts with rural areas, and the influence of urban morphology, particularly building volume density, on land surface temperatures (LST).
- **Chapter 8** addresses Axis 5: prospective modeling of urban trajectories. Through geo-prospective approaches, it projects scenarios of urban spatial evolution and assesses their potential impacts on landscapes.

Chapter 9 offers a general discussion. It integrates and contextualizes the results across the five axes, highlighting their interrelationships and their contributions to understanding the city as a socio-ecosystem. This chapter also discusses the practical implications of the findings.

Finally, Chapter 10 presents the general conclusion. It summarizes the primary outcomes of the research, revisits the initial hypotheses and questions, identifies the study’s limitations, and proposes directions for future research and recommendations for sustainable urban planning.

Chapter 2

Theoretical and conceptual framework of the thesis

2.1. Urban expansion models and implications

Urban expansion is one of the most significant phenomena shaping contemporary territorial transformation. Its understanding relies on a series of theoretical models designed to explain the internal structure of cities, the logic of peripheral growth, and the effects of spatial sprawl. These models, developed in different contexts and at various periods, offer practical analytical frameworks for interpreting current urban dynamics, particularly in cities of the Global South, where urbanization processes are rapid and often weakly regulated (Seto et al., 2012).

2.1.1. Classical models of urban structure

The earliest explanatory models of the spatial organization of cities have their roots in spatial economics theories (Bailly, 1973). Von Thünen's model (1826) describes the concentric organization of agricultural land uses around a central town (Abrami et al., 2021; Bailly, 1973). The central contribution of Von Thünen's model lies in its explanation of the spatial distribution of land rent. According to this approach, the producer primarily seeks to optimize the economic return generated from their plot. This optimization is based on the rational use of land combined with transport costs required to deliver products to the market. The profit obtained thus corresponds to the difference between the selling price and the total costs associated with production and transport. Two main variables structure the model: on the one hand, transport cost, which depends on the type of product and the distance travelled; on the other hand, net profit per unit of surface area, which decreases as the distance from the market increases (Abrami et al., 2021). In a homogeneous and isotropic space, this logic generates a concentric organization: high-value crops with elevated transport costs are concentrated near the market town, while less profitable crops, less sensitive to transport costs, are located in more distant peripheral rings (Figure 2.1).

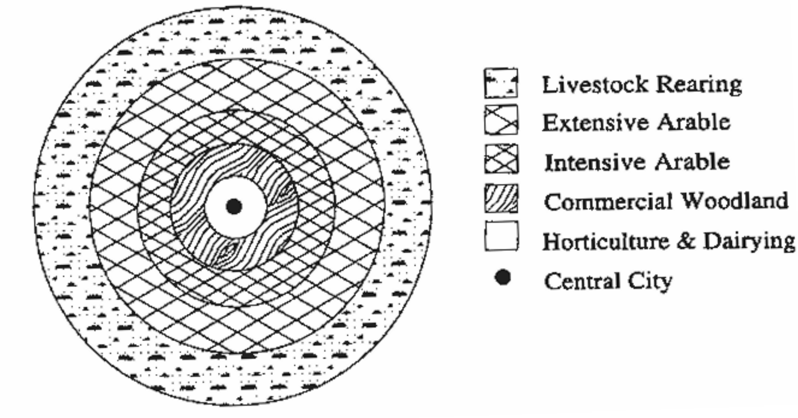


Figure 2.1. Von Thünen Model. The diagram shows a central city represented by a black dot, surrounded by several concentric zones. Each ring corresponds to a type of agricultural production, arranged according to land rent and transport costs (Abrami et al., 2021).

In continuity with this line of thought, Christaller's central place theory (1933) (King, 1985) extends this logic to the urban system. It posits that human settlements are hierarchically organized according to the provision of goods and services, producing a hexagonal spatial structure (King, 1985). Central place theory can thus be considered a spatial model of commercial exchanges. It establishes a hierarchical organization of cities based on the variety and rarity of the goods and services they offer. The centrality of an urban center depends on the extent of its area of influence, defined by the maximum distance people are willing to travel to access what it provides. Thus, the farther a city draws people from, the higher its rank in the urban hierarchy (King, 1985).

Building on Von Thünen and Christaller's theories, William Alonso (1960) (Bailly, 1973) proposes a formalization that transposes the logics of the agricultural land market to the urban land market. His model, known as the monocentric model, constitutes a key step in understanding the structure of modern cities. Reprising the idea of differential rent from Von Thünen, Alonso considers that the value of an urban plot depends directly on its location relative to the center, and thus on the advantages and disadvantages associated with transport costs and accessibility. Urban land operates as an auction market: actors, assuming perfect market knowledge, bid rents according to their ability to derive economic benefit from the location, and the plot goes to the highest bidder. Highly profitable, low-land-consuming activities, such as retail trade, concentrate in the city core, while more land-intensive activities, such as warehousing, move toward the periphery.

Applied to households, this model highlights an urban paradox: low-income households occupy the center despite high rents because they prioritize minimizing transport costs and consume little land. Wealthier households, on the other hand, seek larger plots and settle in suburban areas that are less expensive but more distant (Bailly, 1973). In this way, Alonso develops a genuine economic theory of the urban land market, in which the spatial distribution of inhabitants and activities results from the balance between land prices, accessibility, and space requirements, thereby extending and updating the intuitions of Von Thünen and Christaller.

The Chicago School, for its part, developed several empirical models to account for the internal organization of major American metropolises. Among them, the concentric zone model proposed by Burgess (1925) describes the city as a succession of rings arranged around the central business district (Bailly, 1973). Based on his observations, Burgess identifies certain regular patterns: immediately surrounding the center, where the main lines of communication converge, lies a zone of high residential density marked by immigrants and ethnic minorities. This transition zone is then surrounded by residential areas that become progressively more affluent as the distance from the periphery increases (Figure 2.2).

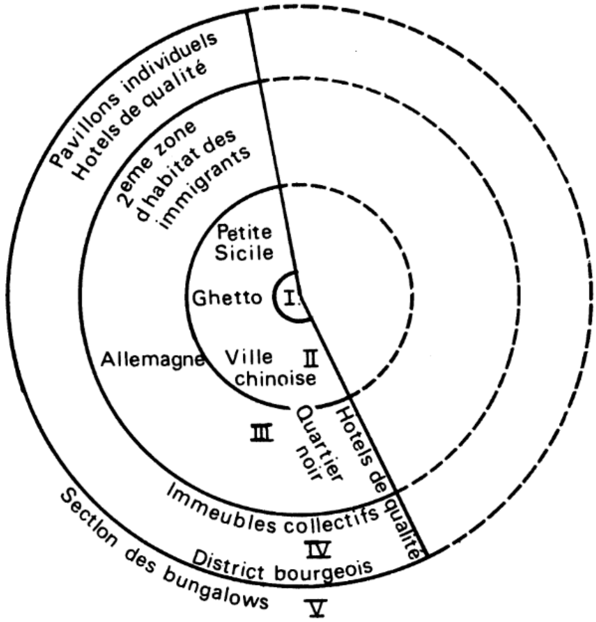


Figure 2.2. The Burgess Model in the Case of Chicago**.** I. Central Business District; II. Transition Zone; III. Workers Residential Zone; IV. Higher-Income Residential Zone; V. Commuter Zone. Source: M.E. Park and E.W. Burgess, *The City*, p. 51.(Bailly, 1973).

In response to the limitations of Burgess's concentric model, Homer Hoyt developed in the 1930s a sector-based approach to the city, drawing on analyses of Chicago and numerous American metropolitan areas (Bailly, 1973). He shows that transportation corridors are structuring elements of urban space, enhancing the accessibility of adjacent land and increasing its value. Urban expansion, therefore, does not occur in regular rings but in sectors that stretch along road and railway axes or in privileged locations, such as non-industrialized lakeshores or certain prestigious peripheral sites. Once formed, these sectors tend to extend outward in the same direction, whether they correspond to high-quality residential areas or industrial zones, the latter developing particularly along railway infrastructures and river corridors.

Following the sector model, Harris and Ullman developed in the 1940s the multiple nuclei theory, which explains that the modern city is no longer structured around a single center but around several poles connected by transport routes (Bailly, 1973). The number and role of these poles depend on the size and development of the city: the larger it becomes, the more secondary centers emerge and specialize. This idea accounts for the growth of American residential suburbs, where residential, commercial, and industrial spaces are organized around several distinct centers. The model also served as a basis for urban planning, notably for organizing shopping centers, facilities, and services at the neighborhood, municipal, or regional scale.

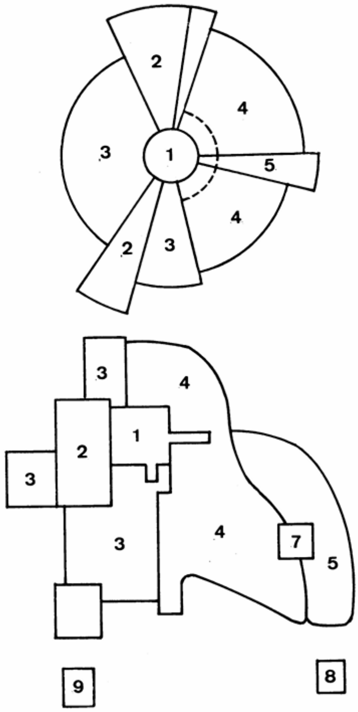


Figure 2.3. Sector theory (top) and multiple nuclei theory (bottom). The diagram shows: 1. Central business district; 2. Light manufacturing and warehousing; 3. Lower-class residential area; 4. Middle-class residential area; 5. Upper-class residential area; 6. Heavy manufacturing; 7. Residential suburb; 8. Industrial suburb; 9. Commuter zones. Adapted from C.D. Harris and E.L. Ullman, *The Nature of Cities*. (Bailly, 1973).

The classical models of spatial economics, from Von Thünen to Alonso, including Christaller, Burgess, Hoyt, and Harris & Ullman, laid the foundations for understanding the organization of cities and territories. Their relevance for tropical contexts lies in highlighting general principles, such as the relationship between accessibility, land rent, and land use. However, their application in these contexts remains limited, as these models are based mainly on the assumption of a homogeneous and isotropic space, that is, uniform and identical in all directions. In contrast, tropical cities are characterized by high spatial heterogeneity, with diverse environments, networks, land-use practices, and urban forms. This requires that these models be adapted or revisited to account for local realities.

2.1.2. Urban sprawl and contemporary models

Since the second half of the 20th century, rapid urbanization and motorization have given rise to urban sprawl (Jacobs, 1961; Rubiera-Morollon & Garrido-Yserte, 2020). This phenomenon is defined as a diffuse, low-density expansion that is highly land-consuming (European Environment Agency, 2006). This process is the corollary of urban de-densification (Figure 2.4), a phenomenon in which city growth occurs more through the increase of built-up area than through population growth (Angel et al., 2010).

This model is often associated with increased automobile dependency, landscape fragmentation, and the consumption of agricultural land (D'Amour et al., 2017). In response, alternative approaches, such as the compact city model, have emerged. These promote densification, functional mix, and the development of public transport, aiming to reduce the ecological footprint of urban expansion (Lehmann, 2016).

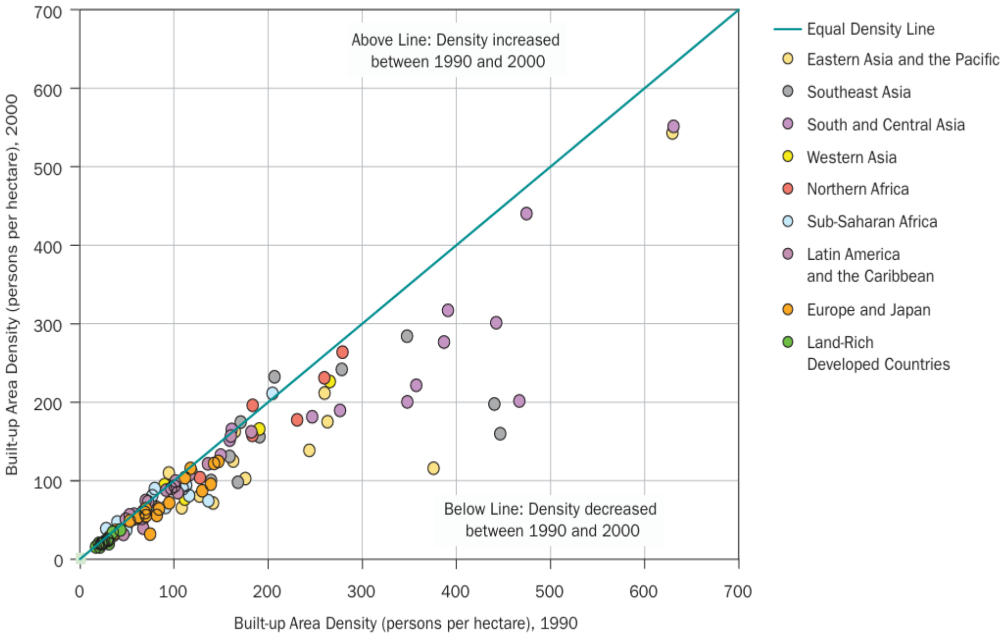
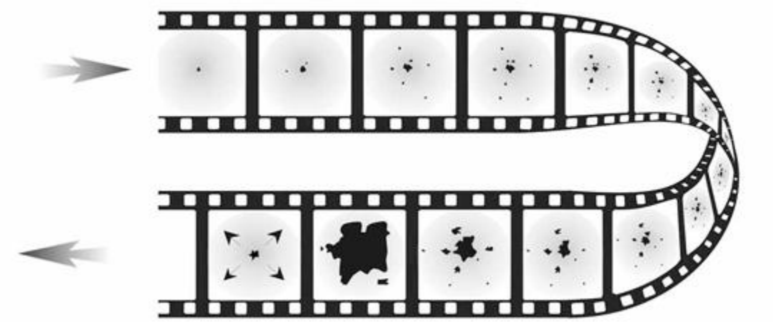


Figure 2.4. Decrease in density in the global sample of 120 Cities, 1990-2000. Statistical analysis of the worldwide sample of 120 cities between 1990 and 2000 shows that the average built-up area density declined significantly, from an average of 144 inhabitants per hectare in 1990 to 112 inhabitants per hectare in 2000 (Angel et al., 2010).

2.1.3. Dynamic models and morphological approaches

To better understand the temporal dynamics of urban expansion, recent models have focused on how cities develop and organize over time. Among these, the diffusion-coalescence theory (Figure 2.5) provides a two-phase explanatory framework: an initial phase of built-up area dispersion, followed by a phase of coalescence and progressive densification, accounting for the transformation of fragmented urban landscapes into continuous agglomerations (Dietzel et al., 2005). At the same time, fractal models offer a quantitative approach for measuring the complexity of urban forms. This method allows for the characterization of the spatial structure of cities by quantifying how urban forms occupy space at different scales (Batty & Longley, 1994). These authors emphasize that the fractal dimension is a key indicator of the complexity of urban form, reflecting both the regularity and heterogeneity of urban fabrics.



Metric	Diffusion	Coalescence
Contagion	decreasing	increasing
Amount of urban land	increasing	increasing
Number of urban patches	increasing	decreasing
Nearest-neighbor distance	increasing	decreasing
Mean patch area	decreasing	increasing
Patch perimeter-to-area ratio	increasing	decreasing

Figure 2.5. Illustration of the diffusion-coalescence model of urbanization and the evolution of landscape metrics**.** The figure depicts the two successive phases of urban development: a diffusion phase, characterized by the dispersion of urban patches and an increase in their number and average distance, followed by a coalescence phase, in which patches merge, leading to an increase in average patch area (Dietzel et al., 2005).

2.1.4. Social and environmental implications

Rapid and often unregulated urban expansion places considerable pressure on ecosystems and human societies (Seto et al., 2012). Projections indicate that between 1.8% and 2.4% of global agricultural land could be converted into urban areas by 2030, with marked regional disparities, particularly in Asia and Africa (D'Amour et al., 2017). This conversion directly threatens global food security, especially in regions where agriculture is already vulnerable.

A significant demographic dynamic accompanies this spatial trend: the global urban population, estimated at 4.4 billion in 2020, is expected to reach nearly 6.7 billion by 2050 (United Nations, 2018), while the total world population is projected to rise to approximately 9.7 billion over the same period (United Nations, 2022)(Figure 2.7). The increase in urban populations is driven mainly by migration from rural areas. These migratory flows, often referred to as rural exodus, result from a complex combination of push factors associated with origin areas and pull factors specific to urban spaces (Bogaert & Halleux, 2015). In rural areas, pressures on agricultural land constitute a central element of this process.

Population growth increases competition for land, limiting opportunities for younger generations. This dynamic highlights the close links between demographic transition and urban transition (Figure 2.6), two interrelated phenomena that mutually influence the reorganization of spaces (Bogaert & Halleux, 2015).

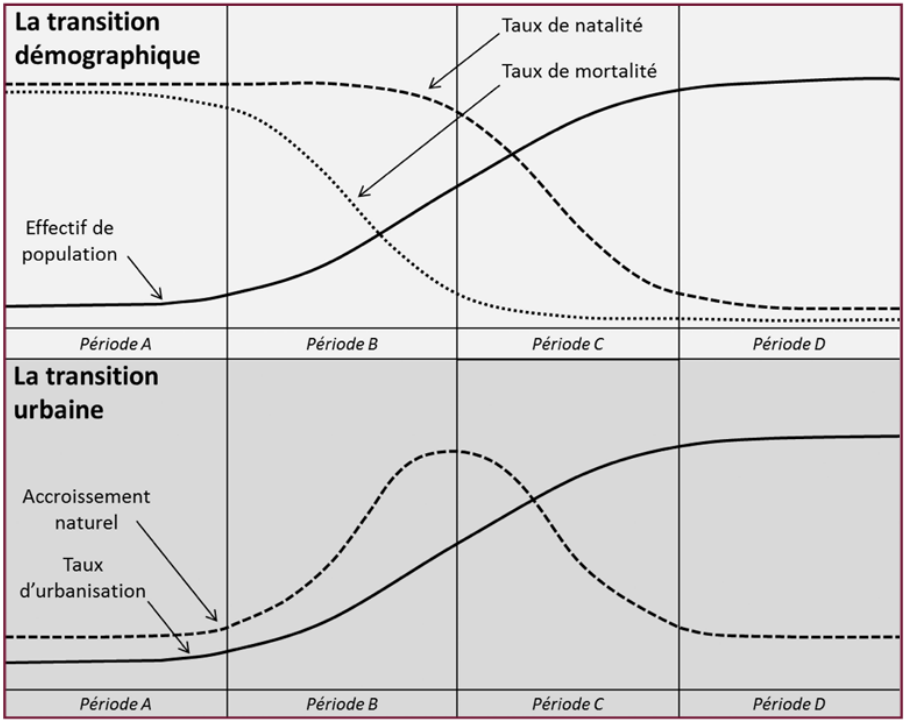


Figure 2.6. Stages of demographic and urban transition**.** Adapted from Le Goix (2005) (Bogaert & Halleux, 2015). In Period A, high birth and death rates limit population growth and keep urbanization low. Period B is characterized by a decline in mortality, resulting in a high natural increase and accelerated urbanization. In Period C, declining birth rates slow population growth, while urbanization continues rapidly. Finally, in Period D, both birth and death rates stabilize at low levels, population growth slows, and urbanization stabilizes.

This population dynamic, however, reveals a marked regional disparity. Since the 1950s, urban growth in less developed regions has accelerated significantly faster than in more developed areas (Figure 2.8). In 1950, the latter accounted for approximately 59% of the global urban population (446 million versus 305 million), but by 1970, they had been surpassed (680 million versus 674 million). Since then, the gap has widened, and projections indicate that nearly all future urban growth will occur in developing countries (United Nations, 2018).

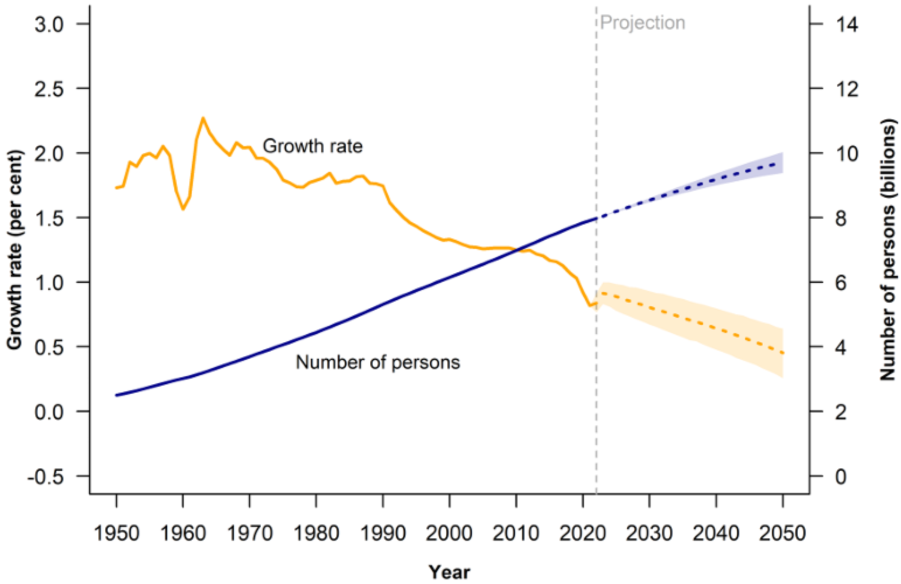


Figure 2.7. World Population and annual growth rate: estimates for 1950–2022 and medium scenario with 95% prediction intervals, 2022–2050 (United Nations, 2022).

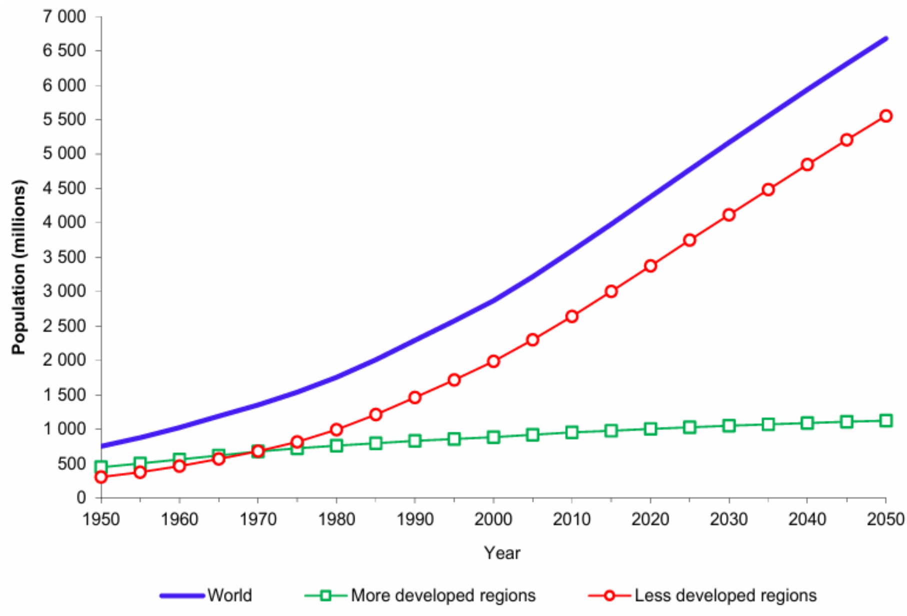


Figure 2.8. Estimates and projections of the global urban population, in more developed and less developed regions, 1950–2050 (United Nations, 2018).

In parallel, urbanized areas are experiencing accelerated expansion: at the global scale, urban sprawl could lead to the conversion of an additional 0.6 to 1.3 million km² by 2050, representing an increase of 78% to 171% compared to 2015 levels (Huang et al., 2019). In Africa, this dynamic is particularly pronounced: between 2000 and 2020, urban areas across the continent increased from 1.93×10^4 km² to 4.18×10^4 km², corresponding to a total expansion rate of 116.49% (Yin et al., 2021).

From an environmental perspective, the combination of high population growth and spatial expansion intensifies pressures on ecosystems. Urbanization fragments natural habitats, accelerating biodiversity loss, intensifying urban heat islands, altering biogeochemical cycles, and increasing air pollution, thereby affecting both ecosystem health and human populations (Grimm et al., 2008; Seto et al., 2012).

From a social perspective, unregulated urban growth exacerbates spatial segregation, inequalities in access to infrastructure, and the vulnerability of peripheral populations. The magnitude of the needs associated with accommodating billions of additional urban residents by 2050, combined with the rapid expansion of urbanized areas, underscores the crucial importance of urban form and infrastructure choices in the cities yet to be built. These choices will determine the capacity of urban systems either to mitigate or to amplify existing inequalities (Angel et al., 2010).

In sum, the convergence of demographic and spatial projections shows that urban expansion is not merely a matter of density or area, but a cumulative process that raises complex challenges. These challenges call for integrated, sustainable planning that reconciles urban development, ecosystem preservation, and social equity. Achieving this requires coordinated strategies that integrate land-use planning, environmental management, and participatory decision-making to guide urban growth in a balanced, sustainable manner.

2.2. Urban management challenges in Kisangani

2.2.1. Historical background and dynamics of Kisangani

The current city of Kisangani, initially known as Stanley-Falls and later Stanleyville, originated from the rivalry between Arab-Swahili groups and Europeans over control of the site (Tshonda et al., 2020). Its founding is associated with Henry Morton Stanley's second expedition in 1877, commissioned by King Leopold II to establish a series of stations along the Congo River. The explorer selected the site of the Wagenia Falls, located in the heart of the Enya territory, as a strategic point (Maindo, 2001).

By the early 19th century, Arab-Swahili traders and their Wangwana allies from Maniema, Kasongo, and Zanzibar had entered the region, introducing the Swahili language and Islam (Renault, 1987). Under the authority of Tippo Tip, these groups exerted a decisive influence on early contacts with Europeans and consolidated their presence through alliances with local populations (Bamanga, Komo, and Enya) (Renault, 1987).

The Falls station was officially established by Stanley on December 2, 1883, on Wana-Rusari Island, for both strategic and economic reasons: possibilities for expansion, fertile soils, and easy access to provisions from the Komo (Tshonda et al., 2020). However, tensions between the Congo Free State (CFS) and the Arab-Swahili led to a series of armed conflicts. In 1887, a compromise was reached by appointing Tippo Tip as governor (wali) of the Falls region, tasked with regulating trade and limiting the slave trade (Tshonda et al., 2020).

Alongside these political rivalries, a missionary presence was established in 1897 with the arrival of the priests of the Sacred Heart of Jesus, led by Gabriel Grison, who founded the Saint-Gabriel mission at Simi-Simi and opened the first school in 1898. Religious and educational structuring gradually consolidated, culminating in the erection of the Apostolic Vicariate of Stanleyville in 1908 (Tshonda et al., 2020).

During the first half of the 20th century, the settlement experienced gradual urbanization, marked by the creation of the Extra-Customary Center (ECC) in 1932 (Figure 2.9), which centralized the urban population. This development was accompanied by significant modern infrastructure, including radio broadcasting (1954; now RTNC), the Tshopo hydroelectric plant (1955), and the establishment of municipal status in 1958, which provided Stanleyville (Figure 2.11) with a formal administrative framework subdivided into communes with local councils.

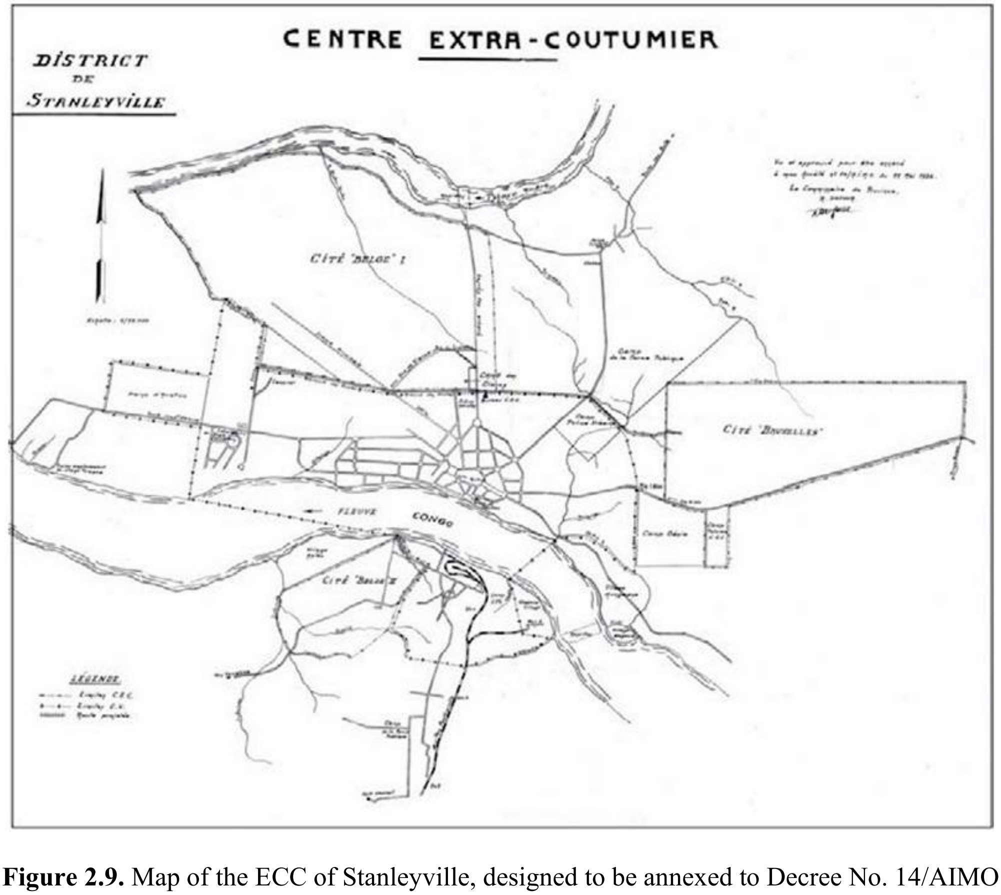


Figure 2.9. Map of the ECC of Stanleyville, designed to be annexed to Decree No. 14/AIMO of May 11, 1936, by Provincial Commissioner R. Dufour. Source: FABV/SHP-MRAC.

Figure 2.10. A white residential neighborhood in Stanleyville. Photo by C. Lamote, 1950s. Source: MRAC Tervuren.

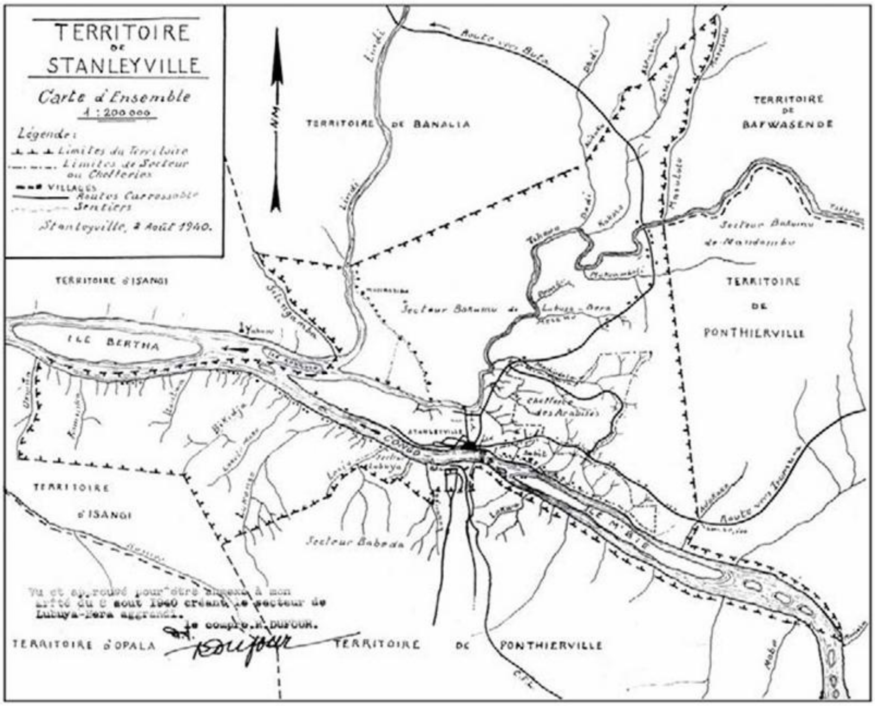


Figure 2.11. Map of the Stanleyville Territory, established on August 2, 1940. Source: FABV/SHP-MRAC.

The city status granted to Stanleyville in 1958 led to a redefinition of local administrative entities. The Extra-Customary Center (ECC), the chiefdom, and the sector were reorganized, resulting in a new institutional configuration. The Kisangani Chiefdom and the Lubuya-Bera sector were incorporated as annexed zones of the urban agglomeration, while the Kisangani Chiefdom gradually evolved into an urban commune. This transformation was consolidated on December 1, 1960, through a referendum validated by the provincial assembly and ratified by presidential decree. The Commune of Kisangani was thus officially established, marking a decisive step in the administrative autonomy of the city following independence (Tshonda et al., 2020).

Currently, Kisangani's territorial organization comprises six communes: Kabondo, Kisangani, Lubunga, Makiso, Mangobo, and Tshopo. Each commune encompasses several neighborhoods, reflecting the city's colonial history, internal migrations, and urbanization dynamics.

The evolution of Kisangani, from a colonial river post to a structured agglomeration, results from the interplay of colonial dynamics, Arab-Swahili influences, and missionary interventions, which shaped its social, religious, and administrative foundations.

2.2.2. Urban management challenges

Urban management in Kisangani faces several major challenges related to demographic, institutional, and environmental dynamics. The city has experienced rapid population growth (Figure 2.12) over the past three decades, increasing from approximately 400,000 inhabitants in the early 1990s to over two million in 2021 (INS, 2022). This exponential growth has contributed to unplanned urban expansion, the emergence of informal settlements, and significant pressure on urban infrastructure and services.

Beyond this demographic dynamic, persistent institutional weaknesses are evident. Despite the existence of urban planning documents prepared in 1978, 2008, and 2010 (UN-Habitat, 2015), their implementation remains limited. In this context, urbanization largely develops outside regulatory control (UN-Habitat, 2015), fostering the proliferation of anarchic constructions and the fragmentation of surrounding natural areas (Bamba et al., 2010).

Environmental constraints further exacerbate urban management challenges. Kisangani's location at the core of a dense hydrographic basin (between the Congo River and the Tshopo and Lindi Rivers) makes the city particularly vulnerable to flooding. Flood intensity is amplified by the occupation of flood-prone areas and the absence of functional drainage systems. In addition, ongoing deforestation and degradation of peri-urban ecosystems continue (Bamba et al., 2010; Bamba & Bogaert, 2010). The spatial expansion of the city and the heavy reliance of households on firewood and charcoal as primary energy sources exert considerable pressure on surrounding forests (Schure et al., 2013).

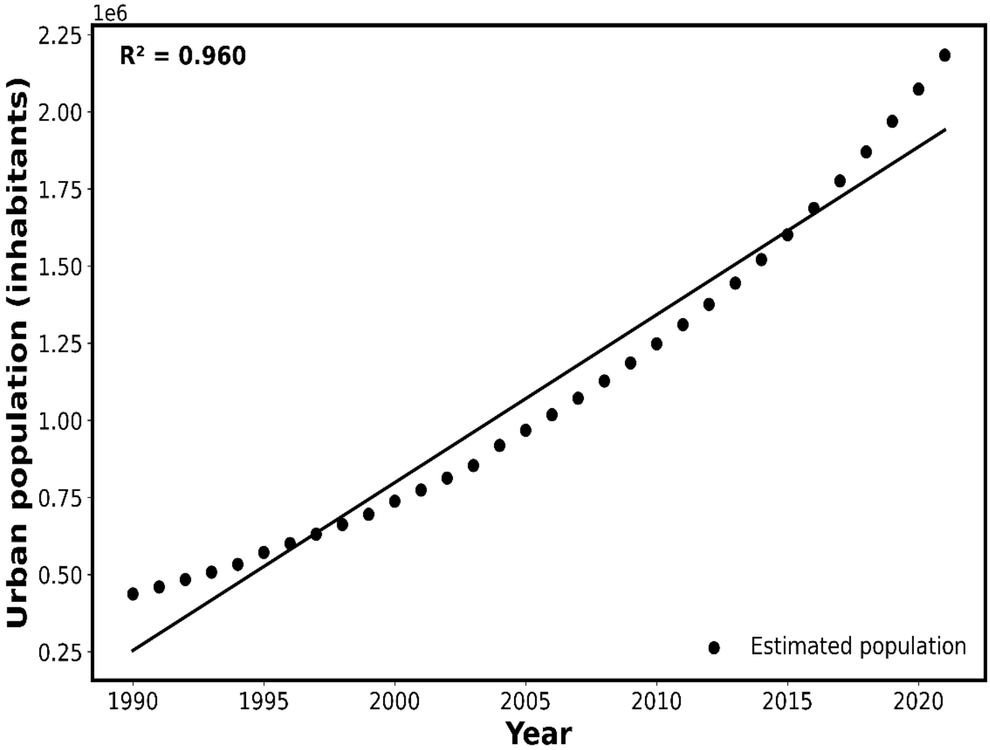


Figure 2.12. Population growth in Kisangani between 1990 and 2021. Data sourced from the National Institute of Statistics (INS, 2022).

These various challenges also reflect the limitations of urban governance in Kisangani. The city's institutional organization involves a plurality of actors: the provincial government, the communes, the deconcentrated state services, local chieftaincies, non-governmental organizations, and development partners. However, the absence of effective coordination among these actors fuels land-use conflicts and limits the effectiveness of land regulation. The resulting informal urbanization increases social and environmental vulnerabilities.

Thus, the challenges of urban management in Kisangani revolve around the complexity of demographic pressures, institutional weakness, and environmental constraints. Addressing these issues requires not only strengthening local planning and governance capacities but also better integrating natural and environmental risks into urban policies.

Consolidating effective urban governance, grounded in inclusion, transparency, and enhanced technical capacity, is essential to ensuring the sustainability of the city of Kisangani and reducing socio-spatial disparities amid rapid population growth.

2.3. Conceptual framework

2.3.1. Urban sprawl, peri-urbanization, urban dedensification

The analysis of contemporary spatial dynamics of cities frequently relies on three central concepts: urban sprawl, peri-urbanization, and urban dedensification. Although interrelated, these processes refer to distinct realities that manifest differently depending on the contextual and morphological, demographic, functional, energy-related, environmental, institutional, and even administrative or legal characteristics (André et al., 2014; Angel et al., 2005; Bogaert & Halleux, 2015).

Urban sprawl refers to the unplanned spatial expansion of cities, characterized by dispersed horizontal growth (Jacobs, 1961), low built-up density (Rubiera-Morollon & Garrido-Yserte, 2020), fragmented land uses (André et al., 2014) and high land consumption (Angel et al., 2005). This process often leads to increased reliance on motorized transport and results in high costs for infrastructure and service provision.

Peri-urbanization refers to the progressive integration of peripheral areas surrounding the city into the urban dynamic. These areas are distinguished by their hybrid character, combining rural functions (agriculture, dispersed housing, customary land tenure) with urban uses (subdivisions, infrastructure, service activities) (Bogaert & Halleux, 2015). A peri-urban area is a space where built-up structures are not dominant and is in the immediate vicinity of a high-density urban area. It maintains significant interactions with the neighboring urban system. These areas are characterized by hybridity, both in their physical organization and in the structuring of social relations, governance modes, and regulatory mechanisms (Bogaert & Halleux, 2015). In peri-urban contexts of the Global South, inadequate governance structures, combined with strong demographic growth and intense pressure on resources, lead to various types of conflicts and contribute to environmental degradation (Bogaert & Halleux, 2015; Sambieni, 2019).

Peri-urbanization thus results from the interaction between rural and urban societies, manifested at the interface of these two worlds (Bogaert et al., 2015). Rural societies often experience population outflows driven by demographic pressure and limited economic or social opportunities. Urban growth, in turn, is fuelled both by this influx of rural populations and by the endogenous dynamics of the urban population, marked by an imbalance between economic opportunities and the rapid increase in the number of inhabitants (Delcourt, 2007). This complex interaction between rural and urban areas represents a major challenge for urban and landscape management, as well as for ecological planning and territorial preservation (Figure 2.13).

In this perspective, McGee (1991) introduced the concept of *desakota*, derived from Malay-Indonesian (desa meaning village and kota meaning city), to describe areas in Southeast Asia where rural and urban functions are intensely intertwined. These spaces, generally located along corridors linking major metropolitan areas, are characterized by high population density, an intensive combination of agricultural, industrial, and service activities, and high mobility of inhabitants (Figure 2.14).

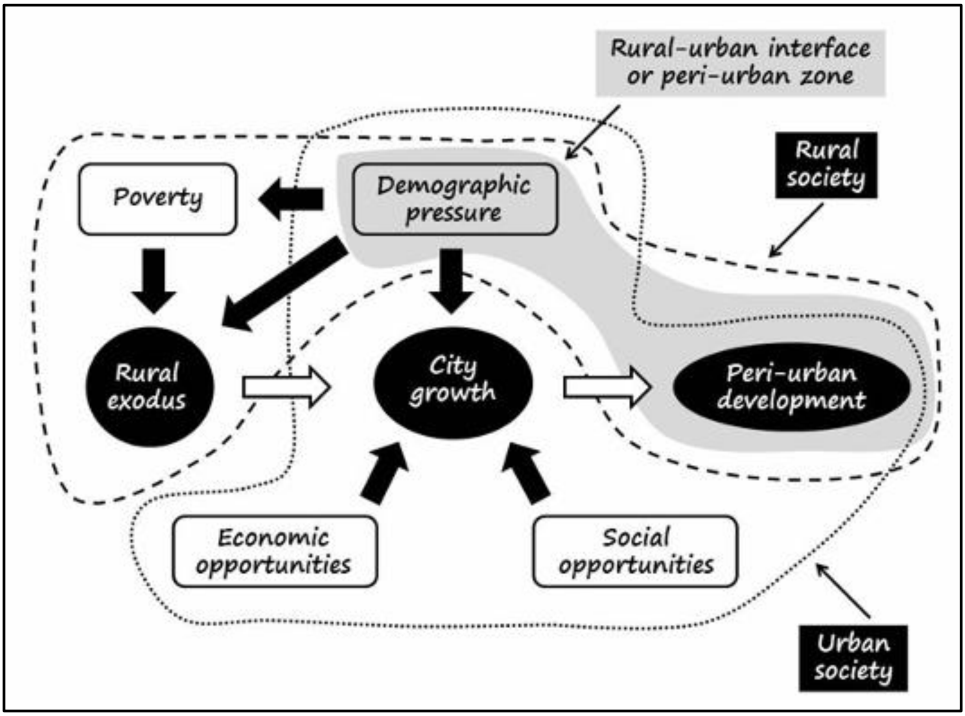


Figure 2.13. Conceptual approach to peri-urban development at the interface between rural and urban societies. From Bogaert et al.(2015).

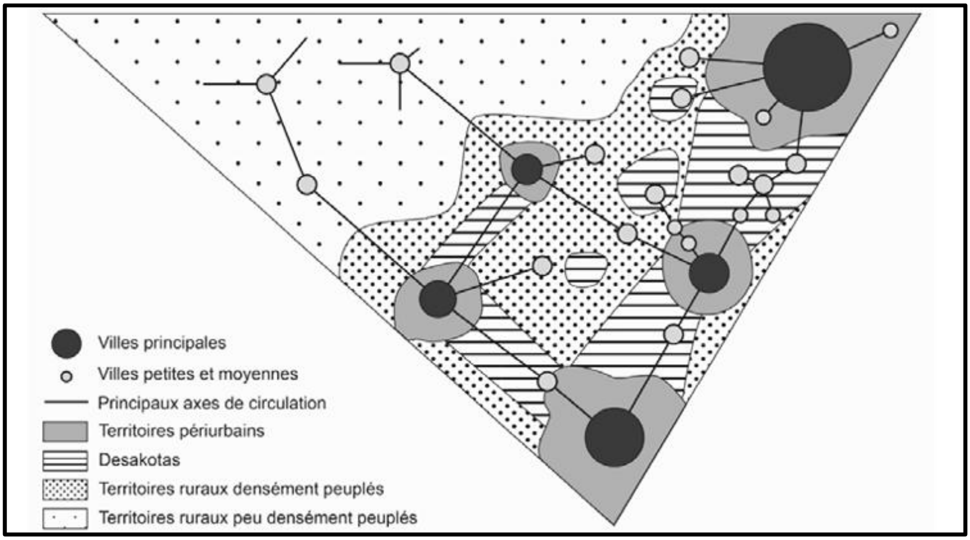


Figure 2.14. Representation of peri-urban and desakota territories (McGee, 1991), produced by Breuer and Halleux, ECOGEO-ULg (Halleux, 2015).

Urban dedensification, for its part, constitutes a phenomenon that has been less studied but is increasingly documented (Angel et al., 2010; Cortinovis et al., 2022). It refers to the decline in population density in certain urban sectors or entire cities (Angel et al., 2005; Angel et al., 2010), often driven by the combined effects of peripheral expansion (urban sprawl or peri-urbanization) and the functional transformation of central areas. In their study of 331 European cities between 2006 and 2018, Cortinovis et al. (2022) observed trends, including a period of de-densification from 2006 to 2012, followed by a phase of densification from 2012 to 2018. The authors emphasise that this shift results primarily from two factors: a more spatially distributed pattern of urban growth and a slowdown in residential land uptake following the 2008 global financial crisis (Cortinovis et al., 2022).

Thus, urban sprawl, peri-urbanisation, and urban dedensification emerge as interdependent dynamics that reflect the complexity of contemporary urban trajectories. These processes pose significant challenges for sustainability, governance, and planning, as they shape not only the spatial organization of cities but also the living conditions of urban populations and the resilience of territories under mounting demographic and ecological pressures.

2.3.2. Urban green infrastructure and ecosystem services

Urban green infrastructure (GI) refers to a strategic network of natural and semi-natural spaces (parks, urban forests, ecological corridors, wetlands, green roofs and walls, blue networks, etc.) which, when coherently planned and managed, provide a wide range of ecosystem services and socio-environmental benefits for cities and their inhabitants (Bixler et al., 2020; Zahoor et al., 2023). These services and benefits enhance the ability of cities to absorb and adapt to sudden or prolonged pressures while contributing to improved air and water quality, mitigation of urban heat islands, reduction of flood risks, enhancement of biodiversity, and provision of recreational and cultural spaces (Tzoulas et al., 2007; Wellmann et al., 2020).

Analyzing the benefits generated by green infrastructure requires a clear conceptual distinction between ecological functions and ecosystem services. Ecological functions refer to the natural processes that ensure ecosystem functioning and stability, whereas ecosystem services denote the tangible and intangible benefits that human societies derive from them (Fisher et al., 2009). Ecological functions can thus be considered intermediate products of ecosystem services (Boyd & Banzhaf, 2007). This distinction (Figure 2.15) is essential for the assessment and planning of green infrastructure, as it helps link underlying ecological processes to observable and valuable outcomes for urban populations (Haines-Young & Potschin, 2012; Rieke & Pauleit, 2014).

Based on the Millennium Ecosystem Assessment, these services can be categorized into four groups: provisioning services (food, water, materials), regulating services (climate, air and water quality, flood control), supporting services (pollination, soil formation, nutrient cycling), and cultural services (recreation, tourism, education, cultural and spiritual values) (MEA, 2005).

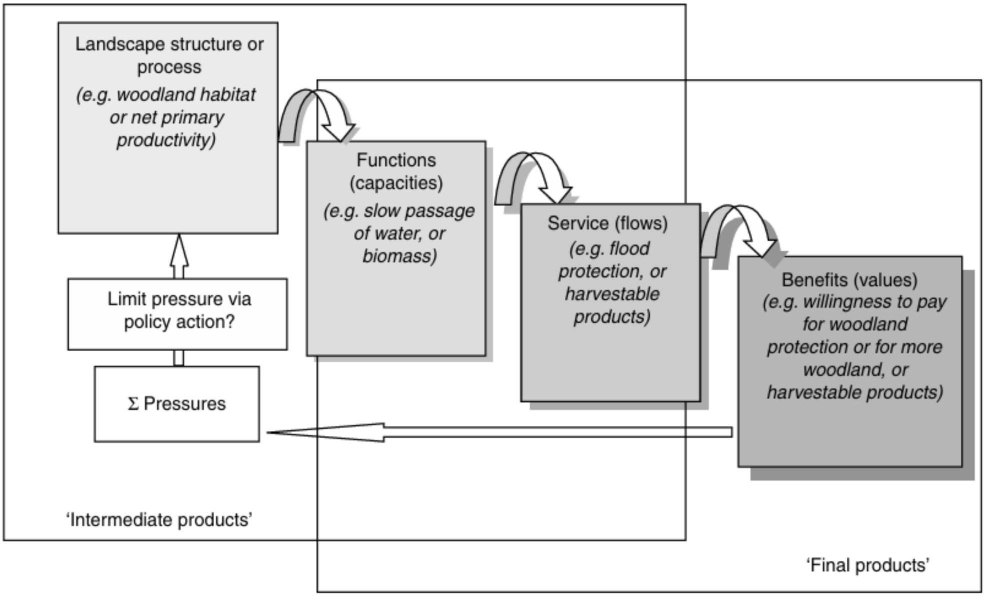


Figure 2.15. Conceptual model linking ecosystems, biodiversity, and ecosystem functions to human well-being. From Haines-Young & Potschin (2012).

This conceptual understanding is directly applied in two major strands of the green infrastructure literature. The first concerns urban ecosystem services: foundational studies highlight the capacity of green spaces to regulate local climate (mitigation of urban heat islands), filter air pollutants, manage stormwater, support biodiversity, and provide recreational and cultural services (Baggethun & David N, 2013; Bolund & Hunhammar, 1999; Tzoulas et al., 2007). These benefits can be directly mobilized in urban planning. These studies also emphasize the need to assess, map, and, when possible, quantify these services to inform planning and land-use decisions (Bolund & Hunhammar, 1999).

The second strand relates to spatial planning and urban resilience. The green infrastructure (GI) approach is presented as an integrated planning instrument aimed at enhancing the resilience of urban systems to climatic risks and anthropogenic pressures (flooding, heatwaves, biodiversity loss) (Ahern, 2011; Meerow & Newell, 2019). These authors link GI with "safe-to-fail" design principles and the socio-ecological perspective of the city. The objective is to articulate modularity (e.g., several small parks rather than a single large one), redundancy (multiple complementary solutions such as retention basins, green roofs, wetlands, etc.), and flexibility (adaptability to various uses or conditions) within green networks so they can absorb and contain disturbances while minimizing negative externalities.

Over the past decade, research has increasingly aligned the concept of green infrastructure with that of Nature-based Solutions (NbS) (Cohen-Shacham et al., 2016). This approach (Figure 2.16) goes beyond the simple provision of ecosystem services by emphasizing principles such as equity, adaptability, and integration into public policy. It highlights the need to design green interventions that can simultaneously address climatic, social, and economic challenges while relying on inclusive governance frameworks (Cohen-Shacham et al., 2016).

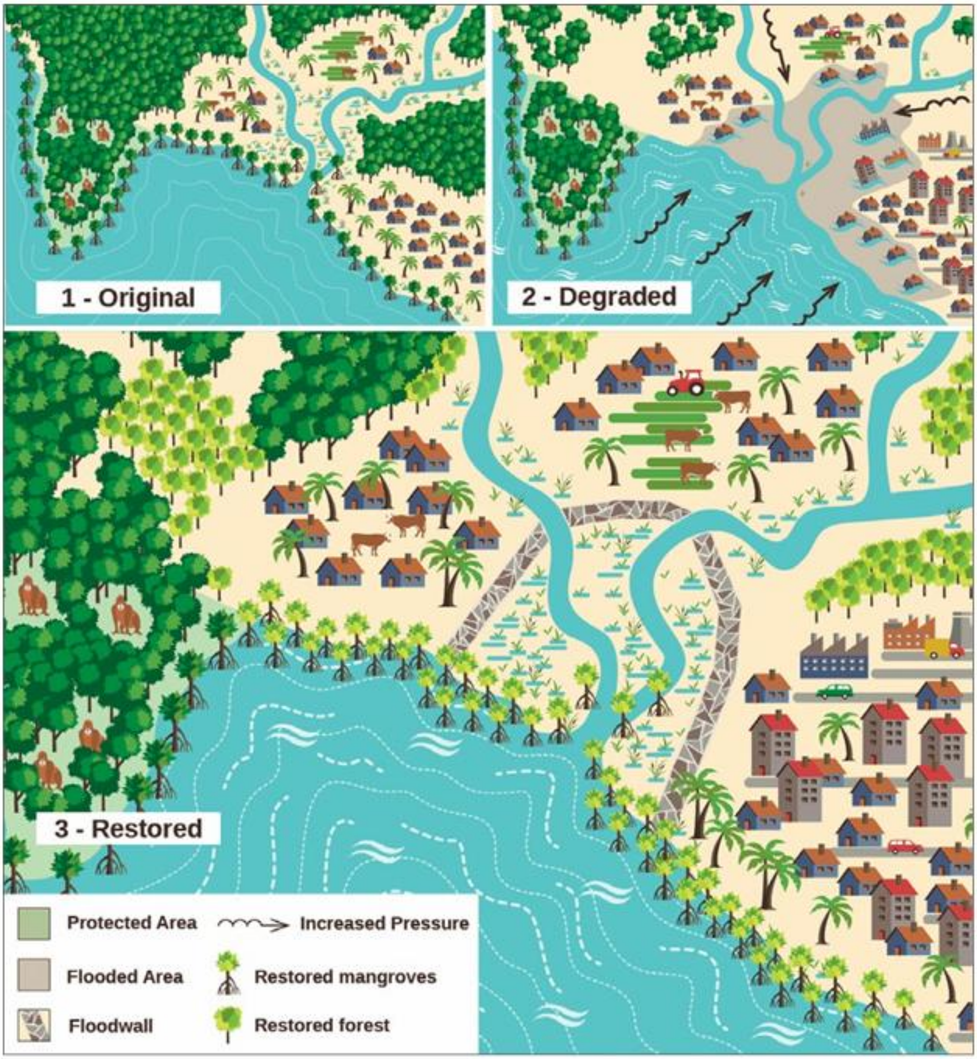


Figure 2.16. Scenario illustrating the integration of nature-based solutions, infrastructure development, and the preservation of protected areas. From Cohen-Shacham et al.(2016).

Contemporary theoretical debates are structured around several major issues: (i) multifunctionality, which concerns the capacity to combine and assess multiple services within the same spatial unit (e.g., recreational functions, hydrological regulation, and biodiversity habitat) (Ahern, 2011). This multifunctionality may be evaluated at different spatial scales (Figure 2.17); (ii) the distinction between quantity and quality (Haase et al., 2014), since vegetated surface area alone does not constitute a sufficient indicator without considering the structure, composition, connectivity, and accessibility of green spaces; (iii) issues of environmental justice (Wolch et al., 2014a), about the equitable distribution of benefits and the prevention of phenomena such as “green gentrification”; and (iv) the integration of green measures into dense urban fabrics, which raises challenges related to the deployment of adequate green infrastructures in contexts of high land-use pressure (Korkou et al., 2023; Rieke & Pauleit, 2014).

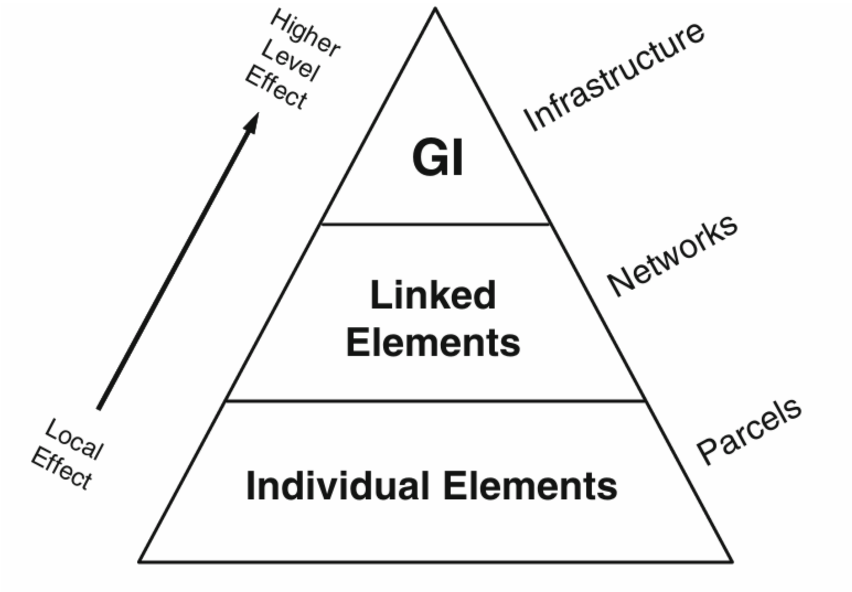


Figure 2.17. Scale of multifunctionality assessment. The pyramid illustrates the hierarchy of elements, ranging from isolated parcels to green infrastructure, and the associated spatial effects. From Davies & Roe (2006).

Recent syntheses emphasize that although the conceptual frameworks (ecosystem services, nature-based solutions, green infrastructure) are now largely consolidated, their implementation remains variable and is strongly conditioned by institutional contexts, available technical capacities, and accessible financial resources (Baggethun & David N, 2013; Cohen-Shacham et al., 2016).

2.3.3. Ecological integrity and vulnerability of ecosystems

Ecological integrity refers to the capacity of an ecosystem to sustain and maintain compositional, structural, and functional characteristics comparable to those of natural habitats in the same region, while preserving the evolutionary processes that ensure its dynamics and resilience (Parrish et al., 2003; Pickett et al., 2014; Unnasch et al., 2018). In forest ecosystems, this notion implies the persistence of representative species diversity, stable biogeochemical cycles, and trophic networks and regeneration dynamics that ensure resilience to disturbances (Ordóñez & Duinker, 2012). Integrity is therefore not a simple, static measure of ecological condition but an emergent property that reflects the coherence among biological composition, functional processes, and the spatial structure of the landscape (Parrish et al., 2003).

In forests located in peri-urban areas, the issue of ecological integrity arises with particular urgency due to the overlap of anthropogenic pressures and the increasing demand for ecosystem services. Mckinney (2002) demonstrated that urbanization tends to homogenize biological communities and increase the dominance of generalist and exotic species, leading to reduced resilience and functional degradation. Moreover, Mcdonald et al.(2009) highlight that protected areas near urban agglomerations are more prone to fragmentation, intensified recreational use, and diffuse pollution, thereby reducing their ability to maintain intact native biodiversity. These observations converge with those of Gentili et al. (2024) who emphasize the paradox of urban forests: while they constitute critical refuges for biodiversity, their integrity is systematically compromised by the intensity of pressures exerted by the urban matrix, rendering them ecologically vulnerable.

The ecological vulnerability of an ecosystem or landscape can thus be defined as its susceptibility to disturbances and its relative inability to tolerate stress across time and space (Williams & Kapustka, 2000). It relates to the risk of losses or damage that stressors may cause to the functioning or structure of the system (Adger, 2006; Fussel, 2007). Vulnerability analysis provides an appropriate method for identifying weaknesses within an ecosystem by focusing on the threats likely to affect it (Weißhuhn, 2018). In tropical landscapes, this approach enables the identification of fragile ecosystems and the definition of management strategies to preserve their ecological characteristics, resilience, and capacity to provide ecosystem services.

Consequently, the ecological integrity of urban and peri-urban forests should be assessed at multiple scales. At the local scale, emphasis should be placed on species composition and regenerative processes. At the landscape scale, by contrast, ecological connectivity and the continuity of corridors become essential to counteract isolation and edge effects (Bogaert et al., 1998; Harper et al., 2005). This multi-scale framework is indispensable for understanding the complexity of interactions between urban dynamics and the conservation of ecological integrity.

2.3.4. Geo-prospective: an integrated approach

Landscape transformations over the twentieth century, driven by increasing human pressures and natural hazards, have had significant impacts on the socio-economic, environmental, and ecological dimensions of territories (Barbault & Teyssèdre, 2005; Ramankutty et al., 2006). They have revealed the vulnerability of contemporary societies and the need for tools capable of analyzing the complexity of territorial dynamics. The emergence of the concepts of sustainability, resilience, and adaptation, as well as the need for informed guidelines, has led to renewed scientific approaches aimed at anticipating desirable or undesirable future trajectories and guiding present action (Godet, 1986).

The prospective, as an approach for medium- and long-term territorial planning, has significantly contributed to this awareness (Houet & Gourmelon, 2014). Territorial prospective (Delamarre, 2002) advances this objective by integrating the spatial dimension as a basis for locating and distributing phenomena. In this perspective, geo-prospective, considered as a specific form of prospective, results from the convergence of geography, modelling, and prospective (Houet & Gourmelon, 2014). It seeks to apprehend the territory in all its complexity (Figure 2.18) by enabling the identification and modelling of spatial interactions between natural dynamics and socio-economic dynamics, an aspect that traditional foresight cannot fully capture (Houet & Gourmelon, 2014). This approach provides a structured framework for guiding development toward sustainable and resilient models.

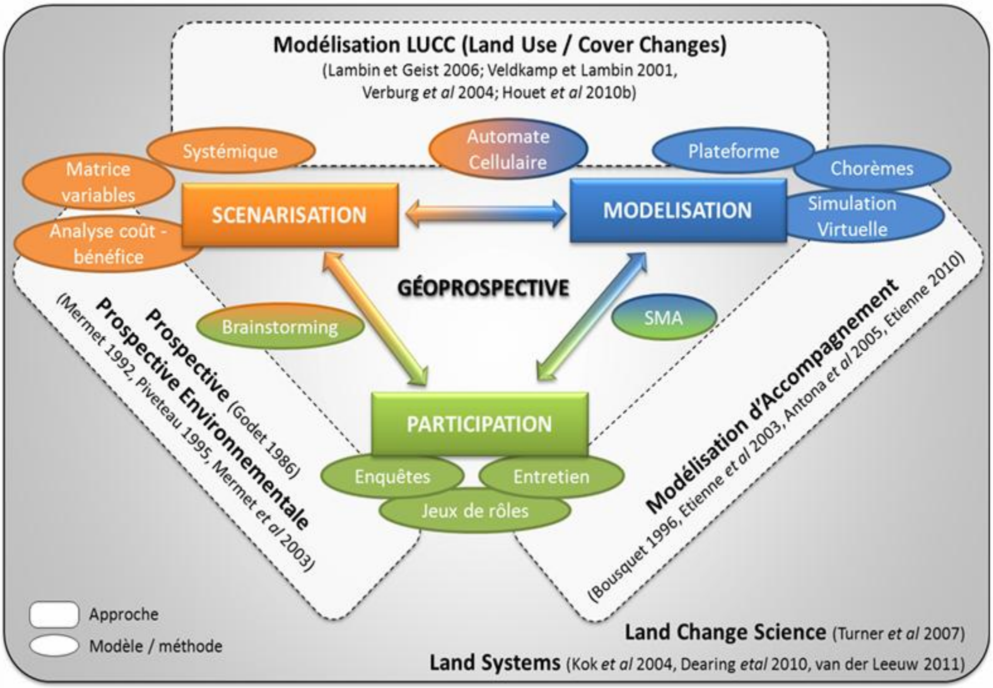


Figure 2.18. Geo-prospective: an integrated approach. From Houet & Gourmelon (2014).

To anticipate future trajectories, geo-prospective initially relies on qualitative approaches focused on scenario development and co-construction of knowledge. These methods include exploratory or normative scenarios, backcasting, and participatory foresight processes (Bibri & Krogstie, 2019; Dixon et al., 2018). Such approaches enable the definition of alternative or desirable visions for a territory and the engagement of local stakeholders to enhance the legitimacy and operational relevance of decisions.

Backcasting is used to examine future uncertainties, identify new opportunities, strengthen capacities, and improve decision-making processes. Its primary objective is to determine alternative pathways to achieve a desirable future (Bibri & Krogstie, 2019). Participatory foresight processes are defined as systematic and inclusive methods for gathering forward-looking information and constructing medium- and long-term visions, aimed at informing current decisions and mobilizing coordinated actions (European Union, 2011).

However, to complement the understanding of territorial dynamics, qualitative approaches must be integrated with quantitative methods. Quantitative approaches allow the simulation and projection of land-use and land-cover changes (LULCC) at multiple scales. Over the past decades, numerous models have been developed to simulate LULCC in support of territorial management and decision-making (Mas et al., 2011). These tools allow for the identification and assessment of LULCC: locating areas of change, measuring their magnitude, and identifying replaced land-use types. They also enable projections of future impacts using both predictive (Hubert-moy et al., 2006) and prospective approaches (Houet et al., 2008).

LULCC modeling and simulation approaches can be categorized into statistical models, machine learning (ML) models, and decision-tree-based models (Pontius et al., 2008; Shafizadeh-Moghadam et al., 2017). Statistical models, such as logistic regressions and Markov chains, are beneficial for identifying linear relationships between explanatory factors and observed changes. ML models, including Random Forests and artificial neural networks (ANNs), capture nonlinear relationships and manage a large number of complex explanatory variables (Feng & Tong, 2018; Kamusoko & Gamba, 2015).

Advances in deep learning, combined with its success in classifying and segmenting satellite imagery, have recently opened up new possibilities for detecting LULCC (Bhusal et al., 2024; He et al., 2019). Convolutional neural networks (CNNs), for example, can learn complex spatial interactions from data while preserving pixel-level details in predictions. These tools thus hold substantial potential for prospective modeling of territorial dynamics, providing finer and more reliable analyses and improving the accuracy of spatial projections. In urban and peri-urban environments, where dynamics are particularly complex and heterogeneous, deep learning represents a major asset for understanding, anticipating, and planning territorial evolution.

2.4. Disciplinary framework

The research conducted in this thesis lies at the interface of several scientific disciplines, whose complementarity enables a comprehensive understanding of contemporary urban and landscape dynamics. Four primary approaches were employed: (i) landscape ecology, providing conceptual and methodological frameworks to analyze relationships between spatial landscape pattern and ecological processes; (ii) remote sensing and geographic information systems (GIS), offering technical tools for the collection, processing, and analysis of spatial data; (iii) urban ecology, which examines interactions between ecological and social systems in urbanized environments, facilitating the understanding of complex urban dynamics; and (iv) chorology, emphasizing the finite nature of land as a resource requiring rational management.

2.4.1. Landscape ecology

a. Genesis and evolution of the discipline

Ecology, a term introduced in 1866 by Ernst Haeckel, refers to the science that analyzes the relationships between living organisms and their environment, combining the notions of habitat (oikos) and "science" (logos). Over time, the discipline expanded its scope: initially focused on the individual (autecology), then on species communities (synecology), it progressively incorporated complex systems (Figure 2.19) encompassing humans and their environment through the concept of the ecosystem (Burel & Baudry, 2003). This evolution reflects an ongoing increase in the complexity of study objects, from the organismal to the landscape scale, in line with scientific and technological advances.

Landscape ecology emerged in this context and is now recognized as a relatively young but scientifically mature discipline (Bogaert et al., 2015). The German geographer and biogeographer Carl Troll first used the term in the 1930s, employing aerial photography to link spatial pattern with ecological processes (Burel & Baudry, 2003; Troll, 1939). This interdisciplinary approach developed significantly after World War II in Europe, where it served as a practical tool for landscape architects, planners, and environmental managers (Naveh & Lieberman, 1994).

In the following decades, landscape ecology experienced significant theoretical development, particularly in North America. The work of Forman & Godron, (1986) contributed to the structuring of the discipline around the central pattern/process paradigm, which posits that the spatial pattern of landscapes influences ecological processes, and conversely, that ecological processes affect the spatial pattern of landscapes (Antrop, 2001; Burel & Baudry, 2003; Turner, 1989). These conceptual foundations, reinforced by increasingly advanced analytical methods, established landscape ecology as an autonomous and recognized field within ecology.

The establishment of the International Association for Landscape Ecology (IALE) has played a significant role in the dissemination and consolidation of both theoretical and applied approaches (Farina, 2000). Today, in the context of increasing anthropogenic pressures and growing resource demands, landscape ecology has become an essential scientific framework for understanding and modeling the interactions between natural dynamics and human activities (Bogaert et al., 2004).

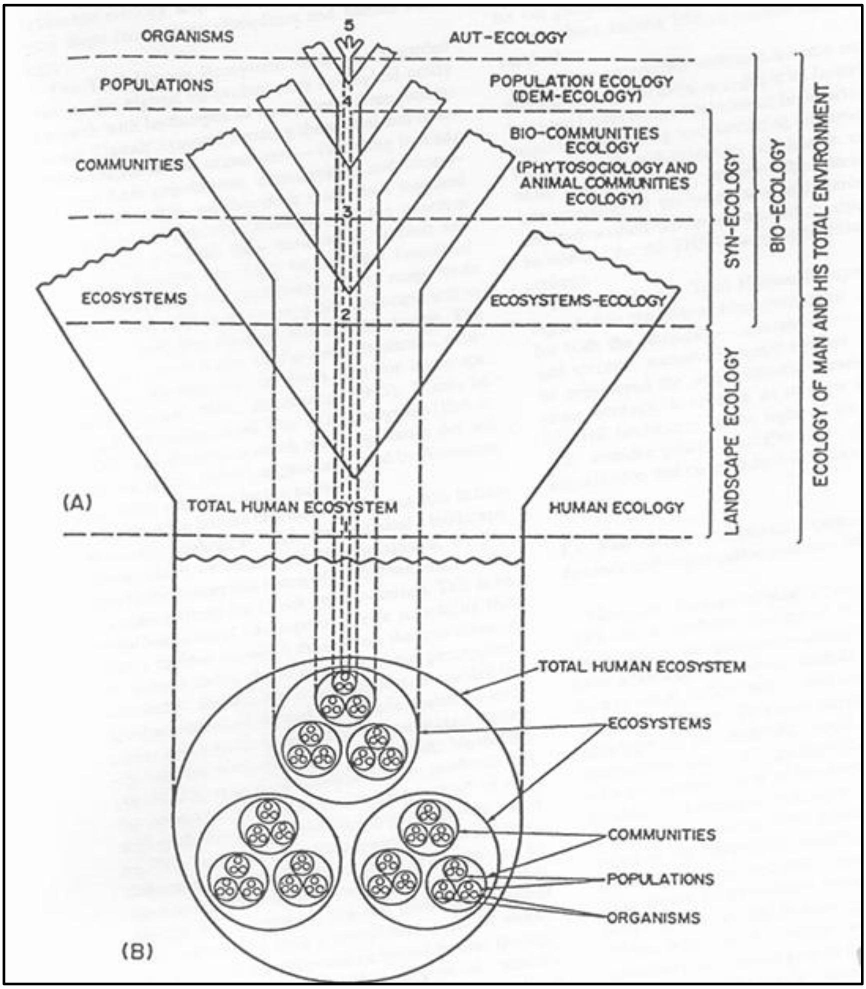


Figure 2.19. Hierarchy of ecological levels and integration within the human system. The main branches of ecology are shown on the right. It should be noted that landscape ecology considers humans as an integral component of their environment. This concept is illustrated in (A) as a horizontal cross-section and in (B) as a diagram showing the nesting of the different disciplines (Naveh & Lieberman, 1994).

b. Key concepts and landscape elements

Landscape is a central concept for understanding the relationships between humans and their environment (Burel & Baudry, 2003). Before being studied in ecology, it was explored in numerous disciplines such as painting, architecture, literature, and geography (Berdoulay & Philipps, 1985). Depending on the discipline, the landscape has been defined either as a territory shaped by interactions between nature and society, with some studies emphasizing description and others focusing on its formation and functioning (Fourneau et al., 1991).

Nowadays, the most widely recognized definition of landscape is that of the European Landscape Convention, adopted in France under Law No. 2005-1272 of 13 October 2005 (Conseil de l'Europe, 2000). It defines landscape as "an area, as understood and experienced by people, with its character shaped by natural and/or human forces and their interactions," highlighting the importance of perception and the interaction between physical and human factors.

Thus, landscapes correspond to relatively extensive areas ranging from a few hectares to several hundred square kilometers (Forman & Godron, 1986), with emphasis on human activities and the scale of human perception (Figure 2.20) (Burel & Baudry, 2003).

To analyze landscapes, Forman & Godron (1981) proposed a classification based on three main components: (i) patches: homogeneous units differentiated from their surrounding matrix by composition, structure, or appearance, varying in size, shape, and heterogeneity; (ii) corridors: linear structures that serve as conduits, filters, or barriers, often interconnected in a network; and (iii) the matrix: the dominant and extensive element that governs the overall functioning of the landscape (Figure 2.21). This framework forms the "patch-corridor-matrix" model, which enables the study of ecosystems based on the distribution, size, shape, number, and spatial organization of these elements (Bogaert & Mahamane, 2005; Burel & Baudry, 2003; Forman & Godron, 1981; Forman & Godron, 1986). The characteristics of patches, particularly their size and shape, significantly influence key ecological processes (Farina, 2000).

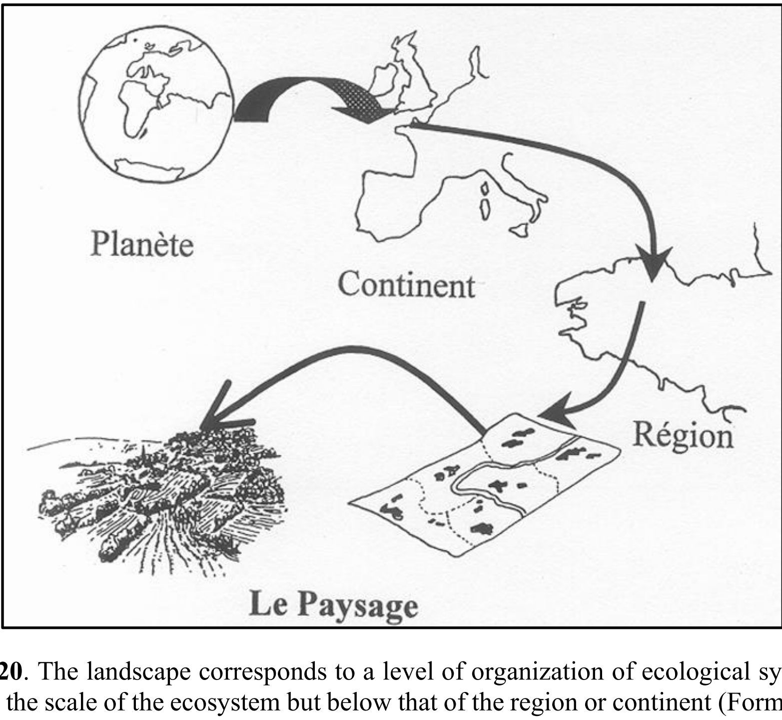


Figure 2.20. The landscape corresponds to a level of organization of ecological systems that lies above the scale of the ecosystem but below that of the region or continent (Forman, 1995).

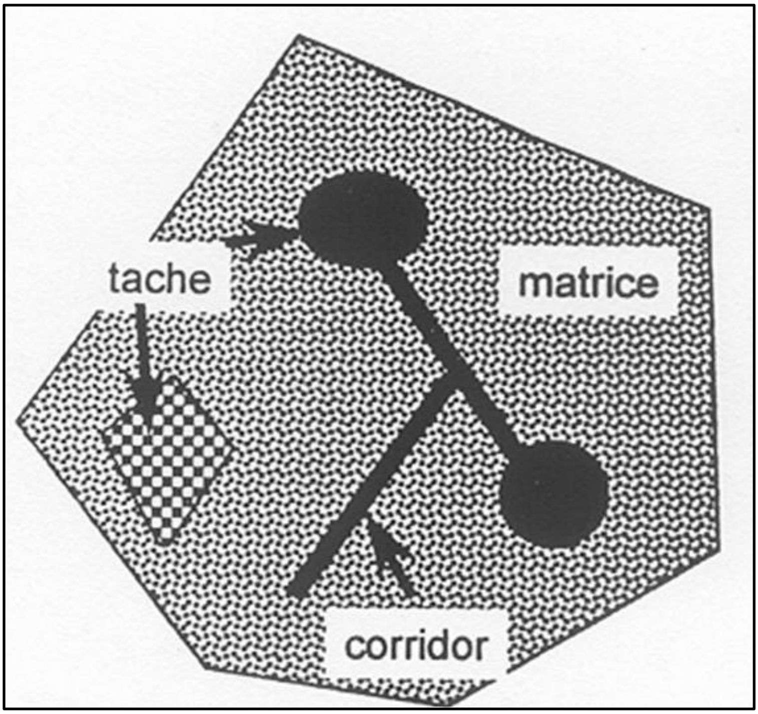


Figure 2.21. Illustration of the three fundamental components of landscapes according to Forman & Godron (1986): patches, corridors, and the matrix (Burel & Baudry, 2003).

c. Spatial pattern and the pattern/process paradigm

In landscape ecology, spatial pattern plays a central role, enabling a better understanding of ecological mechanisms within a landscape. Several authors emphasize that the spatial pattern of a landscape constitutes a key interpretative element for ecological processes (Bogaert & Mahamane, 2005; Wagner & Fortin, 2005). Any ecological system is generally analyzed through three fundamental components (Figure 2.22): composition (i.e., the nature and diversity of its constituent elements), configuration (their spatial arrangement and relative organization), and functioning (the flows and interactions that result from them). These dimensions cannot be considered in isolation, as a change in one inevitably affects the others (Bogaert & Mahamane, 2005; Noon & Dale, 2002).

Thus, a landscape is more than just the sum of its parts; it exhibits emergent properties that surpass those of its individual components. Combined analysis of landscape patterns and dynamics provides valuable insights into fundamental ecological processes. Conversely, studying these processes informs us about the underlying spatial organization (Bogaert et al., 2004). This idea, known as the pattern/process paradigm, is one of the founding principles of landscape ecology. It forms the basis of the discipline's definition as a science dedicated to studying ecological processes within their spatial context (Antrop, 2001; Bogaert & Mahamane, 2005).

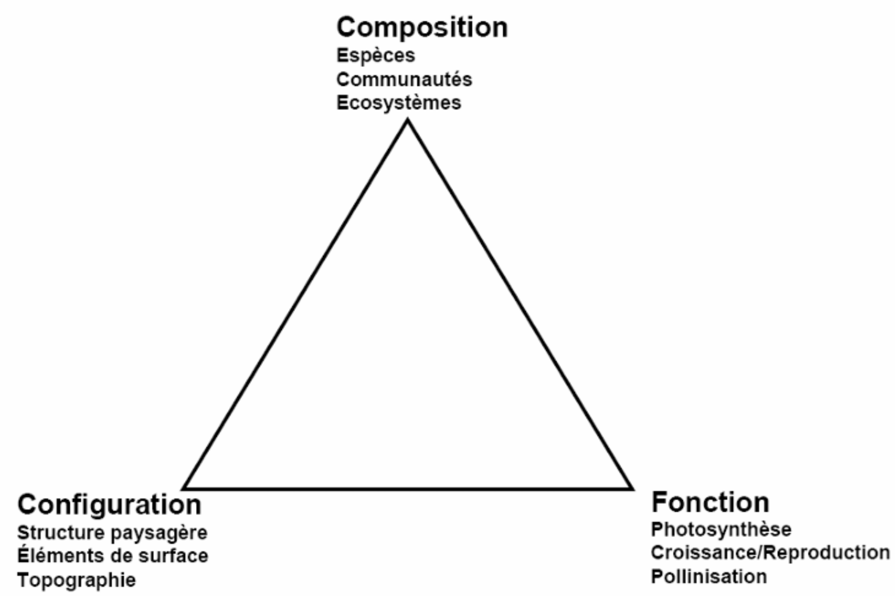


Figure 2.22. Triangular illustration of the reciprocal dependence among the three essential components of ecological systems. From Noon & Dale (2002).

Finally, the triangular relationship among composition, configuration, and process, in which each component depends on the others, constitutes the conceptual foundation of research in landscape ecology. This interconnection enables the comprehension of the complexity of ecological systems and the identification of the mechanisms shaping the structure and functioning of landscapes (Noon & Dale, 2002).

d. Analytical tools in landscape ecology

The study of the links between landscape configuration and ecological processes requires a quantitative measurement of observed structures. This necessity has led to the development of a range of indices known as landscape metrics (Farina, 2000). These indicators, by describing the size, shape, frequency, or dispersion of spatial units, allow the assessment of the impact of human activities on landscape morphology (Burel & Baudry, 2003). Since no single measure can fully capture the complexity of spatial organization, the combined use of multiple indices is generally required (Bogaert & Mahamane, 2005).

Two major categories of metrics are commonly distinguished: (i) composition metrics, which provide information on the diversity, proportion, or dominance of land-use classes, and (ii) configuration metrics, which reflect the geometry and spatial arrangement of patches (McGarigal & Marks, 1995). These should be distinguished from spatial statistics, which describe structure without identifying homogeneous patches, and from change metrics, which track the evolution of landscape mosaics over time. Change metrics enable the identification of transitions between different land-use states (Bogaert & Mahamane, 2005; Botequilha & Jack, 2002).

In this context, the transition matrix (Table 2.1) serves as a synthetic tool for representing conversions among land-use classes. Presented in tabular form, it indicates the areas that have changed or retained their status between two dates (T0 and T1) (Barima et al., 2009; Schlaepfer & Bütler, 2002). Cells along the diagonal represent stability, while off-diagonal cells indicate changes in land use.

Table 2.1. Simplified transition matrix. P = proportion of conversion from i to j. $P_{i,j}$ represents the area of a land-use category i at time T_1 converted to class j at time T_2. Category changes occur from row i to column j. The diagonal values $P_{1,1}$, $P_{2,2}$, $P_{3,3}$ represent land-use categories that remained unchanged over time. All other values correspond to categories that changed between the two-time steps.

	T_2			
T_1	**Category 1**	**Category 2**	**Category 3**	**Total T_1**
Category 1	**$P_{1,1}$**	$P_{1,2}$	$P_{1,3}$	$P_{1,1}$+...$P_{1,3}$
Category 2	$P_{2,1}$	**$P_{2,2}$**	$P_{2,3}$	$P_{2,1}$+...$P_{2,3}$
Category 3	$P_{3,1}$	$P_{3,2}$	**$P_{3,3}$**	$P_{3,1}$+...$P_{3,3}$
Total T_2	$P_{1,1}$ +...$P_{3,1}$	$P_{1,2}$+...$P_{3,2}$	$P_{1,3}$+...$P_{3,3}$	

Beyond mere transition measurement, landscape dynamics can also be addressed through the analysis of spatial transformation processes. These processes reflect compositional and configurational changes that affect the mosaic over time. In this context, Bogaert et al. (2004) proposed a synthetic classification of spatial transformation processes, illustrated by a decision tree that has become a reference in landscape ecology (Figure 2.23).

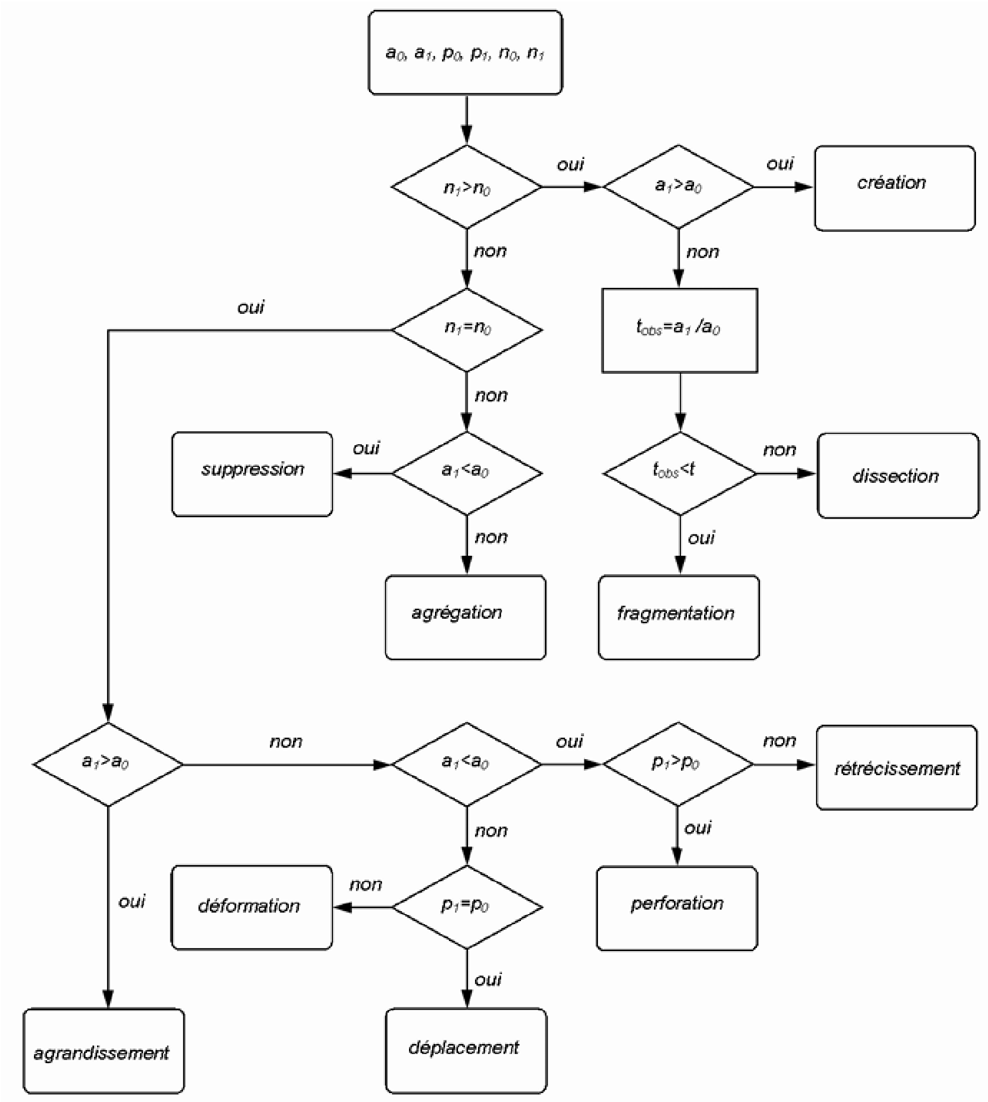


Figure 2.23. Identification of spatial transformation processes. First, it is necessary to assess the area, perimeter, and number of patches of the type under study, both before the transformation (a_0, p_0, n_0) and after it (a_1, p_1, n_1). Subsequently, changes in these three parameters allow characterization of the process and reflect the observed dynamics. The model prioritizes analyzing changes in patch number (the comparison between n_0 and n_1). Then, the variation in area (a_0 versus a_1) guides the identification of one of the possible processes, either directly or by considering the change in perimeter (p_0 versus p_1). Finally, to distinguish between fragmentation and dissection, a predefined threshold of area reduction (t) is applied (Bogaert et al., 2004).

e. Remote sensing and Geographic Information Systems (GIS) as tools for landscape analysis

Landscape ecology uses a variety of tools and methods to characterise the structure and dynamics of territories. Remote sensing and geographic information systems (GIS) play a central role among these. Remote sensing enables the acquisition of diverse data, particularly satellite imagery, at varying spatial and temporal resolutions. GIS, meanwhile, allows the management, integration, and analysis of this data, enhancing our understanding of spatial organisation and landscape evolution (Dale & Fortin, 2014).

The combined use of remote sensing and GIS is fully aligned with landscape research approaches that aim to link composition, configuration, and processes. Integrating these tools enables testing various hypotheses related to landscape dynamics, such as the influence of habitat connectivity on biodiversity and the effect of land-use degradation on ecological resilience. In this context, remote sensing provides quantifiable data and indicators (e.g., vegetation indices and spectral heterogeneity), while GIS enables their exploitation within an explicit spatial framework that integrates socio-economic and institutional variables. This methodological combination meets the requirements of landscape ecology, allowing the examination of spatial interactions and feedback loops among landscape elements (Millington et al., 2001).

Furthermore, in tropical contexts, often characterized by rapid urbanization, land-use and land-cover changes, land pressures, and fragmentation, the use of remote sensing and GIS is particularly relevant. These tools allow not only monitoring landscape evolution at large scales but also identifying transformation “hotspots,” assessing the ecological vulnerability of ecosystems, and guiding planning or territorial management strategies. The combined application of these tools thus contributes to a more comprehensive understanding of landscape trajectories. It constitutes an essential asset for in-depth analysis of rural-urban dynamics and territorial sustainability.

2.4.2. Urban ecology

a. Origins of an emerging discipline

Urban ecology is now recognized as a distinct and rapidly expanding branch of ecology. Initially influenced by the social sciences, it became firmly established from the 1970s onward. Several authors have traced this disciplinary evolution, each highlighting particular aspects (Alberti, 2008; McDonnell, 2011; Pickett et al., 2011). A notable feature of this history is the shift in perspective on cities. Once viewed solely as ecologically impoverished artificial environments, cities are now analyzed as fully functioning ecosystems, socio-economic systems, and, more broadly, complex socio-ecological systems. This conceptual shift has contributed to the substantial expansion of urban ecology over recent decades (Sambieni, 2019).

There are numerous definitions of urban ecology, reflecting diverse approaches (Alberti, 2008; McDonnell, 2011). A widely adopted and concise definition is that of Wu (2014), who suggests viewing urban ecology as the study of the spatial and temporal dynamics of cities, their ecological impacts, and their sustainability. This definition focuses on biodiversity, ecological processes, and ecosystem services.

b. Cities as a human and ecological system

In urban environments, human dynamics generally drive ecosystem evolution through demographic, economic, social, political, and technological dimensions. Some researchers have interpreted the city as a production system governed by market logics, others as a space of consumption (Hallsworth, 1978), and some as a combination of both (Alberti, 2008).

However, environmental factors also play a decisive role in the organization and evolution of urban systems. Climate, topography, hydrology, vegetation cover, and anthropogenically induced environmental degradation directly influence urban dynamics (Alberti, 2008). Furthermore, natural hazards such as hurricanes, floods, or landslides can cause significant disruptions to human systems. Yet most human systems models neglect these forces, often treating them as exogenous variables or constants (Alberti, 2008). Advances have been made, for example, through the incorporation of variables such as air pollution or noise into urban models (Wegener, 1995). Nonetheless, these efforts remain insufficient to fully capture ecological feedback and the complexity of interactions.

c. Gradients, patches, networks, and hierarchies

Modeling urban socio-ecological systems seeks to account for complex interactions between human and biophysical agents. Despite progress, accurately representing emergent behaviors observed in urban landscapes remains challenging. One key difficulty lies in the need to describe human and natural actors at a sufficiently fine scale to link spatial configurations to underlying processes (Portugali, 2000). Moreover, these interactions occur across multiple hierarchical levels simultaneously, complicating their representation in models (Alberti, 2008).

To understand these dynamics, various theoretical approaches are employed (Figure 2.24). Gradient analysis, used since Whittaker (1967), links environmental variation (altitude, moisture, salinity) to ecological functioning and examines the effects of human disturbance along an urban-rural continuum (Figure 2.25). Forman & Godron (1986) demonstrated that increasing human footprint intensity is associated with higher landscape patch densities, which become smaller and less connected. McDonnell & Pickett (1990) extended this approach by conceptualizing metropolitan areas as complex gradients of urban influence, highlighting ecological conditions specific to urbanized regions.

Patch dynamics theory provides a framework for analyzing spatial heterogeneity and the interactions and evolution of landscape fragments (Pickett & White, 1985). Network theory facilitates the understanding of the organization and stability of ecological interactions (Green & Sadedin, 2005). Finally, hierarchy theory considers urban systems as nested structures, where local and global dynamics interact to form complex systems (Wu, 1999).

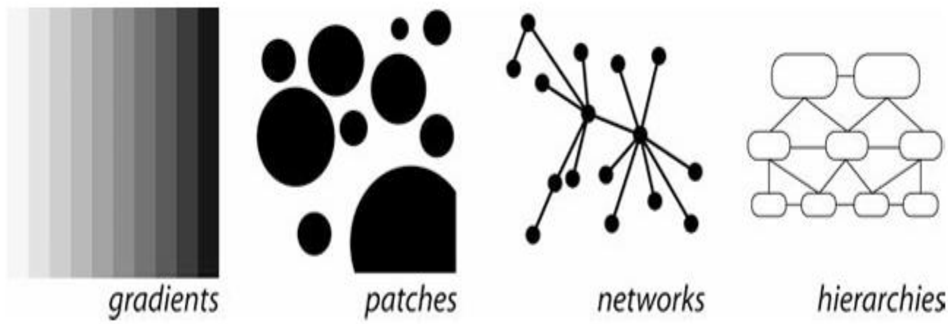


Figure 2.24. Approaches in urban ecology studies. From Alberti (2008).

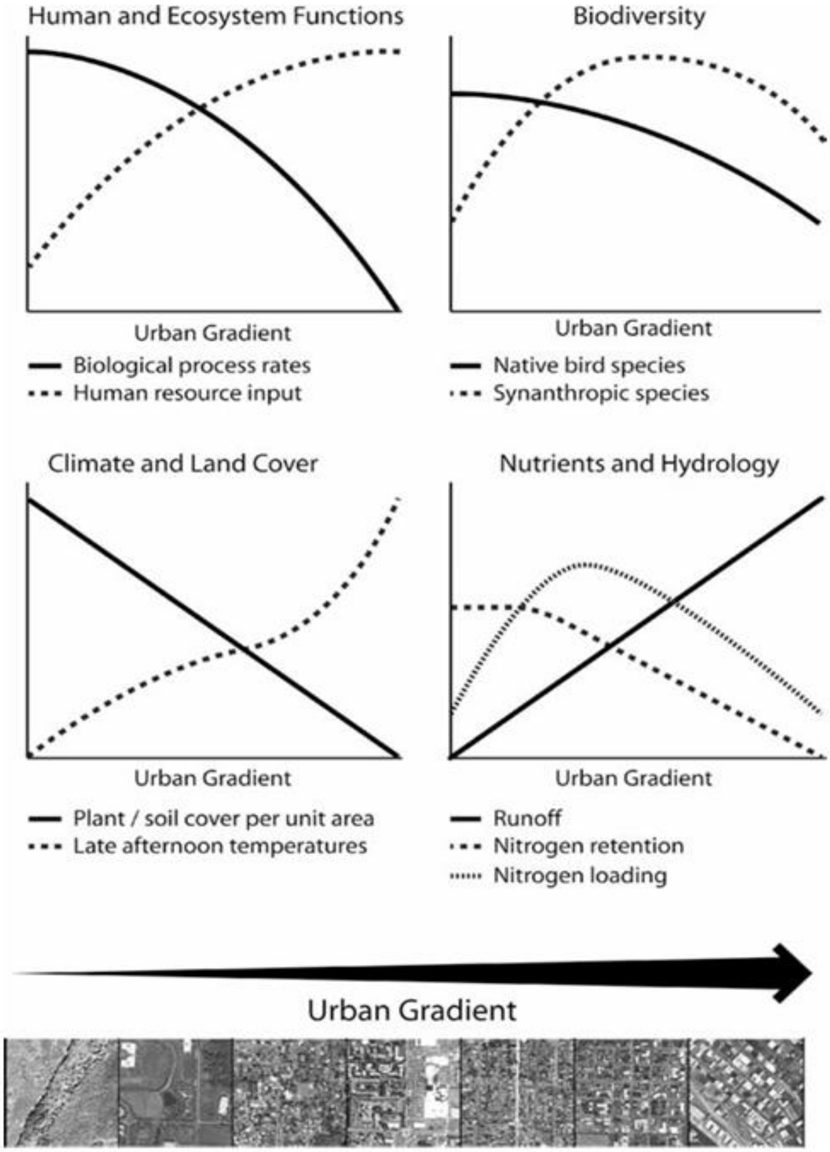


Figure 2.25. Urbanization gradient hypotheses: illustration of the assumed relationships between human and ecosystem functions along the urban-rural gradient. From Alberti (2008).

These complementary approaches constitute essential tools for analyzing urban landscapes, characterizing their responses to anthropogenic pressures, and understanding the multi-scale interactions between human societies and ecological processes.

d. Urban Heat Islands (UHI)

Urban areas generally exhibit higher average temperatures than surrounding rural zones, a phenomenon known as the Urban Heat Island (UHI) (Landsberg, 1981; Oke, 1987). First described in the 19th century by Luke Howard in London, UHI is now one of the most extensively studied phenomena in urban environments. Numerous studies conducted in Europe and North America have shown that cities experience not only a thermal excess but also marked atmospheric peculiarities, including reduced relative humidity and increased cloudiness and fog frequency (Bornstein, 1968; Oke, 1973). These changes are related both to air pollution, which alters condensation processes and the radiative balance, and to urban structure (Figure 2.26), which shapes airflow and energy fluxes. Urbanization directly affects surface properties, including heat storage and reflection, water retention, and wind regimes. These modifications profoundly influence energy and water balances, explaining the persistence and intensity of the Urban Heat Island phenomenon.

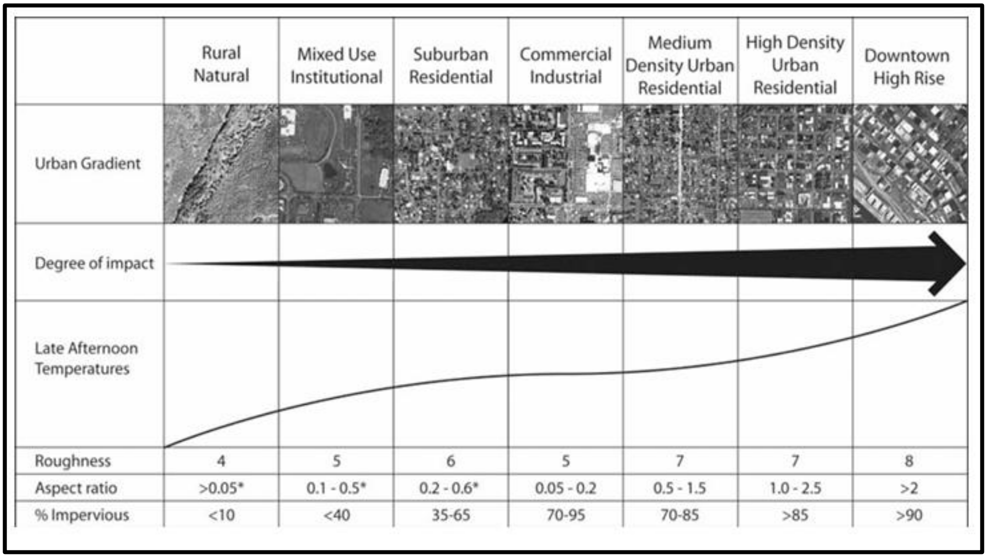


Figure 2.26. Relationship between the urban gradient and the Urban Heat Island. Drawing on the classification of urban environment zones proposed by Ellefsen (1991) and the urban climate zones defined by Oke (2004), observations show that late-afternoon temperatures increase progressively toward the city center (Oke, 1973). Urban roughness corresponds to the irregularity of surface relief created by buildings, trees, and other urban structures, and is measured according to the classification of Davenport et al.(2000). The aspect ratio is computed as the ratio of the mean height of structural elements (e.g., buildings or trees) to their mean spacing. In downtown street canyons, for example, this ratio reflects the relationship between building height and street width. This index affects airflow and thermal processes within the city, particularly shading and protection from solar radiation (Oke, 1987).

2.4.3. Choralogy

Choralogy is proposed as a new discipline that analyzes the structures, values, and functions of geographic spaces, whether rural, urban, or peri-urban, while explicitly considering their finite nature (Bogaert et al., 2015). The term derives from the Greek words χῶρα (land, space) and λόγος (study), thereby emphasising its grounding in the analysis of space as a finite resource. It is based on the recognition that land is a finite resource that must be used sustainably. The finite nature of land means that the values and services it provides, such as biomass production, erosion prevention, climate regulation, and cultural heritage, must be used sustainably. The objective of this emerging discipline is to provide a conceptual framework capable of bringing together researchers and practitioners under a shared vision of land management, to address the needs of humans, society, and nature (Bogaert et al., 2015). In its current phase of development, choralogy builds on established fields such as landscape ecology, urban planning, landscape architecture, and environmental management, drawing on their tools and concepts (Figure 2.27), while progressively developing its own methods and paradigms.

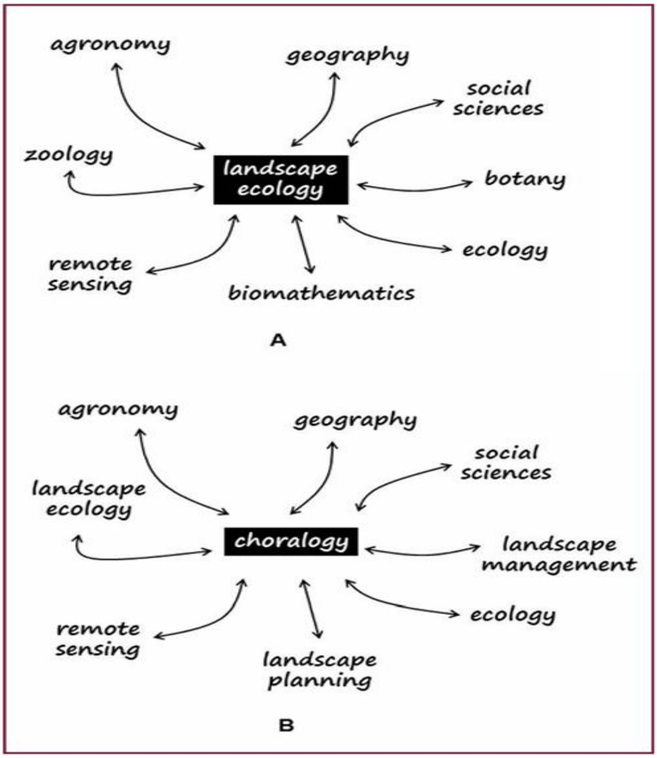


Figure 2.27. Landscape ecology and choralogy: initially regarded as an integration of other disciplines lacking their own conceptual foundations, landscape ecology has gradually established itself by developing its own theoretical frameworks. Today, as a mature discipline, it contributes to choralogy, understood as the science of geographic space as a finite resource. From Bogaert et al.(2015).

2.5. Epistemological positioning

This thesis adopts an epistemological stance grounded in the landscape ecology paradigm, conceived as an integrative framework for studying urbanization processes within socio-ecological systems. This approach is based on the premise that rural, urban, and environmental dynamics must be examined in an integrated manner, as they unfold within a single system characterized by continuous interactions (Wu, 2013). Landscape ecology provides a systemic framework for analyzing territorial dynamics, linking structural (spatial organization), functional (flows and ecological processes), and temporal (patterns of change) dimensions of landscapes (Burel & Baudry, 2003), and enabling the urbanization gradient to be interpreted as a continuum of interactions among rural, peri-urban, and urban environments.

Within this perspective, the thesis draws on insights from classical spatial-economic models, such as patterns of urban growth, land-use organization, and mechanisms of spatial expansion (Abrami et al., 2021; Wikman & Mohall, 2022), to inform the interpretation of urban dynamics in Kisangani. In parallel, the paradigm of sustainable urbanization introduces notions of resilience, territorial governance, and long-term sustainability (Zapata Campos et al., 2022), which are essential for understanding landscape trajectories under intense anthropogenic pressure. The articulation of these conceptual registers enables the construction of a coherent, integrative analytical framework for analyzing landscape dynamics in tropical urban environments.

Finally, this epistemological positioning aims to situate this thesis within a transdisciplinary approach, drawing on contributions from remote sensing and GIS, spatial planning, and environmental sciences. It considers that the study of landscape transformations must integrate ecological processes with the socio-economic dynamics that jointly shape the functioning of territorial systems. From this perspective, landscape ecology provides the conceptual foundation for analyzing the interactions among the spatial organization of Kisangani, its microclimate, the ecological integrity of surrounding forest ecosystems, and the future trajectories of urban development.

Chapter 3

Study area and methodological framework

3.1. Study area

The study area of this thesis focuses on Kisangani, the capital of Tshopo Province in the Democratic Republic of the Congo, located at the core of the Congo Basin. Most of the research was conducted within this urban agglomeration and its surrounding areas, where urban, agricultural, forest, and microclimatic dynamics intersect. However, for Axis 3, dedicated to forest fragmentation and edge effects, the analysis zone was expanded to include several protected areas within the wider Kisangani landscape, notably the Yangambi Biosphere Reserve and the Forest Reserves of Yoko, Masako, and Mbiye. Although all these forests hold protected status, their management regimes, land-use arrangements, and levels of human intervention differ markedly, providing a relevant framework for analyzing pressure gradients and their ecological implications.

The choice of Kisangani as a study area is justified by scientific, historical, and socio-economic considerations. Located at the core of the Congo Basin, Kisangani occupies a strategic position within the national urban system: it serves as a major commercial and logistical hub, connecting the eastern, western, and northern regions of the country, and is surrounded by extensive forested landscapes. This unique configuration makes it a natural laboratory for observing interactions between urban, agricultural, and forest dynamics. Moreover, its recent evolution reflects the broader socio-economic and political transformations experienced by the Democratic Republic of the Congo. Since the economic crisis of the 1980s-1990s, marked by the closure of numerous industrial enterprises (Tshonda, 1991), the population of Kisangani has increasingly relied on agricultural activities, leading to significant expansion of built-up areas and farmland in the periphery. Periods of armed instability during the 1990s further amplified this shift, triggering migration toward peri-urban and rural zones (Gabriel & Omer, 2022; Koluwa, 2020). From the 2000s onward, relative political stabilization and successive electoral cycles (2006, 2011) spurred demographic growth and heightened land-use pressure on surrounding forests. Finally, with more than two million inhabitants in 2021 (INS, 2022), Kisangani exemplifies contemporary challenges of unplanned urban growth in a tropical context. The combined urban, economic, and environmental dynamics confer substantial scientific relevance to this setting for analyzing landscape and microclimatic transformations and future urbanization trajectories.

3.1.1. Biophysical context

The study area, the city of Kisangani and its surroundings, is the administrative center of Tshopo Province in northeastern Democratic Republic of the Congo. Kisangani covers approximately 2,948 km² and comprises six municipalities: five located on the right bank of the Congo River (Makiso, Mangobo, Kabondo, Tshopo, and Kisangani) and one on the left bank (Lubunga). Geographically, the city lies near the equator (00°31′ N, 25°11′ E), with an altitudinal gradient ranging from 0 to 552 meters (Figure 3.1).

The climate is classified as humid equatorial (Af in the Köppen system), characterized by the absence of a pronounced dry season (Kottek et al., 2006;

Sabongo, 2015). Annual precipitation averages between 1,500 and 2,000 mm, with monthly rainfall consistently exceeding 60 mm (Assani et al., 2015; Sabongo, 2015). Temperatures range from 22 to 29 °C, with an annual mean of around 25 °C. These climatic conditions favor the development and persistence of dense humid forests, the region's dominant vegetation type.

The regional landscape is structured by an extensive hydrographic network dominated by the Congo River and its tributaries, notably the Tshopo and Lindi rivers. Forest cover includes both peri-urban forests under increasing pressure and forested landscapes in protected status. The latter includes the Masako Forest Reserve, with approximately 2,105 ha (Iyongo, 2013; Meniko et al., 2020), located roughly 15 km from the city; the insular Mbiye Forest Reserve (38 km²), situated within the Congo River; the Yoko Forest Reserve (70 km²), around 30 km southeast of Kisangani; and the Yangambi Biosphere Reserve (more than 270,000 ha), listed under UNESCO's MAB Programme and serving as a reference site for the study of tropical ecosystems (Toirambe et al., 2020).

The Kisangani region exhibits a vegetation mosaic typical of humid forest zones in the Congo Basin, marked by high floristic diversity and structural heterogeneity. In the Masako Forest Reserve, the vegetation reflects a well-defined successional trajectory. Once largely dominated by primary forests of *Gilbertiodendron dewevrei* (De Wild.) J. Léonard (Meniko et al., 2020), most of this formation has been progressively replaced by secondary forests of varying ages. The area now features a patchwork of young secondary forests, fallows at different stages of regeneration, and cultivated zones, illustrating increasing anthropogenic pressure and gradual forest fragmentation. In the Yoko Forest Reserve, the vegetation comprises varied phytosociological formations: the northern portion is dominated by mesophilic evergreen forests with *Brachystegia laurentii* (De Wild.), while the southern section consists of mixed semi-deciduous forests characterized by *Scorodophloeus zenkeri* (Ncutirakiza et al., 2020). This mixed structure reflects the transition between dense evergreen forests and semi-deciduous formations typical of the central Congo Basin. Further downstream, the Yangambi Biosphere Reserve displays an even more pronounced ecological gradient, representative of the Guineo-Congolian regional center of endemism (Toirambe et al., 2020). Vegetation there is organized into several principal formations: mature secondary forests rich in heliophilous species such as *Petersianthus macrocarpus*, *Pycnanthus angolensis*, and *Pentaclethra macrophylla*; dense semi-deciduous forests combining heliophilous and sciaphilous species (*Scorodophloeus zenkeri*, *Pericopsis elata*, *Cola griseiflora*, etc.); young secondary forests on village outskirts dominated by pioneer species such as *Trema orientalis* and *Myrianthus arboreus*; and dense evergreen forests of *Gilbertiodendron dewevrei* and *Brachystegia laurentii* occupying humid riverine slopes (Toirambe et al., 2020).

Overall, the Kisangani region illustrates a vegetational continuum in which relic primary forests, secondary forests at various successional stages, and agroforestry systems coexist depending on topographic context and the intensity of human disturbances, forming a complex landscape characteristic of forest-urban transition zones.

This ecological diversity is compounded by the region's geological and pedological complexity. Surface layers are dominated by loose materials such as sands, gravels, sandy loams, and clays, while deeper layers consist of harder rocks, including argillite, sandstone, and conglomerate. In the Kisangani area, argillite and sandstone are particularly visible on islands and riverbanks upstream of Bertha Island, forming the riverbed substrate, whereas downstream toward Yangambi, sandstone predominates and conglomerate appears only sporadically (Mukulia et al., 2024). Vertical profiles reveal accumulations of clays and silts in the upper layer, intermediate horizons rich in gravel, and deeper levels composed of sandstone and argillite (mudstone) (Mukulia et al., 2024). These features reflect the substrate's complexity and its influence on fluvial dynamics and landscape organization.

Thus, the Kisangani region offers a biophysical setting characterized by a mosaic of forest environments, a humid equatorial climate, and a dense hydrographic network. Superimposed on these components is a rapidly expanding urbanization process that progressively reshapes the landscape and intensifies transitions between built-up areas, agricultural zones, and forest ecosystems. This combination provides a particularly suitable context for analyzing ecological and landscape dynamics.

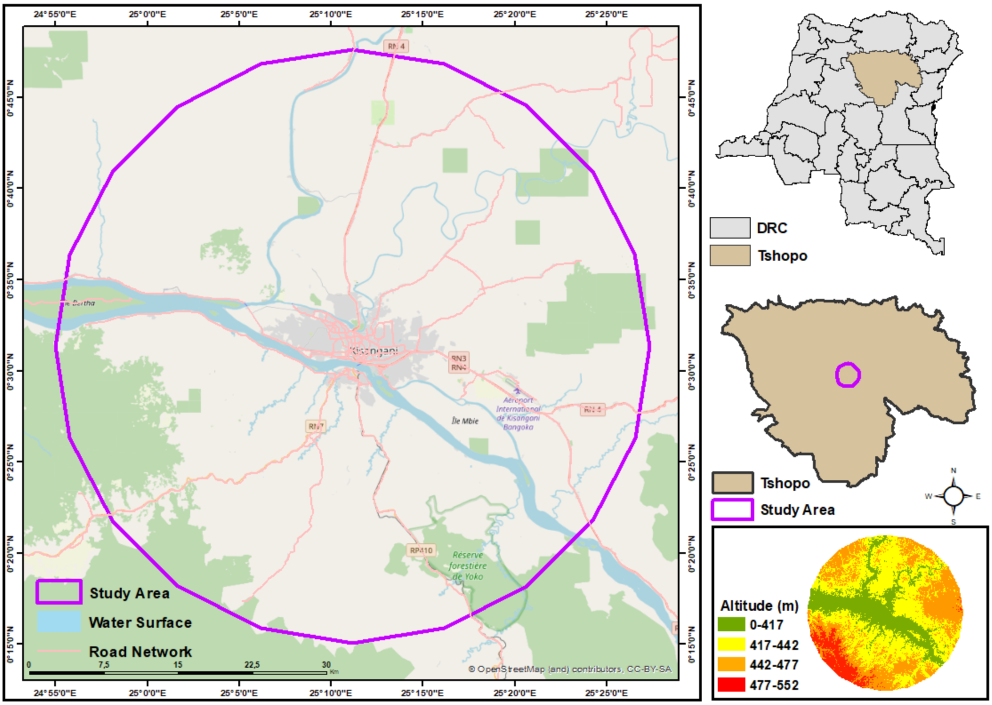


Figure 3.1. Geographical and spatial framework of the thesis in the Kisangani region. In terms of accessibility, the Kisangani region is connected by a road network composed mainly of national (RN) and provincial (RP) roads that serve the surrounding territories: RN4 to the east (Mambassa and Bunia) and to the north (Banalia, Buta), RP408 to the west (Yangambi–Isangi), and RP410 to the south (Ubundu).

3.1.2. Kisangani: historical and socio-economic trajectory

Kisangani, the capital of Tshopo Province, is strategically located in the northeastern Democratic Republic of the Congo and serves as the region's main political, administrative, and commercial center. Its historical role is linked to its location at the furthest navigable point of the Congo River and to its position as a crossroads connecting several land routes linking various administrative entities (Koluwa, 2020; Tshonda, 1991). The city is situated near the Wagenia Falls, known as Stanley Falls during the colonial period and as Boyoma, a local term meaning "falls" in the Enya language. The city itself was named Stanleyville until 1966, when it adopted its current name, Kisangani (Tshonda et al., 2020). Its location was occupied as early as the 19th century by Enya fishing clans, before the explorer Henry Morton Stanley established, in December 1883, a colonial post on Wana-Rusari Island, then called the "Stanley-Falls post" or simply "the Falls." The name "Kisangani" reflects this insular geography: in Swahili, "Kisanga" means "island" and the suffix "ni" means "inside," literally translating as "inside the island," in reference to the waterways surrounding the city: the Congo River to the south, the Tshopo River to the northwest, and the Masendula River to the east (Tshonda et al., 2020). This location shaped a city oriented toward trade and the redistribution of goods while serving as a hub for regional exchanges.

The population of Kisangani has experienced sustained growth since the colonial period. From approximately 105,000 inhabitants in 1959 (Bamba, 2010), it reached over 2.2 million in 2021 (INS, 2022). This demographic expansion is driven by both internal migrations, linked to commercial and administrative activities, and the rural exodus, as populations seek the services and opportunities provided by urban centers. This growth has contributed to the densification of urban areas, increased demand for infrastructure, and intensified interactions among urban, peri-urban, and rural areas.

Kisangani's economic history is characterized by periods of prosperity and slowdown. During the colonial period, the city developed as a transit point for agricultural and mineral products, supported by the construction of transportation infrastructure, including railways and waterways, which reinforced its role as a regional hub (Tshonda et al., 2020). After World War II, a brief industrial boom emerged, supported by the construction of hydroelectric plants and the establishment of small local industries. However, these dynamics were constrained by capital withdrawal, competition from other industrial cities, and successive economic crises, limiting the development of a truly autonomous industrial sector (Tshonda et al., 2020). Despite these constraints, Kisangani remained a major commercial center. The city serves as a redistribution hub for food and manufactured products, as well as for specific natural resources, such as logs from surrounding forests. Most economic activities rely on commerce and the informal sector, with intermediaries and transit operators playing a prominent role. The city has never developed an industrial sector capable of generating significant added value (Tshonda et al., 2020).

Armed conflicts and political crises over the past few decades have also shaped the city's socio-economic and demographic trajectory. Clashes between local and foreign factions, particularly between 1997 and 2002 (Koluwa, 2020), destroyed infrastructure, disrupted economic activities, and disrupted urban dynamics, while intensifying population movements. These events reinforced the city's role as an administrative and commercial center, while limiting industrial development and the accumulation of local wealth.

Nowadays, Kisangani remains a strategic center for the province and the region. Its role as a commercial and logistical platform, combined with strong demographic growth, directly influences population distribution and spatial planning. The city continues to be the main convergence point for economic and human flows, linking rural and forested areas to urban markets and ensuring the circulation of food, manufactured, and forest products. This historical and demographic trajectory illustrates the ongoing interaction among urbanization, population, and socio-economic development in the region.

3.1.3. Spatial planning and land management in Kisangani

The city of Kisangani, as the capital of Tshopo Province, exemplifies the dynamics of rapid urbanization observed in several major Congolese cities, such as Kinshasa, Mbuji-Mayi, Lubumbashi, and Kananga (Sambieni, 2019; UN-Habitat, 2015; Useni et al., 2018). This urban expansion, often characterized by chaotic development (UN-Habitat, 2015) exerts intense pressure on peripheral natural and agricultural areas, leading to increased informal land occupation. Provincial capital cities have nevertheless benefited from successive spatial planning and urban development plans: Kisangani has three historical plans (1978, 2008, 2010), while Kinshasa and Lubumbashi have three and two plans, respectively, since the 1960s (UN-Habitat, 2015). Although technical and financial partners supported these documents, their implementation remains very limited due to insufficient financial and institutional resources, which contributes to unplanned urbanization.

At the national level, the national spatial planning policy, enacted by Law No. 25/045 of 1 July 2025, constitutes the main strategic framework for organizing space and guiding the hierarchy of interventions nationwide. This policy emphasizes the need to better integrate spatial planning into provincial and local government teams, a still nascent sector often attached to public works, urban planning, housing, or land affairs (MAT, 2025). In forested provinces, decrees are gradually adopted to formalize planning tools and coordination frameworks for integrated REDD+ projects, but provincial-central coordination remains limited, and spatial planning administrations remain weakly equipped in material, financial, and human resources (MAT, 2025).

Since 2020, Tshopo Province has developed a provincial spatial planning framework, realized by Tropenbos DRC and commissioned by the United Nations Development Programme (UNDP) under the Integrated Eastern REDD+ Program (PIREDD-O). This provincial framework serves as the main instrument for organizing and structuring land use. However, the province faces major challenges related to land tenure security, directly affecting the effectiveness of spatial planning. In Tshopo, although land and subsoil belong to the State, two land tenure systems coexist: the concession system, mainly in Kisangani's urban center and for large agricultural, mining, or forestry operations, and state-owned land governed by customary rules in rural areas (Monga Ngonga et al., 2020). In the latter case, land allocation relies on customary practices, while the State officially recognizes only titles issued by cadastral services. This situation results in low land security, encourages conflicts, land grabbing, and overlapping titles among mining, forestry, and agricultural uses, thereby limiting investment and agricultural production (Monga Ngonga et al., 2020). It highlights the need for integrated planning and effective coordination of different land uses. The provincial framework, proposed since 2020, provides a basis for guiding urban expansion and promoting integrated and sustainable planning, helping reduce land overlaps and secure land use.

3.2. Methodological framework

3.2.1. Data sources

All research carried out in this thesis is based on a combination of geospatial and field data, integrating direct observations, multi-source satellite imagery, and socio-demographic information. These data enabled a coherent spatio-temporal analysis of landscape and urban dynamics in the Kisangani region.

a. Geospatial data

The analysis of urbanization dynamics and landscape transformations in the Kisangani region relied on a consistent set of multi-source satellite data selected for temporal and spatial complementarity. These data, spanning nearly four decades, enabled an integrated analysis of interactions among urbanization dynamics, green space patterns and evolution, heat island variations, and their impacts on the ecological integrity of surrounding forest ecosystems.

The characterization of urban expansion and the verification of the hypothesis regarding urban dedensification (Axis 1 of the thesis) relied on a combination of SPOT and Sentinel-2 imagery. This methodological choice ensures both temporal continuity and spatial coherence: SPOT imagery provides archival coverage to trace historical dynamics, while recent, freely accessible Sentinel-2 data regularly update the status of urbanized areas. Both sensors offer comparable spectral bands, particularly in the visible and near-infrared ranges, and similar spatial resolutions, facilitating harmonized analyses and fine detection within the urbanization gradient.

The assessment of green infrastructure spatial patterns along the urbanization gradient (Axis 2) was based on Landsat time series (TM, ETM+, and OLI/TIRS) from 1986 to 2021 at 30 m spatial resolution. Scenes with cloud cover below 10% allowed analysis of green infrastructure evolution over 35 years at five-year intervals, identifying transformations within the urban areas. Similarly, the analysis of forest ecosystem ecological integrity in the Kisangani region (Axis 3) used the same Landsat series for 1986, 1991, 1996, 2001, 2006, 2011, 2016, 2021, and 2024 to track edge and fragmentation effects over 38 years.

Urban heat island analysis (Axis 4) used distinct MODIS products via Google Earth Engine (GEE). Land Surface Temperature (LST) analyses employed the MOD11A2 V6.1 product from MODIS/Terra at 1 km resolution with 8-day frequency. Vegetation density was assessed using MOD13A2 (MODIS/Terra), providing the Normalized Difference Vegetation Index (NDVI) at 1 km resolution every 16 days. These datasets enabled the examination of fluctuations in vegetation density and their role in urban thermal regulation.

Global Human Settlement Layer (GHSL) data from the Joint Research Center (European Commission, 2023) were used to characterize the distribution of building volume and population density. Building volume was extracted from the GHS-BUILT-V product, which is available at a 1,000-meter spatial resolution and covers the period 1975-2030. This dataset provides estimates of building volumes, expressed in cubic meters per unit area, enabling assessment of changes in building density over time. Complementarily, population density was obtained from the GHS-POP product, which is also available at a spatial resolution of 1,000 meters and covers the same period, 1975-2030.

Finally, the modeling of urban dynamics and growth, Axis 5 of the thesis, used a complete time series of Landsat images (TM, ETM+, OLI-TIRS) covering the period 1986–2024, processed in Google Earth Engine and Python via Jupyter Notebook. These data enabled the derivation of several explanatory variables: local urban density, calculated from the concentration of built-up areas within 300 × 300-meter grids (i.e., 10 × 10 Landsat pixels); historical change rate between 1986 and 2021; and Euclidean distance to existing built-up areas, reflecting the potential for urban expansion. Several explanatory layers complemented these derived variables: population density (JRC, 1985 and 2021), elevation data from the SRTM Digital Elevation Model (30 meters), and distance to the road network, calculated from OpenStreetMap (OSM) road infrastructure data.

The combination of these satellite and geospatial datasets enabled precise documentation of structural transformations in the Kisangani landscape, from built-up areas to natural zones, while providing a robust empirical basis for diachronic analyses and prospective modeling.

b. Field and socio-environmental data

The field data used in this thesis comprises, on the one hand, GPS surveys and, on the other hand, socio-demographic and ecological information collected at different scales. A total of over 600 georeferenced points (GPX data) were collected across the entire study landscape, including Kisangani's urban center, peri-urban areas (Masako and Mbiye), and remote rural areas (Yoko and Yangambi), to document the mainland-use types. These surveys provided an essential reference base for interpreting and validating remote-sensing-derived classifications. In parallel, local demographic data were obtained from the National Institute of Statistics (INS) for each of Kisangani's six communes, covering the period 1990 to 2021 (INS, 2022). These data enabled an understanding of population dynamics and their interactions with observed landscape transformations, contributing to an integrated interpretation of urbanization processes.

Additionally, a field campaign conducted in March 2023 collected ecological data from more than 87 green spaces across urban, peri-urban, and rural areas. These spaces included mature, secondary, and degraded forests, as well as grasslands and agricultural areas. The analysis of these green spaces provided essential insights into the ecosystem services they provide to urban and peri-urban populations. By considering the types of ecosystem services provided, these data enabled the identification of green infrastructure components in Kisangani.

Furthermore, historical urban maps and plans of Kisangani obtained from the Geographic Institute were integrated into the study. These historical documents enabled a better understanding of uncontrolled urbanization patterns in the city and the assessment of the spatial evolution of the urban areas over several decades.

The combination of field, socio-environmental, and historical data constituted a comprehensive and essential resource for interpreting landscape dynamics observed through remote sensing and supporting the scientific discussion of the analyses conducted in this thesis. Table 3.1 presents and summarizes all the data used.

Table 3.1. Summary of the data used in the thesis

Category	Data Type	Source	Period	Spatial Resolution	Main Use
Remote Sensing	Raster	SPOT-Sentinel-2	1986-2021	10–20 m	Urban expansion
	Raster	Landsat TM, ETM+, OLI-TIRS	1986–2021	30 m	Green infrastructure, fragmentation, and edge effects
	Raster	MOD11A2	2000-2024	1000 m	Analysis of land surface temperature variations
	Raster	MOD13A2	2000-2024	1000 m	Vegetation density assessment
	Raster	GHSL-BUILT-V	1975–2030	1000 m	Building volume
	Raster	GHSL-POP	1975–2030	1000 m	Population density
	Raster	Sentinel-2	2024	10 m	Land surface temperature
	Raster	SRTM	2000	30 m	DEM + topographic variables
	Raster	ALOS World 3D	2024	30 m	Digital Surface Model
Field and Socio-Environmental	GPX	GPS Survey	2022–2024	-	Land use types and classification validation
	Document	INS	1990–2021	Aggregated by commune	Population dynamics and relation to landscape transformations
	GPX / Excel Database	Field collection	March 2023	-	Types of green spaces and ecosystem services provided
Historical	Old Maps and Plans	Geographic Institute	-	-	Understanding uncontrolled urbanization patterns and the evolution of the urban area

3.2.2. Preprocessing of satellite data

The satellite data used in the various studies of this thesis underwent several preprocessing steps to correct geometric, radiometric, and atmospheric distortions and ensure complete spatial and temporal homogeneity. Thus, SPOT scenes acquired between 1987 and 2015, used to characterize the urban growth pattern of Kisangani (Axis 1 of the thesis), were geometrically corrected using the 2021 Sentinel-2 image, selected as the reference image due to its high geometric accuracy. This reference image had been previously corrected using ground control points collected in the field. Resampling was subsequently applied to standardize the pixel size and ensure spatial-resolution consistency at 10 m. All images were reprojected into the WGS-84 geodetic system using the UTM projection, Zone 35 North, thereby guaranteeing perfect scene overlay and comparability across multi-temporal analyses.

For studies focused on the spatial pattern of green infrastructure, forest fragmentation, and edge effects, as well as on prospective scenarios (Axes 2, 3, and 5, respectively), Landsat data derived from Surface Reflectance (SR) products were preferred to minimize the influence of atmospheric variations and inter-sensor differences (Phan & Lehnert, 2020; Roy et al., 2016). Images from Landsat 4-5 TM and Landsat 7 ETM+ were corrected using the LEDAPS (Landsat Ecosystem Disturbance Adaptive Processing System) algorithm, whereas those from Landsat 8-9 OLI were processed with LaSRC (Land Surface Reflectance Code)(Sayler & Zanter, 2021; Sayler & Zanter, 2023).

These two algorithms apply standardized radiometric and spectral corrections, producing homogeneous reflectances that are directly comparable over time and across sensors. Once these corrections were applied, the images were standardized to a 30-meter spatial resolution to ensure consistency across multi-date analyses and minimize sensor-related biases.

To enhance discrimination among land-use types, false-color composites were generated from the most discriminative bands. For SPOT and Sentinel-2 data used to characterize urban growth (Axis 1), combinations of the green, red, and near-infrared (NIR) bands were applied to improve differentiation between urban, peri-urban, and rural areas. For Landsat images used in studies focused on green infrastructure structure, forest fragmentation, edge effects, and prospective scenarios (Axes 2, 3, and 5), combinations of the mid-infrared (MIR), NIR, and red (R) bands were applied, improving the discrimination between green spaces and built-up areas.

These composites highlighted contrasts between vegetation, bare soil, and urbanized areas, while facilitating the selection of training areas for supervised classification. In parallel, MODIS products were used to analyze thermal dynamics (Axis 4). Land surface temperature data (MOD11A2 V6.1) were used as images averaged over eight-day intervals, which reduces the effects of cloud cover and localized anomalies (Wan, 2013).

3.2.3. Supervised classifications

The analysis of urbanization dynamics and landscape transformations (Axis 1) relied on a supervised classification of SPOT and Sentinel-2 satellite images. This approach aimed to discriminate among primary land-use categories along an urbanization gradient, including urban, peri-urban, and rural areas. Defining these zones often constitutes a methodological challenge, as administrative boundaries do not accurately reflect actual transitions between environments (Angel et al., 2010; Wolman et al., 2005). Morphological and population density criteria (André et al., 2014; Clark & Evans, 1954) were therefore prioritized to delineate these zones objectively and consistently. The continuity and dominance of built-up surfaces identified the urban zone (André et al., 2014; Salomon et al., 2022), characterized by the presence of impervious materials such as roofs, pavements, and compacted soils (Angel et al., 2010). The peri-urban zone comprises areas where built-up structures remain but are more fragmented and less dense, often associated with a mosaic of agricultural or grassland surfaces. Finally, rural zones were defined by the predominance of natural or cultivated vegetation cover. These distinctions rely on a decision-making approach inspired by the model proposed by André et al. (2014) based on morphological criteria observable in satellite images.

For the reference classification (year 2021), these morphological criteria were combined with population density data from the Global Human Settlement Layer (GHSL). This second variable served as a validation criterion. Square training areas measuring 250 m per side were defined within 1 km² grids based on population density. This intermediate scale (250 m) allows for supra-parcel analysis, facilitating better discrimination between urban and peri-urban zones (André et al., 2014; Sambieni et al., 2019). A cell is considered urban when more than 50% of its pixels correspond to built-up surfaces, and the population density exceeds 100 inhabitants/km², the minimum threshold identified near the center of Kisangani in 2020. Areas with discontinuous built-up surfaces $\leq$50% and a density $\geq$100 inhabitants/km² fall into the peri-urban category. Areas dominated by vegetation or agriculture with low population density are classified as rural. For earlier years, classifications were based solely on the decision criterion, i.e., the proportion of built-up area within 250 m × 250 m cells, due to the absence of reliable population density data for those periods.

For studies focused on green infrastructure, forest ecosystem fragmentation, and edge effects, prospective modeling (Axes 2, 3, and 5), training areas were selected based on detailed visual interpretation of false-color Landsat composites. These interpretations were supported by high-resolution imagery from Google Earth and PlanetScope (3 m resolution) and by analysis of NDVI variations. This multi-source interpretation approach reduced spectral confusion between classes with similar spectral signatures.

3.2.4. Classification validation

Classification accuracy was assessed using a validation dataset comprising control points collected in urban and peri-urban areas and in peripheral rural zones of the Kisangani region. In total, 642 georeferenced points (GPX format) were collected during field missions conducted in August 2022 and March 2023, according to accessibility. These points enabled the description of the main observed land-use types along the urbanization gradient and within forested landscapes.

For studies focused on the spatial pattern of green infrastructure (Axis 2), the distribution of control points reflects the diversity of the studied landscape components: 33% of points correspond to built-up and bare soil areas (grouped under the “other” class), 27% to agricultural and grassland areas, 20% to short forests (degraded forests), and 20% to mature forests. Two subsamples were derived from this dataset: the first, comprising 310 points, was used to validate the reference classification (year 2021), while the second, consisting of 232 points, was used to compare our local classifications to the global classification of Hansen et al.(2013).

Accuracy assessment was based on confusion matrices, from which overall, user, and producer accuracies were calculated. These metrics estimate classification reliability and the agreement between observed and predicted data. To evaluate the consistency between local classifications and global data, a comparison was made between Hansen’s global change map for 2000-2021 and the map produced in this study for 2001-2021. To harmonize classes and facilitate comparison, observed changes were grouped into two major categories: (1) forest and (2) non-forest. In Hansen’s database, a pixel was considered forested when tree cover reached at least 50% of the pixel. Any decrease below this threshold indicates conversion to the non-forest class, and vice versa. This threshold was adopted in this study to clearly distinguish forested from non-forested pixels. The resulting contingency matrix (Table 3.2) enabled the calculation of overall accuracy (Equation 3.1), user’s accuracy (Equation 3.2), and producer’s accuracy (Equation 3.3) (Olofsson et al., 2014).

Table 3.2. The confusion matrix model adapted from Olofsson et al.(2014)

	Reference				
Map	**Class 1**	**Class 2**	**Class 3**	**Class 4**	**Total**
Class 1	P_{11}	P_{12}	P_{13}	P_{14}	P_1
Class 2	P_{21}	P_{22}	P_{23}	P_{24}	P_2
Class 3	P_{31}	P_{32}	P_{33}	P_{34}	P_3
Class 4	P_{41}	P_{42}	P_{43}	P_{44}	P_4
Total	P_1	P_2	P_3	P_4	1

Equation 3.1. Overall accuracy

$$O = \sum_{j=1}^{q} P_{jj}$$

Overall accuracy is the fraction of correctly classified pixels (the diagonal elements of the confusion matrix divided by the total number of pixels).

Equation 3.2. User's accuracy

$$U_i = p_{ii}/p_i$$

User's accuracy for class i represents the proportion of the area mapped as belonging to class i that actually corresponds to class i in the reference data.

Equation 3.3. Producer's accuracy

$$p_j = p_{jj}/p_j$$

Producer's accuracy for class j corresponds to the proportion of the area belonging to reference class j that has been correctly mapped as class j.

3.2.5. Analysis of urban expansion and dynamics of green infrastructure components

Landscape dynamics analyses were conducted using spatial approaches to characterize the mode of urban expansion observed in the Kisangani region and the changes occurring in the urban landscape (thesis axis 1). These spatial changes were examined using transition matrices, which enabled quantification of conversions among rural, peri-urban, and urban areas. These matrices provide the basis for evaluating the progressive transformation of rural areas into peri-urban and urban zones. Additionally, stability indices were calculated for each zone along the urbanization gradient to assess their temporal evolution.

The hypothesis of alternating diffusion and coalescence (Dietzel et al., 2005) was tested using Bogaert's decision tree (Bogaert et al., 2004). This approach allows the identification of processes of creation and aggregation of urban and peri-urban entities, respectively associated with the diffusion and coalescence phases of urban expansion. Furthermore, the hypothesis of urban dedensification (Angel et al., 2010), was evaluated using spatial indicators developed within the framework of this thesis. Two primary indices were developed: the ratio between peri-urban and urban areas (Equation 4.1) and the peri-urban fraction (Equation 4.2). In the absence of reliable demographic data, these indicators provide a way to characterize urban dedensification or densification by reflecting the relationship between the growth of peri-urban areas, which represent a spatial expression of decreasing urban population densities, and the expansion of urban areas.

Additionally, landscape dynamics analyses focused on evaluating the spatial pattern of green infrastructure (thesis axis 2). These analyses were conducted with the specificities of the urban-rural gradient in mind. To characterize the composition and spatial configuration of green infrastructure, a random sampling method was applied. For the reference year (2021), eight plots of 2.25 km² (1.5 km per side) were selected in each zone (urban, peri-urban, and rural) and distributed across all cardinal directions. The number and status of these plots evolved, reflecting the dynamic nature of the urban-rural gradient zones. This plot-based approach captures spatial variations that linear transect-based (Junxiang et al., 2013; Schneider et al., 2005) or concentric zone approaches (Bamba & Bogaert, 2010; Seto & Fragkias, 2005; Useni et al., 2018) may overlook, providing a more comprehensive view of landscape structure.

Two indices of spatial pattern were calculated for each plot: the percentage or proportion of the landscape (Equation 5.1) and the area of the largest patch (Equation 5.2). While PLAND provides information on landscape composition by measuring the proportion of the landscape occupied by each green infrastructure component, LPI includes information on spatial configuration by measuring the dominance of the largest patch within each component. These complementary indices allow for the simultaneous assessment of landscape composition and configuration. They are particularly suitable for analyzing the effects of urbanization on the continuity and fragmentation of green spaces.

3.2.6. Analysis of the extent and magnitude of edge effects

The analysis of edge effects, thesis axis 3, relied on a series of spatial measurements, including the proportion of forest patches subjected to edge influence and that of interior areas protected from such influences. From these measurements, the Interior/Edge ratio (I/E) was calculated. This index expresses the proportion of forest area located beyond a specified buffer distance relative to the total patch area, serving as an indicator of habitat ecological quality and exposure to external disturbances (Mladenoff et al., 1994; Bogaert et al., 1998). Spatial analysis was performed using vector data and multiple buffer distances (50 m, 100 m, 150 m, and 200 m) to account for variations in ecological sensitivity to edge effects. The percentage of forest area under edge influence was also calculated, enabling comparisons of relative exposure across different landscapes and observation periods.

The amplitude of edge effects was then examined using land surface temperature (LST) as an ecological indicator of microclimatic disturbances. LST values were derived from harmonized Sentinel-2 surface reflectance products at a 10 m spatial resolution. Sentinel-2 was selected for its acceptable spatial resolution, appropriate for analyzing thermal variations in the heterogeneous tropical forest mosaics characteristic of the Kisangani landscape.

The magnitude of edge influence (MEI) on surface temperature was evaluated using two buffer distances. A 20 m buffer was applied around forest patches across all studied landscapes (Masako, Yangambi, Yoko, and Mbiye). A second 50 m buffer was applied in Yangambi and Yoko, where large forest fragments remain and may exhibit deeper penetration of edge effects. MEI was calculated according to Equation 6.3 (Burton, 2002; Harper et al., 2005) describing the mean surface temperature difference between interior zones and forest patches subjected to edge effects.

3.2.7. Analysis of Urban Heat Islands

The assessment of urban heat island (UHI) intensity (thesis axis 4) relied on land surface temperature data from the MOD11A1 product of the MODIS sensor. Analyses employed a relative UHI intensity approach, with thermal deviations expressed relative to the mean temperature of rural areas (Huang et al., 2019; Rendana et al., 2023). This method normalizes comparisons across zones along the urbanization gradient and across time periods, while limiting the influence of seasonal and interannual variation. The mean temperature of rural areas (Ts) was used as a thermal reference (Zhang et al., 2013). Relative UHI intensity was calculated according to Equation 7.1.

To better capture the spatial complexity of the UHI phenomenon along Kisangani's urban-rural gradient, a random sampling approach was implemented. Observation plots were randomly selected in eight main directions, north, south, east, west, northeast, northwest, southeast, and southwest, within each gradient zone. This strategy captures spatial variability often overlooked by linear transects or concentric zone approaches. By integrating short-scale variations, this method enhances data representativeness and strengthens the robustness of thermal analyses at the landscape scale. A total of 86 observation plots (Figure 3), each 1 km² in area, corresponding to the spatial resolution of the MODIS data used, were randomly selected in each gradient zone for the reference year 2024. Random sampling was chosen to reduce potential biases and ensure better representativeness of landscape-scale conditions. This approach enables an objective assessment of UHI spatial variability and provides a comprehensive view of urbanization's influence along the urban-rural gradient. The nature of the plots evolved, reflecting the dynamics of urban, peri-urban, and rural zones.

3.2.8. Prospective models of urban expansion

Land-use simulation models allow for the anticipation of future changes and can rely on statistical approaches, machine learning, or decision tree-based methods (Pontius et al., 2008; Shafizadeh-Moghadam et al., 2017). Recent advances in deep learning, combined with their effectiveness in satellite image classification and segmentation, offer new opportunities for simulating future urban area evolution and detecting forthcoming spatial dynamics (Liu et al., 2021).

In this thesis, urban growth between 2024 and 2060 (thesis axis 5) was projected using a spatial model based on a convolutional neural network (CNN) of the U-Net type. This architecture allows simulations while preserving both contextual information and fine spatial details necessary to delineate future built-up areas accurately (Ronneberger et al., 2015). U-Net captures neighborhood effects essential for the spatial allocation of newly built pixels and provides more precise and dynamic simulations than cellular automata (CA)-based models such as SLEUTH or CLUE-S, which rely on fixed rules and have limitations in resolution and integration of human decision-making. The U-Net architecture allows for the integration of an unlimited number of input variables and models spatial dependencies, providing an acceptable and flexible representation of urban expansion processes (Bhusal et al., 2024; Shojaei et al., 2022).

Three urban growth scenarios were simulated. The first, termed business-as-usual (BAU), projects expansion based on historical trends without additional spatial constraints. The second, termed sustainable urbanization, limits the expansion of built-up areas to a maximum of 1 km from already urbanized areas to promote contiguous urban growth. In this scenario, protected areas, a defined urban green belt, and watercourses are strictly excluded from urbanization. The third scenario, termed hybrid, combines sustainability objectives with Kisangani's local realities. In this model, urban expansion is allowed within a 2 km radius of existing built-up areas, permitting controlled peripheral growth while maintaining urban continuity. Unlike the strictly sustainable scenario, the green belt is not entirely excluded: urbanization is influenced by proximity to agricultural lands and road networks, reflecting existing socio-economic pressures and patterns of land appropriation. Simulations were performed for the years 2024, 2030, 2035, 2040, 2045, 2050, 2055, and 2060, with the maximum distance used to control the spatial distribution of newly built-up areas.

Chapter 4

Urban sprawl and changes in landscape patterns: the case of Kisangani city and its periphery (DR Congo).

4.1. Reference

Balandi, J. B., Meniko, J.-P. P. T. H., Sambieni, K. R., Sikuzani, Y. U., Bastin, J.-F., Musavandalo, C. M., Besisa, T.N., Elangilangi, J. M., Selemani, T. M., Mweru, J. M., & Bogaert, J. (2023). Urban sprawl and changes in landscape patterns : the case of Kisangani city and its periphery (DR Congo). Land 2023, 12(11), 2066. https://doi.org/10.3390/land12112066

4.2. Context

The analysis of urban growth is a fundamental step toward understanding the spatial transformations of cities. The literature shows that many cities are undergoing a process of de-densification accompanied by spatial expansion (urban sprawl), leading to notable changes in the density and organization of peri-urban and rural landscapes (Angel et al., 2010). In the African context, few studies have examined whether these dynamics occur and how they influence landscape patterns. This study, therefore, aims to address this gap.

4.3. Résumé

La forte croissance démographique en Afrique subsaharienne nécessite un suivi régulier de l'expansion spatiale des villes afin de favoriser une planification urbaine efficace. Sur la base de critères morphologiques, cette étude a quantifié la dynamique des zones urbaines et périurbaines de Kisangani entre 1987 et 2021. Les résultats montrent une croissance continue des zones urbaines et périurbaines, avec des taux moyens annuels de variation de 8,2 % et de 7,6 % respectivement. La surface du noyau urbain est passée de 13,49 km² à 100,49 km², résultant d'un processus alterné de diffusion et de coalescence. Les indices de périurbanisation élaborés pour évaluer la tendance à la baisse des densités urbaines indiquent une phase de densification entre 1987 et 2010, suivie d'une diminution de la densité urbaine entre 2010 et 2021, marquée par une expansion significative de la zone périurbaine. Toutefois, malgré la tendance observée entre 2010 et 2021, la baisse de la densité urbaine n'a pas été effective à Kisangani entre 1987 et 2021, la proportion de la zone périurbaine observée en 1987 demeurant équivalente à celle de 2021. Cela suggère une continuité du processus de densification urbaine malgré une périurbanisation croissante.

Mots-clés : urbanisation, indices de périurbanisation, dédensification urbaine, diffusion-coalescence, Kisangani

4.4. Abstract

The rapid population growth in sub-Saharan Africa requires regular monitoring of the spatial expansion of cities to facilitate efficient urban planning. Based on morphological criteria, this study quantified the dynamics of urban and peri-urban areas in Kisangani from 1987 to 2021. Results demonstrate continuous urban and peri-urban growth, with average annual change rates of 8.2% and 7.6%. The urban core area expanded from 13.49 km^2 to 100.49 km^2, resulting from an alternating process of diffusion and coalescence. Peri-urbanization indices developed to assess urban density trends indicate a phase of urban densification from 1987 to 2010, followed by a decline from 2010 to 2021, characterized by a significant expansion of the peri-urban area. However, despite the trend observed between 2010 and 2021, the decrease in urban density was ineffective in Kisangani between 1987 and 2021, as the fraction of peri-urban area observed in 1987 remained equivalent to that observed in 2021. This suggests a continuity of urban densification despite increasing peri-urbanization.

Keywords: Urbanization, peri-urbanization indexes, decline in urban density, diffusion-coalescence, Kisangani

4.5. Introduction

Over the past century, demographic, socioeconomic, cultural, and political changes, as well as technological advances, have profoundly altered natural landscapes (Nancy et al., 2008; Schneider & Woodcock, 2008). In this altered landscape, cities are expanding both within and outside their boundaries, minimizing the time and distance between them (European Environment Agency, 2006). Given the demographic growth observed over the last few decades, this trend is expected to continue in future decades. Indeed, on a global scale, 50% of the population lives in urban environments (Cheng et al., 2013; United Nations, 2014). The proportion of the world's urban population is expected to increase by more than 70% by 2050, rising from 3.6 billion in 2011 to approximately 6.3 billion in 2050 (Cheng et al., 2013; Junxiang et al., 2013), while the global population is projected to reach around 9.7 billion by 2050 (United Nations, 2022). This rapid population growth in urban areas amplifies the demand for accommodation and social facilities, leading to uncontrolled spatial expansion of the city (Zoma et al., 2022). Therefore, the influence of towns extends over spaces that still preserve a rural character, leading to the development of hybrid territories described as peri-urban areas (Bogaert & Halleux, 2015a). However, this expansion is scattered through the development of low-density urban areas that are less compact and more dispersed (European Environment Agency, 2006). This phenomenon, characterized by the physical expansion of cities accompanied by a significant loss of density, is referred to in the international literature as urban sprawl (Rubiera-Morollon & Garrido-Yserte, 2020).

Jane Jacobs, in her book *The Death and Life of Great American Cities* (Jacobs, 1961), was one of the first authors to sound the alarm about the inefficiency of the dispersed city model that was prospering in North America (Rubiera-Morollon & Garrido-Yserte, 2020). This dispersed city model has also been reported in Europe: "European cities were more compact and less sprawled in the 1950s than they are today, and urban sprawl is now a common phenomenon throughout Europe" (European Environment Agency, 2006). More recently, in a global sample of 120 cities between 1990 and 2000, Angel et al.(2010) show that average built-up area densities have significantly declined, from 144 persons/ha in 1990 to a mean of 112 persons/ha in 2000. Spatially, this decline in urban densities is expressed in the formation of peri-urban areas as urban regions advance into rural territories. What has not been so evident is that this phenomenon is global in scope and includes cities in developing countries as well (Angel et al., 2010).

Indeed, the initial claims of Berry et al.(1963) suggest that "non-Western cities experience increasing overcrowding, constant compactness, and a lower degree of expansion at the periphery." More recently, the research of Canning et al. (2016) and that of Marcandalli et al. (2018) have shown that, in developing countries, particularly in Africa, rapid population growth resulting from high birth and fertility rates leads to significant migration of populations from rural to urban zones. This contributes significantly to the spatial expansion of African cities through the development of low-density, less compact, and more dispersed urban areas (Ibtissem & Raham, 2020).

This type of urban expansion is associated with various ecological consequences in sub-Saharan Africa, where cities often expand without adequate urban planning. This, in turn, leads to rapid changes in land cover (Vermeiren et al., 2012). In Lubumbashi, for example, the area of green space decreased from 1989 to 2014 due to population pressure and a lack of sustainable urban planning (Useni et al., 2017). These observations suggest that the major challenges to understanding and resolving the environmental problems related to urbanization will continue to grow (Cheng et al., 2013).

Therefore, managing urbanization and peri-urbanization should be effectively controlled (Banque mondiale, 2018). This involves characterizing urbanization gradient zones of cities, one of the prerequisites for managing their expansion (André et al., 2014), and subsequently, understanding their dynamics. Indeed, Charles Dietzel's theory suggests that the spatial dynamics of cities can be described as a two-phase process involving diffusion, which refers to the expansion of urban areas from existing cores, and coalescence, which consists of the merging of urban patches (Cheng et al., 2013; Dietzel et al., 2005). Landscape ecology tools, spatial remote sensing, and choralogy, a discipline that focuses on studying geographical spaces considering their increasingly limited availability (Bogaert et al., 2015), enable the characterization of zones along the urbanization gradient and reveal their spatial dynamics.

The city of Kisangani is experiencing accelerated demographic growth (Bamba, 2010). Between 1990 and 2021, its total population nearly quintupled, from 437,805 to 2,184,096 (INS, 2022). Its spatial expansion is constrained by the lack of practical implementation of the management plans that were successively developed in 1978, 2008, and 2010 (UN-Habitat, 2015). In addition, urbanization is a less managed situation, as in most DR Congo towns (UN-Habitat, 2015). Consequently, the pressure on natural resources, including protected areas such as the Masako Forest Reserve, is increasing (Meniko et al., 2020).

Despite this alarming fact, studies specifically aimed at understanding the dynamics of urban and peri-urban areas are minimal. Indeed, this study aims to quantify the spatial dynamics of the urbanization gradient zones from 1987 to 2021 in Kisangani. In line with the observations of Angel et al. (2010), we tested the hypothesis that the spatial growth of Kisangani city exhibits a trend toward declining urban density, characterized by urban sprawl. This process affects landscape patterns in urban, peri-urban, and rural areas. Specifically, peri-urban areas are expected to increase gradually within the urbanization gradient. Additionally, a gradual decline in the stability of the rural zone is anticipated as more urban and peri-urban areas are established.

4.6. Materials and methods

4.6.1. Study area

The study area, encompassing 2,947.9 km², comprises six communes of Kisangani city and its peripheral zone (Figure 4.1). Five of these communes are located on the right bank, including Makiso, Tshopo, Kabondo, Mangobo, and Kisangani, while Lubunga is the lone commune on the left bank (Figure 1). Kisangani is geographically located nearer to the Equator, at a latitude of 00°31′ N and a longitude of 25°11′ E (Figure 1), with a climate classified as Af type by Köppen's classification (Kottek et al., 2006). The monthly average temperatures range from 22.4 to 29.3 °C, and the annual rainfall fluctuates between 1,500 and 2,000 mm (Assani et al., 2015). The population of Kisangani has experienced rapid growth, from an estimated 105,666 in 1959 (Bamba, 2010) to around 28,404,496 in 2021 (INS, 2022).

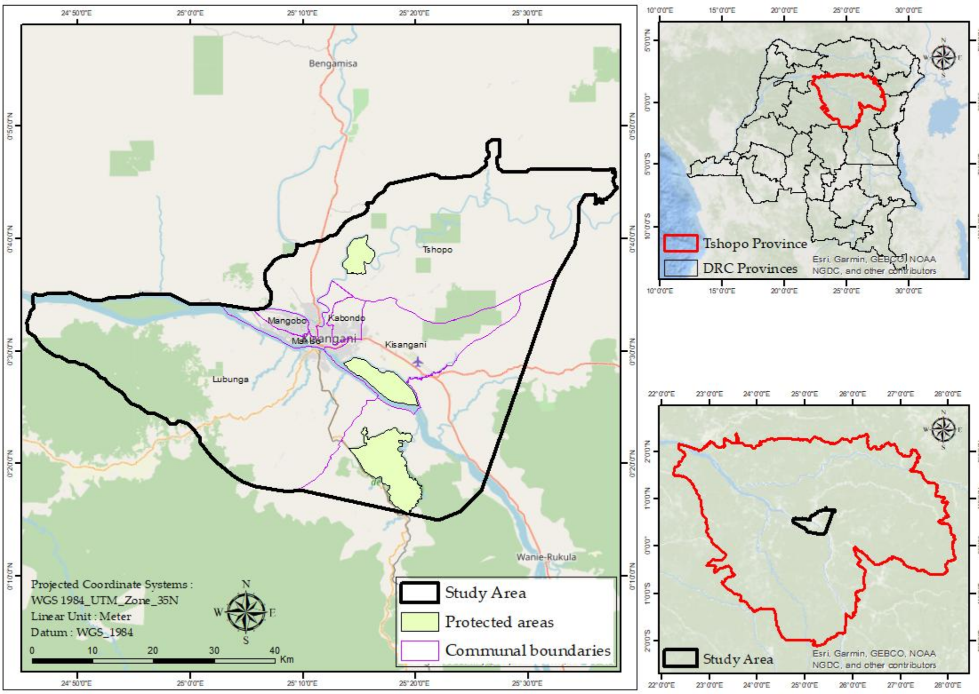


Figure 4.1. Geographical location of Kisangani and its periphery. Kisangani is subdivided into six communes and includes three protected areas on its periphery. The road network shown includes national and provincial road.

4.6.2. Data used

The dynamics of the urbanization gradient zones were characterized using images from the Sentinel-2 and SPOT sensors. This combination of multiple sensors enabled coverage of all the analyzed periods. Additionally, the spatial resolution of the images used was adequate to better discriminate between urban and peri-urban areas. 115 GPS ground surveys supported satellite data collected during a research mission in August 2022, providing detailed information on land use and cover. Spatial demographic data from the Joint Research Centre (European Commission, 2023), with a spatial resolution of 1000 m, were also used to complement satellite images in describing urbanization gradient zones.

4.6.3. Satellite data pre-processing

The images from 1987, 1995, 2000, 2005, 2010, and 2015 were geometrically corrected using the 2021 Sentinel-2 image as a reference to achieve identical geometry. The 2021 image was orthorectified using field-collected control points. Resampling was applied to homogenize the pixel sizes. Subsequently, a false composite color was created by combining the green, red, and near-infrared bands from Spot and Sentinel-2 images (Figure 4.2). This false composite color enables the selection of training areas necessary for supervised classifications.

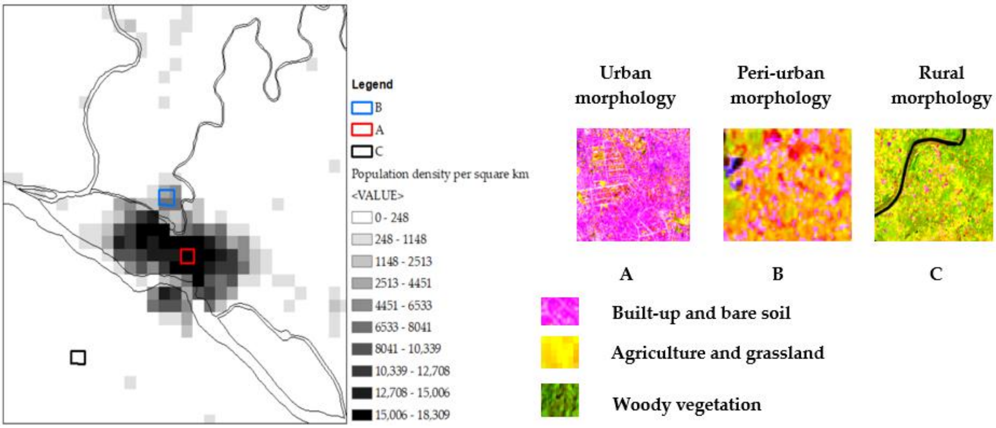


Figure 4.2. The spatial distribution of population density and the morphology of urbanization gradient zones. In A, built-up continuity characterizes the urban center of Kisangani, which has a high population density. In B, the built-up discontinuity describes the peripheral area, and in C, vegetation dominance characterizes the rural zone with low population density per square kilometer.

4.6.4. Classification of urbanization gradient zones

A major problem in mapping and measuring the attributes of urbanization gradient zones concerns the precise and consistent definition of these zones (Angel et al., 2010; Wolman et al., 2005). Using administrative boundaries is typically inadequate because they can be altered from one day to the next by decree and often encompass large rural areas (Angel et al., 2010). However, some criteria relating to patches' density, aggregation, proximity, and dominance are used in most cases (Clark & Evans, 1954; Gustafson & Parker, 1994; Turner & Ruscher, 1988). The built-up area of the city, a morphological criterion (André et al., 2014), is more precise and consistent (Angel et al., 2010). Analysis of satellite images enables the identification of built-up areas based on impermeable surfaces (pavements, rooftops, and compacted ground)(Angel et al., 2010). Therefore, the decision tree proposed by André et al. (2014) and André (2017), based on morphological criteria, delineates zones within the urbanization gradient (André et al., 2014). This decision tree was preferred for its expedient implementation, simplicity, and alignment with the actual ground conditions, characterized by a diverse range of land-cover types. It should be noted that the dominance and continuity of a dense built-up area characterize the urban zone. A discontinuous, less-dense built-up area characterizes the peri-urban zone, whereas vegetation dominance indicates a rural zone (André et al., 2014; Salomon et al., 2022).

To perform the reference classification (2021), these morphological criteria were supported by the spatial distribution of population density (Figure 4.2). Population density is described as a property that can modify the spatial pattern of the landscape and is expected to decrease along the urbanization gradient (Bamba, 2010; Bogaert et al., 2015; Sambieni, 2019). Indeed, the training zones used to calibrate the reference classification were created as a 250 m × 250 m square within a 1 km² cell with a population density of 1 km². The size and shape adopted enabled a supra-parcel analysis, which was less than the km² required to apply the decision tree (André et al., 2014). Thus, an area is classified as urban when it contains a majority of built-up pixels (more than 50%) (André, 2017; Angel et al., 2010), within a perimeter of 250 m × 250 m, created in a cell with a population density of 100 inhabitants per km² or greater. This reference value corresponds to the lowest population density observed near Kisangani's urban center in 2020. Values below 100 correspond to rural areas around the city.

Furthermore, an area is classified as peri-urban when the proportion of built-up pixels within a 250 m × 250 m perimeter is less than or equal to 50%. The other pixels are not exclusively forest or agricultural (André et al., 2014), and are created in a cell with a population density of 100 inhabitants or more per square kilometer. Finally, an area is classified as rural when the 250 m × 250 m perimeter is dominated by vegetation pixels. To classify previous images (2015, 2010, 2005, 2000, 1995, and 1987), the sampling of built-up pixels within 250 m × 250 m cells was used as the sole criterion, given the lack of reliable data on the spatial distribution of population density for all these years. However, using a classification performed as a reference (2021 for this study), urban, peri-urban, and rural patterns, unchanged from previous images, can be identified when creating training zones.

Then, supervised classification was performed on all analyzed images using the random forest algorithm. Random Forest, a non-parametric statistical method (Del Río et al., 2014; Fernández-Delgado et al., 2014; Genuer & Poggi, 2017) was specifically selected for its ability to build several decision trees that independently analyze and assign samples to their respective classes (Del Río et al., 2014). The classified images were then filtered to eliminate isolated pixels.

The normalized difference vegetation index (NDVI) was analyzed for each zone along the urbanization gradient as a predictor of vegetation phenology, potentially influencing the interpretation of the urbanization gradient. The validation data included 115 control points collected from the urban center of Kisangani to the Yoko Forest reserve. These control points describe land cover and land use. The accuracy of the classifications was assessed using the Kappa coefficients, overall accuracy, and producer accuracy obtained from the confusion matrix.

4.6.5. Spatial dynamics and urban sprawl analysis

The dynamics of landscape conversions were analyzed using transition matrices. Indeed, transition matrices enabled the assessment of the conversion of rural areas into peri-urban and urban areas, which are expected to persist over time due to the growing demand for habitable space. The expected consequences include a gradual decline in the stability of rural areas. To this end, stability indexes were calculated for each zone. These conversions are expected to increase the proportion of unchanged urban and peri-urban areas over time, resulting in their gradual stabilization in the landscape. Due to urban pressure, that stability is expected to be more critical on a scale of 336.2 km^2 around the urban center of Kisangani.

The urban expansion resulting from these conversions conforms to the theory of alternating diffusion and coalescence (Dietzel et al., 2005). This theory has been tested through spatial transformation processes. The decision tree of Bogaert et al. (2004) was applied to determine the expected processes, in particular creation, which provides information on diffusion, and aggregation, which in turn provides information on coalescence. Furthermore, the trend toward the decline in urban densities, also described as urban sprawl (Angel et al., 2010; European Environment Agency, 2006), was analyzed using two indices developed in this study, including the ratio of peri-urban to urban (Equation (4.1)), the peri-urban fraction (Equation (4.2)), and the total area of urban and peri-urban spaces.

Indeed, this process occurs when the rate of urban expansion exceeds the population growth rate (Angel et al., 2010; Sainteny, 2008; Simard, 2014). Given the lack of reliable demographic data (from regular population censuses), these indices are relevant. In fact, in terms of space, the decline in urban density is expressed through the development of hybrid zones, described as peri-urban (Bogaert & Halleux, 2015a) or suburban zones (André et al., 2014), which occur in a scattered way (European Environment Agency, 2006).

Equation 4.1. Ratio of peri-urban to urban

$$PU_r = \frac{P_a}{U_a}$$

Equation 4.2. Peri-urban fraction

$$P_f = \frac{P_a}{U_a + P_a}$$

$\boldsymbol{PU_r}$ indicates the ratio of peri-urban to urban areas; $\boldsymbol{P_f}$ indicates the peri-urban fraction; $\boldsymbol{P_a}$ corresponds to the peri-urban area; $\boldsymbol{U_a}$ indicates an urban area.

4.7. Results

4.7.1. Accuracy of supervised classifications

The overall accuracies (Table 4.1) were above 90%, and the Kappa index values were above 80%. These values indicate an acceptable discrimination of urban, peri-urban, and rural zones.

Table 4.1. Overall accuracy and Kappa coefficient values for supervised classifications

	1987	1995	2000	2005	2010	2015	2021
Overall accuracy (%)	96.27	92.84	97.04	97.12	93.33	94.66	95.44
Kappa (%)	91.08	89.95	95.78	95.88	89.26	92.03	92.80

4.7.2. Changes in landscape pattern

Visual analysis reveals a continuous expansion of urban and peri-urban areas, while rural areas constantly decrease (Figure 4.3). From 1987 to 2021, the proportion of urban and peri-urban areas has increased from 2.34% to 15.86%. This indicates a transformation of more than 13% of rural areas (Table 4.2). These transformations peaked between 2010 and 2015, with more than 6% of rural areas affected by peri-urbanization.

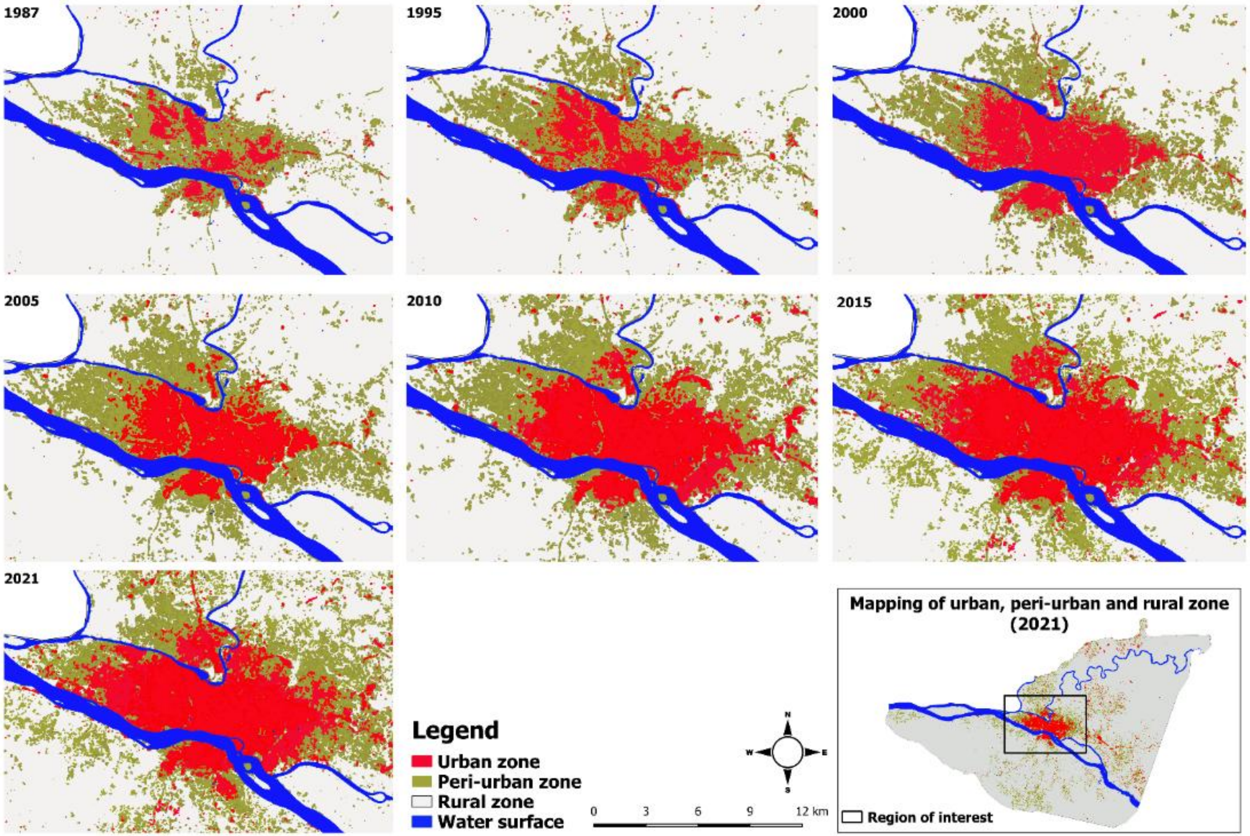


Figure 4.3. Dynamics of urbanization gradient zones. From a primitive urban core estimated at 13.4 km² (1987), urban patches have gradually filled the interstitial spaces, reaching an area estimated at 100.9 km² by 2021.

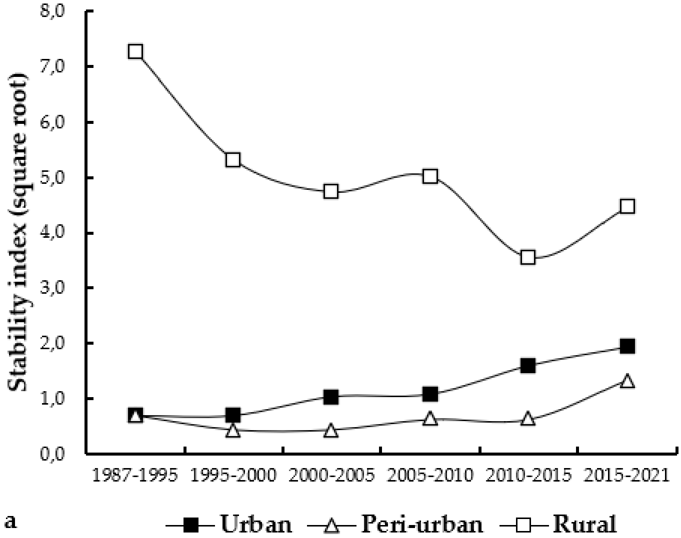
Table 4.2. Transition matrix (%) illustrating the transformations of urban, peri-urban, and rural areas. Each value represents a fraction of the landscape (in the study area) that has changed from the class in the row (initial year) to the class in the column (final year). Values in bold indicate the class stability, while those below the diagonal reflect urban and peri-urban expansion. At the landscape scale, 1% = 28.14 km^2.

Period		Urban	Peri-urban	Rural	Total
1987–1995	Urban	**0.27**	0.12	0.08	0.47
	Peri-urban	0.25	**1.03**	0.59	1.87
	Rural	0.10	1.05	**96.49**	97.64
	Total	0.62	2.20	97.16	**100**
		Urban	Peri-urban	Rural	Total
1995–2000	Urban	**0.47**	0.08	0.07	0.62
	Peri-urban	0.78	**0.67**	0.75	2.20
	Rural	0.09	2.42	**94.65**	97.16
	Total	1.34	3.17	95.47	**100**
		Urban	Peri-urban	Rural	Total
2000–2005	Urban	**1.03**	0.15	0.16	1.34
	Peri-urban	0.64	**1.08**	1.45	3.17
	Rural	0.02	2.50	**92.95**	95.47
	Total	1.69	3.73	94.56	**100**
		Urban	Peri-urban	Rural	Total
2005–2010	Urban	**1.47**	0.13	0.09	1.69
	Peri-urban	1.02	**1.72**	0.99	3.73
	Rural	0.03	2.53	**92.00**	94.56
	Total	2.52	4.38	93.08	**100**
		Urban	Peri-urban	Rural	Total
2010–2015	Urban	**2.34**	0.10	0.08	2.52
	Peri-urban	0.66	**3.12**	0.60	4.38
	Rural	0.05	6.07	**86.96**	93.08
	Total	3.05	9.29	87.44	**100**
		Urban	Peri-urban	Rural	Total
2015–2021	Urban	**2.94**	0.09	0.02	3.05
	Peri-urban	0.46	**8.52**	0.31	9.29
	Rural	0.17	3.68	**83.79**	87.64
	Total	3.57	12.29	84.12	**100**

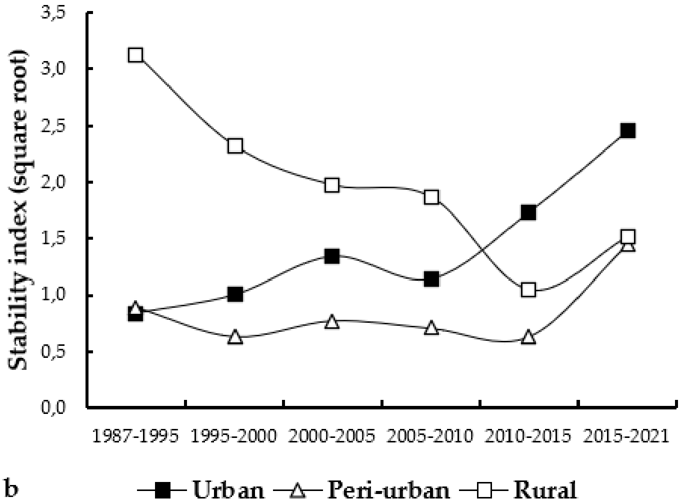
4.7.3. Stability of the urbanization gradient zones

In the city of Kisangani and its periphery, rural areas have maintained the highest level of stability along the urbanization gradient from 1987 to 2021 (Figure 4.4a). However, there is a noticeable decline in the proportion of unchanged rural areas, which are gradually being transformed into urban or peri-urban areas. This trend leads to a progressive decline in the stability of rural areas.

Conversely, the proportion of unchanged urban areas is increasing over time, resulting in a gradual stabilization of the urban zone. In the region of interest, with approximately 336.2 km^2 around the urban center of Kisangani (Figure 4.4b), the proportion of unchanged urban areas has substantially increased, and the urban zone has become the most stable zone along the urbanization gradient during the last two diachronies. The peri-urban area exhibits lower levels of stability than the urban and rural areas on both scales.



a



b

Figure 4.4. Changes in stability index values. Despite their progressive increase, rural areas affected by urbanization and peri-urbanization in Kisangani and its periphery (a) remain less critical than non-urbanized areas. In the region of interest, with approximately 336.2 km^2 around the urban center of Kisangani, rural areas affected by urbanization and peri-urbanization are more critical and remain largely unchanged (**b**).

4.7.4. Urban growth model: trend toward the urban density decline

The change in the number of patches (Figure 4.5a) and the spatial transformation processes (Table 4.3) show an alternating process between diffusion and coalescence in urban and peri-urban dynamics. In urban areas, the initial phase, characterized by the emergence of new patches through the creation process, occurred during the following periods: 1987–1995, 1995–2000, 2010–2015, and 2015–2021. For peri-urban areas, this phase concerns the periods 1987–1995, 2005–2010, 2010–2015, and 2015–2021. The subsequent phase, characterized by patch merging or aggregation, is observed in urban areas from 2000 to 2005 and 2005 to 2010, and in peri-urban areas from 1995 to 2000 and 2000 to 2005.

However, the annual rate of change (Table 4.3), the peri-urbanization indexes, and the evolution of urban and peri-urban areas (Figure 5b) provide a clear distinction between two periods: one characterized by high urban growth (1987–1995, 1995–2000, 2000–2005, and 2005–2010), and the other by significant peri-urban growth (2010–2015 and 2015–2021). These two periods suggest a trend of urban densification and a decline in urban density. However, the peri-urban fraction indicates that the effectiveness of the decline in urban densities has not been realized from 1987 to 2021, as the fraction of peri-urban area observed in 1987 remains equivalent to that observed in 2021 (Figure 4.5b).

Table 4.3. Annual rates of change (%) and spatial transformation processes. ROC: Rate Of Change.

	1987–1995	1995–2000	2000–2005	2005–2010	2010–2015	2015–2021
ROC (***U***)	3.6	23.3	5.2	9.9	3.8	3.2
ROC (***P***)	2.2	8.5	3.8	3.5	22.4	5.4
ROC (***R***)	−0.1	−0.4	−1.0	−0.4	−1.2	−0.6
ROC (***U***)	Creation	Creation	Aggregation	Aggregation	Creation	Creation
ROC (***P***)	Creation	Aggregation	Aggregation	Creation	Creation	Creation
ROC (***R***)	Attrition	Dissection	Attrition	Attrition	Dissection	Attrition

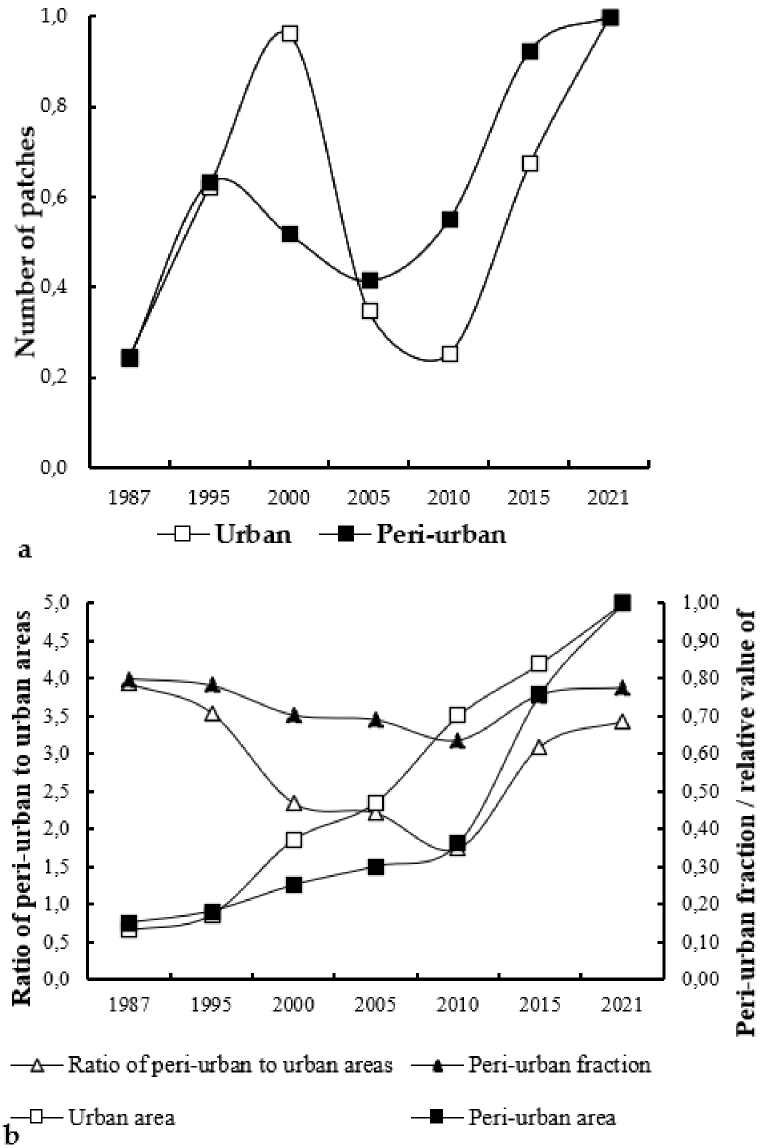


Figure 4.5. Relative values of the number of patches (maximum value for urban zone = 5230, and maximum value for peri-urban = 21,530). (b) Changes in the ratio of peri-urban to urban areas, the peri-urban fraction, and the relative values of urban areas (maximum value = 100.9 km^2) and peri-urban areas (maximum value = 345.7 km^2).

4.8. Discussion

4.8.1. Methodology

Several approaches are available to monitor urban expansion. Zha et al. (2003) propose using an easily measurable built-up area index. This methodology is not well-suited for discriminating between discontinuous built-up areas (peri-urban areas), which is necessary in our case. The analysis performed in this study, based on spatial morphology and the processing of satellite images, is typically applied to identify zones within the urban-rural gradient (André, 2017; Angel et al., 2010; Salomon et al., 2022; Sambieni et al., 2019). However, the morphological criteria used may pose challenges for measurability, depending on the satellite image's spatial resolution (high, medium, or low). In this study, the use of high-resolution images from the Spot and Sentinel-2 sensors enabled the easy identification of built-up pixels at the supra-parcel scale. Furthermore, the implementation of population density, which is expected to decrease with distance from the town center (Angel et al., 2007; Clark, 1951), facilitated a more accurate interpretation of the urban-rural gradient. In addition, the low annual variations in NDVI (0.20 to 0.27) for the urban zone and (0.4 to 0.5) for the peri-urban zone indicate that seasonal variations have minimal effects on the density of green spaces in the Kisangani region. Thus, seasonality would not be an obstacle to interpreting the urban-rural gradient for images acquired on different dates.

The analysis of the decline in urban densities as determined by peri-urbanization indices differs from the approach used by Shlomo Angel, which relies on population density measurements (Angel et al., 2010). Although this approach is not directly related to population density measurements, it enables analysis of urban density decline using spatial characteristics associated with population density. Thus, it should be noted that, in terms of space, the decline in urban densities is expressed by the development of low-density urban areas that are less compact and more dispersed (European Environment Agency, 2006), as well as through the formation of peri-urban patches resulting from the establishment of hybrid zones that occur when urban expansion into rural areas. Thus, analyzing the peri-urban fraction and the ratio of peri-urban to urban areas is relevant for understanding the trend of declining urban density. This approach is particularly relevant in African cities, where population censuses are infrequent.

4.8.2. Changes in landscape pattern

The results reveal a gradual transformation of Kisangani's landscape into an increasingly urbanized one over time, accompanied by the development of peri-urban areas. These observations align with trends in other cities, such as Hanoi (Mauro, 2020) and Bamako (Diallo et al., 2020), where rapid and uncontrolled urbanization results in spatial dilation that extends beyond the urban fringe, transforming it into increasingly impermeable surfaces (Diallo et al., 2020).

As in most cities, these transformations are primarily due to demographic growth over the past few decades (INS, 2022). Indeed, demographic growth remains the primary catalyst for urban expansion worldwide (Diallo et al., 2020; Nancy et al., 2008; Useni et al., 2018). In sub-Saharan Africa, this is exacerbated by precarious socio-economic conditions, leading to a substantial migration of rural populations into urban areas and resulting in a significant spatial expansion of cities (Canning et al., 2016; Mercandalli & Losch, 2018). However, due to precarious socio-economic conditions and the high cost of urban living, which is common in most metropolitan areas in the Democratic Republic of Congo (DR Congo) (Banque mondiale, 2018), most of Kisangani's population resorts to places that still retain their rural character, where access to land resources is relatively affordable (Useni et al., 2018). Consequently, landscapes have been progressively transformed into urbanized patterns, occurring in a scattered manner through the development of low-density, less compact urban areas (European Environment Agency, 2006).

4.8.3. Urban growth model: trend toward the urban density decline

The spatial dynamics of Kisangani city reveal an alternating process between diffusion and coalescence. These two processes, identified through Bogaert's decision tree (Bogaert et al., 2004), correspond to Charles Dietzel's theory (Dietzel et al., 2005), which suggests that the dynamics of cities are a two-phase process involving diffusion, the expansion of urban areas from existing cores, and coalescence, the merging of urban patches. This observation aligns with the findings of several authors (Cheng et al., 2013; Junxiang et al., 2013; Mauro, 2020; Diallo et al., 2020). However, this observation differs from the pattern of urban growth observed in other cities, such as Lubumbashi, where the two phases co-occur (Useni et al., 2018). In Kisangani, this alternating pattern can be attributed to the spatial evolution of the city, which is characterized by the sequential development of urbanization fronts. This sequential development can be explained by four local factors: (i) the missiological approach to the establishment of the Catholic Church in Kisangani, (ii) the geographical distribution of large companies, (iii) the temporality of armed conflicts, and (iv) the evolution of socio-economic categories of the inhabitants.

Indeed, the Catholic Church's strategy for establishing missions in Kisangani involved establishing missionary sites deep within inhabited areas (V. Mbatu, personal communication, April 2023). Over time, these missions developed basic social services that attracted many people, transforming them into urban areas. This gradual process contributed to the creation of urban patches over time. One of the most recent missionary sites is the Scholastica Center north of Kisangani. Furthermore, the location of industrial companies has contributed to the development of residential centers in Kisangani. Proximity to these companies, such as the Textile Society of Kisangani, the Society of Breweries, Limonaderies and Malteries, the National Electricity Society, the National Transport Office, and the National Railway Society, influenced the establishment and development of residential areas. This distribution of industrial companies explains the distribution of isolated urban patches observed in the 1987 image. In addition, armed conflicts in Kisangani throughout its history also impacted the city's sequential development.

During the armed conflict period in Kisangani from 1990 to 2000, certain zones near the city center, including Mutumbe, Cimesta, Cité Paradis, and Cité Canadienne, served as refuge zones. Due to their high population density, these zones underwent gradual development and urbanization, resulting in the formation of urban and peri-urban areas. However, since the end of the armed conflicts (2000–2010), there has been an influx of economic operators from the eastern part of the country, predominantly traders, who sought large spaces in the urban environment for their financial activities. This led to the gradual occupation of interstitial spaces, fostering the aggregation of urban areas. One immediate effect of the establishment and merging of urban and peri-urban areas is an increase in the proportions of each. The peri-urbanization indices examined in this research indicate that, from 1987 to 2010, Kisangani experienced urban densification, characterized by a significant increase in urban space. Geographically, this densification occurred in the Makiso commune. This commune alone concentrates many administrative functions and infrastructures. Like other cities in the DRC, such as Kinshasa, the high concentration of administrative functions and infrastructure, along with the ease of transportation and access to water and electricity distribution networks, make central communes highly attractive compared to peripheral communes (Delbart & Wolff, 2002). In Kisangani, this attraction, which has also intensified the rural exodus, has been exacerbated by the widespread deterioration of socio-economic conditions resulting from prevailing security crises (Koluwa, 2020).

However, the high concentration of the population in central municipalities increases the need for accommodation and social facilities, leading to uncontrolled spatial expansion of the city (Mercandalli & Losch, 2018). Furthermore, the failure to implement various development plans formulated in 1978, 2008, and 2010 (UN-Habitat, 2015), coupled with inadequate control of urban planning matters across most cities in DR Congo (UN-Habitat, 2015) has exposed Kisangani to a gradual decline in urban density, characterized by significant peri-urbanization or the emergence of hybrid zones. This trend observed between 2010 and 2021 is based on Shlomo Angel's observation, according to which urban densities decreased in cities worldwide between 1990 and 2000 (Angel et al., 2010). The trend also aligns with the European Environment Agency's observation that, in the 1950s, European cities were more compact and less sprawling than they are today, and urban sprawl is now a common phenomenon throughout Europe (European Environment Agency, 2006). However, despite this trend observed between 2010 and 2021, the decrease in urban density was ineffective in Kisangani between 1987 and 2021, as the fraction of peri-urban areas observed in 1987 remains equivalent to that observed in 2021. This suggests a continuity of urban densification despite increasing peri-urbanization.

In contrast to other cities, particularly those in developed countries, where the emergence of urban emigration and a reversal of the urban-rural flow hierarchy can be observed (Beauchemin, 2003), the rural exodus remains pronounced in African cities. Therefore, the development of metropolitan areas in most cities, particularly in Kisangani, continues to progress by filling in interstitial spaces, despite the significant peri-urbanization already underway.

4.9. Conclusion

This study has highlighted the rapid spatial growth of urban and peri-urban areas in Kisangani city over the last 34 years, from 1987 to 2021, using a combination of remote sensing, geographic information systems, and landscape ecology tools. The city’s urban core expanded from 13.49 km^2 to 100.49 km^2 between 1987 and 2021, with an average annual growth rate of 8.2%. The identified spatial transformation processes suggest an alternating pattern of diffusion and coalescence in urban and peri-urban areas.

The peri-urbanization indices developed indicate that between 1987 and 2010, the city of Kisangani underwent urban densification, mainly due to the rural exodus. The increase in the demand for accommodation and social facilities in urban areas has led to a substantial expansion of peri-urban areas between 2010 and 2021, a corollary of the decline in urban densities. Nevertheless, despite this trend, the effectiveness of the decrease in urban density has not been realized from 1987 to 2021, as the fraction of peri-urban areas observed in 1987 remains equivalent to that observed in 2021. This suggests a continuity of urban densification despite increasing peri-urbanization.

Therefore, in Kisangani and other cities where urban expansion occurs without sustainable planning, the main spatial challenge revolves around effectively managing urban sprawl. This involves adapting or redeveloping human settlements to meet socio-spatial demands and reduce the uncontrolled occupation of natural spaces. The methods employed in this study enable monitoring of urban expansion. Furthermore, researchers and scientific institutions should contribute to understanding the impact of current urban densification and sprawl on the environment, particularly on green infrastructure in urban and peri-urban zones.

Chapter 5

Anthropogenic effects on green infrastructure spatial patterns in Kisangani city and its urban-rural gradient.

5.1. Reference

Balandi, J. B., Meniko, J.-P. P. T. H., Sambieni, K. R., Sikuzani, Y. U., Bastin, J.-F., Musavandalo, C. M., Besisa, T.N., Jesuka, R., Sodalo, C., Mukubu, L.P., & Bogaert, J. (2023). Anthropogenic effects on green infrastructure spatial patterns in Kisangani city and its urban–rural gradient (DR Congo).
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5.2. Context

The previous analysis highlighted the rapid urban expansion of Kisangani between 1987 and 2021, characterized by persistent urban densification despite the trend toward de-densification observed between 2010 and 2021. These transformations of the Kisangani city area are likely to reshape the landscape by altering the composition and configuration of green spaces, key components of urban green infrastructure that are essential for thermal regulation, air and water quality, erosion control, biodiversity, and recreational and cultural activities. This chapter, therefore, provides a spatial and temporal analysis of changes in green infrastructure, accounting for the specific features of the urban–rural gradient and its dynamic nature.

5.3. Résumé

L'expansion urbaine et périurbaine influence de manière significative la configuration spatiale des villes et des zones environnantes. Cette étude examine les changements spatiaux des composantes de l'infrastructure verte, en se concentrant particulièrement sur les forêts matures, les forêts secondaires, les terres agricoles et les herbacées, sur la période 1986-2021, à partir d'images satellitaires. Deux indices de la structure spatiale du paysage, le pourcentage occupé du paysage (PLAND) et l'aire de la plus grande tache (LPI), ont été utilisés. Le PLAND renseigne sur la proportion des types d'habitats et permet d'appréhender leur étendue globale, tandis que le LPI éclaire leur configuration spatiale. L'étude s'inscrit dans le contexte d'une urbanisation et d'une périurbanisation croissantes à Kisangani, en République Démocratique du Congo.

A l'échelle du paysage, les résultats montrent un déclin des forêts matures et secondaires entre 1986 et 2021, accompagné d'une expansion continue des terres agricoles et des herbacés. De plus, en 2021, la configuration spatiale des forêts matures et secondaires a montré des variations significatives dans les zones urbaines, périurbaines et rurales. Les forêts matures ont représenté moins de 1 % des parcelles de 2,25 km² dans les zones urbaines et périurbaines, contre plus de 35 % dans certaines parcelles rurales. De même, les grandes taches des forêts matures couvrent moins de 0,5 % des parcelles urbaines et périurbaines, alors qu'elles dépassent 20 % dans les zones rurales. Dans le gradient urbain-rural, entre 1986 et 2021, les forêts matures et secondaires ont connu un déclin et une fragmentation importants, particulièrement dans les zones urbaines et périurbaines, tandis que les terres agricoles et les herbacés ont augmenté significativement dans les zones périurbaines et rurales. Ces résultats soulèvent des inquiétudes quant aux fonctions, aux services et aux opportunités offerts par les forêts matures et secondaires dans le contexte du changement global. Ils mettent également en évidence l'importance de la planification urbaine à Kisangani, en privilégiant la préservation de l'infrastructure verte, notamment le maintien de la connectivité forestière et la prévention de la fragmentation. Les politiques doivent promouvoir un usage durable des terres dans les zones périurbaines afin de concilier l'expansion urbaine et la fourniture de services écosystémiques essentiels, renforçant ainsi la résilience urbaine à long terme.

Mots-clés : Gradient d'urbanisation, infrastructure verte, structure spatiale, Kisangani

5.4. Abstract

Urban and peri-urban expansion significantly shapes the spatial patterns of cities and their surrounding areas. This study examines spatial changes in green infrastructure components, with a particular focus on mature forests, short forests, and agricultural and grassland areas, from 1986 to 2021, using satellite imagery. Two landscape ecology indices, the percentage of landscape (PLAND) and the largest patch index (LPI), were applied. PLAND provides insights into the proportion of habitat types, capturing overall extent, while LPI elucidates their spatial configuration. The research is conducted within a specific context of increasing urbanization and peri-urbanization in Kisangani, the Democratic Republic of the Congo. The findings reveal declines in both mature and short forests from 1986 to 2021, as well as from 2006 to 2021, alongside a continuous expansion of agricultural and grassland areas at the landscape scale. Moreover, the spatial patterns of mature and short forests showed significant variation across urban, peri-urban, and rural zones. In 2021, mature forests accounted for less than 1% of the 2.25 km² plots in urban and peri-urban zones, compared to more than 35% in specific rural plots. Similarly, larger patches of mature forest in urban and peri-urban zones cover less than 0.5% of the 2.25 km^2 plots, whereas they exceed 20% in rural zones. From 1986 to 2021, both mature and short forests experienced significant declines and fragmentation, particularly in urban and peri-urban zones, while agricultural and grassland areas increased significantly in peri-urban and rural zones. These results raise concerns regarding the functions, services, and opportunities provided by mature and short forests in the context of global change. They also emphasize the importance of urban planning in Kisangani, prioritizing the preservation of green infrastructure and maintaining forest connectivity to prevent further fragmentation. Policies should promote sustainable land use in peri-urban zones to balance urban expansion with the provision of essential ecosystem services, thereby enhancing long-term resilience.

Keywords : Urbanization gradient, green infrastructure, spatial pattern, Kisangani

5.5. Introduction

The process of urbanization has occurred rapidly on a global scale over the past six decades (United Nations, 2014; Useni et al., 2018). In fact, in 1950, 70% of the world's population lived in rural areas, while less than one-third (30%) resided in urban regions (United Nations, 2014). Since 2007, the global urban population has exceeded the global rural population, and this is expected to continue until 2050 (Cheng et al., 2013; United Nations, 2014), particularly in developing countries, which are projected to account for over 90% of global urban population growth between 2030 and 2050 (United Nations, 2018; Useni et al., 2019).

As a result, most cities are experiencing an increase in urbanized areas that is twice as fast as population growth (Angel et al., 2011). In African cities, this rapid urbanization is accompanied by various ecological challenges (Sambieni et al., 2018; United Nations, 2014). In some unplanned or poorly managed cities, urban expansion leads to rapid urban sprawl (Balandi et al., 2023; United Nations, 2018), pollution, environmental degradation, and unsustainable production and consumption patterns (Sambieni et al., 2018; United Nations, 2018). This pattern of urban expansion threatens urban green infrastructure (Sambieni et al., 2018; Useni et al., 2019) and has the potential to increase carbon emissions significantly (United Nations, 2018).

Indeed, green infrastructure (GI) refers to a network of natural and semi-natural spaces and features, such as parks, wetlands, green spaces, green roofs, and green walls, that provide ecosystem services and benefits to urban communities (Bixler et al., 2020; Zahoor et al., 2023). These benefits may include absorbing, adapting to, and transforming both sudden and chronic stresses in cities, as well as improving air and water quality, mitigating the urban heat island effect, reducing flood risk, enhancing biodiversity, and providing recreational and cultural opportunities (Cornet, 2020; Dupras et al., 2016; Kong et al., 2014; MEA, 2005; Rieke & Pauleit, 2014; Tzoulas et al., 2007; Wellmann et al., 2020; Rogombe et al., 2022). However, the profound transformation of natural structures into urbanized landscapes without effective spatial planning not only results in a loss of biodiversity but also limits human interaction with nature (Useni et al., 2019; Shackleton et al., 2014). Therefore, integrating sustainability into the urbanization process becomes imperative (Jégou, 2012; Wolch et al., 2014).

One solution is to protect existing green infrastructure and strategically incorporate green spaces within built environments (Chaoui, 2023; FAO, 2012; Sambieni et al., 2018). To this end, several research projects focus on understanding, among other things, the spatiotemporal changes in urban green infrastructure (Sambieni, 2019; Useni et al., 2017), their typology and specific composition (Sambieni et al., 2018; Useni et al., 2019), as well as the ecosystem services provided for the benefit of populations (Chaoui, 2023; Cornet, 2020; Sirina et al., 2023; Wavel et al., 2023).

The city of Kisangani, in the Democratic Republic of the Congo (DRC), is experiencing rapid spatial expansion driven by significant demographic growth (INS, 2022). Between 1987 and 2021, the city's urban core expanded from 13.49 km² to 100.49 km², with an average annual growth rate of 8.2% (Balandi et al., 2023). The rising demand for accommodation and social facilities in urban zones has resulted in significant expansion of peri-urban zones between 2010 and 2021 (Balandi et al., 2023), a corollary of the decline in urban densities, now evident in most of the world's cities (Angel et al., 2011). Despite significant urban and peri-urban expansion, the city of Kisangani remains under-researched in terms of its scientific understanding of the spatial dynamics of its green infrastructure. Indeed, in 2010, Bamba & Bogaert (2010) analyzed the effect of roads on the city of Kisangani between 1986 and 2001, as well as the influence of population density on the spatial pattern of dense forest (Bamba et al., 2010). The results revealed highly significant correlations between population density and fragmentation indexes, highlighting the influence of population density on the degradation of natural ecosystems. However, it is crucial not to restrict the concept of green infrastructure solely to the dense forest surrounding the city, especially in the context of peri-urbanization (Sambieni et al., 2018), which leads to the degradation of dense forest through the expansion of agricultural and built-up spaces. In this perspective, in 2014, Kamunukamba & Koy (2014) mapped the different types of green spaces in the city of Kisangani from 1960 to 2010. However, this study is limited to quantifying the number of green spaces and their spatial locations, without examining their spatial configuration and composition within the landscape. Furthermore, the effects of peri-urbanization on the conversion of these green spaces were not examined.

The present study aims to assess the impact of urbanization and peri-urbanization in the city of Kisangani (Balandi et al., 2023), on the spatial pattern of green infrastructure, which consists of three components: mature forests, secondary forests (referred to as short forests), and agricultural areas with grasslands. In Kisangani, these types of green spaces provide essential ecosystem services, including the absorption, adaptation, and transformation of both acute and chronic stressors. They also enhance air and water quality, mitigate the urban heat island effect, reduce flood risks, promote biodiversity, and offer recreational and cultural opportunities. These green spaces are therefore integral components of the city's green infrastructure.

Therefore, this study addresses a key research gap: the lack of empirical data on the impacts of urbanization on green infrastructure, specifically regarding the spatial and temporal patterns of green space loss and fragmentation. While the effects of urbanization on green spaces have been widely studied in other regions, Kisangani's unique urban–rural gradient and its implications for green space coverage and ecosystem services have not been adequately examined. This research offers crucial insights into how urban expansion impacts green infrastructure, informing sustainable planning and policy initiatives for rapidly urbanizing tropical cities. The effects of urban and peri-urban growth are evaluated at two spatial scales: (i) at the landscape scale (Kisangani and its periphery) and (ii) along the urban–rural gradient. The analysis of green infrastructure spatial patterns along the urbanization gradient, as conducted in this study using randomly selected plots in all spatial directions, provides a more comprehensive and representative perspective of the variations in spatial patterns among the components of green infrastructure.

Thus, at the landscape scale, we hypothesize that urban expansion in Kisangani from 1986 to 2021 has significantly affected green infrastructure, particularly by reducing the proportion of mature and short forests while increasing the area of agricultural and grasslands. This expansion is anticipated to fragment the largest patches of mature and short forests, decreasing their size and altering their spatial configuration. Along the urban–rural gradient, we anticipate distinct variations in forest composition and configuration, with urban zones exhibiting lower proportions and smaller patches than peri-urban and rural zones, primarily due to the prevalence of intensive human activities. Agricultural and grassland areas are expected to show similar variations, with peri-urban zones featuring larger, more continuous patches due to greater land availability and proximity to urban trade.

Over time, from 1986 to 2021, we anticipate a significant decline and fragmentation of mature and short forests across all zones due to unmanaged urban expansion (Balandi et al., 2023; UN-Habitat, 2015) while agricultural and grassland areas increase in peri-urban and rural areas. In urban zones specifically, agricultural and grassland areas are expected to decline and fragment over time as they are gradually converted into built-up areas.

5.6. Materials and methods

5.6.1. Study area

Covering 2,947.9 km², the study area includes six communes of Kisangani and a surrounding peripheral zone (Figure 5.1). Five of these six communes, including Makiso, Mangobo, Kabondo, Tshopo, and Kisangani, are situated on the right bank of the Congo River, while Lubunga is the only commune located on the left bank of the same river (Figure 5.1). Kisangani receives an average annual rainfall of 1724 mm, based on data collected over 50 years (1956–2005), with an average annual temperature of 25.3°C (Sabongo, 2015). Monthly precipitation exceeds 60 mm (Sabongo, 2015). These climatic data collectively categorize the city of Kisangani as having an Af-type climate according to Köppen's classification (Assani et al., 2015; Sabongo, 2015). The population has grown significantly over time (Balandi et al., 2023). Estimated at 105,666 inhabitants in 1959 (Bamba, 2010), demographic data from the National Institute of Statistics (INS) indicate that the population exceeded 2,184,096 inhabitants by 2021 (INS, 2022). The population comprises several ethnic groups from various provinces of the DRC and neighboring countries, primarily relying on agriculture, commercial activities, and fishing (Gabriel & Omer, 2022).

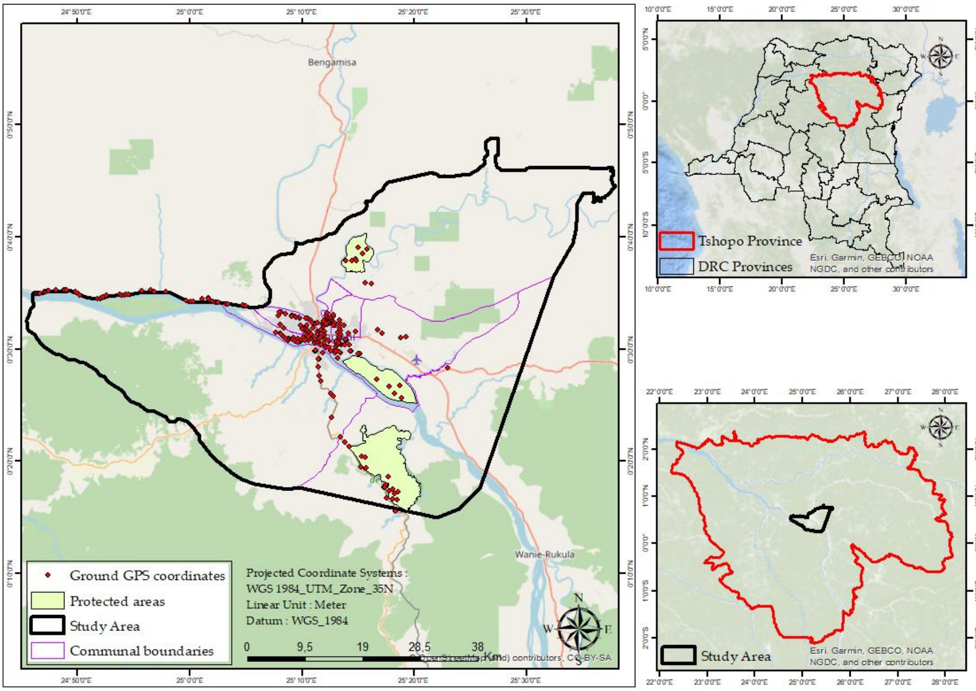


Figure 5.1. The geographical location of Kisangani and its periphery. Three protected areas surround Kisangani (Masako, Mbiye, and Yoko). The road network includes national and provincial roads.

5.6.2. Data used

The spatial pattern of green infrastructure was assessed using images from Landsat TM (1986–1991–1996), ETM+ (2001–2006–2011), and OLI-TIRS (2016–2021) with a spatial resolution of 30 m. Images with low cloud cover (<10%) were obtained, enabling 35 years of analysis at 5-year intervals. These satellite data were supplemented by 310 GPS surveys that provide detailed information on land use and land cover (Table 5.1).

Table 5.1. The characteristics of the data used

Data	Months Filtered	Years	Spatial Resolution
Landsat images (MSS–TM)	15 Dec–28 Feb	1986–1991–1996	30 m
Landsat images (ETM+)	15 Dec–28 Feb	2001–2006–2011	30 m
Landsat images (OLI)	15 Dec–28 Feb	2016–2021	30 m
Hansen Global Change Map	-	2000–2021	30 m
GPS data	August–March	2022–2023	-

The selected dates correspond to various periods marked by social and political changes anticipated to influence spatial landscape patterns. Notably, 1986 falls within the 1980s–90s decade, a time affected by a national economic deficit.

Faced with this financial situation, several companies, including SOLBENA, ALIPOST (Postal Supply), INNOVATION, and PRODIMPEX, chose to shut down (Tshonda, 1991). In total, 84 companies closed in 1989 (Tshonda, 1991), resulting in the city's residents relying heavily on agricultural activities. The timeframe from 1991 to 1996 encompassed a decade (1990 to 2000) marked by numerous confrontations among various armed groups (Gabriel & Omer, 2022; Koluwa, 2020), compelling a large segment of the population to migrate from urban centers to peripheral areas. In contrast, 2001 was marked by the return of stability following six days of armed confrontation in 2000 (Gabriel & Omer, 2022). Additionally, 2006 and 2011 were significant due to the general elections, while 2016 coincided with the dismemberment of the DRC's provinces (Ngoie, 2016). Lastly, 2021 witnessed substantial demographic growth, with over 2,000,000 residents living in the city (INS, 2022).

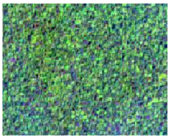
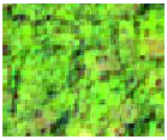
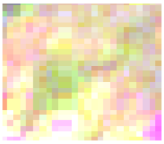
5.6.3. Satellite data preprocessing

To minimize atmospheric effects and radiometric variations caused by differences between the Landsat sensors (Phan & Lehnert, 2020; Roy et al., 2016), surface reflectance (SR) images were used. The surface reflectance for Landsat 4–5 TM and Landsat 7 ETM+ is generated using the Landsat Adaptive Ecosystem Disturbance Processing System (LEDAPS) algorithm, whereas for Landsat 8–9 OLI, it is obtained through the Land Surface Reflectance Code (LaSRC) (Sayler & Zanter, 2021; Sayler & Zanter, 2023). These algorithms provide images with optimal radiometric and spectral characteristics (Padró et al., 2017), thus enabling comparisons among multiple images of the same region (Sayler & Zanter, 2023). Using the Global Geodetic System (WGS-84), these images were resampled to the exact spatial resolution (30 m), at the same extent, and reprojected in Universal Transverse Mercator, Zone 35 North. A false-color composition combining the mid-infrared (MIR), near-infrared (NIR), and red (R) bands was produced for each date to better discriminate land-cover types.

5.6.4. Supervised classification of satellite images

The false-color compositions created by combining green, red, and near-infrared bands from Landsat imagery improve the differentiation of green spaces. This analysis was further supported by high-resolution images, especially those obtained from Google Earth in Earth Engine, along with PlanetScope images with a spatial resolution of 3 m and NDVI variation. These advanced imaging techniques facilitated the selection of training points for calibrating the supervised classification of the land cover types studied, including (1) mature forests, (2) short forests, and (3) agricultural lands and grasslands (Table 5.2). In this study, all other land cover types not part of the green infrastructure, particularly built-up areas, bare soil, and water, have been merged into the 'other' class. The use of high-resolution imagery helped reduce confusion arising from variations in NDVI values across mature forests and agricultural land. The Random Forest algorithm (Del Río et al., 2014; Muteya et al., 2023) was used to train the supervised classification model. To achieve optimal accuracy and performance, the number of decision trees was set to 100 for all analyzed images. The benefit of this algorithm lies in its ability to generate multiple decision trees that independently analyze and assign samples to their respective classes, thereby enhancing classification performance (Balandi et al., 2023; Phan & Lehnert, 2020).

Table 5.2. Descriptions of land cover types on a false-color composition combining the mid-infrared (MIR), near-infrared (NIR), and red (R) bands and variations in NDVI values.

Land Cover Type	Descriptions	NDVI Values
Mature Forest 	A type of climax forest structured into several individual strata. This type of forest is characterized by the presence of gregarious species, including *Brachystegia laurentii* and Gilbertiodendron dewevrei, as well as other wetland species.	0.74–0.82
Short Forest 	Forest types that succeed regeneration and constitute the transitional phase to the establishment of the mature forest (which refers to secondary forests). The prevalence of heliophilous species characterizes this type.	0.80–0.87
Agricultural and grassland 	Land covered by crops and herbaceous plants. In the city of Kisangani, farmers' fields generally include cassava, rice, and maize. This is also land that has been left to rest post-cultivation.	0.70–0.84

5.6.5. Assessment of classification accuracy

Classifications were evaluated using global, user, and producer accuracies derived from the confusion matrices. During the field missions conducted in August 2022 and March 2023, 642 GPX control points were sampled, depending on the accessibility of the respective zones. It should be noted that 33% of these control points represent built-up and bare soil included in the class 'other', 27% agricultural land, 20% short forest, and 20% mature forest. Two samples were thus constituted: the first, with 310 points, was used to validate the reference classification (2021), and the second, with 232 points, was used to compare our classifications with Hansen's classification (Hansen et al., 2013). For the reference classification (2021), four strata were formed, corresponding to the four land-cover types studied. Thus, 102 points (33% of 310 points) were randomly selected for the built-up and bare soil included in the class 'other', 84 points (27%) for the agricultural and grassland, 62 points (20%) for the short forest, and 62 points (20%) for the mature forest. Due to the absence of field data for earlier dates (1986-1991-1996-2001-2006-2011-2016), the validation samples for each date were defined using archival imagery available in Google Earth Pro, supplemented by unchanged landscape areas identified in the reference classification (2021). To compare our classifications with a global classification and discuss the level of accuracy, the change map between 2000 and 2021 produced by Hansen was compared to our change map between 2001 and 2021.

To facilitate this comparison, spatial changes observed in both maps were simplified into two classes: (1) forest and (2) non-forest, and compared to 232 randomly selected reference points. In this study, we defined a forest in Hansen's classification as any pixel with 50% or more forest cover, making the forest patch the dominant feature in the pixel. Therefore, for a forest pixel, any spatial change between 2000 and 2021 that reduced the forest cover rate to less than 50% was considered a pixel transformed into non-forest, and vice versa. Consequently, a contingency table was produced to compare the changes classified as forest with those classified as non-forest, using the reference data. This table allowed us to determine the user, producer, and global accuracies by applying Equations (1)–(3) from Ref. (Olofsson et al., 2014).

5.6.6. Delineation of urban-rural gradient zones

To delineate and classify the zones of the urbanization gradient, built-up areas, which represent some of the most precise, coherent, and dynamic morphological criteria (Angel et al., 2011; Sambieni, 2019), were analyzed. For each date, including 1986, 1991, 1996, 2001, 2006, 2011, 2016, and 2021, the analysis of satellite images enables the identification of built-up areas based on impermeable surfaces (pavements, rooftops, and compacted ground) (Angel et al., 2011; Balandi et al., 2023). Thus, an area is defined as urban when it consists of a majority of built-up pixels (exceeding 50%) within training zones of 250 m × 250 m (Balandi et al., 2023). Additionally, an area is categorized as peri-urban if the proportion of built-up pixels within a 250 m × 250 m training zone is 50% or less, and the remaining pixels are not exclusively designated as forest or agricultural land. In contrast, an area is defined as rural when the 250 m × 250 m training zone is predominantly composed of vegetation pixels (Balandi et al., 2023).

5.6.7. Analysis of green infrastructure spatial patterns

Spatial pattern analysis was conducted at the scale of Kisangani's landscape and within the urban-rural gradient. Two primary approaches are typically used to analyze spatial patterns within the urban-rural gradient (Junxiang et al., 2013). The first involves implementing a transect that extends from the urban center to the rural periphery, where spatial pattern indices are analyzed (Junxiang et al., 2013; Schneider et al., 2005). The second methodology uses buffer zones to compute indices for a series of concentric zones surrounding the urban center (Bamba & Bogaert, 2010; Seto & Fragkias, 2005; Useni et al., 2018). To obtain a more comprehensive and representative view of the spatial pattern within an urban–rural gradient and to better understand the complexity and variability of the studied landscape, sampling plots were randomly selected in all directions (north, south, east, west, northeast, northwest, southeast, and southwest) for each zone of the urban–rural gradient (Figure 5.2). This approach captures significant variations that may be perpendicular to a transect, including short-distance variations that can be overlooked in concentric zone-based methods.

As urban, peri-urban, and rural zones vary significantly in both spatial extent and distribution, a total of eight observation plots, each measuring 1.5 km on each side (equivalent to 2.25 km²), were randomly selected from each zone for the reference year (2021). These eight plots, sized at 2.25 km², were chosen to represent the larger landscape by capturing a range of ecological conditions and land uses, including variations in forest cover, agriculture, and urban development. Random sampling was used to minimize bias and ensure generalizability, allowing for an unbiased assessment of landscape variability. This method enhances the validity of the findings, providing a comprehensive understanding of the impacts of urbanization on green infrastructure across the entire urban–rural gradient. However, it is essential to note that the status of these observation plots has changed over time, reflecting the dynamics of urban, peri-urban, and rural zones.

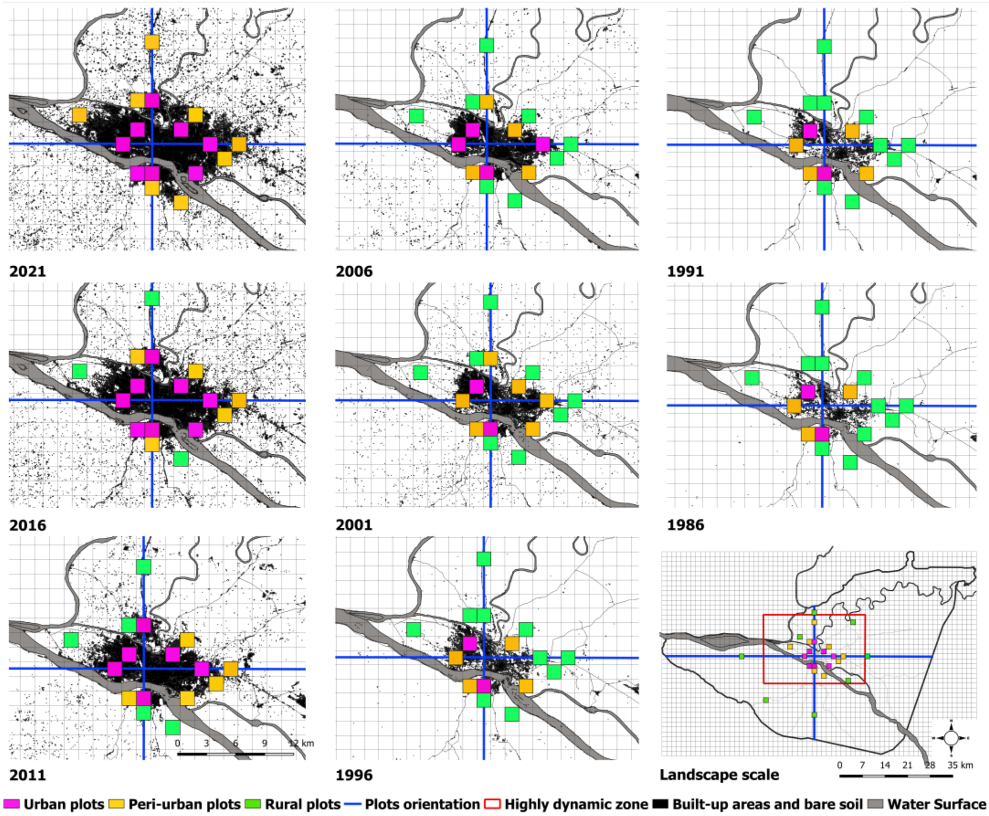


Figure 5.2. The sample plots in the urban–rural gradient were randomly selected in the north, south, east, west, northeast, northwest, southeast, and southwest directions. The changes in the status of these plots highlight the dynamic nature of urban, peri-urban, and rural zones.

For each plot analyzed, two landscape ecology indices were examined: the percentage of landscape (PLAND) and the largest patch index (LPI). We selected PLAND and LPI because they provide complementary insights into landscape composition and configuration. PLAND quantifies the proportion of green infrastructure within the landscape, capturing its overall extent, while LPI identifies the largest contiguous patch, reflecting connectivity and dominance. Together, these indices effectively capture both the composition and configuration of green infrastructure, making them well suited to analyzing temporal and spatial changes in its patterns. It is important to note that both indices are sensitive to landscape changes induced by human activities (Bogaert & Mahamane, 2005; Krummel et al., 1987).

Therefore, the percentage of the landscape occupied by each green infrastructure component (Equation (5.1)) was quantified to verify the following: (i) the expected decline in both mature and short forest and the anticipated increase in the proportion of agricultural land and grassland from 1986 to 2021 at the landscape scale; (ii) the lower proportions of mature and short forest expected in urban zones compared to peri-urban and rural zones due to urban sprawl and intense human activities; and (iii) the higher proportions of agricultural land and grassland expected in peri-urban zones compared to urban and rural zones due to land availability and proximity to urban trade. Furthermore, the proportion covered by the largest patch (Equation (5.2)) was calculated to assess (i) the fragmentation of both mature and short forest larger patches from 1986 to 2021 at the landscape scale, and (ii) their fragmentation in urban zones compared to peri-urban and rural zones, alongside an aggregation of agricultural and grass land patches in peri-urban as compared to urban and rural zones.

Equation 5.1. $$PLAND = \frac{\sum_{j=1}^{n} aij}{A} \text{ x } 100$$

PLAND = Percentage of Landscape
a_{ij} = Area (m^2) of patch *ij;*
A = Total landscape area (m^2)

Equation 5.2. $$\text{LPI} = \frac{max_{j=1}^{n}\,(a_{ij})}{A} \text{ X } 100$$

LPI = Largest Patch Index

For the reference year (2021), data on the composition (PLAND) and configuration (LPI) of green infrastructure components in the eight sample plots, categorized by zones along the urbanization gradient, which were initially asymmetric, were subjected to a logarithmic transformation to meet the normality assumption required for the ANOVA test. However, for previous years, the data's constant asymmetry, reflecting the reduction in the number of urban and peri-urban plots over time (Figure 5.2), attributable to the dynamics of urban-rural gradient zones, necessitated the use of non-parametric tests. Thus, a Kruskal-Wallis test was employed to assess the temporal effects on green infrastructure components within each urbanization gradient zone. Given the sample variations, group size inequalities, and resulting data asymmetry, this test is well-suited for drawing solid conclusions about the spatio-temporal dynamics of the spatial pattern of green infrastructure components across urban, peri-urban, and rural zones.

5.7. Results

5.7.1. Validation of classifications and mapping of land cover

The indicators derived from confusion matrices, including user, producer, and overall accuracy, with values above 80% (Table 5.3), confirm a reliable level of land cover discrimination. Moreover, comparing our change map to the one produced by Hansen et al. (2013) reveals that the local classification is slightly more representative and consistent with the reference data than the global classification (Table 5.4). Visual interpretation of the land-use maps reveals a gradual expansion of agricultural areas in the Kisangani landscape. In addition, there is evidence of a steady decline in mature forests between 1986 and 2021. However, low forests exhibit two phases of evolution, the first, from 1986 to 2006, characterized by an increasing trend, and the second, from 2006 to 2021, characterized by a decreasing trend (Figure 5.3).

Table 5.3. The validation of land cover classifications based on the Landsat images using the Random Forest classifier. MF corresponds to the mature forest; UA is the user's accuracy; PA is the producer accuracy; SF corresponds to the short forest; AGL is the agricultural and grassland; BBS corresponds to the built-up and bare soil; WS is the water surface; OA is the overall accuracy. The land use types and years are highlighted in bold.

MF	**1986**	**1991**	**1996**	**2001**	**2006**	**2011**	**2016**	**2021**
UA	99.62	99.99	99.79	98.21	99.70	99.99	100	95.65
PA	99.80	99.20	99.95	99.85	99.41	99.63	99.01	100
SF	**1986**	**1991**	**1996**	**2001**	**2006**	**2011**	**2016**	**2021**
UA	96.99	81.61	97.26	99.63	90.09	90.20	91.98	99.46
PA	94.93	89.73	85.01	94.22	94.79	89.09	99.11	82.99
AGL	**1986**	**1991**	**1996**	**2001**	**2006**	**2011**	**2016**	**2021**
UA	91.05	88.75	86.37	95.60	92.27	90.18	80.41	86.33
PA	92.56	96.70	92.99	94.98	85.98	88.07	100	99.04
BBS (in other)	**1986**	**1991**	**1996**	**2001**	**2006**	**2011**	**2016**	**2021**
UA	100	97.29	99.36	98.33	100	100	100	96.25
PA	99.13	100	93.82	100	100	100	100	100
WS (in other)	**1986**	**1991**	**1996**	**2001**	**2006**	**2011**	**2016**	**2021**
UA	100	100	100	100	100	99.27	100	100
PA	100	99.97	100	99.82	100	99.27	100	99.91
OA	99.38	99.24	99.57	98.82	98.81	98.11	98.26	97.18

Table 5.4. A comparison with a global classification: the case of High-Resolution Global Maps of Hansen between 2000 and 2021. UA is the user's accuracy, PA is the producer's accuracy, and OA is the overall accuracy.

Hansen Classification	UA	PA	OA
Forest	78.12	78.12	93.96
Non-Forest	96.5	96.5	
Local classification	**UA**	**PA**	**OA**
Forest	90.62	96.66	98.70
Non-Forest	99.50	98.52	

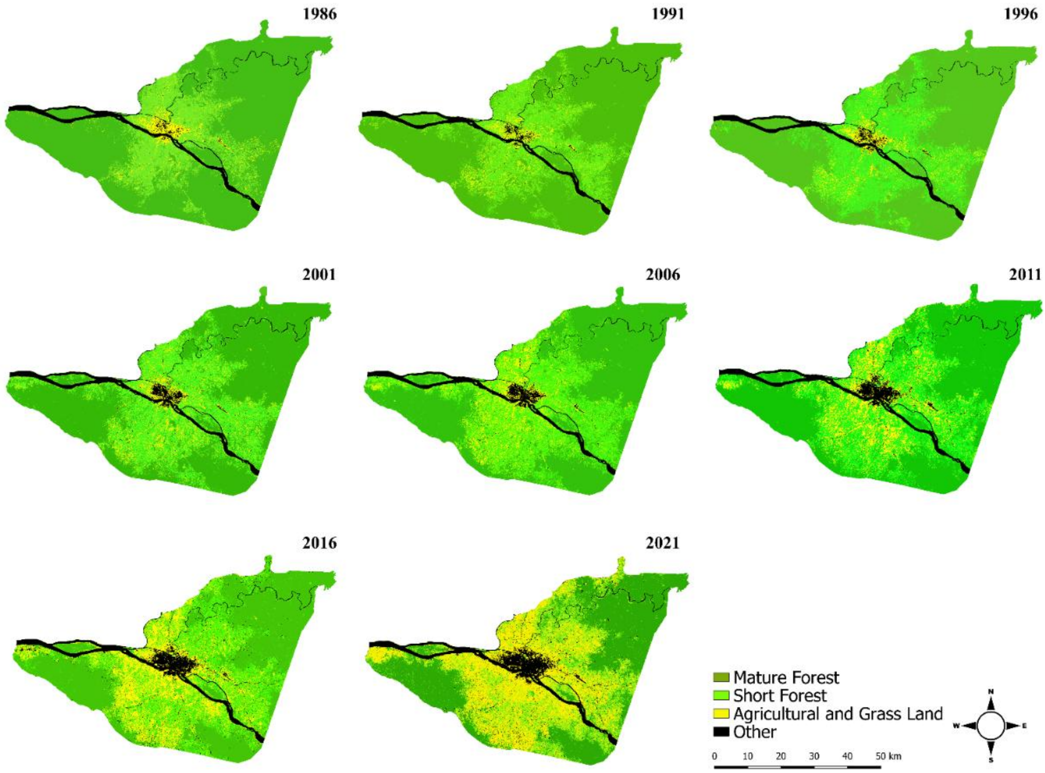


Figure 5.3. The mapping of green infrastructure components based on a supervised classification of Landsat images using the Random Forest algorithm. The expansion of agricultural and grassland is occurring alongside a decrease in mature and short forests.

5.7.2. The spatial pattern of green infrastructure in the landscape of Kisangani

As expected, between 1986 and 2021, mature forests exhibited a regressive trend characterized by a consistent decline in the proportion within the landscape composition (Figure 5.4a). Specifically, an estimated 100,711.32 hectares of land were lost during this period, representing a reduction of over 47% from the initial area of mature forests in the landscape. This trend of loss has intensified in recent years, with 19,211.42 hectares lost between 2011 and 2016, and an additional 22,138.41 hectares lost between 2016 and 2021. However, the years 1996 and 2006 had a particularly positive impact on the dynamics of the largest patches of mature forest, fostering their spatial restoration (Figure 5.4b).

Conversely, at the landscape scale, the area of short forest increased by 9,695.69 hectares from 1986 to 2021. However, the dynamics of short forests at the landscape level exhibited two primary trends (Figure 5.4a). Between 1986 and 2006, the area of short forest increased by approximately 38,000 hectares, representing a rise of more than 35% compared to the initial area. In contrast, from 2006 to 2021, short forests lost approximately 28,000 hectares, representing a decrease of more than 29% from 2006 levels. Additionally, a general trend of decreasing proportions of the largest patches of both mature and short forests has been observed between 1986 and 2021 (Figure 5.4b). Notably, the largest patch of mature forest experienced a decrease of over 60% in area during this timeframe.

In comparison, the largest patch of short forest experienced a staggering reduction of more than 84% (Figure 5.4b). The expansion of agricultural and grassland has offset the loss of both mature and short forests in recent years. Indeed, agricultural land has expanded by 7,852.70 ha between 1986 and 2021. In 1986, farming and grassland constituted 4% of the landscape. By 2021, this land use type had risen to 32% (Figure 5.4a). This expansion of agricultural land has intensified over the periods 2011–2016 and 2016–2021. The proportion of agricultural land in the landscape increased from 14.2% to 20.6% between 2011 and 2021.

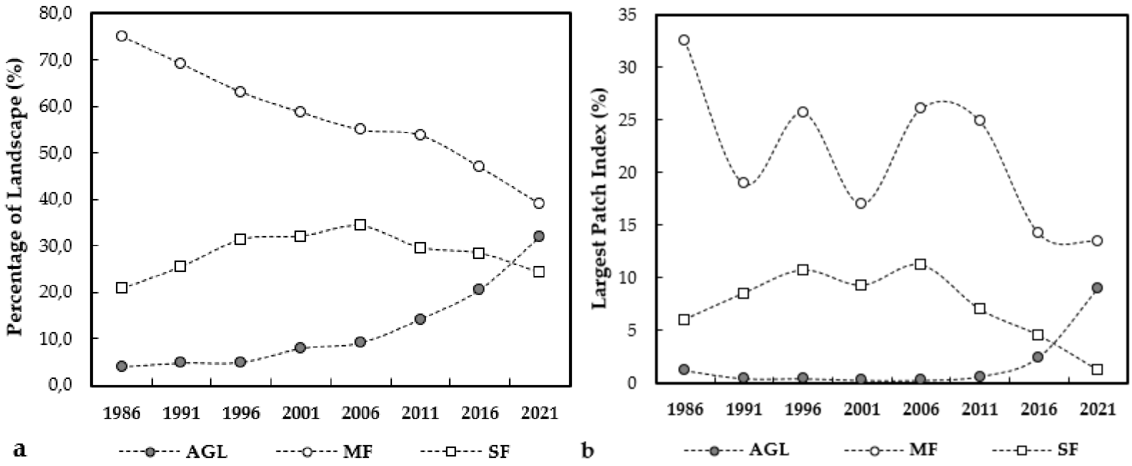


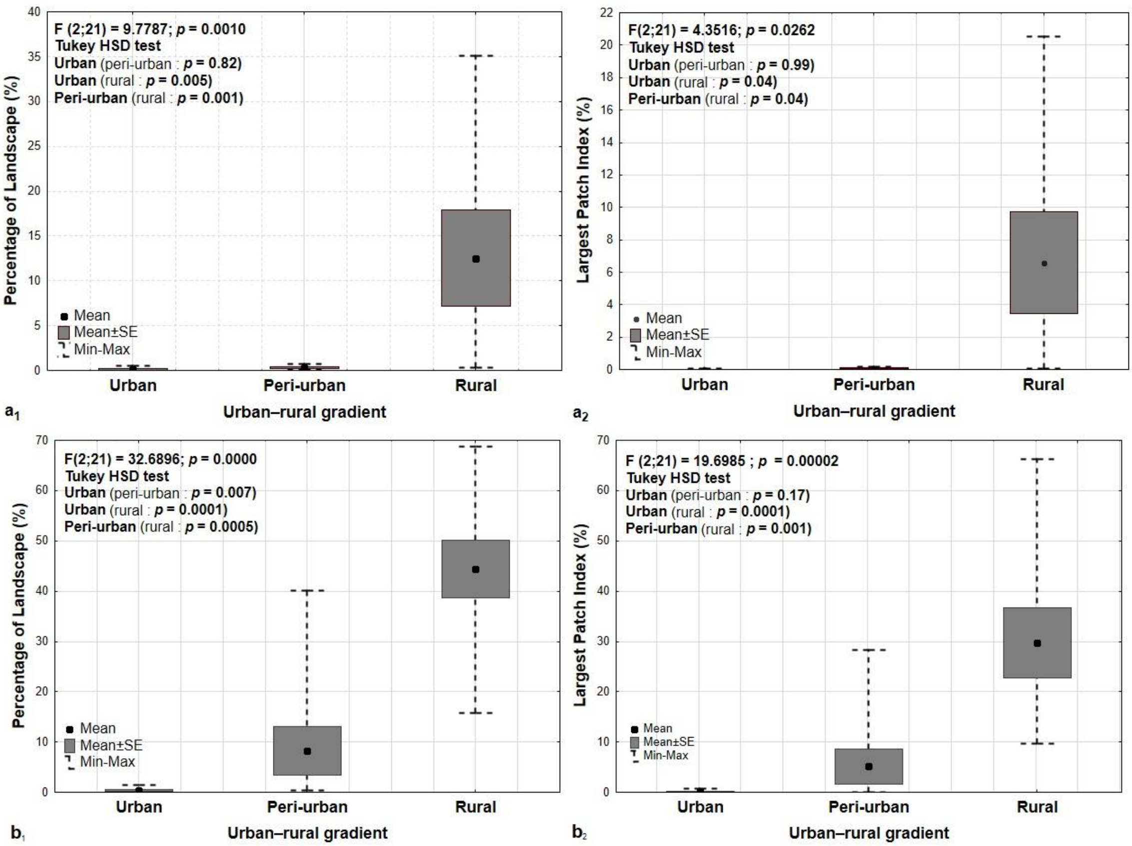
Figure 5.4. The spatial pattern of green infrastructure in the Kisangani landscape. The landscape composition is illustrated in (a), and the spatial configuration in (b). Agricultural and grassland (AGL); mature forest (MF); short forest (SF). *The results in this figure reveal a significant transformation in both the composition and spatial configuration of the green infrastructure.*

5.7.3. The spatial pattern of green infrastructure within the urban–rural gradient

Along the urbanization gradient, as anticipated, the composition and configuration of mature and short forests differ significantly between urban, peri-urban, and rural zones of Kisangani, according to the 2021 data (p-value < 0.05) (Figure 5.5 (a_1–b_2)). However, Tukey's post hoc test reveals that the low proportions of mature forest in urban zones are not significantly different from those observed in peri-urban zones (*p*-value = 0.82) (Figure 5.5 (a_1)). In addition, the areas covered by the largest patches of mature forest within urban zones are not significantly different from those in peri-urban zones (*p*-value = 0.99) (Figure 5.5 (a_2)). Specifically, in plots measuring 2.25 km^2, mature forests typically account for less than 1% of the area in both urban and peri-urban zones. In contrast, some plots in rural zones exhibit mature forest coverage exceeding 35%. Additionally, the largest patches of mature forest in both urban and peri-urban zones generally represent less than 0.5% of the 2.25 km^2 plots, whereas some rural plots contain patches that surpass 20%. In contrast to mature forests, the Tukey test identifies significant compositional and configurational differences in short forests between urban and peri-urban areas.

Short forests, which emerge from regeneration and agricultural land abandonment, are typically characterized by heliophilous, fast-growing species and represent higher proportions in peri-urban zones than in urban zones. In specific 2.25 km^2 plots within peri-urban zones, short forests can account for over 40% of the area, while in urban zones, their coverage barely reaches 1.3% (Figure 5.5 (b_1)). In rural areas, short forests are significantly more prevalent than in urban and peri-urban zones, sometimes covering over 65% of specific plots. Urban and peri-urban areas tend to have smaller forest patches (Figure 5.5 (b_2)).

Agricultural and grassland areas, the final component of green infrastructure, also vary notably in both composition and configuration across the three zones ($p < 0.05$) (Figures 5.5(c_1) and 5.5(c_2)). Peri-urban zones in Kisangani exhibit higher proportions of agricultural land, characterized by larger, more continuous patches, than urban areas. In peri-urban plots of approximately 2.25 km², agricultural and grassland cover over 89%, with constant patches exceeding 87%, compared to a maximum of 41% in urban plots. However, there is no significant difference between peri-urban and rural zones in terms of agricultural land composition and patch configuration ($p > 0.05$), highlighting the greater availability of land for agriculture in these zones.



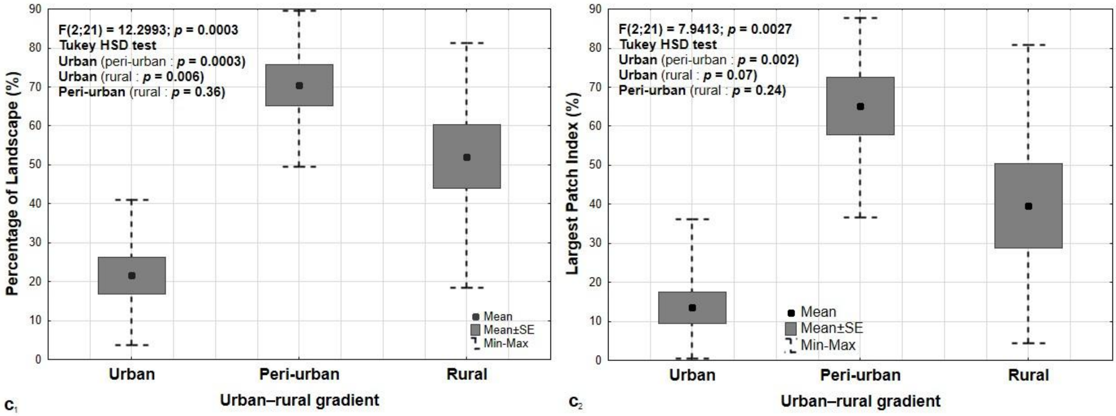


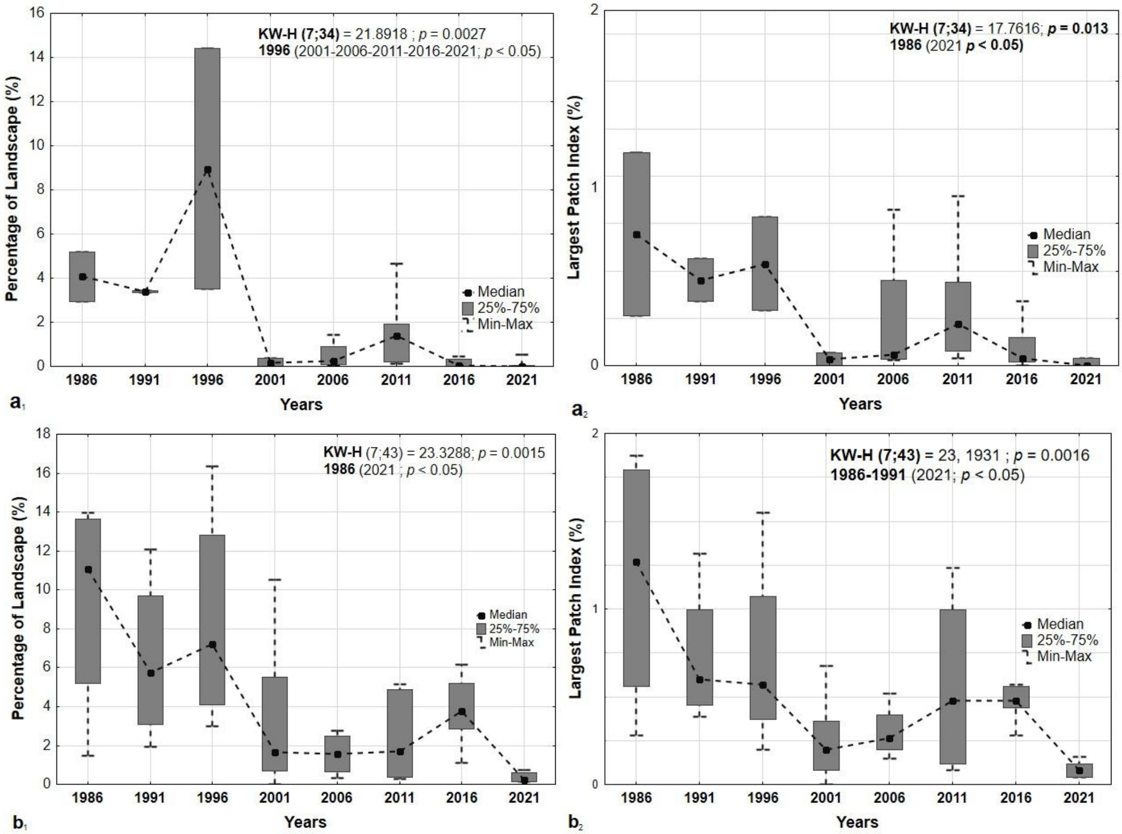
Figure 5.5. The spatial pattern of mature forests (a_1, a_2), short forests (b_1, b_2), agricultural and grass lands (c_1, c_2) within the urban–rural gradient using 2021 data. The standard error (SE) of the mean in this context is greater when the PLAND and/or *LPI are highly variable within the urbanization gradient.*

5.7.4. Temporal changes in the spatial pattern of green infrastructure within the urban-rural gradient

Statistical analysis reveals that from 1986 to 2021, mature forests globally experienced declines in their proportions and in the fragmentation of the largest patches in urban, peri-urban, and rural areas (Figure 5.6). These changes in both composition and configuration are especially significant in urban and peri-urban zones (Figures 5.6(a_1), 5.6(a_2), 5.6(b_1), and 5.6(b_2)). It is worth noting that in 1996, a trend towards the restoration of mature forests began in urban and peri-urban areas. Rural zones also exhibit a continuous decrease and a change in both the proportion and the spatial configuration (Figure 5.6(c_1, c_2)). However, these spatial changes in rural zones are not statistically significant (p-value > 0.05).

Short forests, as well as mature forests, experience changes in their composition and configuration along the urban–rural gradient from 1986 to 2021 (Figure 5.7). Urban areas exhibit a statistically significant decrease (p-value < 0.05) in the proportion of the landscape covered by short forest, as well as substantial fragmentation into larger patches (Figure 5.7(a_1, a_2)), despite a trend towards restoration observed in 1991. Despite an insignificant temporal effect, the highly dynamic nature of peri-urban zones indicates fluctuating changes in the composition and configuration of short forests between 1986 and 2011 (Figures 5.7(b_1) and 5.7 (b_2)). However, from 2011 to 2021, a consistent decline and increased fragmentation were observed in peri-urban areas. Rural zones also showed no significant temporal effects (p-value > 0.05) on changes in the composition and configuration of short forests. Additionally, two contrasting trends are evident over time: a steep increase in the proportion of short forest between 1986 and 1996, followed by a decline and fragmentation from 1996 to 2021 (Figures 5.7(c_1) and 5.7 (c_2)).

The results further indicate significant changes in the composition and configuration of agricultural and grasslands over time within urban, peri-urban, and rural zones (*p*-value < 0.05) (Figure 5.8). However, the pattern of these changes varied by zone. In urban areas, the proportion of agricultural land has significantly decreased, and larger patches have become notably more fragmented (p-value < 0.05) from 1986 to 2021 (Figure 5.8 (a_1, a_2)). Conversely, in peri-urban areas, the proportion of agricultural land remained relatively stable from 1986 to 2006. A sharp decline occurred between 2006 and 2011, followed by a notable increase from 2011 to 2021 (Figures 5.8(b_1) and 5.8(b_2)). Rural zones experienced a substantial increase in the proportion of agricultural land, accompanied by a significant expansion of the largest patches (Figure 5.8(c_1, c_2)).



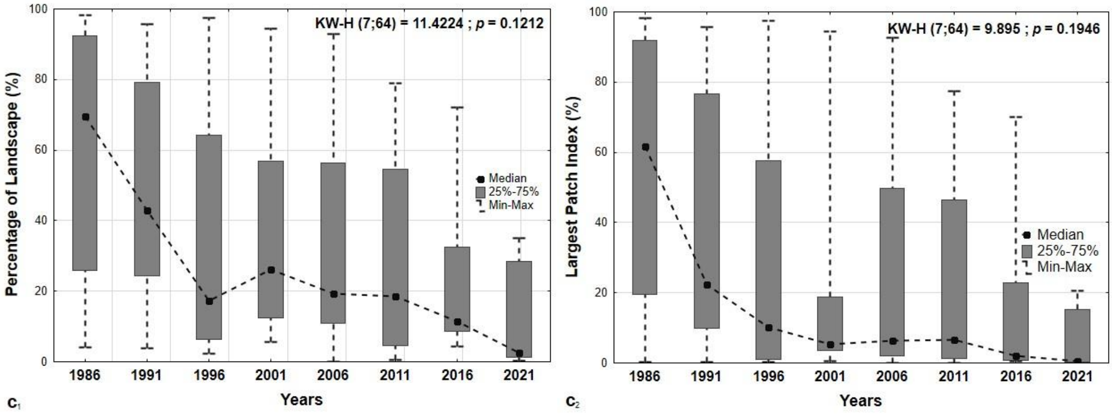
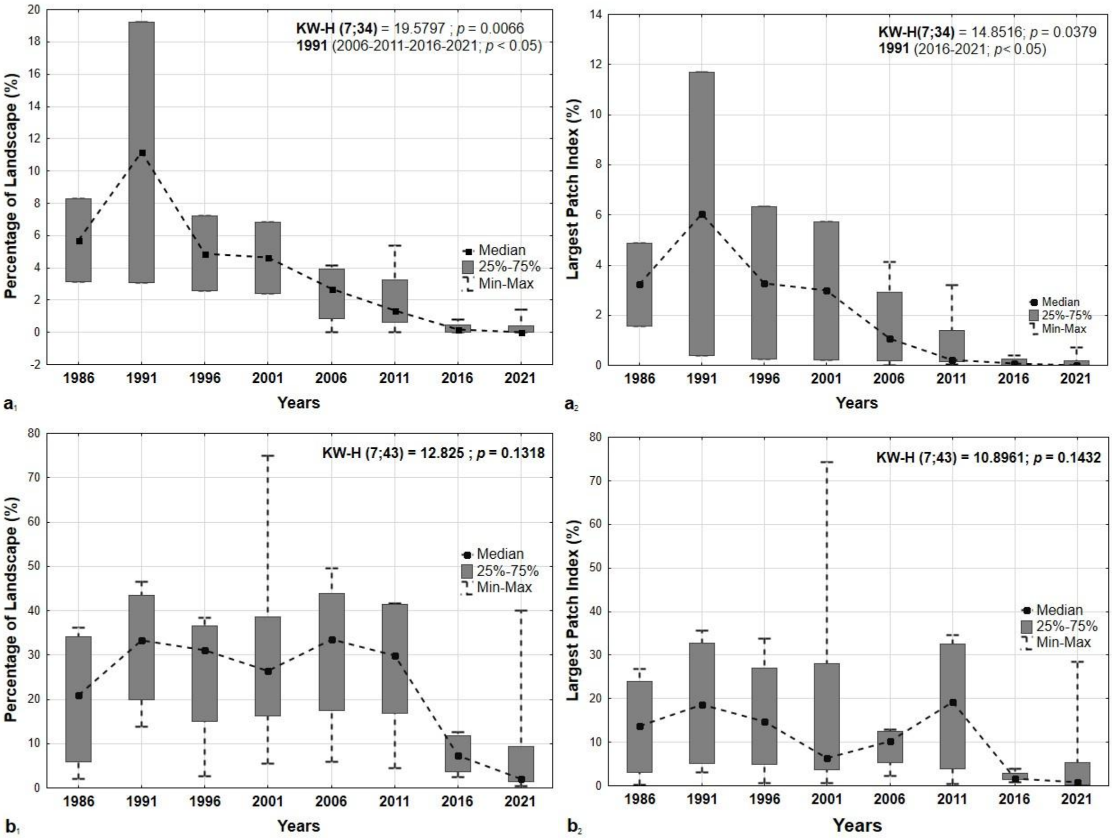


Figure 5.6. Temporal changes in the composition and the spatial configuration of mature forests in urban zones (a1, a2), peri-urban zones (b1, b2), and rural zones (c1, c2).



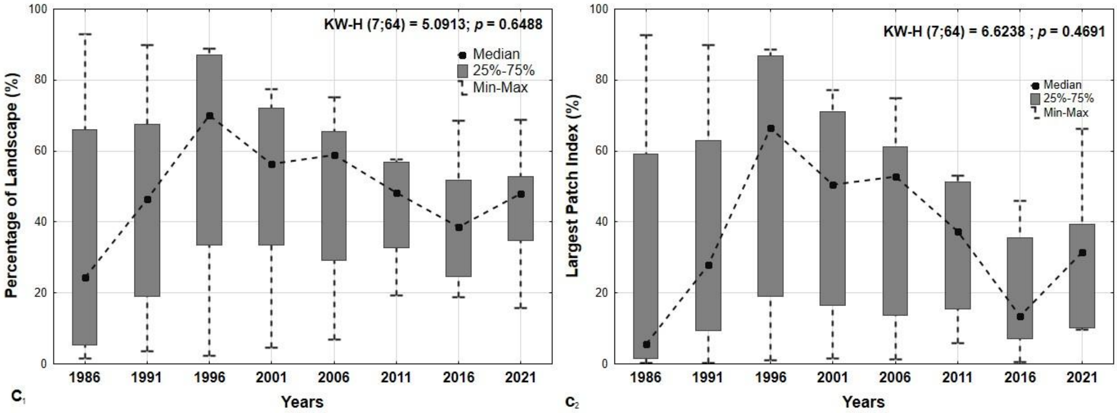
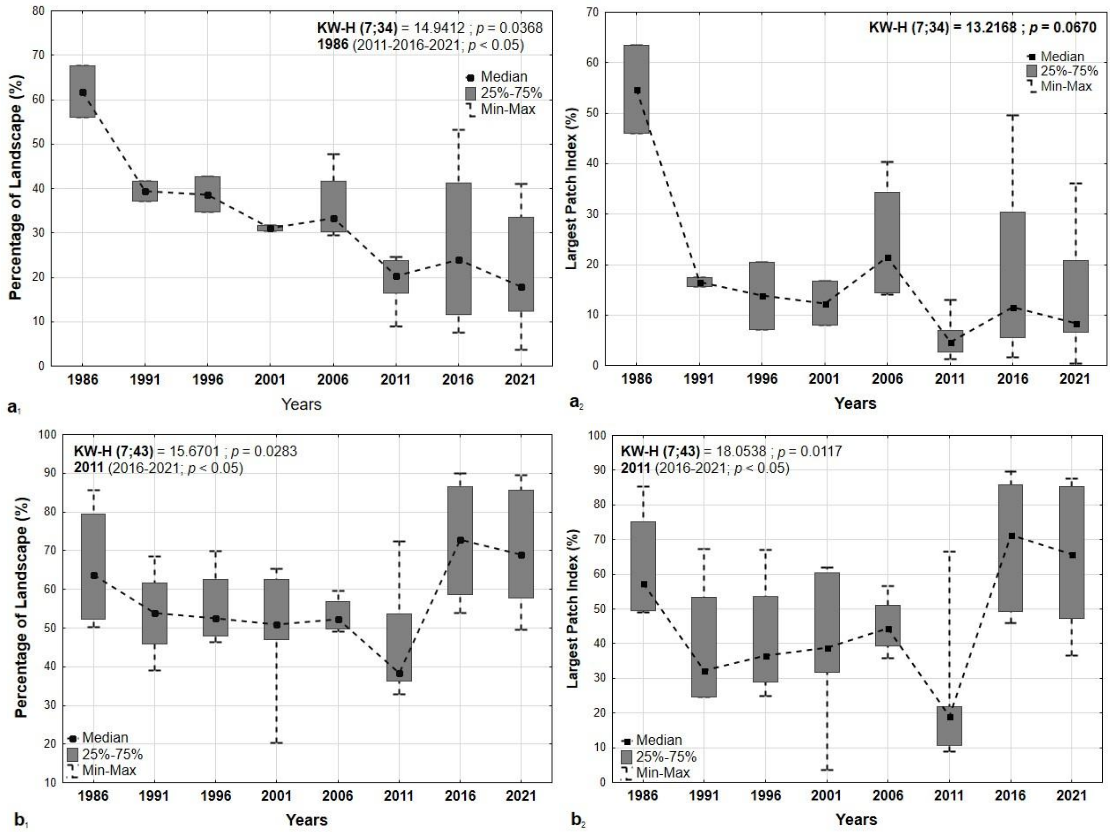


Figure 5.7. Temporal changes in the composition and the spatial configuration of short forests in urban zones (a_1, a_2), peri-urban zones (b_1, b_2), and rural zones (c_1, c_2).



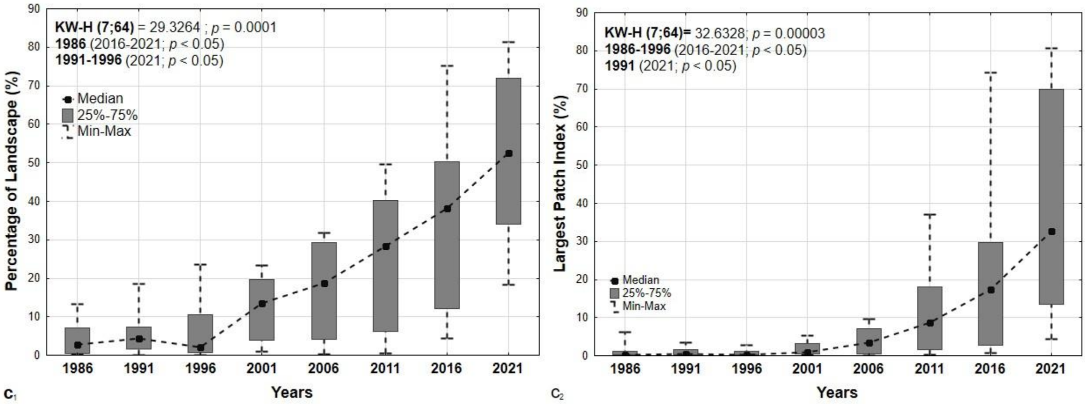


Figure 5.8. Temporal changes in the composition and the spatial configuration of agricultural and grassland in urban zones (a_1, a_2), peri-urban zones (b_1, b_2), and rural zones (c_1, c_2).

5.8. Discussion

5.8.1. Classifications and analyses of the green infrastructure spatial patterns

Validation indicators, including user, producer, and global accuracy (Foody, 2013; Olofsson et al., 2014), supported by field data, attest to the reliability of classification results. Furthermore, comparing the change map from 2001 to 2021 derived from the local classification to Hansen's global classification (Hansen et al., 2013) enhances the credibility of the local classifications. User, producer, and global accuracies are higher for local classifications, underlining the importance of detailed knowledge of the local context. However, the quality of reference data can be questioned, potentially leading to inaccurate estimates of change areas and classification accuracy indicators (Foody, 2013). Furthermore, the criteria for forest cover on the Hansen map remain debatable. For this study, 232 reference points were randomly selected and categorized into forest and non-forest areas. These data underwent quality control by overlaying them onto high-resolution PlanetScope images (3 m spatial resolution) to ensure data quality. Additionally, in the Hansen map (Hansen et al., 2013), a criterion of at least 50% overlap was used to determine a pixel as forest. Thus, the forest is the dominant land cover within a pixel.

As no single index can provide a comprehensive view of the landscape's complexity [54,55], the spatial pattern of the green infrastructure was assessed using two main indices: composition (PLAND) and configuration (LPI). These metrics, which are often indicators of human impact on landscape morphology (Bogaert & Mahamane, 2005; Krummel et al., 1987), revealed significant changes in the composition and configuration of mature forests, short forests, agricultural lands, and grasslands in Kisangani and its urbanization gradient.

5.8.2. The spatial pattern of green infrastructure in the landscape of Kisangani

Due to various socio-political crises that occurred between 1980 and 2000, in particular, the national economic crisis (Tshonda, 1991) and armed conflicts (Koluwa, 2020), a significant portion of the population relocated away from the urban environment of Kisangani. This demographic shift is believed to have contributed to the restoration of the largest patch of mature forests, facilitated by the transition from short to mature forests between 1991 and 1996, as well as between 2001 and 2006. However, as a result of resolving these various crises, the city of Kisangani has transformed into a commercial hub that connects Kinshasa to other provinces in the eastern region of the Democratic Republic of the Congo (Ministère de l'urbanisme et de l'habitat, 2005). This economic role has led to massive population influxes into Kisangani, resulting in rapid demographic growth. From 2000 to 2021, the population of Kisangani increased from 738,160 to over 2 million (INS, 2022). In tropical regions, population growth increases the need for residential accommodation and agricultural land (Balandi et al., 2023; Diallo et al., 2020; Useni et al., 2017).

To meet these needs, Kisangani has lost more than 47% of its mature forest area since 1986, a trend that has intensified between 2011 and 2021, also affecting short forests. Conversely, agricultural land, which covered 4% of the landscape in 1986, has expanded to over 32% in 2021. Indeed, the region of Kisangani, like many other regions in the Democratic Republic of the Congo, exhibits a low level of industrialization (Banque mondiale, 2018). Industrial infrastructure is limited, with few manufacturing facilities or alternative employment opportunities beyond the agricultural sector. Thus, the local population remains heavily dependent on agriculture for economic sustenance.

Consequently, mature forests, which were previously vast and continuous, are increasingly being fragmented into small patches. This steady fragmentation, which has occurred since 2011 due to agricultural expansion and forest exploitation, primarily through artisanal means, should restrict connectivity between habitats, thereby increasing the vulnerability of remaining ecosystems. These spatial changes in Kisangani are similar to those in Kinshasa, where the proportion of forest has decreased by more than 7% between 1995 and 2010 due to urban expansion (Sambieni, 2019). In the Lubumbashi plain, from 2001 to 2011, the clear forests underwent significant degradation due to the development and expansion of other land uses, particularly the bare soil habitat complex (Cabala et al., 2018). Furthermore, in the city of Lubumbashi, over the 25 years from 1989 to 2014, green space has decreased in all the city's communes (Useni et al., 2017). In contrast to Lubumbashi, where various components of the green infrastructure have decreased, particularly in forests, grassy savannah, wooded savannah, fields, and swamps, Kisangani has primarily experienced a decrease in mature and short forests, while agricultural land has steadily increased.

In Africa, the anarchic expansion of built-up land, driven by rapid population growth and ineffective urbanization policies, is leading to the degradation of urban green infrastructure (Diallo et al., 2020; Sambieni, 2019; Useni et al., 2017). In the city of M'sila, Algeria, green infrastructure is constantly sacrificed for urban expansion (Mili et al., 2019). In Kisangani, despite ineffective urban development policies (UN-Habitat, 2015), mature forests are heavily exploited for energy purposes. Indeed, wood remains the primary energy source for 90% of urban residents and some local industries (Schure et al., 2013). Combined with slash-and-burn agriculture, wood-energy activities contribute to the degradation of mature forests (Kambale et al., 2016). These transformations lead to a loss of biodiversity and limit contact with nature (Shackleton et al., 2014).

5.8.3. The spatial pattern of green infrastructure within the urban-rural gradient: temporal changes in the composition and the spatial configuration

Within the urbanization gradient, the spatial pattern of mature and short forests differs substantially, with high proportions in rural zones (p-value < 0.05). However, the differences in the proportion of mature forests between urban and peri-urban zones are not statistically significant (p-value = 0.82). The low proportions of mature forest in urban and peri-urban zones can be attributed to the ineffective implementation of urban development plans successively developed in 1978, 2008, and 2010 (Balandi et al., 2023; UN-Habitat, 2015), as well as the inadequacy of the current national urban development law in addressing contemporary urban development challenges (Ministère de l'urbanisme et de l'habitat, 2005; Useni et al., 2017). Forest components, particularly mature forests, have been marginalized within the urban development framework.

Consequently, a significant decline in the proportion of both mature and short forests, coupled with substantial fragmentation, has been observed over the period from 1986 to 2021, particularly in urban zones. In addition, the noticeable decline in agricultural land within urban zones over the years further illustrates the relationship between agricultural development, the evolution of sedentary human lifestyles, and landscape transformation (Bogaert et al., 2014). However, the highly dynamic nature of peri-urban zones indicates fluctuating changes in the composition and configuration of short forests between 1986 and 2011. Furthermore, in these highly dynamic peri-urban zones, agricultural trends are notably variable, reflecting major events in the city. Indeed, from 1986 to 2006, a series of armed conflicts and social crises at both national and local levels led to the displacement of populations to rural zones. This likely reduced demand for agricultural products in the city, explaining the stable trend in the proportion of agricultural land between 1986 and 2001. However, the demographic boom from 2011 to 2021 (INS, 2022), mainly driven by immigrants from the east of the country, many of whom engage in trade and utilize extensive peri-urban land for agriculture, has likely contributed to the increase in agricultural land in peri-urban zones. In addition, the proximity of peri-urban zones to urban centers facilitates the commercialization of agricultural products, as farmers can more easily export their goods to the city, where demand is typically higher. Furthermore, in the Kisangani landscape, land governance across both peri-urban and rural zones, characterized by a mix of formal regulations and informal practices, provides local farmers with relatively easy access to land. Farmers often use the land through local practices and customary agreements. These agricultural activities, which are dominant in peri-urban areas, ensure food security for the population in urban, peri-urban, and rural areas.

Nevertheless, to limit the steady degradation of both mature and short forests, urban planners should prioritize the integration of green infrastructure into urban development plans. This can be operationalized through zoning regulations that protect existing mature forests, the creation of green corridors connecting urban, peri-urban, and rural landscapes, and the inclusion of green infrastructure requirements in building permits and municipal plans. Promoting sustainable agricultural practices in peri-urban zones can be supported by providing technical guidance on agroecological techniques, offering financial or policy incentives for urban agriculture, and establishing demonstration plots in collaboration with local farmers. Reforestation initiatives targeting urban areas can be launched via community tree-planting programs in underutilized spaces, coordinated with local NGOs, schools, and municipal agencies to ensure maintenance and long-term stewardship. By combining regulatory measures, incentives, and community engagement, these strategies can be implemented in practice to enhance ecological resilience and local food security.

Moreover, expanding and maintaining urban green spaces, such as parks and recreational areas, is vital for enhancing ecological functions and the overall quality of life. Designing multifunctional spaces that incorporate native plant species and wildlife habitats, combined with public awareness campaigns, can further support urban biodiversity (Useni et al., 2017), in meeting the current challenges of sustainable development.

Finally, strengthening land-use management policies requires the development of a robust assessment framework, including key indicators such as forest cover, agricultural land distribution, and urban green spaces, combined with GIS-based monitoring systems and periodic reporting to ensure adaptive decision-making. Active community engagement can be fostered through participatory workshops, local advisory committees, and online consultation platforms, aligning land-use policies with local ecological and social needs. By combining regulatory measures, incentives, technical support, monitoring tools, and community participation, these strategies can be practically implemented to support sustainable urbanization, ecosystem preservation, and local food security in Kisangani.

5.9. Conclusion

The green infrastructure components examined in the Kisangani landscape, including mature forests, short forests, agricultural lands, and grasslands, underwent substantial spatial changes from 1986 to 2021, as revealed by the combined use of satellite images and landscape ecology tools. More than 47% of mature forest has been lost from 1986 to 2021 at the landscape scale. Furthermore, a decline of more than 29% in short forest is observed between 2006 and 2021.

Within the urban–rural gradient in the reference year (2021), spatial patterns of both mature and short forests vary significantly. However, the proportions of mature forests in urban areas do not considerably differ from those observed in peri-urban areas. This proportion represents less than 1% of the 2.25 km^2 plots, whereas in some rural plots, it exceeds 35%. Additionally, the largest patches of mature forest in urban and peri-urban zones represent less than 0.5%, while they exceed 20% in rural zones. In contrast, short forests vary significantly between urban and peri-urban areas, comprising over 40% of specific peri-urban plots compared to just 1.3% in urban areas and more than 65% in rural zones. Agricultural and grasslands vary significantly across the urban–rural gradient, covering over 89% of specific 2.25 km^2 plots and forming continuous patches exceeding 87% in peri-urban zones, compared to 41% in urban areas. Over time, from 1986 to 2021, mature and short forests have shown significant declines in their proportions and increased fragmentation, particularly in urban and peri-urban zones. However, these spatio-temporal changes are not substantial in rural zones. Agricultural land, conversely, shows a significant decrease in its proportion and increased fragmentation of patches in urban zones, while experiencing significant growth in peri-urban and rural zones, accompanied by patch aggregation.

The changes observed in both mature and short forests raise concerns regarding the functions and services these forests provide and their sustainability in the context of global change. Therefore, findings suggest that synergistic development pathways are crucial for managing the interactions among regional urbanization, changes in landscape patterns, and the provision of ecosystem services. As urban areas expand, both mature and short forests face loss and fragmentation, weakening their ability to support ecosystem services. However, preserving larger contiguous patches in rural zones and enhancing connectivity in peri-urban areas through adjustments to landscape models, such as promoting ecological corridors, urban parks, and buffer zones, may mitigate some of the negative impacts. This balanced approach can better align urban growth and economic development with the conservation of ecosystem services across the urban–rural gradient.

Chapter 6

Ecological integrity of forest landscapes in the Kisangani Region (DRC) using spatial analysis of edge effect exposure and magnitude of edge influence.

6.1. Reference

Balandi, J.B., Meniko, J.-P. P. T. H., Sambieni, K.R., Sikuzani, Y.U., Bastin, J.-F., Iyongo, L.W.M., Mobunda, J.T., & Bogaert, J. Ecological integrity of forest landscapes in the Kisangani region (DRC) using spatial analysis of edge effect exposure and magnitude of edge influence.
Article under review in the journal *Discover Forest*

6.2. Context

The previous chapter highlighted a marked decline and a progressive fragmentation of the components of urban green infrastructure, particularly mature and secondary forests along the urban–rural gradient of Kisangani, revealing a notable loss of ecological connectivity. This trend reflects increasing anthropogenic pressures extending beyond urbanized areas and progressively affecting the surrounding large forest landscapes. Urban expansion and intensified land conversion are likely to increase the number of forest edges and heighten the ecological vulnerability of these forests by altering their microclimatic conditions and internal structure. Building on this, the present chapter deepens the analysis by assessing fragmentation dynamics and exposure to edge effects in the peripheral forest landscapes (Masako, Mbiye, Yoko, and Yangambi), while also considering the role of forest patch size in modulating microclimatic conditions.

6.3. Résumé

L'évaluation à long terme de la fragmentation forestière est essentielle pour mesurer l'intégrité écologique des paysages tropicaux. Cette étude analyse les tendances historiques de la perte forestière, de la configuration des taches et des perturbations liées aux lisières dans quatre paysages forestiers situés près de Kisangani, en République Démocratique du Congo : Masako, Mbiye, Yoko et Yangambi, à partir d'images satellitaires couvrant la période de 1986 à 2024. Des indices paysagers, tels que la variation relative de la surface forestière et l'indice de la plus grande tache (LPI), ont été utilisés pour caractériser les changements à la fois compositionnels et configurationnels. Les rapports intérieur/lisière (I/E), les superficies absolues des taches d'intérieur et des taches de lisière, ainsi que les pourcentages de zones affectées par les lisières ont été calculés pour quatre distances (50, 100, 150 et 200 m) afin d'évaluer l'influence des lisières. Par ailleurs, les taches forestières ont été analysées en relation avec la variation de la température de surface terrestre (LST) induite par les lisières, afin de comprendre le rôle de l'aire des taches dans la modulation des perturbations qu'elles induisent. Les résultats révèlent une fragmentation accélérée des paysages périurbains de Masako et de Mbiye, particulièrement après 2016. Ces deux sites ont perdu plus de 80 % de leur couvert forestier entre 1986 et 2024, avec une forte diminution du LPI, la quasi-disparition des taches forestières d'intérieur et des rapports I/E proches de zéro. En revanche, Yangambi a conservé plus de 90 % de son couvert initial et Yoko plus de 60 %, avec des valeurs élevées de LPI et une exposition limitée aux lisières, ce qui indique des structures plus stables. Les effets thermiques liés aux lisières ont mis en évidence une relation inverse significative entre l'aire des taches et le LST à Yangambi et à Yoko, suggérant que les grandes taches atténuent le réchauffement en bordure. Pour Masako et Mbiye, les faibles valeurs de R^2 traduisent une fragmentation avancée et une capacité réduite des fragments forestiers à moduler les variations thermiques. Ces résultats mettent en évidence des risques écologiques importants, notamment la perte de biodiversité et la dégradation des services écosystémiques, liés à ces perturbations environnementales. Des stratégies adaptées à chaque paysage sont recommandées : la restauration de la connectivité des fragments résiduels, ainsi que l'intégration de l'agroforesterie et de la gestion communautaire des ressources. Pour les paysages encore relativement intacts, un renforcement du cadre légal, un suivi spatial et une éducation environnementale sont préconisés afin de prévenir toute dégradation future.

Mots-clés : Fragmentation forestière, Intégrité écologique, Exposition aux effets de lisière, Télédétection, Kisangani.

6.4. Abstract

Assessing long-term forest fragmentation is essential for understanding the ecological integrity of tropical landscapes. This study investigates historical trends in forest loss, patch configuration, and edge-related disturbances across four forest landscapes near Kisangani, Democratic Republic of the Congo: Masako, Mbiye, Yoko, and Yangambi, using satellite imagery from 1986 to 2024. Landscape metrics, including Relative Forest Area Change and Largest Patch Index (LPI), were used to characterize both compositional and configurational changes. Interior-to-edge (I/E) ratios, interior and edge areas, and edge-affected percentages were computed across four buffer distances (50–200 m) to assess edge influence, while patch area was analyzed in relation to edge-induced Land Surface Temperature (LST) variation. Finds reveal accelerating fragmentation in the peri-urban landscapes of Masako and Mbiye, especially after 2016. Both landscapes lost over 80% of their forest cover between 1986 and 2024, with sharp declines in LPI, near-complete disappearance of interior forests, and I/E ratios approaching zero. By contrast, Yangambi retained over 90% of its initial cover and Yoko over 60%, with higher LPI and limited edge exposure, indicating more stable spatial patterns. Edge-related thermal effects exhibited a significant inverse relationship between patch size and LST in Yangambi and Yoko, indicating that larger patches mitigate edge warming. In Masako and Mbiye, low R^2 values reflected advanced fragmentation and diminished thermal buffering capacity. These results highlight significant ecological risks, including biodiversity loss and declines in ecosystem services. Landscape-specific strategies are recommended, including restoration, reconnecting remnant patches, integrating agroforestry, and community resource management. For relatively intact landscapes, legal reinforcement, spatial monitoring, and environmental education are proposed to prevent further degradation.

Keywords: Forest fragmentation, Ecological integrity, Edge Effect Exposure, Remote Sensing, and Kisangani.

6.5. Introduction

Tropical forest landscapes are essential for maintaining biodiversity, regulating microclimatic and ecological processes, and providing key ecosystem services (Eckehard et al., 2017; Edwards et al., 2019). These functions are increasingly critical in regions exposed to accelerating anthropogenic pressures (Bogaert et al., 2008; Edwards et al., 2019). Tropical forests also constitute a cornerstone of nature-based climate solutions, which are estimated to provide more than 30% of the cost-effective mitigation needed to keep global temperature rise below the 2°C threshold of the Paris Agreement (Griscom et al., 2017). Unfortunately, these tropical forests are increasingly subjected to degradation (Lewis et al., 2015; Malhi et al., 2014). Over recent decades, agricultural expansion, logging, and urban growth have reshaped forested regions, intensifying fragmentation and habitat degradation at multiple scales (Balandi et al., 2024; Mansingh et al., 2025). According to Hansen et al.(2013), between 2000 and 2012, tropical forests were the only climatic region showing a statistically significant increasing trend in forest loss, with the annual rate of forest loss increasing by approximately 2,101 km² per year. In Central Africa, tropical forests experienced an estimated decline exceeding 8.2% between 2010 and 2019 (Vancutsem et al., 2021), contributing to the increased fragmentation and isolation of remaining forest patches (Brinck et al., 2017; Franziska et al., 2018).

Forest fragmentation is widely recognized as a primary indicator of landscape degradation (Bogaert et al., 2008). One of its most pervasive outcomes is the expansion of forest edges, transitional zones between interior habitats and adjacent disturbed environments (Hending & Randrianarison, 2023; Iyongo, 2013; Meniko et al., 2020). These zones are prone to abrupt microclimatic shifts, altered species composition, and reduced ecological functioning, which ultimately compromise forest integrity (Coe et al., 2013; Fahrig, 2009; Laurance et al., 2007). Consequently, edge effects have become a central focus in tropical landscape ecology, given their substantial influence on biodiversity patterns, habitat quality, and ecological interactions (Turner et al., 1996).

Research across tropical regions has extensively documented how edge effects modify species diversity, habitat affinity, and animal mobility (Dantas et al., 2016; Hending & Randrianarison, 2023; Iyongo, 2013; Laurance et al., 2007; Meniko et al., 2020). Spatial metrics have also emerged as critical tools for quantifying forest vulnerability to fragmentation, enabling the assessment of interior versus edge-affected forest and helping identify priority areas for conservation (Bogaert et al., 1998; Bogaert et al., 1999; Turner & Ruscher, 1988). Complementary modelling approaches have further demonstrated the importance of preserving interior forest patches to maintain ecological processes and structural resilience (Mladenoff et al., 1994; Zheng & Chen, 2000). These insights highlight the need to integrate spatial metrics and ecological indicators to assess the integrity of fragmented forest landscapes more effectively.

Despite the growing body of research on this topic, there are still limited spatially explicit assessments of fragmentation and edge influence in the Congo Basin, one of the least documented major tropical forest regions, despite its global importance. This knowledge gap is evident throughout the region, including in the Kisangani area of the Democratic Republic of the Congo (DRC), where forest landscapes face increasing pressure from agricultural expansion, the growth of informal settlements, and the development of peri-urban infrastructure (Balandi et al., 2023; Balandi et al., 2024). In such rapidly changing environments, it is essential to characterize both the structural dimensions of fragmentation (e.g., forest loss, patch isolation) and the functional implications of edge exposure for forest integrity. Metrics capable of quantifying edge-affected forest, when coupled with ecological indicators such as Land Surface Temperature (LST), provide a robust framework for identifying microclimatic degradation and detecting vulnerable forest habitats. Integrating these spatial and environmental perspectives is crucial for evidence-based conservation planning, as it enables the identification of priority areas for intervention, monitoring of degradation trajectories, and formulation of adaptive management strategies tailored to the socio-ecological contexts of Central African forests.

This study addresses these gaps through a spatio-temporal analysis of four forest landscapes, Yangambi, Yoko, Masako, and Mbiye, representing distinct conservation contexts within the Kisangani region. Their strategic locations, varying distances from the urban center, and differing levels of disturbance provide a relevant gradient for understanding how fragmentation processes evolve under different socio-ecological pressures. A particular focus is placed on assessing the temporal expansion of edge-affected forest using multiple ecological edge distances and on examining how patch size influences microclimatic disturbance as inferred from LST, a recognized indicator of canopy degradation and surface thermal alteration (Balandi et al., 2025; Oliveira et al., 2011; Zhang et al., 2013). In fragmented landscapes, reduced vegetation density and increased exposure to solar radiation near edges often result in elevated surface temperatures, which likely indicate increased microclimatic stress that may affect plant physiology and soil moisture retention. Such microclimatic changes could potentially influence species composition, disrupt ecological interactions such as pollination, and reduce the overall resilience of forest ecosystems to climatic variability. Moreover, LST can be reliably derived from satellite observations at high spatial and temporal resolutions, enabling the detection of fine-scale thermal variations across heterogeneous forest mosaics. By linking spatial fragmentation patterns with an ecological stress indicator, this approach offers a robust framework for assessing forest integrity. These analyses further highlight how fragmentation influences both the spatial configuration and ecological functioning of tropical forests within rapidly transforming peri-urban landscapes.

Therefore, we hypothesize that forest fragmentation has increased across all four landscapes, leading to measurable declines in forest composition and configuration, including negative trajectories in Relative Forest Area Change and reductions in the Largest Patch Index (LPI). We further expect that the proportion of edge-affected forest has expanded over time, especially at broader ecological distance thresholds where microclimatic disturbances are more pronounced. Finally, we anticipate that smaller forest patches exhibit stronger LST-based thermal anomalies due to their greater exposure and reduced buffering capacity. Together, these analyses contribute a spatially explicit understanding of fragmentation patterns and edge influence in the Kisangani region, supporting evidence-based conservation planning in Central African forest ecosystems.

6.6. Materials and methods

6.6.1. Study areas

The study area includes four forest landscapes surrounding Kisangani in northeastern DRC (Figure 6.1). These landscapes span a gradient from peri-urban forests to large, protected areas. The Masako Forest Reserve, located about 15 km northeast of Kisangani, covers 2,105 ha and represents a peri-urban forest under increasing human pressure (Iyongo, 2013; Meniko et al., 2020). The Mbiye Forest Reserve, a 38-km² island southeast of the city, is similarly exposed to local anthropogenic activities (Bamba et al., 2010). The Yoko Forest Reserve, situated 32 km southeast of Kisangani, extends over 70 km² and lies at an average elevation of 450 m (Ncutirakiza et al., 2020). Further west, the Yangambi Biosphere Reserve covers 273,955 ha across the Isangi and Banalia territories and includes the N'Gazi Reserve and the INERA concession, both incorporated since its UNESCO recognition in 1977 (Koy et al., 2019). As part of the MAB Programme, Yangambi constitutes a key site for ecological research and forest conservation in Central Africa (Toirambe et al., 2020).

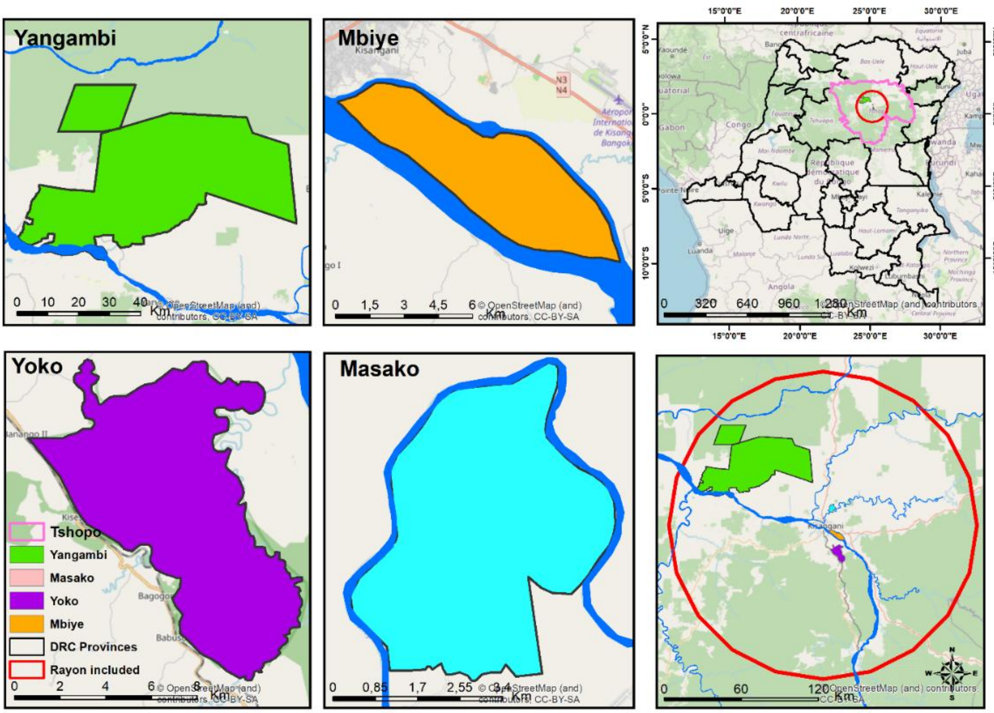


Figure 6.1. The geographical location of the four forest landscapes studied near Kisangani, Democratic Republic of the Congo: Masako, Mbiye, Yoko, and Yangambi.

6.6.2. Data and preprocessing

The analysis of ecological integrity by quantifying forest areas impacted by edge effects in the four protected reserves was conducted using Landsat satellite imagery from TM (1986, 1991, 1996), ETM+ (2001, 2006, 2011), and OLI-TIRS (2016, 2021, 2024), all with a spatial resolution of 30 meters. Consequently, satellite images with less than 10% cloud cover were selected, allowing for a multi-temporal assessment over 38 years. While the temporal resolution generally follows five-year intervals, slight variations are present for the most recent observations (2021 and 2024). These satellite data were supplemented by GPS field surveys that provided detailed ground information (Table 6.1).

Table 6.1. Characteristics of the geodata used

Satellite Images	Months Filtered	Years	Spatial Resolution
Landsat images (MSS–TM)	15 Dec–28 Feb	1986–1991–1996	30 m
Landsat images (ETM+)	15 Dec–28 Feb	2001–2006–2011	30 m
Landsat images (OLI)	15 Dec–28 Feb	2016–2021-2024	30 m
Hansen Global Change Map	-	2000–2024	30 m
GPS data	August–March	2022–2023	-

To reduce atmospheric interference and radiometric inconsistencies among different Landsat sensors (Roy et al., 2016), surface reflectance (SR) imagery was used. SR data for Landsat 4-5 TM and Landsat 7 ETM+ were processed using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS), while reflectance data from Landsat 8-9 OLI were generated with the Land Surface Reflectance Code (LaSRC) (Sayler & Zanter, 2021; Sayler & Zanter, 2023). These correction algorithms ensure consistent radiometric and spectral quality, enabling reliable comparisons between several images (Sayler & Zanter, 2023). These images were georeferenced to the WGS 84 coordinate system, resampled to a uniform spatial resolution of 30 meters, and reprojected to UTM Zone 35 North.

To enhance the differentiation of land cover types, false-color composites were generated for each date using the mid-infrared (MIR), near-infrared (NIR), and red (R) spectral bands. These composites improve the visual interpretation of vegetation and anthropogenic features and were cross validated using high-resolution imagery from Google Earth. For the supervised classification, training samples were collected for three main land cover categories: (1) Human Altered Landscape, encompassing all anthropogenic features such as built-up areas, bare soil, agricultural fields, and herbaceous cover; (2) Old-Growth Vegetation, corresponding to mature forest stands characterized by closed canopies and minimal human disturbance; and (3) Water Surface, including the Congo and Tshopo. Although relatively simple, this three-class scheme has limitations, as it does not distinguish among different types of anthropogenic land cover or vegetation stages. Nevertheless, it was deliberately chosen to maintain temporal and spatial consistency, as these classes can be reliably identified across all study landscapes. Importantly, this approach aligns with the study objective: aggregating all human-modified areas enables consistent delineation of forest edges, enabling robust assessment of the proportion of mature forest exposed to edge effects over time.

6.6.3. Classification and accuracy assessment

The supervised classification was carried out using the Random Forest algorithm (Balandi et al., 2024; Del Río et al., 2014). To ensure reliable accuracy and consistent performance, the number of decision trees was set to 100 for all image classifications. This algorithm is particularly effective due to its use of multiple decision trees, which independently evaluate the training samples and assign them to the most appropriate land cover classes, thereby improving classification accuracy (Balandi et al., 2023; Phan & Lehnert, 2020). For the calibration of land cover classifications, a minimum of 100 points per class was collected for each of the three land cover categories. These training points were selected based on visual interpretation of false-color composites generated from the mid-infrared (MIR), near-infrared (NIR), and red (R) spectral bands, and supported by high-resolution imagery from Google Earth. To assess the accuracy of land cover classifications for earlier years, independent validation samples were derived from Google Earth historical imagery. In the Kisangani study area, high-spatial-resolution archival imagery was available years 2011, 2016, and 2021, allowing year-specific validation samples to be collected for each corresponding Landsat epoch. For earlier dates (2006, 2001, 1996, 1991, and 1986), although Google Earth imagery was available for the study region, its spatial resolution was relatively coarser. Consequently, validation samples for these periods were derived from land cover features exhibiting clear spatial patterns and long-term temporal stability (e.g., persistent forest patches and stable non-forest areas), ensuring consistency across the time series. All validation samples were selected independently from the training data to avoid bias in the accuracy assessment. Given the geographical proximity of the Masako and Mbiye reserves, a single combined area was defined for the land cover classification. For subsequent spatial analyses, however, the classified maps were subdivided, and each reserve was analysed separately. During field missions conducted in March 2023, a total of 642 GPX control points were collected across the four study landscapes, depending on site accessibility, and used to validate the 2024 reference classification. These points were allocated to the three land cover classes as follows: 33% to built-up areas and bare soil, 27% to agricultural land and grasslands, and 20% to degraded or secondary forest, all grouped into the human-altered landscape class; the remaining 20% corresponded to mature forest (old-growth vegetation). Two separate subsets were used for analysis: 310 points for validating the 2024 reference classification, and 232 points for comparing the locally produced land cover classifications with the global tree cover dataset developed by Hansen et al.(2013). To support this comparison, land cover classes were harmonized into two broad categories: (1) non-forest and (2) Forest. In Hansen's dataset, we defined a forest pixel as any pixel with 50% or more forest cover, indicating a dominant presence of forest (Balandi et al., 2024). Therefore, any forest pixel that experienced a decrease in canopy cover below 50% between 2000 and 2024 was considered to have transitioned to non-forest. Conversely, pixels that reached or exceeded 50% canopy cover during the same period were classified as forest. A contingency table was generated to compare the local classification results with the global dataset provided by Hansen, discriminating between forest and non-forest classes. This matrix was then used to compute users' accuracy, producers' accuracy, and overall accuracy, as defined by Equations (1) and (3) in Olofsson et al.(Olofsson et al., 2014).

6.6.4. Spatial analysis of fragmentation and ecological integrity

To assess the spatial patterns and temporal dynamics of forest fragmentation across the four landscapes surrounding Kisangani (Masako, Mbiye, Yoko, and Yangambi), a set of complementary landscape metrics was computed. The Relative Forest Area Change (**RFAC**) (Equation 6.1) was used to quantify compositional changes in total forest cover over time, providing a baseline for comparing forest loss trajectories across different anthropogenic contexts. The Largest Patch Index (**LPI**) (Equation 6.2) captured shifts in the spatial dominance and cohesion of the largest remaining forest patch, serving as an indicator of landscape connectivity and configuration.

To better understand the spatial consequences of fragmentation, we computed the total area of interior forest, defined as forest located beyond the influence of the ecological edge effect, and the total area of edge-affected forest, which is more exposed to external disturbances. From these values, the Interior-to-Edge Ratio (**I/E**), defined as the area beyond a specified edge buffer distance relative to the total patch area (Bogaert et al., 1998; Mladenoff et al., 1994) was derived. This provides insight into habitat quality and susceptibility to edge effects. The analysis was conducted using vector data and multiple buffer distances (50 m, 100 m, 150 m, 200 m) to account for varying ecological edge sensitivities. These distances were selected based on previous studies in tropical forests, capturing both short- and medium-range microclimatic and ecological effects. Using multiple thresholds enables a robust assessment of edge influence on forest patches of varying sizes and exposure levels. Additionally, the percentage of forest area influenced by edge effects was calculated to facilitate standardized comparisons of edge exposure across landscapes and time periods. These metrics are used due to their effectiveness in quantifying the spatial configuration, extent, and degree of isolation of forest patches, which are critical indicators of habitat integrity and landscape connectivity (Bogaert et al., 1998; Li et al., 2005; Mladenoff et al., 1994; Yamashita et al., 2024). These metrics provide a robust analytical framework for characterizing both the spatial pattern of fragmentation and the degree to which forests remain functionally intact under ongoing anthropogenic pressure.

Equation 6.1. $$\boldsymbol{RFAC} = \frac{a_f}{a_i}$$

Where $RFAC$ is the Relative Forest Area Change, $\boldsymbol{a_f}$ refers to the forest area of a given landscape at the final time point (Year 2), and $\boldsymbol{a_i}$ represents the forest area of a given landscape at the initial time point (Year 1). RFAC values greater than 1 indicate a net gain in forest area over the observed period, suggesting reforestation or natural regeneration, while RFAC values less than 1 indicate a net loss in forest area, reflecting deforestation or degradation. An RFAC of 1 indicates that the forest area has remained stable over time. This index provides a straightforward yet robust method for quantifying long-term changes in forest extent. It enables direct comparison of forest dynamics across multiple landscapes, regardless of their initial forest cover, spatial scale, or socio-ecological context.

Equation 6.2. $$\boldsymbol{LPI} = \frac{max_{j=1}^{n}(a_{ij})}{A} \text{ x } 100$$

Where: a_{ij} = Area (m^2) of patch ij; A = Total landscape area (m^2)

6.6.5. LST retrieval, patch area, and edge-effect magnitude

To evaluate the influence of forest patch area on edge-effect magnitude, land surface temperature (LST) was used as a biophysical indicator of thermal stress for the year 2024, representing current thermal edge conditions in the Masako, Mbiye, Yoko, and Yangambi landscapes. LST was estimated from harmonized Sentinel-2 data. Two biophysical predictors were derived: (i) the Normalized Difference Vegetation Index (NDVI), calculated from bands B4 and B8, and (ii) broadband surface albedo, calculated from bands B2, B3, B4, B8, B11, and B12 using specific weighting coefficients from Bonafoni et al.(2020). The broadband surface albedo α is estimated by integration of narrowband reflectances across the SW spectrum, as (Equation 6.3)(Bonafoni et al., 2020):

Equation 6.3. $$\alpha = \sum_{B=1}^{N} \rho_B . w_B$$

Where ρ_B is the surface reflectance for a specific band B of a multispectral instrument (MSI), and w_B is the weighting coefficient (Bonafoni et al., 2020).

An empirical linear regression model was then calibrated to link LST to Sentinel-2 NDVI and albedo (Equation 6.4), as adapted from Equation 7 of Nasseri et al.(2023).

Equation 6.4. $$LST = a_0 + a_1 * NDVI + a_2 * Albedo$$

Where a_0, a_1, and a_2 are regression coefficients.

To ensure a region-specific calibration, Landsat 8 LST was used as the reference target variable, while the Sentinel-2 imagery used to compute NDVI and albedo was resampled to 30 m to match the Landsat LST pixel resolution. This resampling ensured that each Sentinel-2-derived pixel corresponded directly to a Landsat LST pixel for regression analysis. This approach was chosen because the spectral responses and band-specific albedo coefficients differ between Landsat 8 and Sentinel-2, as highlighted by Liang (2001), Smith (2010), and Bonafoni et al.(2020). Consequently, the Landsat-based NDVI and albedo coefficients (a_1, a_2) are not directly transferable to Sentinel-2 variables, which are derived from different spectral bands and albedo formulations. The regression coefficients linking LST to NDVI and albedo are therefore sensor-specific, and those derived for the Kisangani region were then applied to estimate LST from Sentinel-2 data. Sentinel-2 was selected as the LST primary source because its spatial resolution (10-20 m) allows the detection of fine-scale thermal heterogeneity within the highly fragmented tropical forest mosaics of the Kisangani landscape. Model performance was assessed using both the root-mean-square error (RMSE) and the coefficient of determination (R^2). LST values for 2024 were then averaged across 21 cloud-free Landsat scenes to reduce atmospheric variability, residual clouds, and seasonal fluctuations, providing a robust representation of patch-level microclimatic conditions for the current year.

To measure the magnitude of edge influence (MEI) on land surface temperature (LST), a framework distinct from structural edge analysis was applied. Specifically, two distance buffers were used for the LST-based MEI. A 20-m buffer was consistently applied across all four landscapes, as this distance captures microclimatic edge effects that occur even in highly fragmented forests such as Masako and Mbiye, where most remaining patches are small and rarely contain interior habitat beyond 50 m. An additional 50-m buffer was applied only to the Yangambi and Yoko landscapes, where larger and more continuous forest blocks still existed in 2024. In these less fragmented forests, edge-related temperature gradients are expected to penetrate further into the forest interior, thereby justifying the use of a larger buffer. Importantly, two distinct edge-distance frameworks were used in this study: multidistance thresholds (50-200 m) were applied exclusively to structural edge exposure metrics, whereas fixed distances (20 m across all landscapes, and additionally 50 m for Yangambi and Yoko) were used solely for the LST-based Microclimatic Edge Influence (MEI) analysis. Therefore, the MEI was calculated using the formula (Equation 6.3) (Burton, 2002; Harper et al., 2005):

Equation 6.3. $$\boldsymbol{MEI} = \frac{e-i}{e+i}$$

Where $\boldsymbol{e}$ represents the value of the parameter (here, LST) measured within the edge zone, and $\boldsymbol{i}$ corresponds to the mean value within the forest interior beyond the edge buffer. This index ranges from −1 to +1, with values near zero indicating negligible edge effects, while higher values indicate a greater thermal contrast between the edge and interior zones. A simple linear regression was then applied to assess the effect of patch area on the magnitude of edge influence on LST, enabling a quantitative assessment of how patch size moderates thermal edge responses across forest landscapes. Given the highly asymmetric distribution of patch area, with many small patches and a few very large ones, patch area is log-transformed prior to regression. The transformation is applied to reduce skewness, limit the disproportionate influence of large patches, stabilize variance, and improve the linearity of the relationship with edge influence.

6.7. Results

6.7.1. Classification accuracy and Sentinel-2 LST model evaluation

The metrics obtained from the confusion matrices, users', producers', and overall accuracy, show values exceeding 80% (appendix 2), indicating a reliable performance in distinguishing land cover types. Furthermore, comparing our change map with that generated by Hansen et al.(2013), demonstrates that the local classification provides a slightly more accurate and consistent representation of the reference data (Table 6.2). Validation of the recalibrated Sentinel-2 LST model shows good agreement with Landsat 8 observations, with an R^2 of 0.76 and an RMSE of 0.29 °C. These values suggest that the model accurately reproduces surface temperature patterns, providing reliable LST estimates to support subsequent analyses.

Table 6.2. A comparison with a global classification: the case of High-Resolution Global Maps of Hansen between 2000 and 2024**.** UA is the user's accuracy, PA is the producer's accuracy, and OA is the overall accuracy.

Hansen Classification	**UA**	**PA**	**OA**
Forest	79.5	79.5	94.2
Non-Forest	97.5	97.5	
Local classification	**UA**	**PA**	**OA**
Forest	90.8	97.1	98.8
Non-Forest	99.7	98.6	

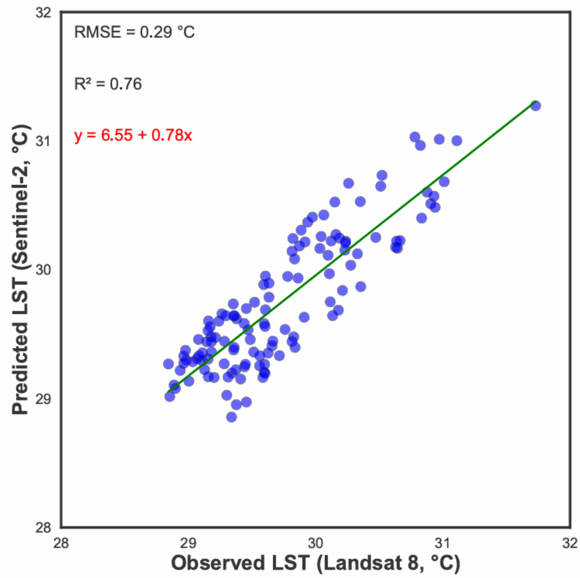


Figure 6.2. Validation of Sentinel-2 predicted LST using Landsat 8 observations. This scatterplot confirms the reliability of the recalibrated Sentinel-2 LST for spatial analyses.

6.7.2. Multi-temporal mapping of mature forest

The visual interpretation of land cover maps from 1986 to 2024 across the four studied landscapes reveals a general trend of increasing landscape artificialization (Figure 6.2). The Yoko Forest Reserve is experiencing increasing anthropogenic pressure, especially in its Northern section. While the Yangambi Biosphere Reserve still retains large forest aggregates, significant human disturbances are evident along the Bengamisa road corridor, particularly in the eastern and southwestern zones. In contrast, the Masako and Mbiye Forest Reserves are experiencing near-total disappearance. Since 2016, anthropogenic pressure around these reserves, which are situated near urban areas, has intensified, leaving only a few scattered forest patches.

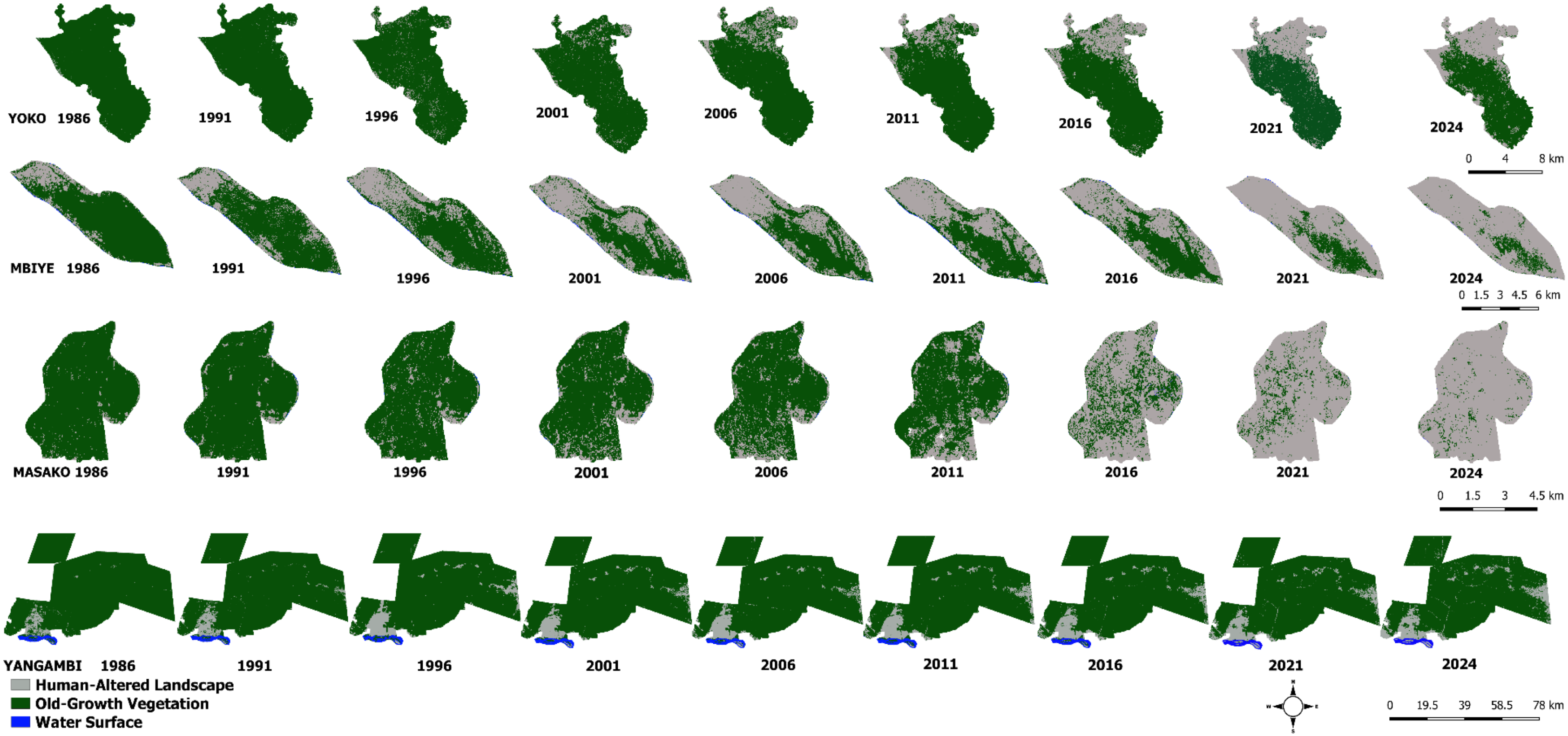


Figure 6.3. Changes in the forest landscapes areas of the Kisangani region (1986–2024): progressive decline of mature forest and expansion of anthropized areas.

6.7.3. Historical trends of forest landscape fragmentation

As expected, the overall results reveal a consistent trajectory of forest degradation over time, characterized by a significant decline in both the Relative Forest Area Change and the Largest Patch Index (LPI) across all four landscapes (Figure 6.3). These two metrics capture distinct but complementary aspects of landscape dynamics: the relative forest area reflects changes in landscape composition, while the LPI captures aspects of landscape configuration, notably the spatial dominance of the largest remaining forest patch. Between 2021 and 2024, Masako and Mbiye experienced a dramatic collapse in forest cover, losing over 80% of their initial forest area. This sharp decline in forest composition suggests an accelerated conversion of forest land to other uses, likely driven by intense urban expansion from the city of Kisangani. In parallel, the significant drop in LPI in these landscapes indicates a pronounced fragmentation process, whereby formerly dominant forest patches have been progressively disaggregated into smaller and more isolated fragments, leading to a substantial loss of spatial cohesion. In contrast, Yangambi maintained over 90% of its initial forest area, and Yoko retained more than 60% by 2024, suggesting comparatively higher resilience in both composition and configuration. Despite some decline, these landscapes still preserve larger, more cohesive forest patches, as reflected by their relatively higher LPI values. The diverging trajectories among the landscapes highlight how socio-economic pressures and land-use dynamics shape both the extent and spatial configuration of tropical forest ecosystems.

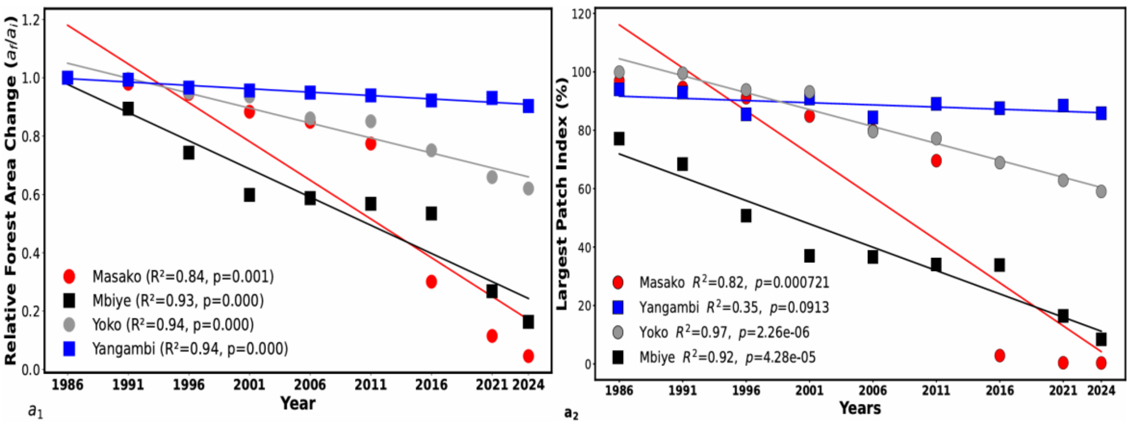


Figure 6.4. Changes in relative forest area (a_1) and Largest Patch Index (a_3) in forest landscapes around the Kisangani region (1986–2024). The relative forest area was calculated as the ratio of the final to the initial forest area, providing a standardized measure of overall forest loss across landscapes. The results show a consistent decline in both the total proportion of forest cover and the dominance of the largest patch over time, reflecting ongoing degradation in both the composition and configuration of forest landscapes. The loss of forest extent and the shrinking of the largest patches indicate increasing fragmentation and reduced spatial cohesion, particularly in Masako and Mbiye.

6.7.4. Temporal changes in forest landscape integrity

Between 1986 and 2024, the Masako Forest Reserve experienced significant losses in its interior forest areas (Figure 6.4). As a result, from 2016 to 2024, all forest patches, regardless of the edge effect distance considered, were entirely exposed to edge influences. The interior-to-edge (I/E) ratio dropped significantly, approaching zero, while the percentage of edge-affected forest area increased notably over time. This suggests that forest patches are becoming increasingly vulnerable to edge effects. These trends, characterized by more fragmented and edge-dominated patches, were especially noticeable in recent years (2016–2021 and 2024), particularly in the Mbiye Forest Reserve (Figure 6.5) and even more so in the Masako landscape.

Since 2016, all remaining forest patches in these two landscapes appear to be entirely influenced by edge effects, regardless of the buffer distance considered. The Yoko Forest (Figure 6.6) also shows alarming indicators of ecological integrity. The area of core forest patches has consistently decreased across all edge effect distances. For an edge effect distance of 200 m, the interior area declined by more than 40 km² between 1986 and 2024. As a result, the interior-to-edge (I/E) ratio declined markedly, from 2.0 in 1986 to approximately 0.5 in 2024. In contrast, the Yangambi Biosphere Reserve (Figure 6.7), located approximately 100 km from the urban center of Kisangani, has remained relatively well-preserved. Although a general reduction in core forest area in favor of edge-dominated zones was observed, the impacts in Yangambi appear to be less severe, likely due to its relative remoteness from urban-induced disturbances.

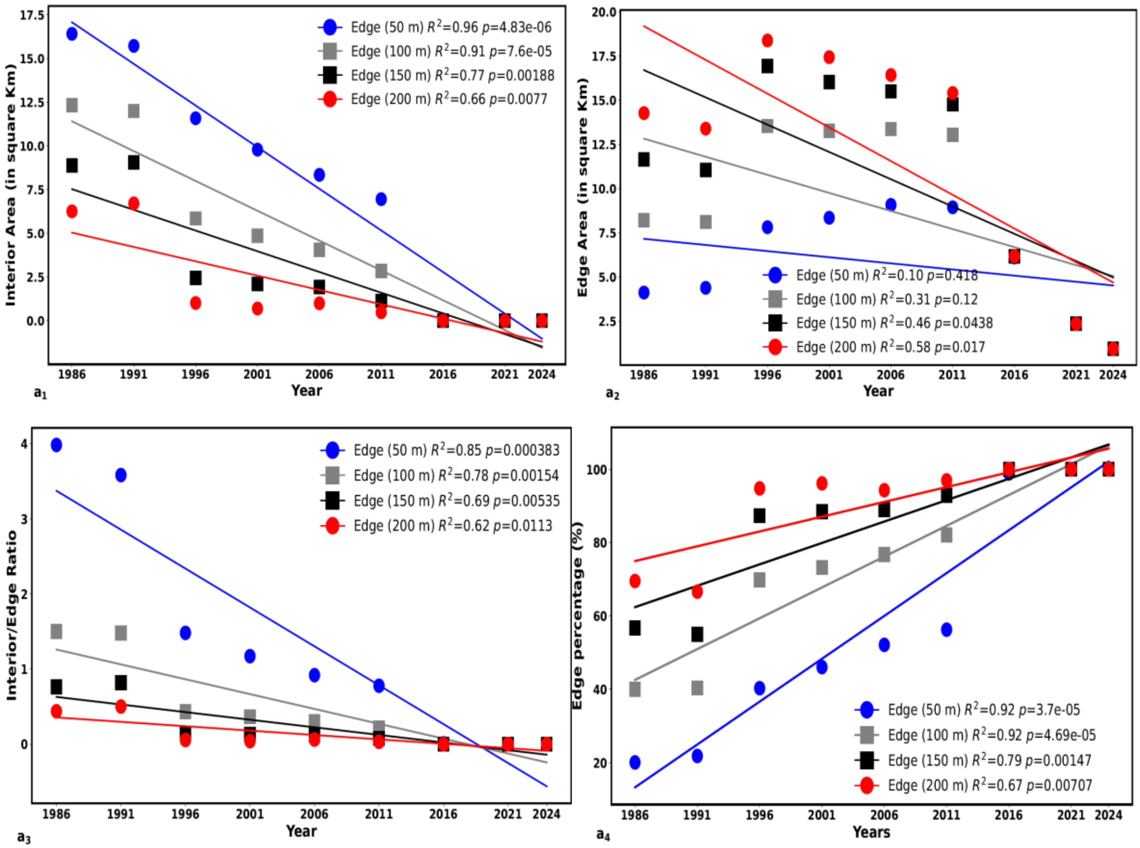


Figure 6.5. Changes in interior area (a_1), edge patch area (a_2), interior-to-edge ratio (a_3), and edge percentage (a_4) in Masako Forest Reserve (1986–2024). Over time, particularly since 2016, the total edge area has significantly declined. However, this decline does not reflect an improvement in forest integrity, but rather the progressive shrinking of forest patches, which reduces the total area available for both interior and edge zones. As patch sizes decrease, the interior area contracts more rapidly than the edge, leading to a relative increase in edge exposure. This trend is clearly illustrated by the declining interior-to-edge (**I/E**) ratio and the rising percentage of edge area, indicating that the remaining patches are more vulnerable to edge-related ecological processes.

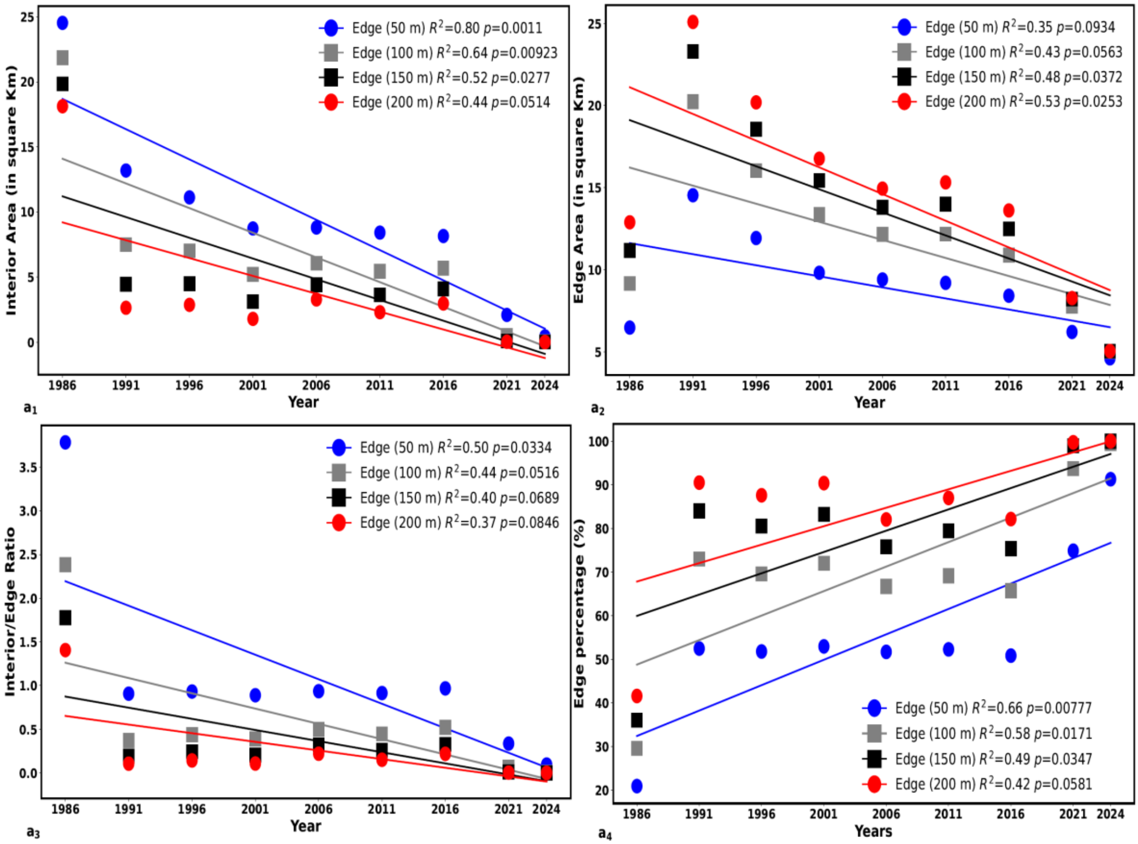


Figure 6.6. Changes in interior area (a_1), edge patch area (a_2), interior-to-edge ratio (a_3), and edge percentage (a_4) in Mbiye Forest Reserve (1986–2024). Since 2016, and assuming an edge effect depth of 200 meters, the remaining patches of mature vegetation in the Mbiye Forest Reserve have experienced a near-total loss of interior area. This shift is a direct consequence of continued patch shrinkage, which reduces the spatial extent available for the forest interior. As forest fragments become smaller, interior zones disappear while edge conditions become dominant. This dynamic is reflected in the decline of the interior-to-edge (**I/E**) ratio and the rising edge percentage, underscoring the increasing exposure of remnant patches to edge-related disturbances.

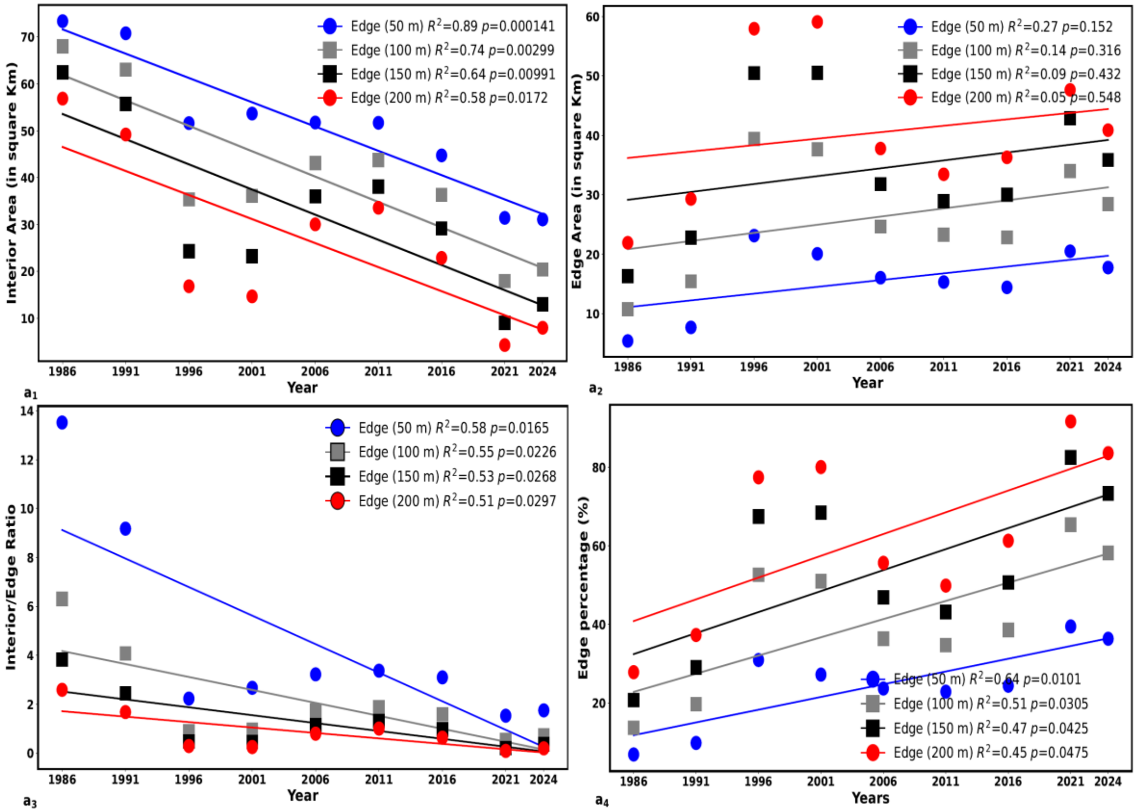


Figure 6.7. Changes in interior area (a_1), edge patch area (a_2), interior-to-edge ratio (a_3), and edge percentage (a_4) in the Yoko Forest Reserve (1986–2024). For edge effect distances of 100 m, 150 m, and 200 m, the percentage of edge-affected forest area has increased significantly over time, indicating a continuous expansion of zones subjected to edge influences. This trend reflects a progressive contraction of core interior forest habitats, which are crucial for maintaining ecological integrity and mitigating the effects of external disturbances. The decrease in the interior-to-edge (**I/E**) ratio further underscores the growing dominance of edge conditions within the landscape. Such shifts in forest spatial structure may have significant ecological consequences, including altered microclimates, increased vulnerability to invasive species, and changes in species composition.

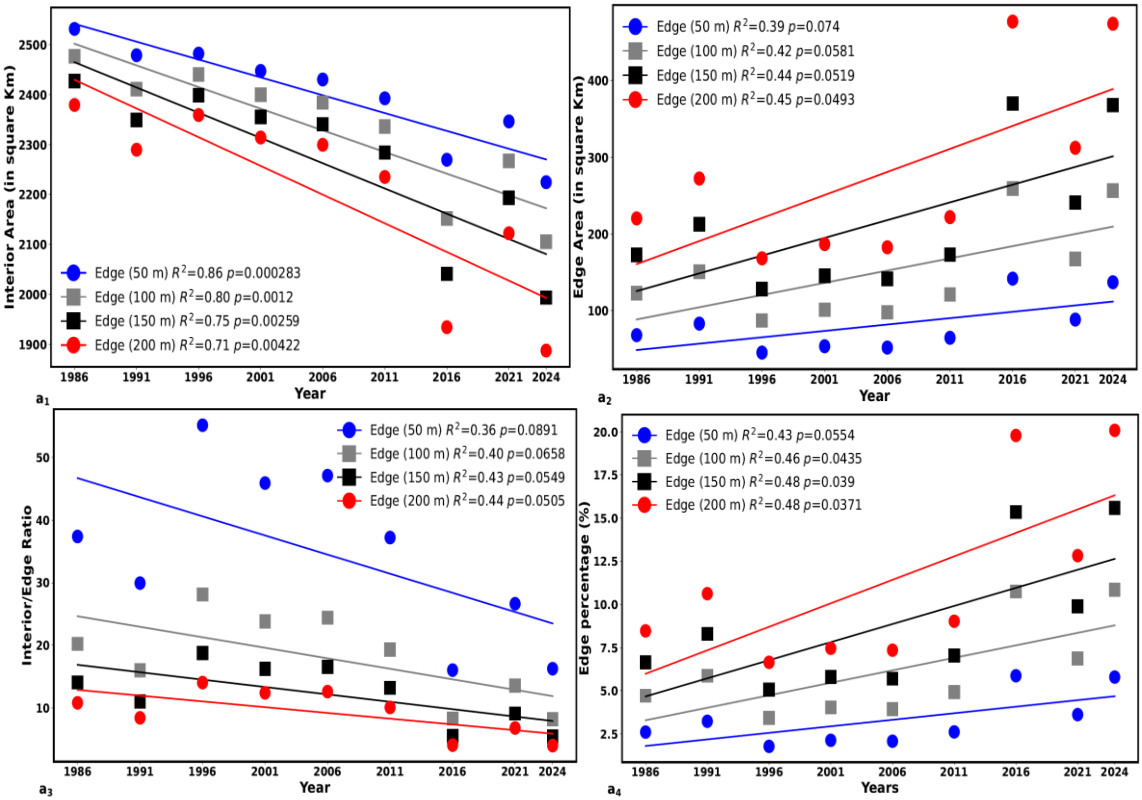


Figure 6.8. Changes in interior area (a_1), edge patch area (a_2), interior-to-edge ratio (a_3), and edge percentage (a_4) in the Yangambi Biosphere Reserve (1986–2024). Although the percentage of forest area affected by edges has increased over time, it remains relatively low compared to other forest landscapes in the Kisangani region. This pattern indicates that Yangambi's forest retains a relatively intact and compact spatial configuration, characterized by large, contiguous patches with well-preserved core interiors. The high interior-to-edge (**I/E**) ratio further reflects limited fragmentation and reduced susceptibility to edge effects, which are critical for maintaining stable microclimates and biodiversity within the reserve.

6.7.5. Exploring the influence of patch size on the LST edge effect magnitude

The analysis reveals an inverse relationship between patch size and the magnitude of edge effects on Land Surface Temperature (LST). Across all four landscapes, analyses conducted at a 20 m buffer distance (Figure 6.8a_1, a_2, a_3, and a_4) show that larger patches are associated with lower edge-related thermal gradients, indicating a mitigation of edge influence as patch area increases. This relationship was also assessed at a 50-m scale for Yangambi and Yoko, where sufficiently large forest remnants remained intact in 2024 (Figures 6.8b_1 and 8b_2), yielding similarly robust and statistically significant results. The reduced thermal contrast in larger patches likely reflects their higher core-to-edge ratios, which protect the forest interior from external climatic stress.

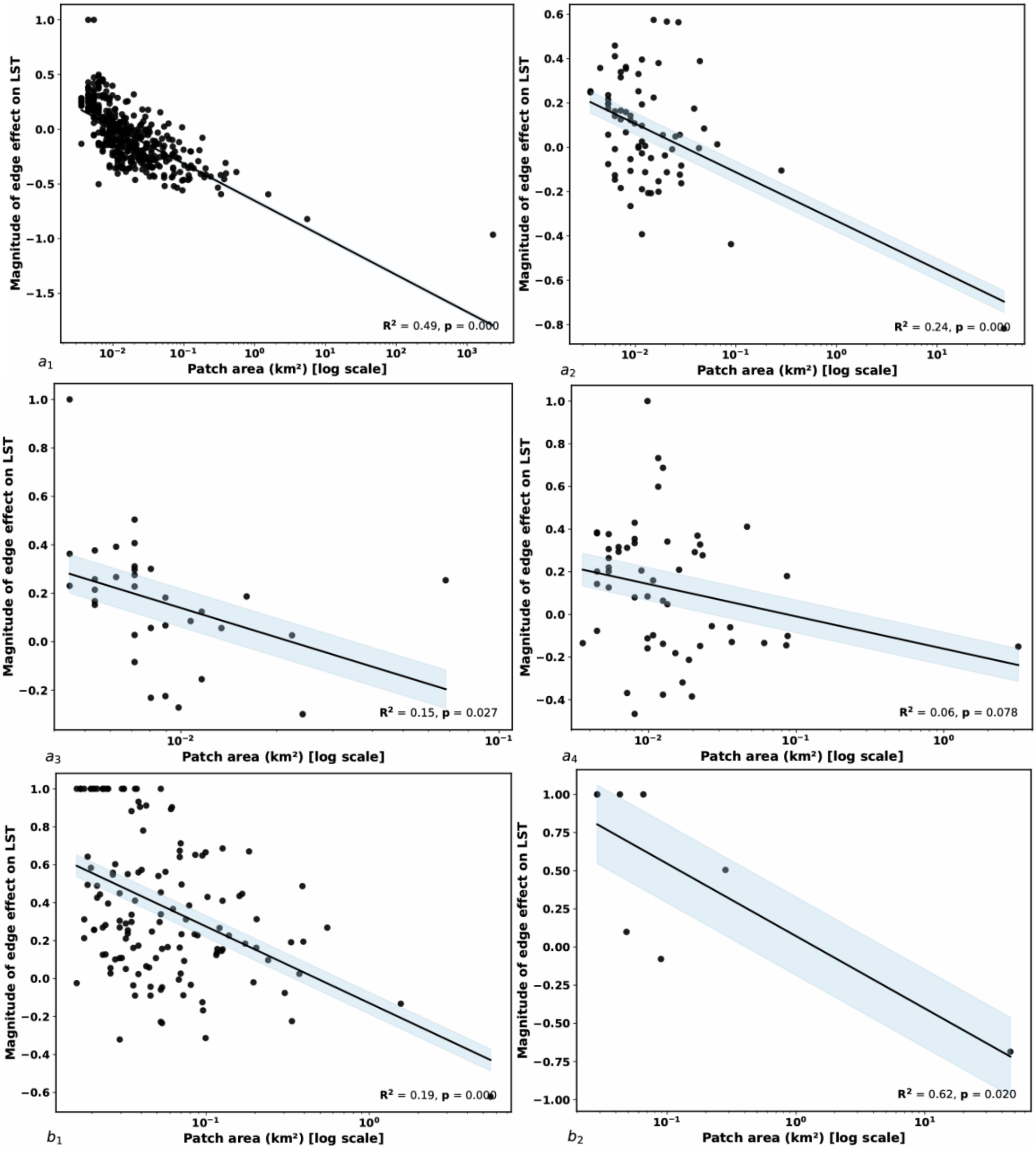


Figure 6.9. Variation in edge effect magnitude on LST as a function of patch size: Yangambi (a_1), Yoko (a_2), Masako (a_3), and Mbiye (a_4) within 20 m of the forest edge; Yangambi (b_1) and Yoko (b_2) within 50 m. The analysis reveals a negative relationship between patch size and the magnitude of edge effects on LST. Larger patches exhibit lower magnitudes of edge influence, suggesting a reduced impact of thermal disturbances in more extensive forest remnants. This attenuation likely results from higher core-to-edge ratios, which limit the spatial extent of edge-exposed forest zones.

6.8. Discussion

6.8.1. Quantification of forest landscape exposure to edge influence

The exposure of forest landscapes to edge influences was quantified using widely applied indices, including the interior-to-edge ratio (I/E), the area of interior patches, and the area of patches affected by edge effects (Mladenoff et al., 1994; Ripple, 1991; Turner & Ruscher, 1988), at various distances (50 m, 100 m, 150 m, and 200 m). These distances were chosen to address variability in edge-influence penetration across various ecological processes and disturbance agents. The extent of edge effects into forest interiors can vary widely depending on the type and intensity of disturbance, as well as the ecological parameters affected. Edge-related changes in microclimate, such as relative humidity, air temperature, and wind speed, often penetrate different distances from the forest edge (Bogaert et al., 1998; Harper et al., 2005). For example, in northern Queensland, Australia, edge effects on light intensity have been observed to penetrate up to 50 meters into the forest interior (Pohlman et al., 2007), while in Czechia, near Prague, edge effects on mean air temperature can reach 100 meters inside the forest (Hofmeister et al., 2019). These examples illustrate that the depth of edge effects varies across ecosystems and parameters. Previous pantropical analyses indicate that edge effects on forest biomass can extend hundreds of meters, with measurable impacts up to 500 m from the forest edge, highlighting the broad range of possible edge-effect depths in tropical forest landscapes (Chaplin-Kramer et al., 2015). To account for this inherent variability, we evaluated multiple buffer distances (50, 100, 150, and 200 m) for structural edge exposure metrics. This approach allows a comprehensive assessment of edge effects across the Masako, Mbiye, Yoko, and Yangambi forest landscapes, accommodating both highly fragmented patches with limited interior habitat and larger, more continuous forest patches. Therefore, the I/E ratio, a simple yet effective metric, provides a strong estimate of edge influence, a crucial aspect of landscape ecology. It reflects the relative exposure of a habitat to edge effects, which can significantly impact the ecological quality of a patch (Bogaert et al., 1998; Bogaert et al., 1999; Mladenoff et al., 1994).

6.8.2. Forest landscape integrity: the death of Masako and Mbiye forest landscapes

Among the four forest landscapes analyzed, Masako and Mbiye exhibited the most alarming signs of ecological degradation. Unlike Yangambi, where forest integrity remains relatively intact due to several initiatives linking conservation to sustainable development, particularly in line with Sustainable Development Goal 15, which emphasizes the protection, restoration, and sustainable use of terrestrial ecosystems (United Nations, 2015b), Masako and Mbiye have exhibited critical levels of degradation in recent years. Since 2016, the remaining forest patches in Masako have nearly lost their interior core areas. The interior-to-edge (I/E) ratio steadily approached zero between 2016 and 2024 across all buffer distances considered (50 m, 100 m, 150 m, and 200 m), indicating that almost all remaining forest patches are subject to edge effects. Furthermore, in both Masako and Mbiye, the relationship between patch area and the magnitude of edge influence (MEI) exhibited low R^2 values, indicating that patch size explains only a small proportion of the variation in LST in these areas. This suggests that, in these landscapes, the thermal dynamics of remaining forest fragments are only weakly influenced by patch size, with edge effects prevailing across patches regardless of their area, reflecting a high degree of degradation where true interior forest conditions are largely absent or severely compromised.

Both landscapes are located near urban areas and face intense anthropogenic pressures, including urban and agricultural expansion, charcoal production, and artisanal logging, with the latter being particularly frequent in Mbiye. Several studies have highlighted the negative impact of these anthropogenic factors on forest landscapes in Central Africa, particularly in contexts where spatial management is poorly regulated. Urban and peri-urban expansion (Balandi et al., 2023; Balandi et al., 2024), as well as the rural complex, comprising small-scale agriculture, settlements, and road networks (Kondjo et al., 2023), are identified as the leading drivers of deforestation and degradation. While several studies (Iyongo, 2013; Meniko et al., 2020) have raised concerns in recent years about the impact of fragmentation in the Masako Forest Reserve on animal diversity, the near disappearance of interior forest patches, as observed in this study, may have far-reaching consequences not only for animal and plant biodiversity, thermal regulation, as revealed in this study, but also for the functioning and resilience of key ecosystem services such as carbon sequestration (Li et al., 2022; Ryan & Mitchard, 2010) and landscape connectivity.

In contrast, the Yangambi landscape shows a more favorable trajectory. Throughout the study period, it consistently exhibited relatively low levels of edge exposure across all distance thresholds, including the more conservative 200 m buffer. This suggests that a substantial portion of the forest remains protected from edge-related disturbances, thereby preserving the interior forest conditions. These patterns reflect a higher degree of structural and functional integrity, likely sustained by the presence of large, contiguous forest patches and reinforced by multiple, long-standing management efforts. Coordinated initiatives by various research and development entities operating within the Yangambi Biosphere Reserve have played a critical role in promoting conservation, sustainable land use, and forest restoration. These efforts have helped maintain ecological functionality and distinguish Yangambi from the more fragmented and vulnerable landscapes of Masako and Mbiye.

The Yoko Forest landscape, despite experiencing anthropogenic expansion in its northern section (Figure 2), remains relatively well preserved. However, some indicators reveal emerging risks. Notably, the interior-to-edge (I/E) ratio has declined significantly at edge-effect distances of approximately 200 m, indicating an increased vulnerability of interior forest areas to peripheral disturbances. These findings emphasize an urgent need for targeted management interventions to maintain ecological functionality and prevent further degradation.

6.8.3. Effective and resilient strategies

Based on the observed patterns of forest loss and fragmentation, our results suggest that priority actions could include identifying and protecting remnant forest patches in Masako and Mbiye, which may serve as ecological cores supporting natural regeneration. These core areas could potentially be managed as strictly protected zones to maintain habitat refugia and provide local seed sources for forest recovery. Enhancing ecological connectivity by establishing forest corridors linking isolated patches may help mitigate edge-related microclimatic stress and facilitate species movement, potentially combining natural regeneration with reforestation using native species. Agroforestry systems around these patches and corridors might act as buffers, helping to reduce pressure on remaining forests while also supporting local subsistence needs.

Unregulated wood extraction and charcoal production have contributed to fragmentation, and the results indicate that community-based management strategies could help formalize these practices and reduce ecological impact. Additionally, integrating forest conservation into spatial planning around Kisangani, such as maintaining exclusion zones around remaining forest patches, may help mitigate pressures from urban expansion. Overall, the results highlight that restoration and management strategies could aim to balance conservation objectives with local land-use needs, with measures directly informed by observed patterns of forest loss, fragmentation, and microclimatic stress.

6.9. Conclusion

This study examined the historical trends of forest fragmentation and measured the extent of edge-affected forest areas across four Forest landscapes near Kisangani, Democratic Republic of the Congo: Masako, Mbiye, Yoko, and Yangambi. Additionally, it examined the relationship between forest patch size and the magnitude of edge influence, using Land Surface Temperature (LST) as an indicator of edge-related ecological stress. Using satellite data from 1986 to 2024 and applying a suite of spatial landscape metrics, the study quantified changes in both forest composition, as measured by Relative Forest Area Change, and spatial configuration, particularly using the Largest Patch Index (LPI). To assess forest exposure to edge effects, we evaluated four key indicators: Interior area, Edge area, Edge percentage, and the Interior-to-Edge (I/E) ratio. These metrics were calculated across four ecologically relevant edge-effect distances: 50 m, 100 m, 150 m, and 200 m, allowing for a multi-scale analysis of forest vulnerability.

Findings revealed a significant decline in forest cover and spatial cohesion in the Masako and Mbiye landscapes. Between 2021 and 2024, over 80% of the forest area was lost, and interior forest patches had almost entirely disappeared by 2016 across all edge distances (50, 100, 150, and 200 m). By contrast, Yangambi and Yoko have maintained higher levels of forest cover and larger, more connected patches, reflecting greater resilience to fragmentation. Edge effect metrics, including interior area, edge area, edge percentage, and the interior-to-edge (I/E) ratio, confirm the increased vulnerability of forest patches to edge disturbances in Masako and Mbiye, whereas Yangambi and Yoko are comparatively less exposed. Furthermore, analyses of land surface temperature (LST) show a significant inverse relationship between patch size and edge-related thermal influence in Yangambi and Yoko. However, in Masako and Mbiye, this relationship exhibited low R^2 values, likely reflecting the small size and advanced fragmentation of the remaining forest patches, which constrains their influence on thermal edge effects.

Such advanced degradation in Masako and Mbiye is likely to compromise critical ecosystem services and threaten both plant and animal biodiversity. Therefore, context-specific restoration strategies are required, including the protection and reforestation of remnant forest cores, the establishment of ecological corridors, the promotion of agroforestry systems, and the regulation of artisanal wood harvesting and urban expansion. For Yoko and Yangambi, proactive measures, including legal reinforcement, agricultural zoning, community-based monitoring, and environmental education, are recommended to safeguard forest integrity in the long term.

Chapter 7

Spatiotemporal analysis of urban heat islands in Kisangani city using MODIS imagery: exploring interactions with urban-rural gradient, building volume density, and vegetation effects.

7.1. Reference

Balandi, J. B., Selemani, T. M., Meniko, J.-P. P. T. H., Sambieni, K. R., Sikuzani, Y. U., Bastin, J.-F., Tshomba, P. W., Elangilangi, J. M., Mobunda, J.T., Agassounon, B.M., & Bogaert, J. (2025). Spatiotemporal analysis of urban heat islands in Kisangani city using MODIS imagery: exploring interactions with urban-rural gradient, building volume density, and vegetation effects.
Climate **2025**, *13*(5), 89. https://doi.org/10.3390/cli13050089

7.2. Context

Landscape transformations affecting components of urban green infrastructure, together with the progressive degradation of surrounding forest ecosystems, have the potential to directly alter the urban microclimate of Kisangani. The reduction of green spaces, coupled with the sustained increase in building density and urban sprawl, promotes heat accumulation and consequently intensifies Urban Heat Island (UHI) effects (Arnfield, 2003; Oke, 2002; Stewart & Oke, 2012). Most studies on this phenomenon have focused on large metropolitan areas, emphasizing changes in land cover, vegetation, and surface temperature. By contrast, the role of urban morphology, particularly the volumetric characteristics of buildings, has been examined far less extensively. Furthermore, variations along the urban-rural gradient are rarely considered, despite their crucial role in understanding how horizontal and vertical urban expansion contribute to heat accumulation. This chapter aims to address this gap by combining an analysis of the spatiotemporal dynamics of Urban Heat Islands with an assessment of the interactions between Land Surface Temperature (LST) and Building Volume Density (BVD). In addition, spatial variations are examined along the urban-rural gradient to highlight the contribution of both horizontal and vertical expansion to heat accumulation.

7.3. Résumé

Le phénomène d'îlot de chaleur urbain (UHI) est apparu dans la littérature comme un enjeu majeur pour le bien-être urbain, principalement lié à l'intensification de l'urbanisation. Pour aborder cette problématique, la présente étude examine la dynamique spatio-temporelle de l'UHI dans la ville en forte croissance de Kisangani et le long de son gradient urbain-rural entre 2000 et 2024, à partir des données de température de surface (LST) issues du produit MODIS 11A2 V6.1. Des analyses statistiques descriptives et inférentielles ont été appliquées afin d'examiner les tendances de l'UHI et les relations avec la densité volumétrique des bâtiments (BVD) et la densité de végétation, exprimée par l'indice de végétation par différence normalisée (NDVI).

Les résultats montrent que l'étendue spatiale de l'UHI modéré a progressivement augmenté de 16 km² à 38 km², tandis que celle de l'UHI élevé est passée de 9 km² à 19 km². Par ailleurs, bien que des valeurs élevées d'UHI ($0{,}2 < UHI \leq 0{,}3$) soient observées dans les zones urbaines et que des différences significatives de variation de l'UHI soient relevées entre les zones urbaines, périurbaines et rurales, les résultats indiquent que la valeur moyenne de l'UHI dans les zones urbaines de Kisangani reste inférieure à 0,2. Ainsi, en s’appuyant sur les variations moyennes de l’UHI, les zones urbaines de Kisangani présentent des écarts de LST modérés par rapport aux zones rurales. De plus, les variations du LST présentent une corrélation significative avec les densités volumiques des bâtiments et de la végétation. Cependant, l’influence de la densité de végétation en tant que facteur explicatif de la LST diminue progressivement, tandis que celle de la densité volumétrique des bâtiments augmente au fil du temps. Cela suggère la nécessité de mettre en œuvre une voie de développement synergique permettant de gérer les interactions entre l’urbanisation, la transformation du paysage et la fourniture de services écosystémiques. Cette approche intégrée pourrait constituer une solution essentielle pour atténuer l’effet d’îlot de chaleur urbain dans les régions classées comme zones à forte température.

Mots-clés : Îlot de chaleur urbain, Température de surface, Densité volumétrique des bâtiments, Gradient d’urbanisation, Kisangani.

7.4. Abstract

The urban heat island (UHI) effect has emerged in the literature as a significant challenge for urban well-being, primarily driven by increasing urbanization. To address this challenge, this study investigates the spatiotemporal pattern of the UHI in the fast-growing city of Kisangani and within its urban–rural gradient from 2000 to 2024 using land surface temperature (LST) data from the MODIS 11A2 V6.1 product. Inferential and descriptive statistics were applied to examine patterns of UHI and relationships among the LST, building volume density (BVD), and vegetation density, as measured by the Normalized Difference Vegetation Index (NDVI). The results showed that the spatial extent of moderate UHI gradually increased from 16 km^2 to 38 km^2, while that of high UHI increased from 9 km^2 to 19 km^2. Furthermore, although high UHI values ($0.2 < UHI \le 0.3$) are observed in urban areas and significant differences in UHI variations are detected across urban, peri-urban, and rural zones, the results indicate that the mean UHI in Kisangani’s urban areas remains below 0.2. Therefore, based on average UHI variations, Kisangani’s urban zones exhibit moderate LST disparities relative to rural areas. Moreover, the LST variations show significant correlation with building volume and vegetation densities. However, the influence of vegetation density as a predictor of LST gradually decreases while the influence of building volume density increases over time, suggesting the need to implement a synergistic development pathway to manage the interactions between urbanization, landscape change, and ecosystem service provision. This integrated approach may represent a crucial solution for mitigating the UHI effect in regions categorized as high-temperature zones.

Keywords: Urban Heat Island, Land Surface Temperature, Building Volume Density, Urbanization Gradient, Kisangani.

7.5. Introduction

Increasing global, regional, and local urbanization fosters various environmental challenges, including urban heat islands (UHIs) (Dwivedi & Khire, 2018; Jato-espino, 2019). This phenomenon arises from the temperature contrast between rural and urban zones, whereby the daily thermal amplitude of urban zones is decreased due to the diurnal absorption of solar energy, which gradually dissipates during the night (Kolokotroni et al., 2006). Several factors, including land-use and land-cover changes (Liu et al., 2015), urban architecture (Arnfield, 2003; Oke, 2002), and human activities, are closely linked to the UHI phenomenon, which shapes local environmental conditions (Stewart & Oke, 2012a). The increased use of materials such as asphalt in urban landscapes enhances heat retention (Liu et al., 2015), while changes in urban architecture, particularly in building geometry, including construction patterns with tall buildings situated closely together in small spaces, create “urban canyons” that trap heat (Arnfield, 2003; Oke, 2002). Additionally, emissions from transport and industry further amplify UHI effects (Stewart & Oke, 2012; Taha, 1997).

Beyond environmental impacts, UHIs pose significant social and economic challenges, including increased energy consumption, deteriorating air quality, heightened health risks, and reduced water availability (Candra et al., 2016; Martínez et al., 2004; Stewart & Oke, 2012). These impacts align with several United Nations Sustainable Development Goals (SDGs), particularly SDG 11 (Sustainable Cities and Communities), SDG 3 (Good Health and Well-being), and SDG 13 (Climate Action) (Garcia-Herrera et al., 2010). Furthermore, the UHI effect disrupts not only the environmental equilibrium but also social dynamics, limiting outdoor activities and reducing the quality of urban life. In tropical regions, such as Kisangani City in the Democratic Republic of the Congo (DRC), where high baseline temperatures constrain livelihoods, the UHI phenomenon may exacerbate existing vulnerabilities, including food security (SDG 2) (Garcia-Herrera et al., 2010). Elevated temperatures alter local microclimates (Stewart & Oke, 2012a), increase the spread of diseases, intensify the need for irrigation, and accelerate the decomposition of soil organic matter, thus reducing agricultural productivity and urban resilience. Due to these cross-cutting impacts, understanding and mitigating the effects of UHI is critical for advancing sustainable urban development and climate resilience in line with the 2030 Agenda.

Previous studies highlight the factors influencing UHI dynamics and their impacts across diverse geographic contexts. For example, extreme heat events, such as the 2003 European heatwave, have been linked to significant increases in mortality, as observed in France, where excess deaths rose by 60% (Garcia-Herrera et al., 2010). In rapidly urbanizing areas such as Shanghai and Kolkata (Mandal et al., 2022; Zhang et al., 2013), reduced green spaces, population growth, and changes in land cover have intensified UHI effects, leading to higher surface temperatures than in surrounding regions. Different mitigation strategies have emerged in response: In the UK, for example, building design and reflective materials help reduce heat accumulation

(Malley et al., 2014), while in tropical cities like Kampala, well-managed urbanization has shown the potential to counteract rising temperatures (Li et al., 2021). However, some cities, such as Accra, continue to experience worsening extreme heat due to unchecked urban sprawl (Wemegah et al., 2020). These findings underscore the need for tailored urban planning strategies to mitigate UHI effects in different climatic and socio-economic contexts.

Despite global research efforts, the manifestation and impact of UHI in Kisangani, DRC, remain largely unexplored. As a rapidly expanding tropical city, Kisangani has undergone significant changes in land cover between 1987 and 2021 (Balandi et al., 2023; Balandi et al., 2024; UN-Habitat, 2015). In contrast to densely populated megacities, Kisangani presents a unique case in which urban growth occurs in a tropical context with distinct climatic and land-use dynamics. While most previous UHI studies have focused on densely populated megacities, emphasizing land-cover change, vegetation loss, and surface-temperature patterns as primary drivers of urban heat dynamics, fewer have examined the role of urban morphology, particularly the volumetric characteristics of built environments. This research addresses this gap by integrating a spatiotemporal analysis of surface urban heat island (SUHI) dynamics with an assessment of the interactions between land surface temperature (LST) and building volume density (BVD), accounting for both building footprint and height, to provide insights into how urban morphology modulates thermal dynamics. Furthermore, spatial variations are explored across urban–rural gradients, revealing how vertical and horizontal expansion contribute to heat accumulation. This dual approach offers a more comprehensive understanding of UHI formation in rapidly expanding tropical cities, highlighting key factors for urban planning and climate adaptation strategies.

Therefore, we hypothesize that LST will vary significantly over time, accompanied by a progressive expansion of areas with moderate and high UHI intensity, driven by spatial transformations that influence Kisangani’s local thermal environment. Along the urbanization gradient, we expect that LST and UHI intensity in 2024 will significantly differ between zones, with higher values in urban areas likely resulting from increased landscape artificialization. Additionally, we anticipate that when analyzing the period from 2000 to 2024, LST and UHI fluctuations will show significant spatiotemporal differences across the three zones and within each zone over time. Furthermore, we expect that building volume density (BVD) and vegetation density significantly modulate the spatiotemporal patterns of LST, with the impact of BVD increasing over time as Kisangani’s urban architecture shifts towards denser, taller buildings.

7.6. Materials and methods

7.6.1. Study area

The area examined comprises the city of Kisangani and its surroundings in north-eastern DRC (Figure 7.1). Covering an area of 2,947.9 km², the studied region comprises six municipalities. Five of these municipalities are on the right bank of the Congo River, while one is on the left. Over the 50 years (1956–2005), the region recorded an average annual rainfall of 1,724 mm and a mean annual temperature of 25.3 °C (Sabongo, 2015). Monthly rainfall consistently surpasses 60 mm year-round (Sabongo, 2015), classifying Kisangani as an Af climate type under the Köppen classification system (Kottek et al., 2006; Sabongo, 2015). Kisangani has reported substantial population growth in recent years. According to the National Statistics Institute, the city's population surpassed 2,184,096 in 2021 (Balandi et al., 2023). A diverse mix of ethnic groups from different regions of the DRC and neighboring countries characterizes the city. Most residents sustain their livelihoods through agriculture, fishing, and trade (Gabriel & Omer, 2022). The rising demand for social infrastructure has driven significant urban and peri-urban expansion in recent years (Balandi et al., 2023).

7.6.2. Methodological flowchart

The methodological framework (Figure 7.2) outlines the research process for analyzing urban heat island (UHI) patterns, providing a structured approach for a comprehensive assessment of UHI effects across different urban contexts.

7.6.3. Data used

The spatiotemporal pattern analysis of the urban heat island (UHI) and vegetation density, as measured by NDVI, was performed using MODIS satellite data available in Google Earth Engine. Data regarding building volume and population density were obtained from the Global Human Settlement Layer (GHSL) project of the Joint Research Centre (JRC), as updated in 2023 (European Commission, 2023). Furthermore, high-resolution satellite imagery from Google Earth was employed to identify and characterize urban, peri-urban, and rural zones along the urbanization gradient. Table 7.1 below describes the data used.

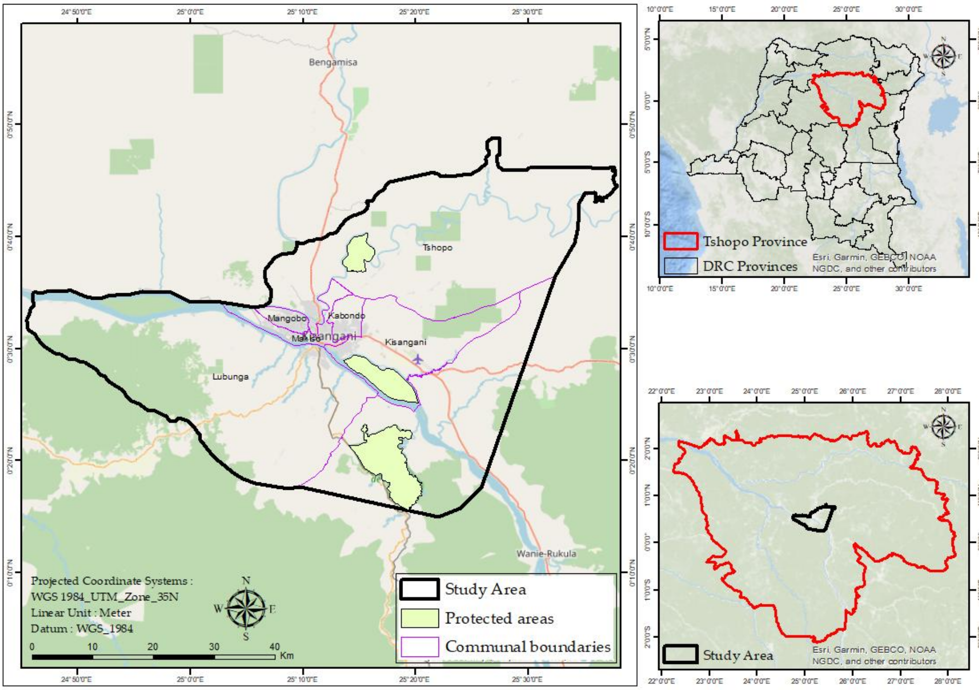


Figure 7.1. Kisangani and its surrounding area. The city is organized into six municipalities and is surrounded by three protected areas. Its transport infrastructure includes both national and provincial road networks.

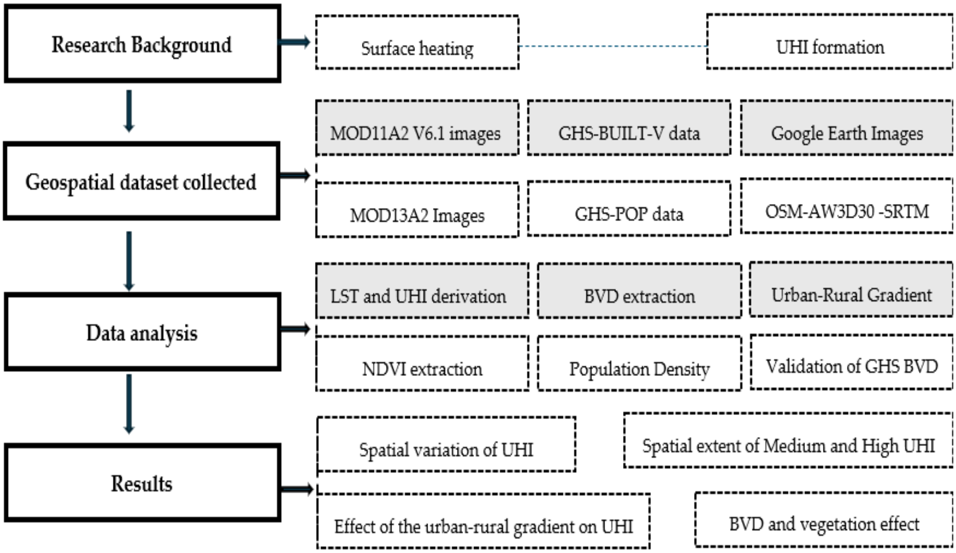


Figure 7.2. Methodological flowchart of the study.

Table 7.1. Spatial characteristics, time scale, and product type of the geospatial dataset used.

Product ID	Layer	Spatial resolution	Time scale
MOD11A2 V6.1	LST Emissivity	1 Km	2000–2024
MOD13A2	NDVI	1 Km	2000–2024
GHS-BUILT-V	Building Volume	1 Km	1975–2030
GHS-POP	Population Density	1 Km	1975–2030
Google Earth	GE Images	1 m	2000–2024

7.6.4. Data-processing

The Google Earth Engine (GEE) platform provides access to MODIS Land Surface Temperature (LST) products through the "MOD11A2 V6.1" image collection. Each pixel in MOD11A2represents the mean value derived from all corresponding MOD11A1 LST pixels recorded over the 8-day interval (Wan, 2013). This approach reduces the effects of punctual anomalies, such as clouds or sensor errors, by averaging data. It is, therefore, more reliable than products based on a single daily or instantaneous observation. In addition, MODIS LST data (including MOD11A2) have been extensively validated through comparisons with in situ measurements, which have consistently shown high accuracy under clear and stable atmospheric conditions (Lu et al., 2018; Wan et al., 2002). Although MODIS offers a coarser spatial resolution (1 km) than other sensors such as Sentinel-2 or Landsat, which provide data at 10 to 30 m, it was deliberately chosen in this study for its high temporal coverage; consistent data processing algorithms that minimize anomalies; and suitability for large-scale analyses, such as urban–rural gradient assessments. With its 1 km spatial resolution, MOD11A2 remains well adapted for medium-scale studies examining thermal variations across broader spatial patterns, such as urban expansion and land-use transitions.

We extracted NDVI from the "MODIS/061/MOD13A2" dataset to assess vegetation density. This dataset provides NDVI values at 1 km spatial resolution and 16-day temporal resolution. Positive NDVI values indicate vegetated areas, while values near or below zero represent bare soil or water bodies (Azizi & Azizi, 2024; Didan et al., 2015). Geospatial data on building volume and population density were obtained through the Global Human Settlement Layer (GHSL) project (European Commission, 2023). The GHSL building volume dataset provides a global distribution of built-up volumes (in cubic meters) at a 1 km spatial resolution. These estimates are based on data from Advanced World 3D 30 m (AW3D30), Shuttle Radar Topography Mission (SRTM30), Sentinel-2, and Landsat composites, distinguishing between total and non-residential (NRES) building volumes (European Commission, 2023). Since GHSL data can be subject to interpolation errors, especially in rapidly urbanizing areas, we cross-validated them with building volume estimates derived from OpenStreetMap footprints and building height values computed by subtracting digital terrain model (DTM) values (SRTM30) from digital surface model (DSM) values (AW3D30). The absence of a significant difference ($p < 0.05$) between GHSL building volume data and estimates derived from OpenStreetMap footprints combined with ALOS World 3D and SRTM models supports the reliability of GHSL-based analyses for Kisangani.

Furthermore, data on population density depict the distribution of the human population, expressed as the number of people per square kilometer (European Commission, 2023). These data cover the period from 1975 to 2030 and are spatiotemporally interpolated at five-year intervals. Intermediate-year estimates were derived using each pixel's annual percentage change calculated between consecutive five-year periods. Thus, for example, data on building volume and population density per pixel for 2001, 2002, 2003, and 2004 were obtained by applying the annual percentage change calculated between 2000 and 2005 within each pixel.

7.6.5. Land Surface Temperature (LST) and Urban Heat Island (UHI) Derivation

The daily MOD11A1 LST product is generated using pixel-level LST data from individual granules, derived under clear-sky conditions through the generalized split-window algorithm. This method adjusts LST values in the 31 and 32 thermal infrared bands to compensate for atmospheric influences. Surface emissivity values are assigned based on a reference knowledge base informed by MODIS ancillary products, including land cover and vegetation indices such as NDVI (Azizi & Azizi, 2024; Wan, 2013). As such, NDVI may influence LST estimates through its role in emissivity determination, and this possible interdependence should be considered when interpreting correlations between LST and vegetation metrics.

The land surface temperature (LST) data from the MOD11A2 product were initially converted from Kelvin to Celsius by applying a scale factor of 0.02 and subtracting 273.15 (Mandal et al., 2022; Wan, 2013). We adopted a relative urban heat island (UHI) approach to analyze the UHI intensity, where temperature differences are expressed as a proportion of the rural background temperature (Jain et al., 2019; Rendana et al., 2023). This method enables standardized comparison across various urbanization gradient zones and periods, thereby making the metric more robust to seasonal and interannual variations. In this context, the average LST in rural zones served as the reference temperature (T_s), representing the baseline thermal condition of the study area (Rendana et al., 2023; Huang et al., 2019; Zhang et al., 2013). The relative UHI intensity was then calculated using the following formula (Huang et al., 2019; Rendana et al., 2023).

Equation 7.1. $$\text{UHI} = \Delta T/T_s = (T_i - T_s)/T_s$$

Where UHI refers to the urban heat island intensity (UHI), measured as the relative LST in the area; ΔT is the difference between the i-th pixel LST (Ti) in °*C* and the average rural LST (Ts) in °C.

This method enables evaluation of temperature fluctuations across the urban–rural gradient and distinguishes thermal anomalies specific to urban areas. To facilitate the interpretation of UHI patterns, UHI values were classified into five intensity levels, as summarized in Table 7.2. These thresholds were adapted from previous studies (Huang et al., 2019; Rendana et al., 2023) and contextualized to the thermal characteristics of our study region. This classification enables a spatial and temporal mapping of UHI hotspots, contributing to a better understanding of thermal risks and urban planning needs.

Table 7.2. The UHI level.

UHI	Level	Description
UHI ≤ 0	Very low	An extreme low-temperature zone, characterized by no difference in LST between urban and rural areas.
0 < UHI ≤ 0.1	Low	Low-temperature zones mean minimal LST variation between urban and rural areas.
0.1 < UHI ≤ 0.2	Medium	Medium-temperature region, meaning that the LST differs moderately between urban and rural areas.
0.2 < UHI ≤ 0.3	High	High-temperature zone, referring to a large urban-rural LST difference.
0.3 < UHI	Very high	An extremely high-temperature zone, characterized by a significant urban/rural LST difference.

7.6.6. Spatial analysis and delineation of urban–rural gradient zones

An analysis of urban heat islands (UHIs) was conducted within the urban–rural gradient of Kisangani city. In many cases, spatiotemporal analyses of the UHI effect across the urban–rural gradient are performed using either a transect-based approach (Marando et al., 2019) or a concentric zone method (Mandal et al., 2022). However, to improve our understanding of the UHI phenomenon along the urban–rural gradient, we employed a methodology that captures the landscape's spatial complexity. To achieve this, a strategic randomized sampling approach was adopted, selecting plots in different directions within each defined gradient area: north, south, east, and west, as well as northeast, northwest, southeast, and southwest. This approach enriches the collected data and accounts for significant spatial variation that can occur perpendicular to a traditional transect. By capturing and incorporating variations at short distances, this approach avoids potential oversights that a concentric zone methodology might introduce (Balandi et al., 2024).

The decision tree proposed by André et al. (2014), based on morphological criteria, was preferred for delineating urbanization gradient zones because it better reflects reality. These morphological criteria encompass vegetation, agricultural, and built-up areas and represent one of the most precise, consistent, and evolving morphological indicators (Angel et al., 2011; Balandi et al., 2023; Balandi et al., 2024; Sambieni, 2019). Thus, for each year from 2000 to 2024, high-resolution satellite imagery available on Google Earth was used. Using a Geographic Information System (GIS), the intensity of each pixel was displayed on a scale from 0 to 255. Built-up pixels, characterized by impermeable surfaces (such as roads, roofs, and compacted floors), exhibited intensity values ranging from 80 to 255. Agricultural and grassland pixels were represented by intensity values ranging from 50 to 80, depending on their stage of development (cultivated or fallow). In contrast, forest pixels were characterized by intensity values below 50. Data on population density supported the morphological criteria, increasing the credibility of the urbanization gradient. Population density, which varies across urban and rural areas, affects landscape configuration and composition, and this variable is expected to decline from urban to rural areas (Balandi et al., 2023; Bogaert et al., 2015; Sambieni, 2019).

Thus, for each year, a plot is classified as urban if more than 50% of its area is covered by built-up pixels (André et al., 2014; Angel et al., 2011; Balandi et al., 2023; Salomon et al., 2022) within a cell with a population density greater than 100 inhabitants per km2 (Balandi et al., 2023). The population density threshold of 100 inhabitants per square kilometer was chosen because it represents one of the lowest densities observed in the vicinity of Kisangani's urban center from 2000 to 2024. It serves as a practical marker for identifying areas transitioning to urban characteristics and distinguishing them from rural zones. Conversely, a parcel with 50% or fewer built-up pixels in a cell with a population density greater than or equal to 100 inhabitants per km2 is considered peri-urban, as long as the remaining pixels do not exclusively represent forest or agricultural zones (André et al., 2014; Balandi et al., 2023). On the other hand, a parcel is considered rural if it consists mainly of vegetation pixels (André et al., 2014; Balandi et al., 2023; Salomon et al., 2022).

A total of 86 plots (Figure 7.3), each covering a spatial dimension of 1 km², corresponding to the spatial resolution of the MODIS data used, were randomly selected from each zone in the reference year (2024). The random sampling technique was employed to reduce potential bias and improve the applicability of the results on the landscape scale. This method is essential for objectively assessing landscape variability and providing a comprehensive view of the impact of urbanization on the UHI across the urban-rural gradient. However, it is critical to note that spatial features in these observation plots have evolved, reflecting the dynamic properties of urban, peri-urban, and rural zones.

As the samples satisfied the key assumptions for parametric tests, including normality and homogeneity of variances, we applied an analysis of variance (ANOVA) to assess spatial variation in LST and the UHI effect across urban, peri-urban, and rural zones. Additionally, this approach was used to examine the temporal effects on LST and UHI variations. Furthermore, we conducted linear regression analyses to assess the impacts of building volume density (BVD) and vegetation density. The historical trends in the slope and coefficient of determination from these regressions have enhanced our understanding of the roles of building and vegetation density as predictors of LST.

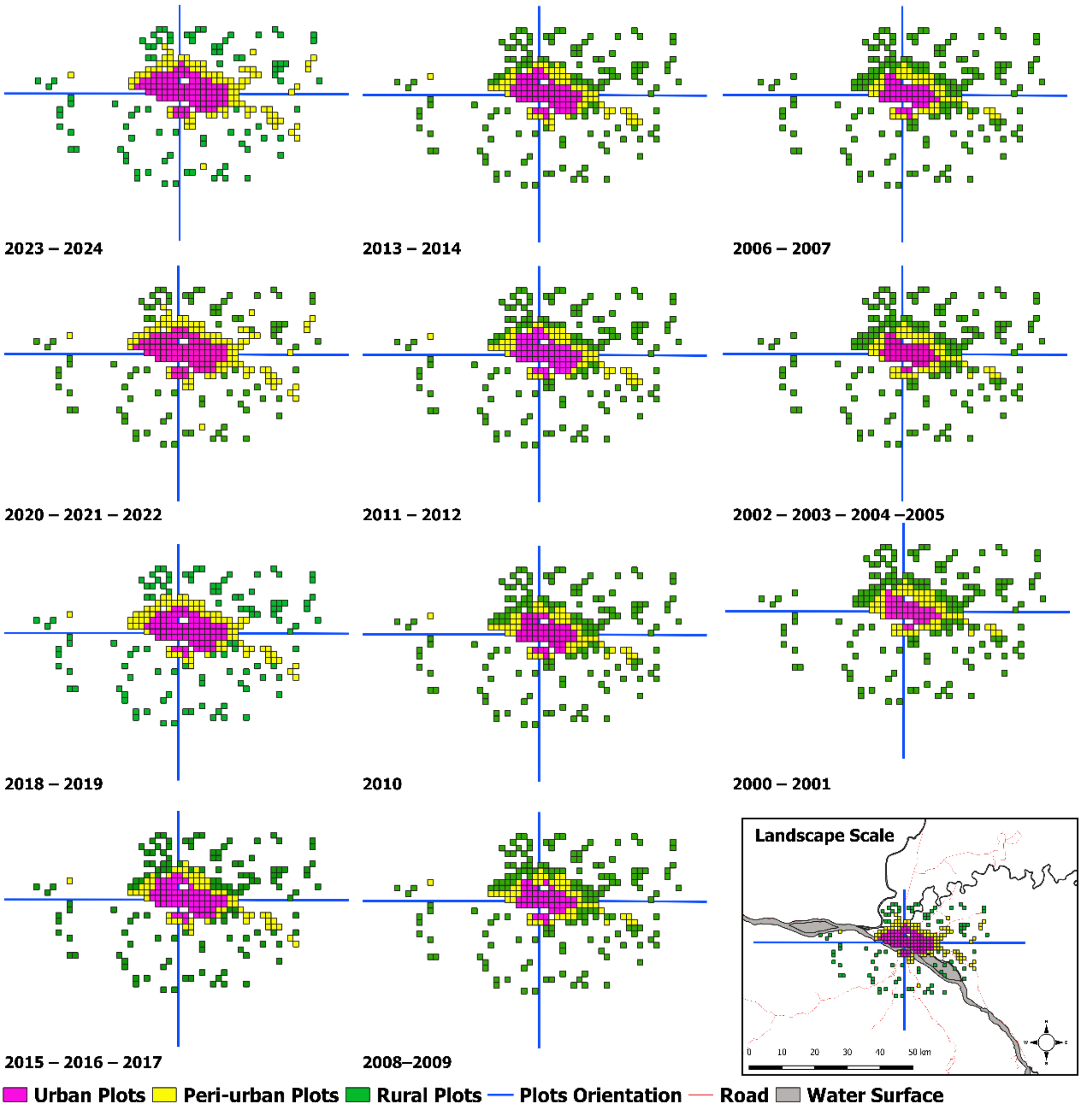


Figure 7.3. Sample plots along the urban–rural gradient. A series of randomly selected sample plots was analyzed along the urban–rural gradient, encompassing the following directional perspectives: north, south, east, west, northeast, northwest, southeast, and southwest. The evolving characteristics of these plots highlight the dynamic, ongoing shifting of urban, peri-urban, and rural areas.

7.7. Results

7.7.1. Spatiotemporal patterns of Urban Heat Island (UHI)

The spatial pattern of urban heat islands (UHIs) exhibits significant temporal variation. From 2000 to 2009, the landscape of Kisangani was predominantly dominated by areas with UHI values at or below 0, with the lowest UHI values consistently observed along river corridors. In contrast, between 2010 and 2024, areas with UHI values exceeding 0 expanded. The spatial pattern of urban heat islands (UHIs) exhibits significant temporal variation. From 2000 to 2009, the landscape of Kisangani was predominantly dominated by areas with UHI values at or below 0, with the lowest UHI values consistently observed along river corridors. In contrast, between 2010 and 2024, areas with UHI values exceeding 0 expanded significantly, and consistent annual UHI values exceeding 0.1 and 0.2 were observed in the city center (Figure 7.4). Furthermore, the spatial extent of medium UHI gradually expanded from 16 km² to 38 km², while the high UHI increased from 9 km² to 19 km². Consequently, the total area of UHIs greater than 0.1 exceeded 50 km² in 2024 (Figure 7.5).

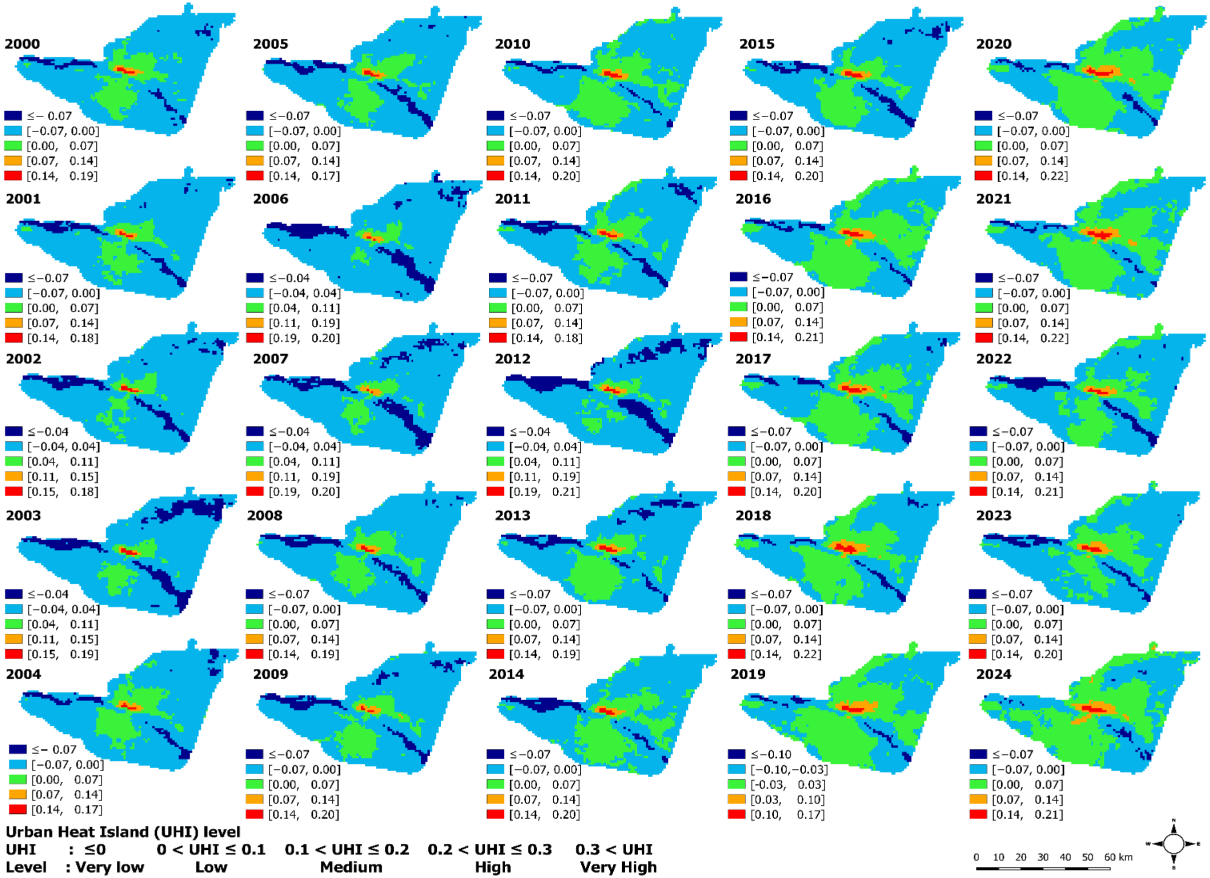


Figure 7.4. Spatial variations of diurnal Urban Heat Island (UHI). The UHI corresponds to the land surface temperature (LST) per pixel relative to the rural average temperature. Data from the MODIS sensor (MOD11A2 V6.1) covering the period from 2000 to 2024.

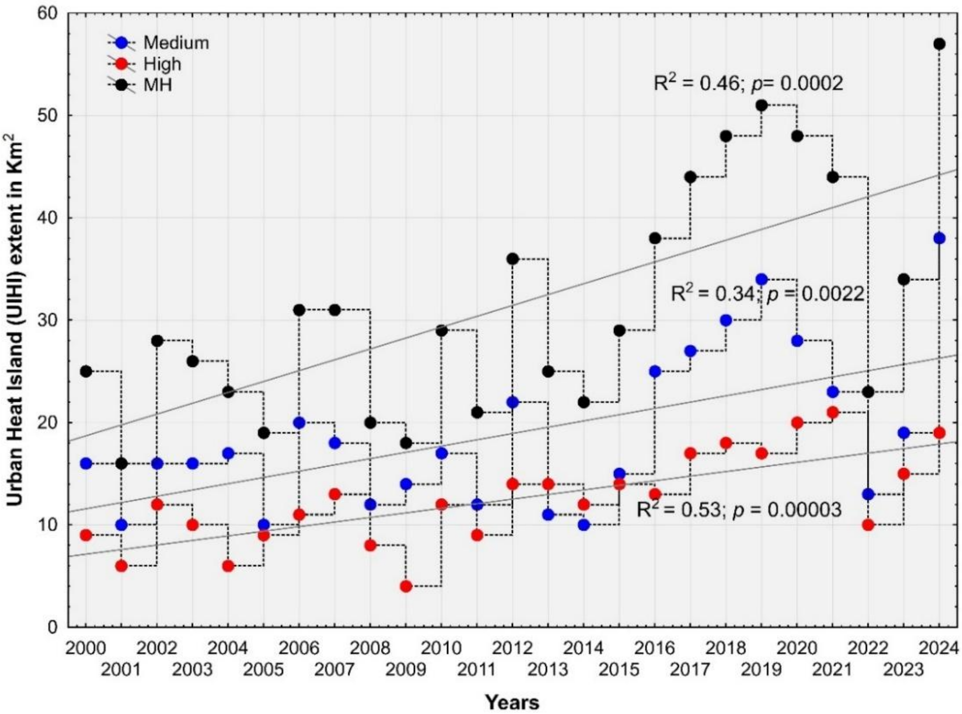


Figure 7.5. The spatial extent of urban heat islands (UHIs) is expressed in square kilometers. Medium (0.1 < UHI < 0.2); high (0.2 < UHI ≤ 0.3); MH expresses the sum of medium and high UHI extent.

7.7.2. Variation in LST and UHI across the urban–rural gradient in 2024

Along the urban–rural gradient, significant variations in land surface temperature (LST) and the urban heat island effect (UHI) are observed in 2024, with urban zones exhibiting substantially higher averages than peri-urban and rural zones (Figure 7.6). LST and UHI variations in peri-urban areas also differ significantly from those observed in rural areas. Furthermore, areas with a maximum LST of around 34 °C and maximum UHI values exceeding 0.2 are observed in urban zones. In comparison, peri-urban and rural zones reach a maximum LST of 31 °C and maximum UHI values of slightly more than 0.1.

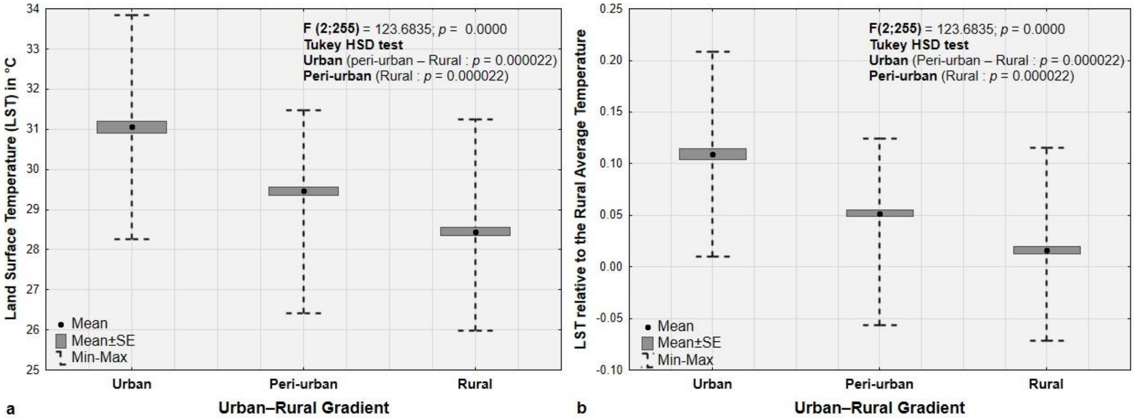


Figure 7.6. (a) Land surface temperature (LST) and (b) the UHI variation in urban, per-urban, and rural zones based on the landscape context of the last year studied (2024). In b, the UHI is computed as the difference between the per-pixel LST and the mean LST in rural areas (Ts = 28 °C).

7.7.3. Historical variations in LST and UHI across the urban–rural gradient

Statistical analysis (Figure 7.7) revealed significant historical trends in annual land surface temperature (LST) and urban heat island (UHI) variations within each urbanization gradient zone from 2000 to 2024 ($p < 0.05$). Tukey's post hoc tests identified specific years with significant differences within each gradient, indicating notable temporal shifts. In urban areas, notable differences in LST were observed between earlier years (e.g., 2000, 2003, 2006) and more recent years (e.g., 2018, 2019, 2021). For instance, 2000 significantly differs from 2012, and 2003 differs from 2018, 2019, and 2021. Additionally, 2012 shows significant variations compared to a broader range of years, including 2017, 2018, 2019, 2020, and 2024. UHI variations similarly highlight substantial differences between earlier years (e.g., 2000, 2002, 2003) and recent periods, such as 2019 and 2022, with 2022 also differing significantly from 2024.

In peri-urban zones, significant differences in land surface temperature (LST) were observed across multiple time intervals. The early years, such as 2000 and 2001, showed significant differences with later years, including 2002, 2003, 2006, 2007, 2012, 2013, and 2022. For example, 2002 differed significantly from 2010, 2016, and 2020, while 2003 differed from earlier years, such as 2004 and later years, including 2016-2020, 2023, and 2024. Similarly, in more recent years, such as 2012-2015, significant variations were observed compared to 2016-2024, and 2022 differed significantly from 2024. There were also substantial temporal differences in the variations of the urban heat island (UHI). The early years, such as 2000 and 2002, showed notable differences with years like 2013-2019 and 2022. For example, 2002 differed significantly from the years 2005-2022. Later years, such as 2013-2015, exhibited significant differences from 2016-2024, while 2016-2018 differed from 2019 and 2022. Notable contrasts also emerged between more recent years; for instance, 2022 differed significantly from 2024.

Rural areas showed the greatest range in LST and UHI variations. LST differences spanned several pairs of years, such as 2000 vs. 2002, 2006 vs. 2008, 2017 vs. 2024, and 2022 vs. 2024. In recent years, specifically from 2016 to 2020, there have been consistent differences relative to earlier periods (e.g., 2012–2015) and to later years, including 2022 and 2024. For example, LST in 2016 differed significantly from 2022, while 2023 differed from 2024. Similarly, UHI variations in rural areas showed significant differences between earlier years (e.g., 2000 and 2002) and later periods (e.g., 2019, 2022, and 2023). For instance, UHI in 2006 and 2007 showed significant differences from multiple years, including 2008, 2016, and 2024. Additionally, 2022 and 2023 showed consistent differences from 2024, indicating persistent changes in rural thermal environments.

Furthermore, as expected, the annual comparison of the urban heat island (UHI) effect from 2000 to 2024 across Kisangani's urbanization gradients reveals significant differences. Annual UHI variations in urban zones consistently differed from those in peri-urban and rural zones ($p < 0.05$). Moreover, UHI variations in peri-urban zones were significantly distinct from those observed in rural zones throughout the study period. These findings highlight clear and consistent disparities in UHI dynamics across the urban, peri-urban, and rural gradients.

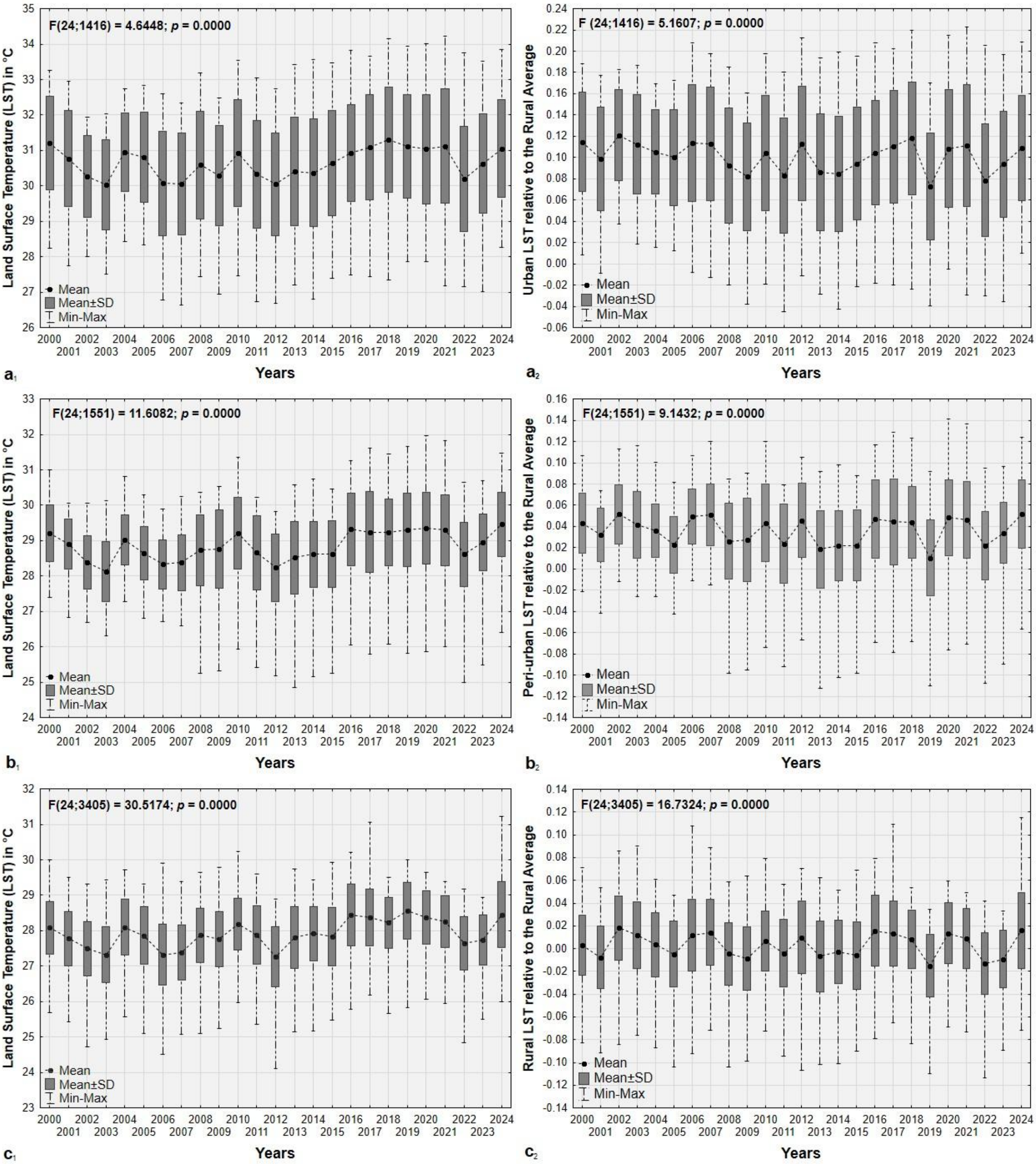
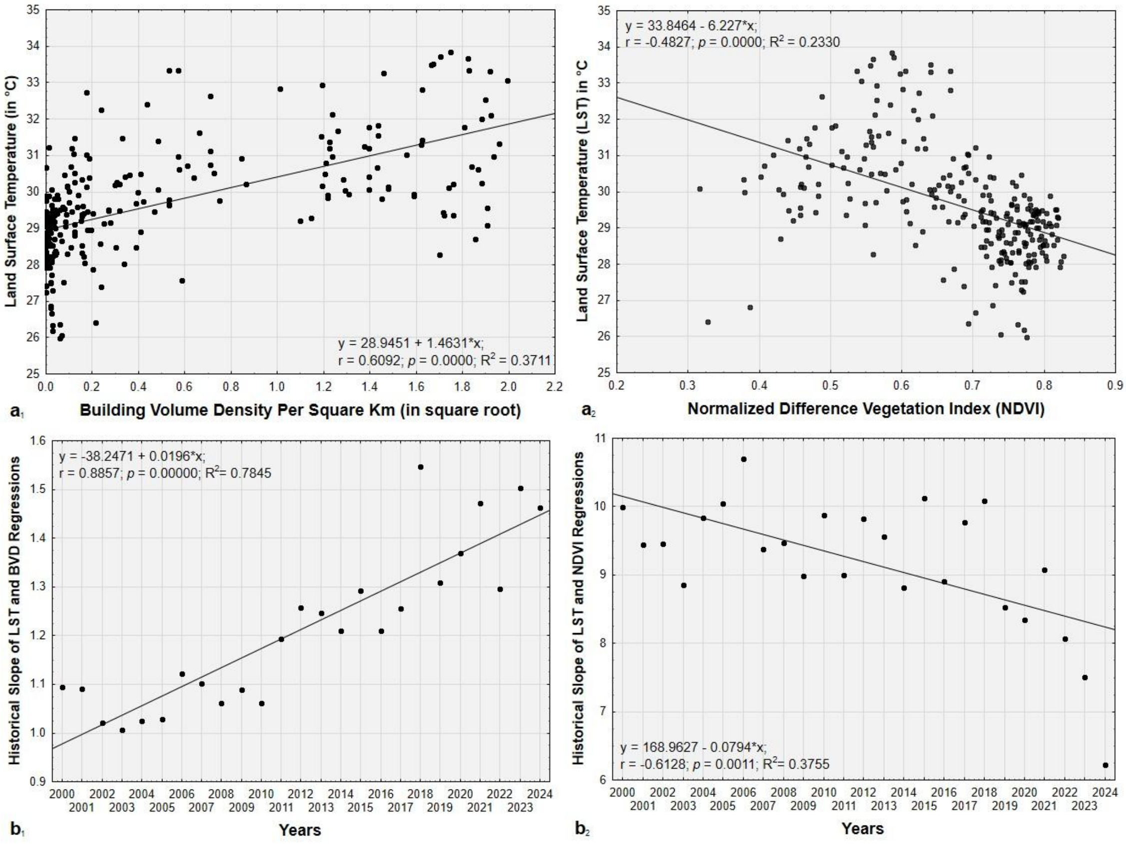


Figure 7.7. Historical variations in land surface temperature (LST) and urban heat island (UHI) in urban areas (a1) and (a2), peri-urban areas (b1) and (b2), and rural areas (c1) and (c2).

7.7.4. Building volume density (BVD) and vegetation effects

As expected, the LST variations are significantly correlated with BVD and vegetation density (Figures 7.8a_1 and a_2). Over time, the influence of BVD as a predictor of LST increases, as shown by progressively higher slope and R^2 values (Figure 7.8b_1, c_1), highlighting the growing role of urban development in shaping thermal patterns. Conversely, the influence of vegetation density decreases, as reflected in the significant reduction in regression slope values (Figure 7.8b2), indicating a decline in LST sensitivity to vegetation cover. However, the change in the coefficient of determination (R^2) over time is not statistically significant (Figure 7.8c_2), suggesting that while the relationship weakens in strength (slope), the overall model fit remains relatively stable.



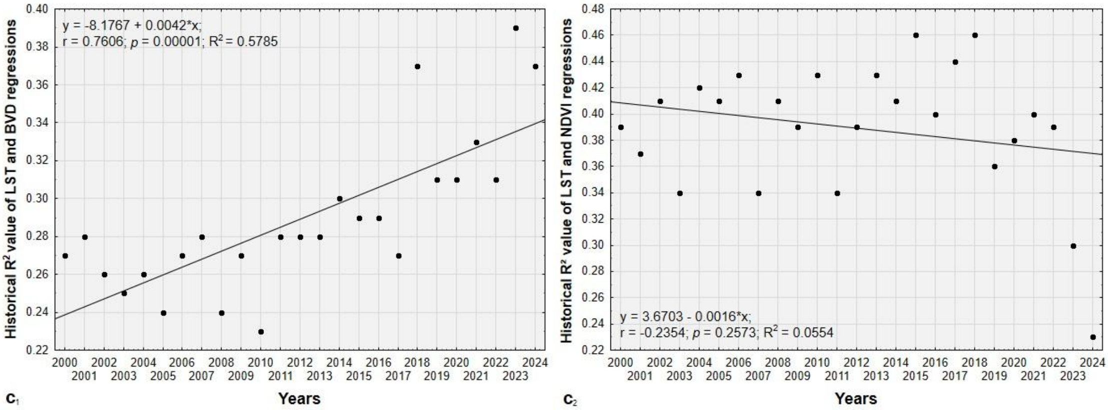


Figure 7.8. Linear regression was performed between building volume density (BVD) and LST (a1); vegetation density expressed by NDVI and LST (a2); and the historical trends in the regressions' slope (b1) and (b2) and coefficient of determination values (**c1**) and (**c2**). In **a**, each point corresponds to a pixel of 1 km^2.

7.8. Discussion

7.8.1. Spatiotemporal patterns of Urban Heat Island

In this study, we observed significant temporal variations in the spatial patterns of urban heat islands between 2000 and 2024. During this period, the extent of medium UHI (0.1 < UHI < 0.2) gradually expanded from 16 km^2 to 38 km^2, while high UHI (0.2 < UHI ≤ 0.3) increased from 9 km^2 to 19 km^2. Furthermore, the UHI intensity gradually increased between 2000 and 2024, reaching maximum values of more than 0.21 in the last four years (2020, 2021, 2023, and 2024) compared to maximum values of 0.17 and 0.18 observed in 2001, 2004, and 2005.

Despite observing maximum UHI values exceeding 0.21 and significant differences across urban, peri-urban, and rural areas, the findings indicate that the average UHI values in the urban zones of Kisangani remain below 0.2. Consequently, on average, Kisangani's urban zones exhibit moderate LST disparities relative to rural areas. Various factors associated with urban development, land use, land cover, land cover change, and socio-economic transformation may elucidate the coexistence of maximum UHI values exceeding 0.21 in certain regions while maintaining an overall average below 0.2, which is relatively low compared to other urban centers.

Rural landscapes are generally covered by vegetation, whereas impervious surfaces, such as concrete, asphalt, pavements, rooftops, and compacted soils, characterize urban areas (Angel et al., 2011; Balandi et al., 2023; Wen et al., 2023). This land cover conversion profoundly alters the local microclimate and urban thermal environment, notably by increasing heat absorption and reducing ventilation (Dutta et al., 2021; Wen et al., 2023). In Kisangani, the rapid population growth observed between 2000 and 2021 (INS, 2022) has driven the expansion of urban and peri-urban zones at the expense of natural areas (Balandi et al., 2024; Balandi et al., 2023). These spatial transformations may have altered the thermal properties, as artificial materials such as concrete and asphalt absorb and retain more solar radiation than natural surfaces. This process is a key driver of the urban heat island (UHI) phenomenon (Haodong et al., 2024; Lima et al., 2019; Ren et al., 2023). The continued spread of built-up areas has likely contributed to the progressive intensification of UHI in certain Kisangani zones between 2000 and 2024, with maximum recorded values exceeding 0.21. In parallel, there has been a notable increase in the spatial extent of moderate and high UHI zones.

These observations are consistent with trends documented in other urban contexts. For instance, Li et al. (2021) reported that Kampala, Uganda, experienced rapid urban expansion, from 12,133 hectares in 1995 to 25,389 hectares in 2016, accompanied by an increase in the UHI extent from 22,910 hectares in 2003 to 27,900 hectares in 2016. Similar findings were reported in Accra, Ghana, where Wemegah et al. (2020) demonstrated that land surface temperatures (LSTs) were significantly higher in urbanized and bare-soil areas than in vegetated zones and water bodies. The mitigating effect of water bodies on UHI intensity, as observed in Accra, may help explain the relatively low average UHI values (<0.2) recorded along Kisangani's urbanization gradient, in contrast to cities like Seoul (South Korea), where mean UHI intensities exceed 0.2 (Kim & Baik, 2002). Kisangani's unique hydrographic context, with the Congo River to the south and the Tshopo and Lindi Rivers to the north and northwest, contributes to this moderation, as water bodies possess high specific heat capacities and facilitate evaporative cooling (Cheung et al., 2021).

Although land artificialization is less pronounced in peri-urban zones compared to urban zones, the findings of this study highlight its influence on the urban heat island (UHI) effect relative to rural areas. Indeed, in peri-urban zones, the progressive conversion of natural landscapes into semi-artificial areas such as intensive agricultural fields and informal settlements reduces the connectivity of vegetative cover, thereby weakening its ability to moderate local temperatures through evaporation and transpiration, as well as passively providing shade (Yan et al., 2023). Moreover, peri-urban zones are also influenced by the thermal effects of adjacent urban centers. The UHI effect generated within the city can extend to these peripheral areas through heat transfer driven by mixed convection. This phenomenon is exacerbated by local atmospheric currents that transport warm air from the urban core to the surrounding zones (Omidvar et al., 2020; Zhang et al., 2022).

It is crucial to emphasize that variations in LST across urban, peri-urban, and rural environments directly influence fluctuations in the urban heat island (UHI), as the UHI is fundamentally dependent on LST. This corresponds to the same level of significance as observed in Figure 7.6. Therefore, strategies to mitigate high LST values should also be instrumental in narrowing the temperature disparities observed between urban, peri-urban, and rural areas.

7.8.2. Impact of building architecture on the LST

This study shows that the influence of building volume density (BVD) on LST increases over time in Kisangani. This trend is evidenced by progressively higher slopes and coefficients of determination. This increasing correlation suggests that as urban areas expand, with changes in urban architecture involving building geometry, particularly construction patterns with tall buildings situated closely together (as illustrated in Figure 7.9 for a typical area (the urban center)), the capacity of these densely built environments to retain and emit heat intensifies. Combined with vegetation degradation, as reflected in increasingly low NDVI values in the urban center (Figure 7.8), this architectural model contributes to the phenomenon known as the "urban canyon" (Arnfield, 2003; Oke, 2002). In fact, since the end of the armed conflict (1990–2000) (Koluwa, 2020), Kisangani has experienced continuous spatial growth (Balandi et al., 2023), primarily driven by economic operators who exploit interstitial spaces by constructing large commercial complexes and high-rise hotels. This installation of buildings accentuates their spatial footprint and, thus, the canyon effect. This urban canyon effect significantly influences local conditions, including wind patterns, light availability, air quality, and temperature, thereby exacerbating the intensification of urban heat islands (Stewart & Oke, 2012a). In Kisangani, this could affect urban residents in various ways, shaping their comfort, air and water quality, access to ecological services, opportunities for recreation, and overall living conditions (Candra et al., 2016; Prilandita, 2009).

However, it is essential to note that NDVI and BVD may be interrelated, potentially introducing interaction or confounding effects when analyzing their influences on LST. Future studies should aim to better distinguish the specific impact of each factor, as their potential interdependence may obscure or exaggerate observed patterns in LST variations. Additionally, while NDVI and BVD are key indicators, they do not fully explain LST variability. Other variables, such as albedo, surface moisture, soil type, topography, and land cover composition, should be integrated to gain a comprehensive understanding of the mechanisms driving LST dynamics in evolving urban environments.

7.8.3. Effective and resilient mitigation strategies of UHI

It is worth noting that, when correctly managed, urbanization does not necessarily lead to environmental degradation in terms of UHI (Li et al., 2021). However, mitigating the urban heat island (UHI) effect in Kisangani requires a set of strategies carefully tailored to its unique socioeconomic, environmental, and climatic realities. Located in a humid equatorial zone and undergoing rapid urban growth with limited planning (Balandi et al., 2023; Balandi et al., 2024), Kisangani faces challenges such as informal settlements and loss of vegetation cover. Therefore, proposed solutions must be both practical and locally adaptable. In addition, it is crucial to integrate climate change projections into urban planning to develop more robust and long-term mitigation and adaptation strategies. Climate models from the Coupled Model Intercomparison Project Phase 6 (CMIP6), particularly under the Shared Socioeconomic Pathways (SSPs), suggest that temperatures will increase across all regions of Africa under all future emissions scenarios. By the end of the century, under RCP8.5 or SSP5-8.5, all African regions are likely to experience warming greater than 3 °C. In Central Africa, warming is expected to exceed 2.5 ◦C (IPCC, 2021). Such warming trends are expected to intensify the urban heat island effect, particularly in rapidly urbanizing contexts like Kisangani.

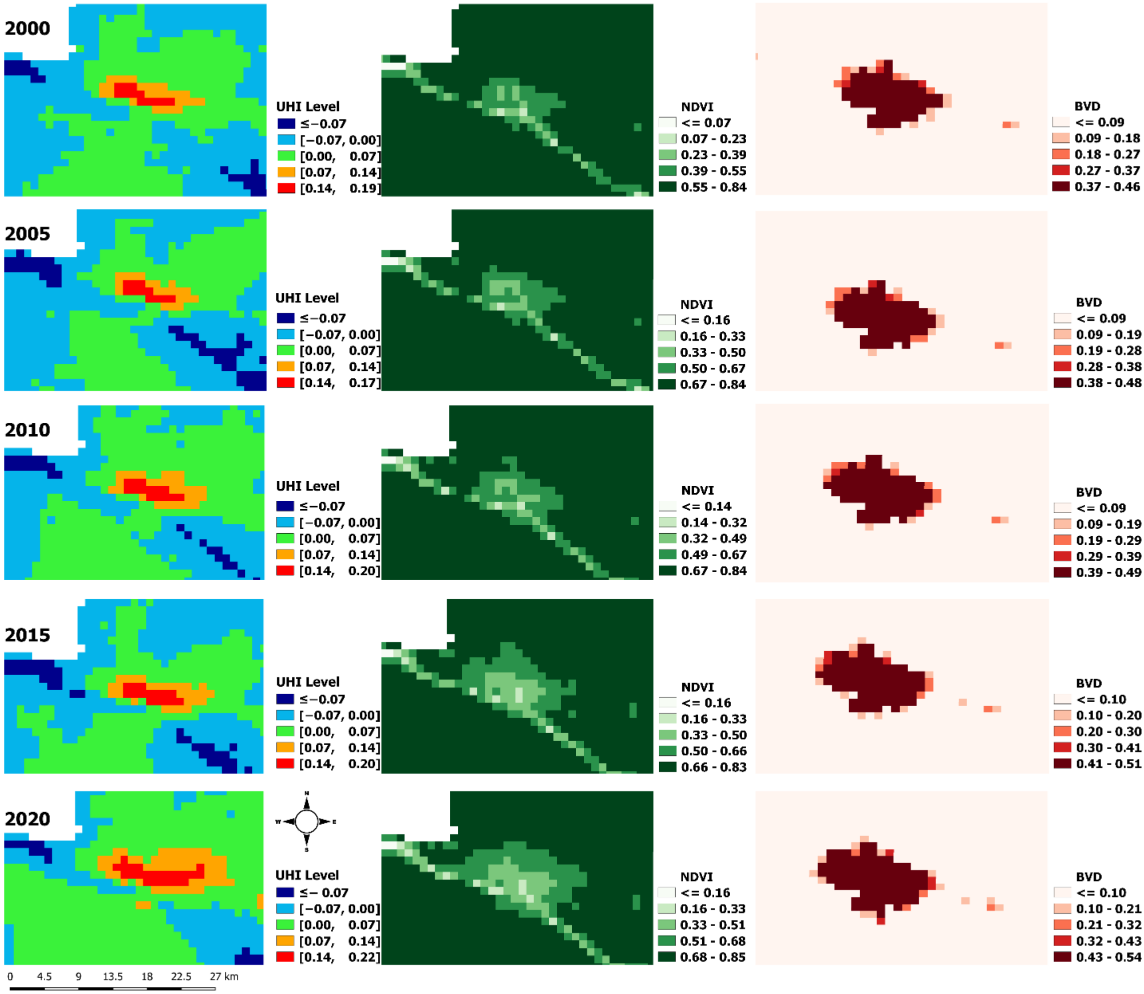


Figure 7.9. An illustration of the spatiotemporal evolution of the urban heat island (UHI), NDVI, and building volume density for a typical area (urban center of Kisangani).

Therefore, integrating green infrastructure is a key strategy in Kisangani, where proximity to the Congo rainforest provides access to a wide range of native plant species. Expanding urban green spaces, such as parks, urban forests, roadside vegetation, and green corridors, can significantly lower surface and air temperatures. These effects are driven by increased shading and evapotranspiration (Fengjiao et al., 2020; Kim & Baik, 2002), especially on hotter days. Previous studies have shown that in cities with a UHI effect, such as Hong Kong and Lisbon, the cooling effect of urban green spaces is more pronounced on hot, dry days (Kwan et al., 2020; Oliveira et al., 2011). In drier environments, rising temperatures and higher transpiration rates amplify the vegetation's humidifying effects (Cheung et al., 2021; Kim & Baik, 2002). This cost-effective approach aligns with local biodiversity and can provide co-benefits such as improved air quality and recreational areas. To be effective, green spaces in Kisangani must be strategically located in dense urban cores, along heat-prone transportation corridors, and in peri-urban buffer zones to maintain ecological connectivity. Restoring and preserving peri-urban vegetation can provide dual benefits: controlling urban sprawl and enhancing the cooling potential of peripheral green belts. Mobilizing residents for the planning and maintenance of these spaces can be operationalized through pilot urban gardening projects in selected neighborhoods, the establishment of local green committees to coordinate and maintain the spaces, and participatory zoning workshops that actively involve community members in decision-making. Technical support, including training in urban agriculture and the provision of tools and seeds, can facilitate engagement, while awareness campaigns, school programs, and community events can reinforce stewardship and foster long-term sustainability. By combining strategic spatial planning, community participation, and capacity-building measures, these initiatives can ensure the ecological, social, and climatic benefits of green spaces are sustained across urban, peri-urban, and rural areas. Regarding urban form, Malley et al. (2014) highlighted that building design, including form, orientation, and layout, plays a crucial role in mitigating the urban heat island effect. Additionally, incorporating high-albedo (reflective) materials for structures and roadways can significantly decrease heat absorption in Kisangani.

Effectively implementing these strategies requires reinforcing land-use planning and governance frameworks. This includes the spatial delineation of priority areas for green infrastructure, the establishment of urban growth boundaries, and the integration of ecological criteria into zoning regulations. Coordinating action between governmental and traditional authorities in Kisangani's rural and peri-urban areas is essential. Such collaboration enhances the enforcement of spatial planning measures and contributes to achieving the Sustainable Development Goals (SDGs). By supporting the development of climate-resilient infrastructure, mitigating heat-related health risks, and promoting sustainable land-use practices, this approach directly aligns with SDG 11 (Sustainable Cities and Communities) while also advancing progress on SDG 13 (Climate Action) and SDG 3 (Good Health and Well-Being). This study thus underscores the pivotal role of locally coordinated governance in translating global sustainability agendas into effective territorial action.

Scientific research plays a critical role in guiding these efforts. Local institutions should prioritize interdisciplinary studies on the cooling effects of green infrastructure in Kisangani's microclimates. Scenario modeling can help project the long-term benefits of sustainable land-use strategies. Although Kisangani is spared mainly from major natural disasters, rising UHI intensity due to urbanization and climate change could increase the city's vulnerability to heat-related risks. Addressing these emerging challenges requires capacity-building through training programs focused on climate-sensitive urban design, participatory land-use planning, and ecosystem-based adaptation. Strengthening partnerships with international institutions can also enhance technical expertise, attract funding, and promote the development of context-specific solutions.

7.9. Conclusion

This paper analyzes MOD11A2 V6.1 data to map urban heat islands (UHIs) in Kisangani from 2000 to 2024. The findings reveal a significant temporal shift in the spatial pattern of UHI, with an increase in areas exhibiting UHI values above 0.1 over the study period. Specifically, areas of moderate UHI ($0.1 < UHI < 0.2$) increased from 16 km² to 38 km², while areas of high UHI ($0.2 < UHI \leq 0.3$) increased from 9 km² to 19 km². Furthermore, although maximum UHI values exceeding 0.21 were observed in urban zones, significant differences in UHI variations are noted across urban, peri-urban, and rural zones. The findings indicate that the average UHI in Kisangani's urban zones remains below 0.2. Therefore, based on the average UHI variations, the urban zones of Kisangani exhibit moderate disparities in LST compared to rural areas.

Moreover, regression analyses show that variations in land surface temperatures (LSTs) are significantly correlated with building volume density (BVD) and vegetation density, as measured by the Normalized Difference Vegetation Index (NDVI). In addition, the influence of BVD on LST variation has increased over time, as indicated by rising slopes and the coefficients of determination. This trend suggests that urban expansion and architectural changes, particularly the construction of large, closely spaced buildings, enhance the heat retention and emission capacity of these dense environments.

These findings underscore the importance of integrated development policies in effectively managing the interface between urbanization, changes in landscape patterns, and the supply of ecosystem services. As urban and peri-urban areas expand, vegetation faces loss and fragmentation, weakening its ability to regulate the urban heat island (UHI) effect, especially in regions with UHI values equal to or exceeding 0.21, categorized as high-temperature zones.

However, the UHI mitigating strategies tailored to the specific socio-economic, environmental, and climatic context of Kisangani are increasingly essential. These practical and resilient solutions should integrate green infrastructure, urban planning, and community engagement to create a more sustainable and resilient urban environment. Indeed, expanding green spaces, including parks, urban forests, roadside vegetation, and green corridors linking urban, peri-urban, and rural areas, should lower surface and air temperatures through shading and evapotranspiration. This holistic strategy offers a way to balance urban expansion and economic progress while preserving ecosystem services across the urban–rural gradient.

Chapter 8

Perspectives on urban futures: contrasting business-as-usual, hybrid growth and sustainable urbanization pathways in Kisangani, (DR Congo).

8.1. Reference

Balandi, J.B., Sikuzani, Y.U., Meniko, J.-P., Sambieni, K.R., Bastin, J.-F., Iyongo, L.W., Mobunda, T.J., Mabicka, L.D., Sodalo, C., Mbusa, WM., Jesuka, R., Cirezi, N.C., & Bogaert, J. Perspectives on urbanfutures : contrasting business-as-usual, hybrid growth, and sustainable urbanization pathways in Kisangani, (DR Congo). Article under review in the Journal of Urban Management.

8.2. Context

The landscape dynamics described in the preceding chapters, including urban dedensification between 2010 and 2021, transformations in green infrastructure along the urban-rural gradient, forest fragmentation and intensified edge effects, and the expansion of urban heat islands, highlight the need to extend the analysis toward a forward-looking perspective to better anticipate the spatial and ecological evolution of Kisangani. This chapter, therefore, adopts a prospective approach by using spatial modelling to analyze three possible trajectories of urban growth in Kisangani: first, a Business-As-Usual (BAU) expansion that continues historical trends without spatial constraints (Morales et al., 2025; Tang et al., 2024; Thorne et al., 2013) ; second, a sustainable urbanization scenario that incorporates explicit spatial constraints to promote compact, managed growth; and finally, a hybrid urbanization scenario that combines sustainability principles with the local realities of Kisangani. This approach helps address the lack of prospective studies on intermediate African cities while providing a quantitative and spatial assessment of the differentiated impacts of these three trajectories on landscape dynamics, the fragmentation of non-built spaces, and the preservation of ecological resources.

8.3. Résumé

L'expansion urbaine non régulée constitue une caractéristique majeure des villes en forte croissance des pays en développement, où la faiblesse des cadres institutionnels et l'application limitée des réglementations en matière d'urbanisation engendrent une expansion urbaine dispersée et fragmentée. En République démocratique du Congo (RDC), ces dynamiques soulèvent des inquiétudes quant à la dégradation des terres, à l'inefficacité des infrastructures et à la perte des potentialités agricoles et écologiques. A cet effet, cette étude analyse les dynamiques historiques et prospectives de la croissance urbaine à Kisangani, dans le nord-est de la RDC, en comparant trois trajectoires contrastées : un scénario tendanciel (Business-as-Usual, BAU), un scénario de Croissance Durable, et un scénario Hybride de Croissance urbaine.

L'analyse s'est focalisée sur des séries temporelles d'images Landsat, des variables spatiales explicatives et un modèle U-Net modifié. Les résultats montrent que la croissance urbaine de Kisangani a historiquement suivi un modèle d'étalement urbain non encadré. Le scénario BAU prolonge cette tendance, caractérisée par la dispersion des zones bâties et la pression accrue sur les espaces non bâtis. Le scénario de croissance durable, inspiré par la nouvelle discipline de la choralogie, favorise une configuration compacte et continue, tout en préservant les zones non bâties. Le scénario hybride de croissance urbaine présente des tendances intermédiaires : il favorise une expansion périphérique modérée le long des zones agricoles et des axes routiers, tout en préservant la cohésion du noyau urbain. Ce compromis met en évidence la capacité des approches hybrides à concilier les exigences de développement et la préservation des terres.

Les résultats soulignent la nécessité d'une planification urbaine anticipée, fondée sur des contraintes spatiales explicites, pour orienter la ville de Kisangani et, plus largement, les villes congolaises vers des trajectoires de développement plus durables, plus compactes et plus résilientes.

Mots-clés : Étalement urbain ; croissance durable et hybride ; scénario tendanciel ; choralogie ; apprentissage profond ; Kisangani.

8.4. Abstract

Unregulated urban expansion is a common feature of many rapidly growing cities in developing countries, where weak planning frameworks and limited enforcement lead to dispersed and fragmented spatial growth. In the Democratic Republic of the Congo (DRC), these dynamics are particularly evident, raising concerns over land degradation, inefficient infrastructure provision, and the loss of agricultural and ecological assets. To address this gap, the present study examines the historical and projected dynamics of urban growth in Kisangani, north-eastern DRC, by contrasting three scenarios: a Business-as-Usual (BAU) trajectory, a Sustainable Growth scenario, and a Hybrid Sustainable Growth scenario.

Building on historical Landsat data, spatial explanatory variables, and a modified U-Net model, the analysis reveals that urban growth in Kisangani has historically followed an outward sprawl pattern, with limited regard for planning instruments or ecological constraints. Projections under the BAU scenario suggest that this trend will continue, with dispersed built-up patches gradually encroaching on non-built areas and increasing environmental pressures at the urban fringe. The Sustainable Growth Scenario, inspired by the new proposed discipline of Choralogy, spatially preserves non-built zones by promoting a compact, contiguous urban form. The Hybrid Sustainable Growth scenario produces intermediate outcomes, allowing moderate peripheral expansion near agricultural zones and road networks while maintaining a relatively consolidated urban core. Sensitivity analysis demonstrates the critical role of built-up contiguity as a catalytic threshold governing urban expansion, revealing that demographic pressure and spatial growth rates become effective only once local urban clusters reach sufficient spatial coherence.

Overall, the findings underscore the need for proactive and spatially explicit planning to guide Kisangani and other Congolese cities toward more sustainable, compact, and resilient urban development.

Keywords: Urban sprawl, sustainable and hybrid growth, business-as-usual, choralogy, deep learning, Kisangani.

8.5. Introduction

Accelerated urban growth often results in unregulated and dispersed spatial expansion of cities (Jacobs, 1961; Angel et al., 2010). This model of dispersed expansion, known as urban sprawl (European Environment Agency, 2006; Balandi et al., 2023) has been linked to environmental degradation, reduced infrastructure efficiency, and the fragmentation of agricultural and natural landscapes (Useni et al., 2017; Balandi et al., 2024). This challenge is likely to be intensified in developing countries, where additional pressure is set to be placed on urban areas due to rapid demographic growth. The global population is projected to rise from 8.0 billion in 2022 to 9.7 billion by 2050. Over 90% of this increase (approximately 1.5 billion people) is expected to occur in these regions, with Africa accounting for over half of the total growth (United Nations, 2022). In contexts where spatial planning frameworks are weak or poorly enforced, such dispersed urban expansion patterns may, unfortunately, persist, along with the full range of associated environmental degradation. Addressing these environmental challenges requires an in-depth knowledge of potential future changes in land use and land cover (LUCC) (Mitchley et al., 2006; Houet et al., 2015). Understanding these dynamics is crucial for designing effective adaptive strategies and managing limited resources efficiently. At the global scale, observed patterns of urban expansion underscore the rapid and extensive nature of this process.

Globally, built-up areas have grown significantly. An analysis of a representative sample of 30 cities revealed that 28 of them expanded more than 16 times during the 20th century (Angel et al., 2011). Furthermore, on average, cities are now expanding at twice their population growth rate and cover nearly 0.5% of the Earth's land surface (Angel et al., 2011). Africa remains the world's least urbanized region, yet it is experiencing the fastest pace of urbanization (UN-Habitat, 2022). Currently, around 44% of the population lives in urban areas. By 2035, half of its inhabitants are expected to reside in cities, and by 2050, the continent is projected to be predominantly urban, with around 60% of its population living in urban settlements (UN-Habitat, 2022). Several densely populated African countries rank among the fastest in the world for built-up area expansion. Between 2001 and 2019, the continent's urban land cover increased at an average annual rate of 5.92%, while the urban population grew by about 4.91% per year. Nigeria, the Democratic Republic of the Congo, and Ethiopia stand out as the three countries experiencing the most intense urbanization (Jiang et al., 2021).

Urban expansion has led to significant environmental degradation. It is projected that by 2030, there will be a global loss of cropland of between 1.8% and 2.4%, with notable regional variations. While Asia is expected to record the most significant absolute loss, African countries are likely to experience the most significant proportional decline (D'Amour et al., 2017). These land-cover changes also threaten biodiversity and ecosystem functioning by reducing habitat availability, biomass, and carbon storage. In tropical regions alone, vegetation biomass loss in areas with a high probability of urban expansion is estimated at 1.38 PgC (0.05 PgC yr^{-1}) by 2030, equivalent to roughly 5% of emissions from tropical deforestation and land-use change (Seto et al., 2012). Such environmental pressures underline the importance of how cities are planned and managed. As complex systems, cities grow, transform, and occasionally contract in response to multiple forces. Without adequate planning, urban growth often takes the form of inefficient sprawl, weak connectivity, and inadequate municipal services (UN-Habitat, 2022).

In Kisangani, DRC, uncontrolled expansion of urban and peri-urban areas occurred largely beyond the reach of formal spatial planning frameworks, resulting in a dispersed urban footprint and encroachment into ecologically sensitive zones (Balandi et al., 2023). Such patterns have placed increasing pressure on the city's green infrastructure, particularly the Mature Forest and Short Forest formations (Balandi et al., 2024), which are among the most critical ecological assets for Kisangani. These forested areas play a vital role in sustaining biodiversity, regulating local microclimates, and land surface temperature (LST) (Balandi et al., 2025), and providing essential ecosystem services such as carbon storage and flood mitigation. The degradation and fragmentation of these habitats decrease their ecological function and undermine the city's ability to adapt to climate change and withstand environmental hazards.

This emphasizes the crucial role of proactive urban planning in steering urban growth toward more sustainable trajectories. Good urban planning is one of the three main pillars of sustainable cities; without it, cities are unlikely to realize the most promising urban futures (UN-Habitat, 2022). In line with Sustainable Development Goal 11 (*Sustainable Cities and Communities*) (United Nations, 2015b), the compact city model, rooted in sustainable urbanism theory, promotes higher densities, mixed land use, and urban containment to curb sprawl while enhancing liveability, resource efficiency, and resilience (Lehmann, 2016; Bibri, 2020; Zapata Campos et al., 2022). This approach also aligns with the recent discipline of choralogy, which considers spatial planning in light of the growing scarcity and ecological significance of geographic space. Choralogy emphasizes the importance of managing land as a finite and vulnerable resource that is under pressure from unsustainable socio-economic and environmental factors (Bogaert et al., 2015). This reinforces the need for long-term spatial responsibility in urban development. Both empirical and theoretical studies support this approach: compact development reduces per capita energy use and greenhouse gas emissions, cuts infrastructure and travel costs, and fosters innovation and social cohesion (Zapata Campos et al., 2022).

Despite the relevance of such contrasting approaches, few studies have quantified the long-term spatial dynamics of built-up and non-built land under these conditions, particularly in rapidly urbanizing mid-sized cities where governance strategies may decisively influence peri-urban growth trajectories. To address this gap, our study analyses three urban growth trajectories in the Kisangani region.

Therefore, we hypothesize that in the absence of effective planning mechanisms, the continuation of the current urban growth trajectory, represented by the business-as-usual (BAU) scenario, would lead to a faster increase in the total built-up area than in the expansion of the urban core, as measured by the Largest Patch Index (LPI).

Built-up pixels are expected to grow more prominently along the urban fringe, where land availability is higher, indicating a predominance of outward expansion over infilling within the core. Conversely, implementing a functional green belt and limiting urban expansion to a maximum distance from existing built-up areas, while ensuring new developments are close to agricultural zones and the road network, is expected to generate more compact, ecologically protective, and spatially balanced urban configurations under the Sustainable Growth or Hybrid scenario. Furthermore, the two extreme planning trajectories, BAU and Sustainable Growth, are expected to exhibit distinct sensitivities to key modeling parameters that influence urban expansion. Variations in (i) demographic pressure, (ii) spatial growth rate, (iii) contiguity thresholds, (iv) minimum distance from existing built-up pixels, and (v) tolerance within the green belt are anticipated to produce contrasting effects on the simulated built-up area.

8.6. Materials and methods

8.6.1. Study area

The study area encompasses the city of Kisangani and its surrounding peri-urban and rural zones, located in north-eastern Democratic Republic of the Congo (Figure 8.1). It covers a circular region extending 30 km in all directions from the urban center of Kisangani, thus including all six of the city's municipalities. Out of the six municipalities, five lie on the right bank of the Congo River, with only one established on the left bank. This 30 km radius area spans a total surface of approximately 2,780.6 km². Over the 50 years from 1956 to 2005, the region experienced a mean annual rainfall of 1,724 mm and an average temperature of 25.3 °C (Sabongo, 2015). According to the Köppen climate classification system, the region is classified as having a tropical rainforest climate (Af), as monthly rainfall consistently exceeds 60 mm (Kottek et al., 2006). In recent decades, Kisangani's population has expanded significantly. Data from the National Statistics Institute reports that it reached over 2.18 million inhabitants by 2021(Balandi et al., 2025). Land-use planning and governance in the Kisangani region remain limited (UN-Habitat, 2015), and urban development often occurs in an unregulated manner. This contributes to the proliferation of informal settlements and increases pressure on peri-urban agricultural land and natural ecosystems (Balandi et al., 2024). The area also includes ecologically sensitive zones and patches of natural forest, some of which fall under formal or informal protection. These ecosystems provide essential services and contribute to the regulation of urban–rural interactions.

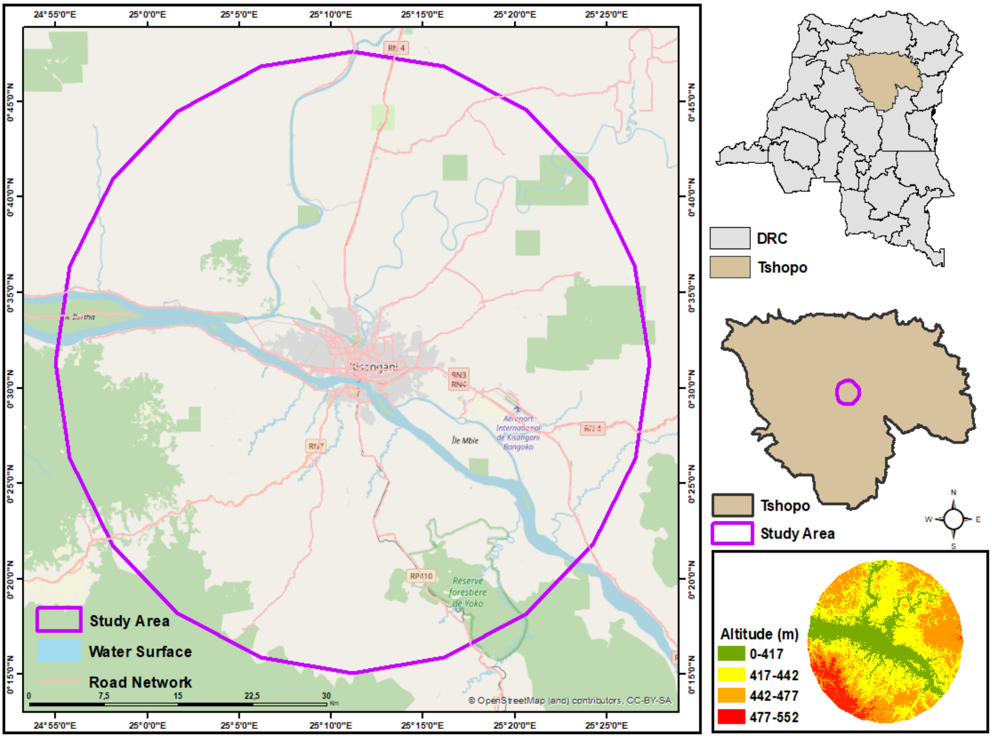


Figure 8.1. Location and extent of the study area. The study area encompasses the city of Kisangani and its surrounding peri-urban and rural zones in north-eastern Democratic Republic of the Congo. The delineated area corresponds to a circular buffer of 30 km radius centred on the urban core of Kisangani.

8.6.2. Data used and methodological flowchart

This study employs a comprehensive set of geospatial datasets to analyse both the historical and projected dynamics of urbanization in Kisangani. The primary data consist of a time series of Landsat satellite imagery spanning 1986, 1991, 1996, 2001, 2006, 2011, 2016, 2021, and 2024, processed through Google Earth Engine. From these data, several variables were derived through historical analyses to characterise past urban dynamics. These include local urban density, which is calculated based on the concentration of built-up areas within spatial grid squares of 10×10 pixels, corresponding to approximately 300 × 300 meters, given a pixel size of 30 meters; historical change rate between 1986 and 2021; and Euclidean distance to built-up areas, which reflects proximity to existing built-up areas and the potential for urban expansion. In addition to these historically derived variables, several explanatory datasets were directly integrated into the urban growth model to capture key spatial drivers of landscape change.

These include population density for the years 1985 and 2021, obtained from the Joint Research Centre (JRC) database; elevation data derived from the Shuttle Radar Topography Mission (SRTM); Euclidean distance to the road network, the distance to agricultural land, and a delineated urban green belt, which was incorporated as one of the spatial constraints (Figure 8.2).

Figure 8.3 shows the overall methodological workflow. Binary classification maps from 1986, 2021, and 2024, along with the explanatory variables described above, serve as inputs. Preprocessing includes data normalization, indicator calculations, distance-to-built-up measurements, and creation of sliding patches. The modified U-Net model, implemented in Python within a Jupyter Notebook, produces probability maps of built-up area conversion. These outputs are then used in spatio-temporal simulations under business-as-usual and sustainable scenarios, resulting in annual simulated maps, spatial error maps, scenario comparisons, and landscape metrics.

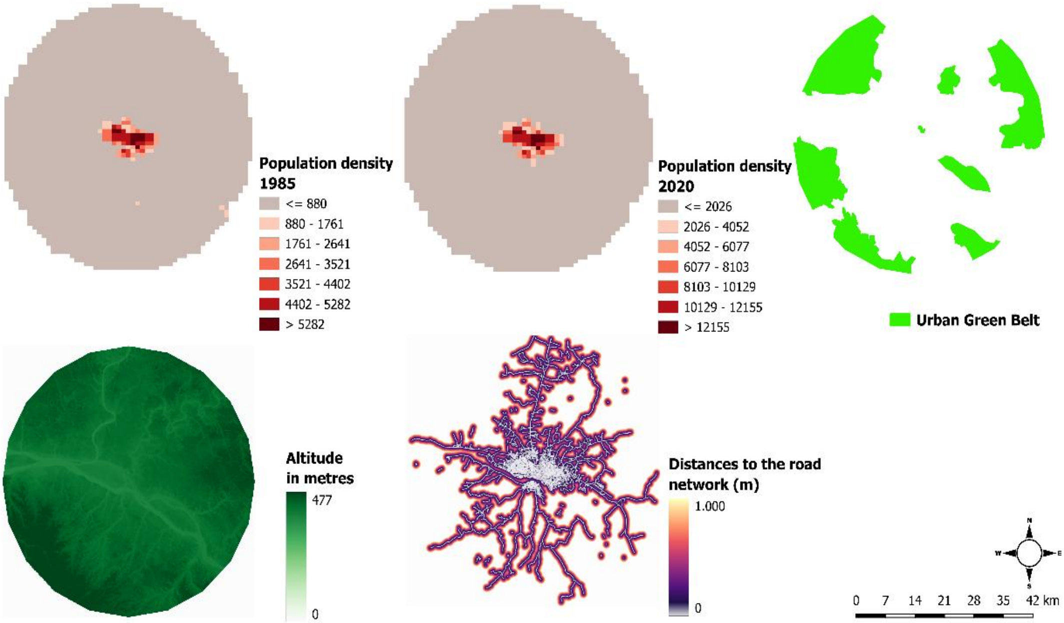


Figure 8.2. Additional spatial variables integrated into the Kisangani urban growth model, supplementing core historical change metrics (local urban density, historical change rate, Euclidean distance to built-up areas). These include population density (1985, 2021), elevation (SRTM), distance to roads, and the urban green belt boundary**.**

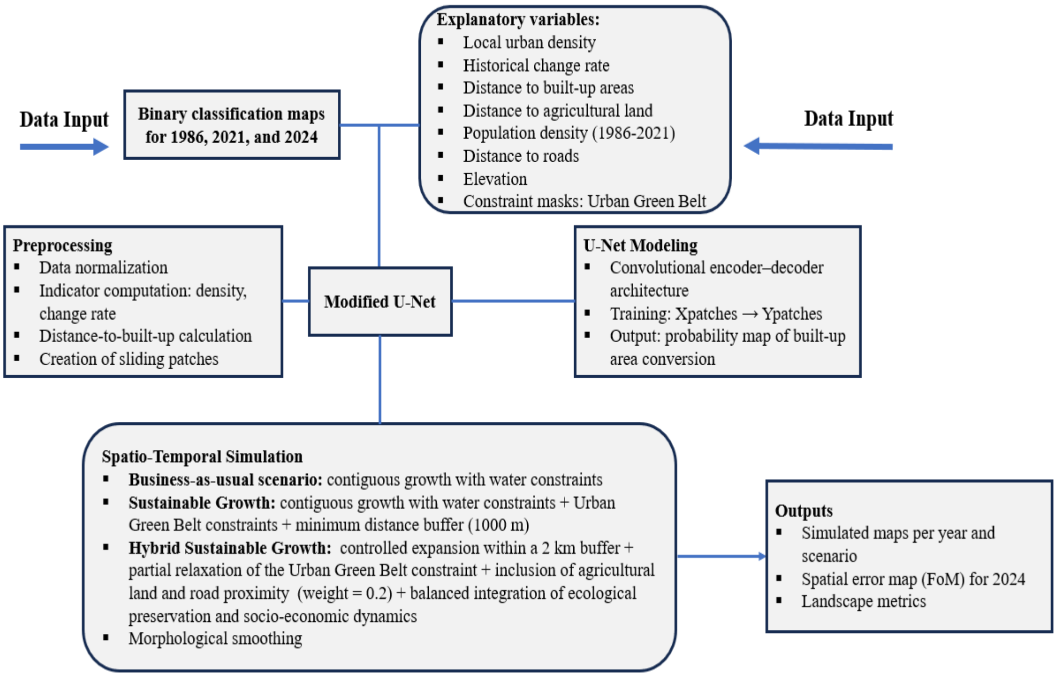


Figure 8.3. Workflow of the modified U-Net-based urban expansion modeling and simulation, integrating historical and explanatory spatial variables to simulate urban growth scenarios in Kisangani.

8.6.3. Urban growth modeling approach

Land use and land cover change (LULCC) models can be categorized into statistical models, machine learning (ML) models, and tree-based models (Pontius et al., 2008; Shafizadeh-Moghadam et al., 2017). However, advances in deep learning, coupled with its successful application to satellite image classification and segmentation, have paved the way for its use in detecting land use changes (He et al., 2019; Liu et al., 2021). In this study, urban expansion between 2024 and 2060 was simulated using a deep-learning-based spatial prediction framework. Specifically, a convolutional neural network (CNN) with a U-Net architecture (Ronneberger et al., 2015; Shojaei et al., 2022) was trained on multi-temporal built-up land cover data to capture spatial patterns and predict the probability of urban growth. Given that the result produced by conventional convolutional networks is the class label attributed to each input image, they do not inherently perform pixel-wise classification or preserve precise localization. In contrast, U-Net is specifically designed to assign a class label to each pixel while retaining both contextual information and fine-scale spatial details. This property is essential for accurately delineating future built-up areas (Ronneberger et al., 2015).

In this study, a modified U-Net architecture was employed to address practical challenges associated with built-up land expansion simulation, notably the strong imbalance between relatively small areas of change and extensive unchanged backgrounds, as well as the limited availability of training data (Ronneberger et al., 2015; Shojaei et al., 2022). The modifications include training the model on multi-variable input data structured as a data cube, in which each pixel is characterized by multiple spatially explicit variables that influence urban growth, such as local urban density, historical change rate, distance to built-up areas, distance to agricultural land, population density, road proximity, and elevation. Furthermore, an informed patch-extraction strategy was applied to select overlapping patches containing changed pixels, thereby mitigating class imbalance and reducing the training dataset size. The convolutional filters of the U-Net inherently capture neighborhood effects critical to urban expansion, enabling a top-down spatial allocation of new built-up pixels based on pixel-wise probability maps.

Compared to rule-based cellular automata (CA) models, such as SLEUTH and CLUE-S, which depend on predefined transition rules and often lose detail through coarse cell abstractions, the U-Net reduces expert bias while maintaining high spatial resolution (Shojaei et al., 2022). These CA models also face challenges related to sensitivity to the number of driving factors, fixed cellular states, and limited integration of human decision-making processes, which hinder their ability to represent the dynamic nature of spatial change (Bhusal et al., 2024). In contrast, U-Net's flexible encoder-decoder architecture can incorporate any number of inputs, handle spatial dependencies through convolutional filters, and adaptively learn intricate local and contextual features, enabling more precise and dynamic urban expansion simulations (Bhusal et al., 2024).

8.6.4. Scenario development framework

Three urban growth scenarios were simulated to assess potential patterns of urban expansion in Kisangani. The first scenario, Business-as-Usual (BAU), extrapolates historical growth rates without imposing additional spatial constraints (Thorne et al., 2013; Tang et al., 2024; Morales et al., 2025). Under this scenario, urban expansion follows existing dynamics, gradually extending into surrounding non-built areas. It represents uncontrolled growth, capturing the continuation of past trends without deliberate planning interventions. The second scenario, Sustainable Growth, imposes strict spatial limitations on urban expansion. New development is allowed only within 1 km of existing built-up areas. This threshold is iteratively applied for each simulation year (2024, 2030, 2035, 2040, 2045, 2050, 2055, and 2060) to ensure that growth occurs contiguously around existing urban cores (Lehmann, 2016; Zapata Campos et al., 2022). Notably, urban green belts and waterways are entirely excluded from development, reflecting a strong commitment to preserving non-built spaces and ecological features.

The third scenario, Hybrid Sustainable Growth, combines sustainability objectives with Kisangani's local realities. In this model, urban expansion is permitted within a 2 km radius of existing built-up areas, allowing for controlled peripheral growth while maintaining contiguity. Unlike the strict sustainable scenario, green belts are not entirely off-limits: urbanization is influenced by proximity to agricultural lands and road networks, which reflect existing socio-economic pressures and patterns of land appropriation. These factors are weighted at 0.2, moderately increasing the probability of conversion for nearby cells without undermining the ecological function of green spaces. This scenario represents a pragmatic balance between conservation and realistic urban dynamics, simulating a sustainable yet contextually grounded pattern of urban growth.

For each simulation year, the model calculates the probability of urbanization per pixel, allocating new built-up areas according to these probabilities while enforcing exclusion constraints to ensure spatially coherent and sustainable urban patterns. Both the Sustainable Growth and Hybrid Sustainable Growth scenarios are inspired by the principles of choralogy, a discipline formalized and promoted by Bogaert et al.(2015). The term choralogy derives from the Greek *χώρα* (*chôra*, meaning space, rural or urban area, land, or territory) and *λόγος* (*logos*, meaning science). It refers to the study of spaces, land, or territory, considering their availability as increasingly limited due to unsustainable ecological and socio-economic trends.

Choralogy treats land as a finite and fragile resource subject to social, economic, and environmental pressures. From this perspective, land is not merely a physical substrate but also a medium that sustains ecological functions, social values, and economic opportunities. Applied to urbanization, choralogy emphasizes the interdependence between spatial structures and socio-economic processes, highlighting the need for rational land management that reduces fragmentation, preserves ecological integrity, and enhances land-use efficiency. It supports compact, spatially coherent urban development patterns aligned with the territorial capacity to sustain long-term socio-ecological systems (Figure 8.4). By grounding both the Sustainable and Hybrid scenarios in these principles, the model ensures that urban expansion respects ecological limits while accommodating realistic socio-economic dynamics.

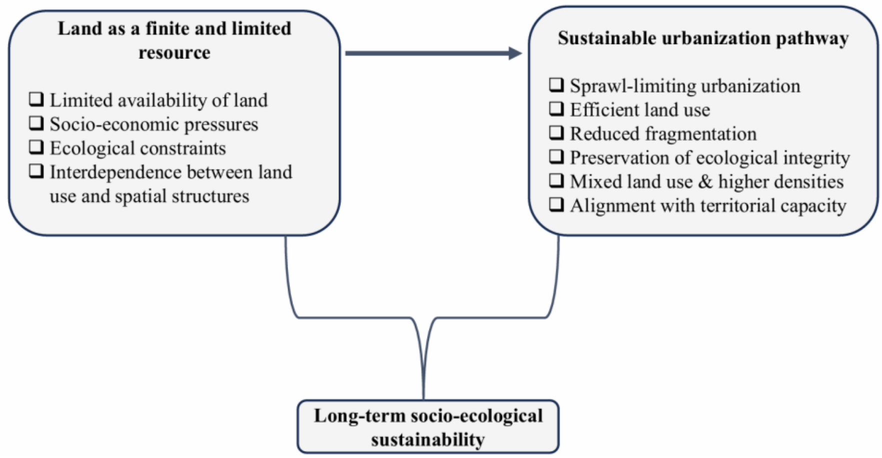


Figure 8.4. Conceptual pathway from land as a finite resource to compact and sprawl-limiting urbanization.

8.6.5. Model validation

Model validation involved comparing binary predicted urban maps for 2024 with observed land cover data from the same year. The focus of the validation was to assess the model's ability to accurately identify areas of both land cover change (urbanization) and persistence (no change). This was achieved by classifying pixels spatially into five mutually exclusive categories, as outlined by Pontius et al. (2008) :

- MISSES (**A**): Pixels where the observed data indicate change (new urbanization) but the simulation incorrectly predicts persistence (no change).
- HITS (**B**): Pixels correctly predicted as changed by the model, matching the observed new urbanization.
- WRONG HITS (**C**): Pixels where both observed and simulated data indicate a change, but the change is assigned to the incorrect category or class.
- FALSE ALARMS (**D**): Pixels predicted as changed by the simulation but observed as persistent (no actual change).
- CORRECT REJECTIONS (**E**): Pixels correctly predicted as persistent (no change) by the model, matching the observed persistence.

In this study, urban growth prediction is strictly binary, distinguishing only between built-up and non-built-up land. Therefore, the Wrong Hits category (C), which refers to misclassification across multiple change categories, is effectively minimal or not applicable because there are no alternative change classes to confuse it. This binary classification simplifies validation and ensures that any pixel classified as changed directly reflects urban growth, avoiding ambiguity in change-type assignment. To evaluate the model's performance quantitatively, the Figure of Merit (FoM) was calculated using the formula (Equation 8.1) (Pontius et al., 2008; García-Álvarez et al., 2022):

Equation 8.1. $$\boldsymbol{FoM} = \frac{B}{A+B+C+D}$$

This metric indicates the ratio of correctly predicted change pixels (hits) relative to the total number of pixels involved in observed or simulated changes, excluding correct rejections. The FoM effectively evaluates the spatial agreement between predicted changes and actual changes, considering both omission errors (misses) and commission errors (false alarms)(García-Álvarez et al., 2022). This validation framework offers a reliable assessment of the model's capacity to simulate urban expansion spatially and temporally, which is essential for evaluating the accuracy of future projections under various urban growth scenarios.

8.6.6. Landscape change analysis

Several key landscape metrics were analyzed to gain a deeper understanding of historical changes and the implications of urban growth scenarios: the Business-as-Usual (BAU) model, the Sustainable Growth model, and the Hybrid Sustainable Growth model. The Relative Built-up Area Change (RBAC) (Equation 8.2) was considered to capture the temporal dynamics of built versus non-built areas, which are expected to increase and decrease, respectively, over time due to ongoing urban expansion. In addition, the Built-to-Non-Built Ratio was calculated to reflect the balance between built and non-built land, and it is expected to rise significantly as built areas continue to expand. To further assess urban densification under the Sustainable Growth and Hybrid Sustainable Growth models, and urban sprawl under the BAU scenario, the Largest Patch Area (LPI) (Equation 8.3) was analyzed relative to the total area. For built areas, this metric is expected to increase gradually under the Sustainable Growth and Hybrid Sustainable Growth models, while the BAU scenario is likely to exhibit a slower increase. Conversely, for non-built areas, the BAU model is expected to show a faster decline in the extent of the largest patch, reflecting increased fragmentation due to sprawl. Finally, the spatial distribution of built-up pixels was examined relative to distance from the urban center, with the BAU model predicted to generate a higher number of built-up pixels in peripheral areas than the more compact growth under the Sustainable Development model and the Hybrid Sustainable Model.

Equation 8.2. $$\text{RBAC} = \frac{a_b}{a_i}$$

Where $RBAC$ is the Relative Built-up Area Change, $\boldsymbol{a_b}$ refers to the built-up area of a given landscape at the final time point (Year 2), and $\boldsymbol{a_i}$ represents the built-up area of a given landscape at the initial time point (Year 1).

Equation 8.3. $$\text{LPI} = \frac{max_{j=1}^{n}(a_{ij})}{A} X\ 100$$

Where LPI is the Largest Patch Area, a_{ij} = Area (m^2) of patch ij; A = Total landscape area (m^2).

8.7. Results

8.7.1. Historical patterns of urban growth and landscape change

Historical mapping (Figure 8.5) and quantitative analysis (Figure 8.6) highlight changes in urban growth in the Kisangani region over the last forty years. Between 1986 and 2024, built-up areas expanded significantly, accelerating and spreading over a larger area, particularly after 2011. While the built-to-non-built ratio (Figure 8.6a$_2$) indicates that non-built areas still predominate, built-up land now covers an area 17 times greater than in 1986 (Figure 8.6a$_1$), underscoring the magnitude of the change. Overall, these findings suggest a substantial and ongoing transformation of natural or undeveloped land into built-up areas.

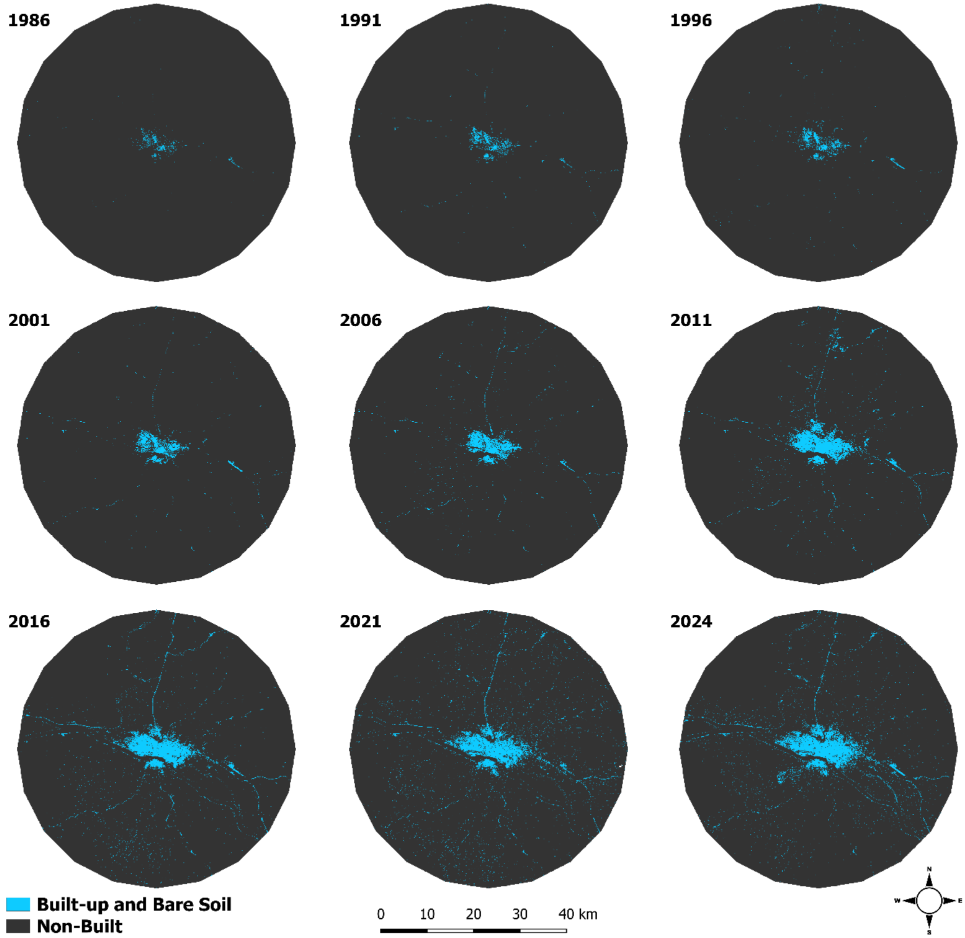


Figure 8.5. Historical mapping of built-up and non-built-up zones in the Kisangani region from 1986 to 2024. A visual analysis reveals accelerated urban expansion and increasingly dispersed settlement patterns since 2011.

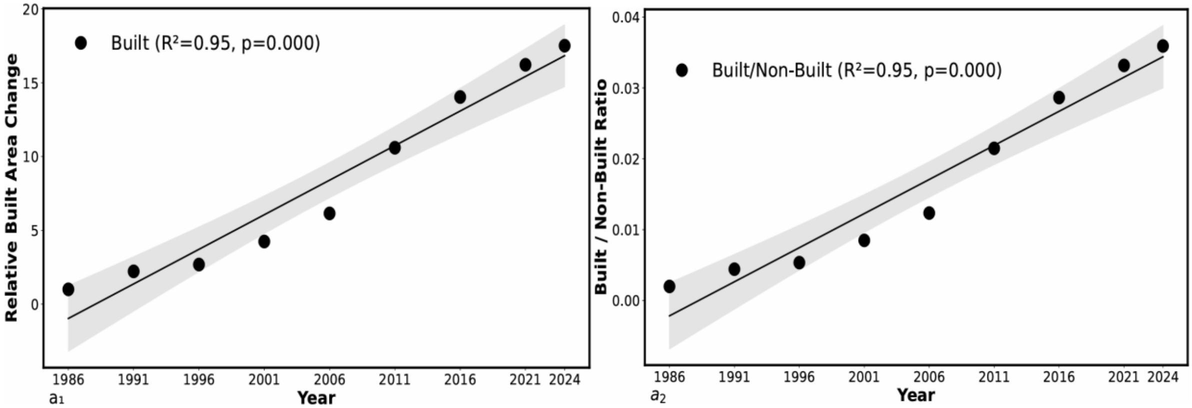


Figure 8.6. Temporal analysis of built-up and non-built-up areas from 1986 to 2024: (a_1) Relative change and (a_2) built-up to non-built-up ratio, highlighting the steady increase of built-up land at the expense of non-built-up areas over time.

8.7.2. Validation of urban growth simulation

Figures 8.7 and 8.8 demonstrate the spatial accuracy and categorical composition of the 2024 urban simulation.

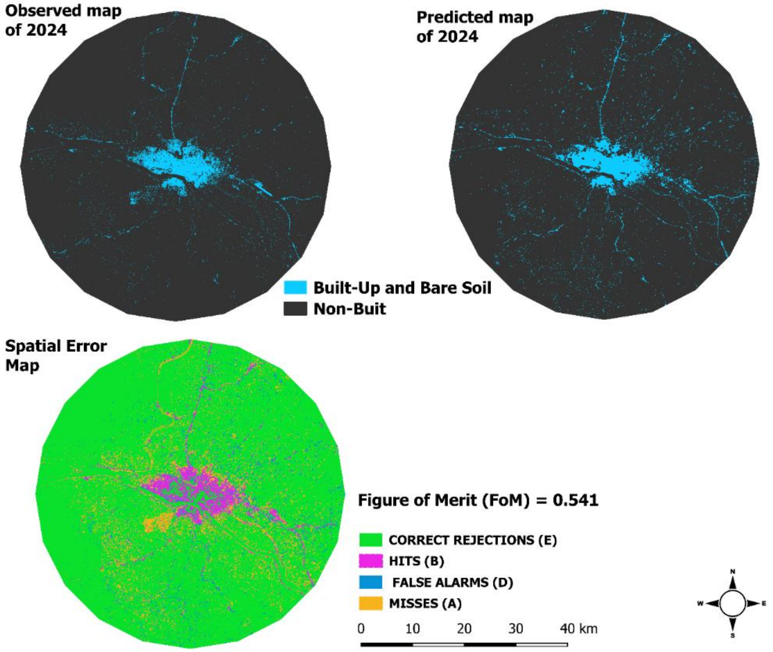


Figure 8.7. Observed and Simulated Built-up Maps for 2024. The spatial allocation appears accurate, with pixels classified as Correct Rejections and Hits dominating the landscape. This indicates a reliable spatial allocation of urban pixels.

Figure 8.8 further quantifies this, showing that these two categories account for the vast majority of pixels, while misses and false alarms remain marginal. This distribution suggests that the model effectively captures the location and extent of built-up land, with only limited errors in predicting changes.

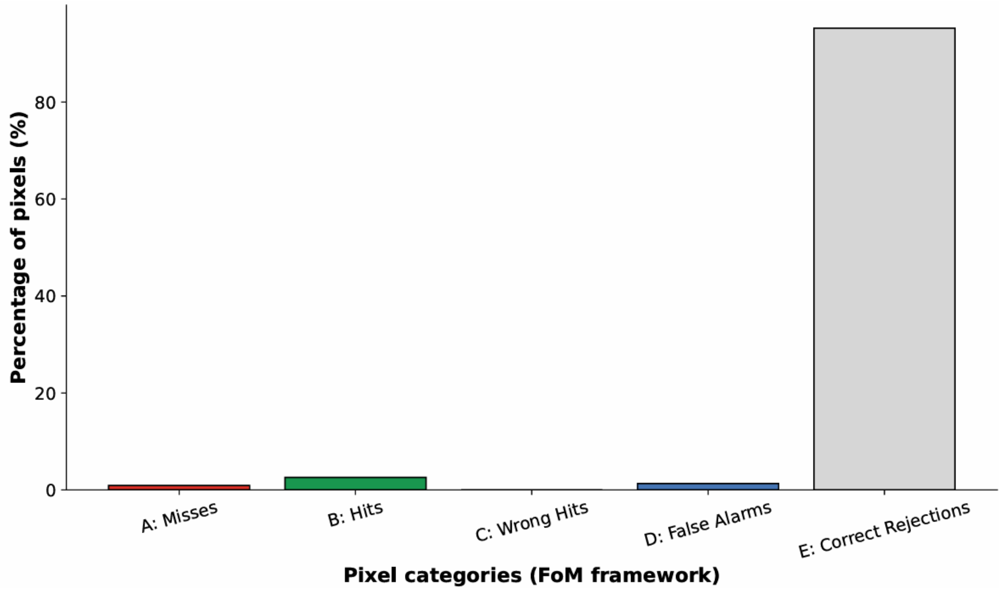


Figure 8.8. The proportion of pixel categories in the 2024 simulation. The results clearly show the dominance of correct rejections and hits, with misses and false alarms accounting for only a small proportion of the landscape.

8.7.3. Prospective urban development patterns

Figures 8.9 and 8.10 provide complementary insights into the spatial and structural dynamics of urban expansion under the Business-as-Usual (BAU), Sustainable Growth, and Hybrid Sustainable Growth scenarios. Figure 9 illustrates that the BAU scenario results in a more dispersed pattern of built-up pixels, gradually encroaching on non-built areas, whereas the sustainable scenario spatially preserves non-built zones by promoting urban densification. In contrast, the hybrid model, which combines sustainability principles with the local realities of Kisangani, ensures a more balanced distribution of built-up areas across the urban core, major roads, and peripheral rural zones.

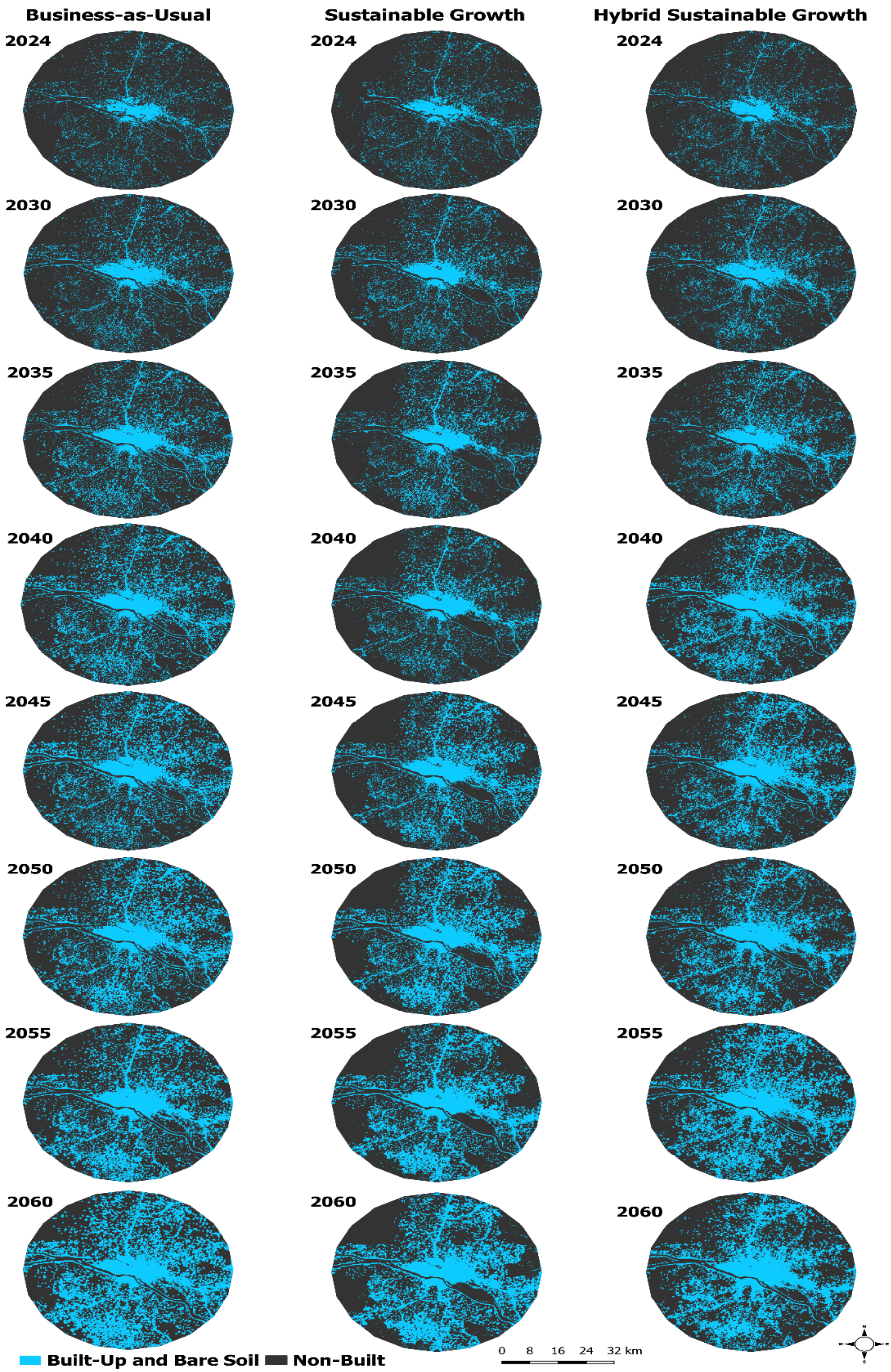


Figure 8.9. Simulated urban expansion under three scenarios: Business-As-Usual (BAU), Sustainable Growth, and Hybrid Sustainable Growth from 2024 to 2060. BAU shows highly

dispersed growth, gradually encroaching on non-built areas. Sustainable Growth focuses on densification, preserving non-built land by concentrating development around existing cores. The Hybrid scenario combines controlled densification with moderate peripheral expansion. Over time, Sustainable and Hybrid scenarios consolidate the largest urban patches, while BAU produces many small, scattered developments, resulting in a more fragmented landscape.

Figure 8.10a indicates that while total built-up area grows faster under BAU, the largest built-up patch expands more under the Hybrid and Sustainable Growth scenarios, particularly after 2045, reflecting a consolidation of urban form and suggesting improved connectivity among urban cores. Conversely, Figure 8.10b further shows that, over time, land artificialization intensifies under the BAU scenario, with Built-up/Non-Built-up ratios increasing more sharply than in the other two scenarios, indicating a progressively less balanced spatial distribution. Total non-built area shrinks with a steeper decline in BAU than in both Sustainable and Hybrid scenarios, highlighting greater landscape fragmentation under uncontrolled growth. These results highlight that sustainable urbanization not only slows the consumption of undeveloped land but also encourages a more compact, contiguous urban structure, with the Hybrid scenario achieving a moderately more organized spatial distribution than the dispersed pattern under BAU, though less strictly compact than in the fully Sustainable Growth scenario.

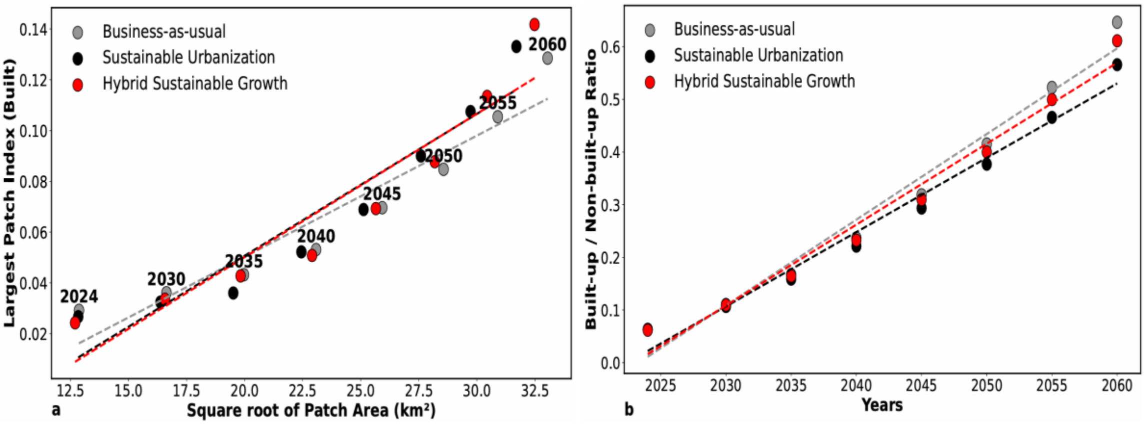


Figure 8.10. Evolution of the largest built-up and the Built-up/Non-built-up ratio under Business-As-Usual (BAU), Sustainable Growth, and Hybrid Sustainable Growth from 2024 to 2060. In a, the largest built-up patch becomes denser and expands more over time under Sustainable and Hybrid Growth, particularly after 2045. In b, the Built-up/Non-built-up ratio rises more sharply in BAU than in the other scenarios, reflecting a progressively less balanced spatial distribution of built-up areas.

Figure 11 illustrates the progressive growth of built-up areas in the urban fringe over time. While all scenarios show an overall increase, the BAU scenario results in substantially higher built-up pixel counts beyond 20 km from the city center, indicating more pronounced peripheral urban sprawl. This increase is statistically significant ($p < 0.05$), particularly from 2045 onwards. The Sustainable Growth and

Hybrid Sustainable Growth scenarios also exhibit expansion in the urban fringe, but at lower intensity, reflecting a more moderate increase in the number and extent of built-up patches in outlying areas. This pattern suggests that urban expansion under BAU is more likely to fragment surrounding landscapes, whereas the other scenarios help to partially preserve non-built spaces at the periphery.

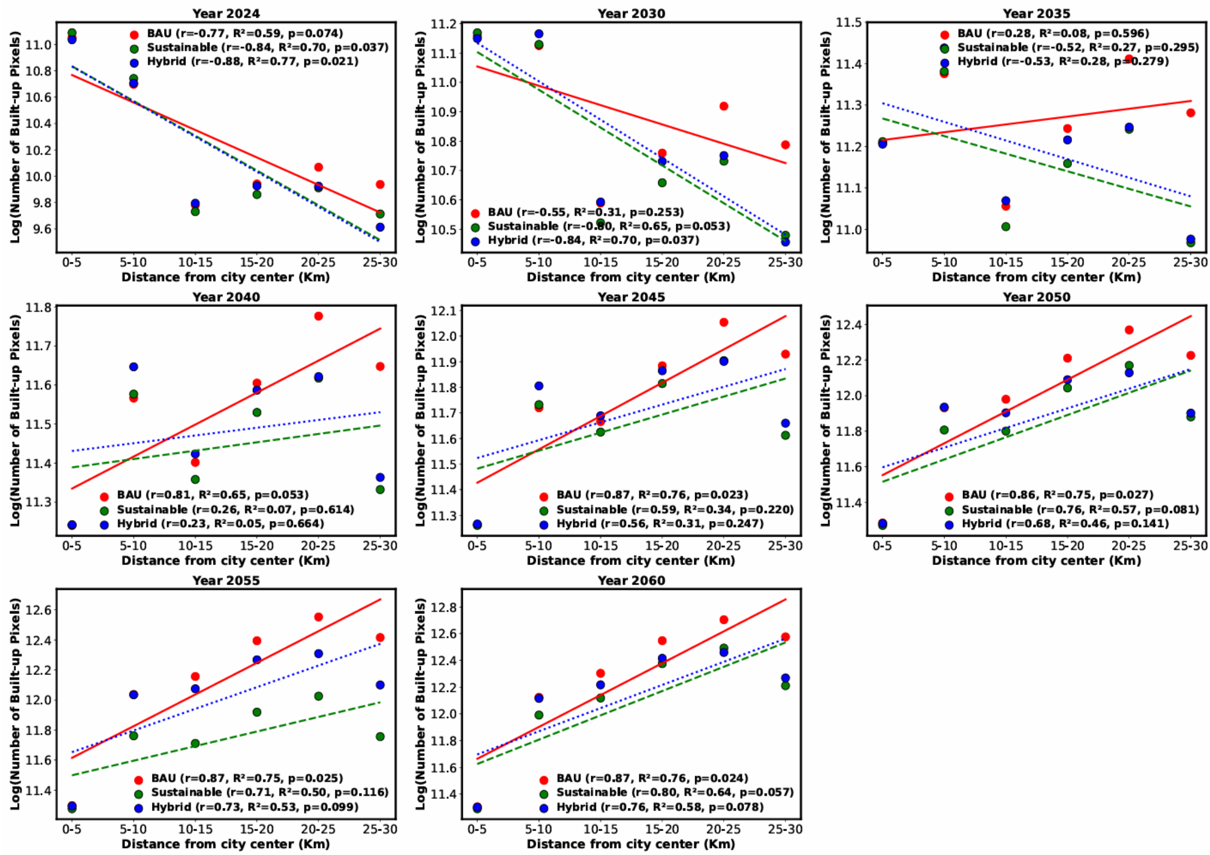


Figure 8.11. Temporal evolution of built-up pixels in the urban fringe of Kisangani (2024-2060). Beyond 20 km from the city center, the BAU scenario shows a statistically significant ($p < 0.05$) increase in built-up pixel counts, particularly after 2045, indicating more pronounced peripheral urban sprawl compared to the Sustainable and Hybrid Sustainable Growth scenarios.

8.7.4. Sensitivity analysis of urban growth scenarios

The sensitivity analysis shows that the built-up area responds differently to the five modelling parameters tested. The expansion is governed primarily by the spatial configuration of existing built-up pixels, with contiguity emerging as the most influential parameter. This parameter defines the minimum number of adjacent built-up pixels required for a new cell to be urbanized (0, 1, or 2 neighbours). In the BAU scenario (Figure 8.12), when examined individually, parameters such as demographic growth and the annual spatial change rate produce relatively modest variations in total built-up area. However, their collective effects become pronounced when the contiguity threshold increases. At low contiguity levels (0 pixel), even substantial demographic growth or higher spatial expansion rates generate only limited additional urbanization. In these conditions, the model simulates a weak capacity for outward propagation, as isolated or sparsely connected built-up pixels do not provide sufficient structural support for new development. In contrast, when the contiguity threshold increases, the influence of all other parameters is considerably greater. A denser built-up structure acts as a catalytic condition, enabling demographic demand and spatial growth rates to translate more effectively into new urbanized surfaces. This pattern is also visible in the interaction between demographic growth and the annual rate of spatial change: demographic pressure alone has a limited effect under stable growth rates, but becomes significantly more impactful when combined with higher spatial growth rates. The model, therefore, reflects a system where urbanization propagates more rapidly once local clusters of built-up pixels reach a critical threshold. Overall, this sensitivity structure highlights the opportunistic and spatially permissive nature of BAU growth, which favors peripheral expansion and contributes to sprawling patterns.

In the Sustainable Growth scenario, the minimum distance to existing built-up areas and the tolerance applied within the green belt introduce additional regulatory constraints that limit outward expansion. Although these constraints reduce the model's overall sensitivity, they do not eliminate parameter interactions. Contiguity remains the primary driver of built-up area change, and its increase substantially amplifies the effects of annual spatial growth rates, demographic pressure, and tolerance levels. When built-up pixels form contiguous clusters, the system becomes more permissive to development, allowing demographic, tolerance levels, and spatial growth inputs to translate into larger increases in urbanized surface.

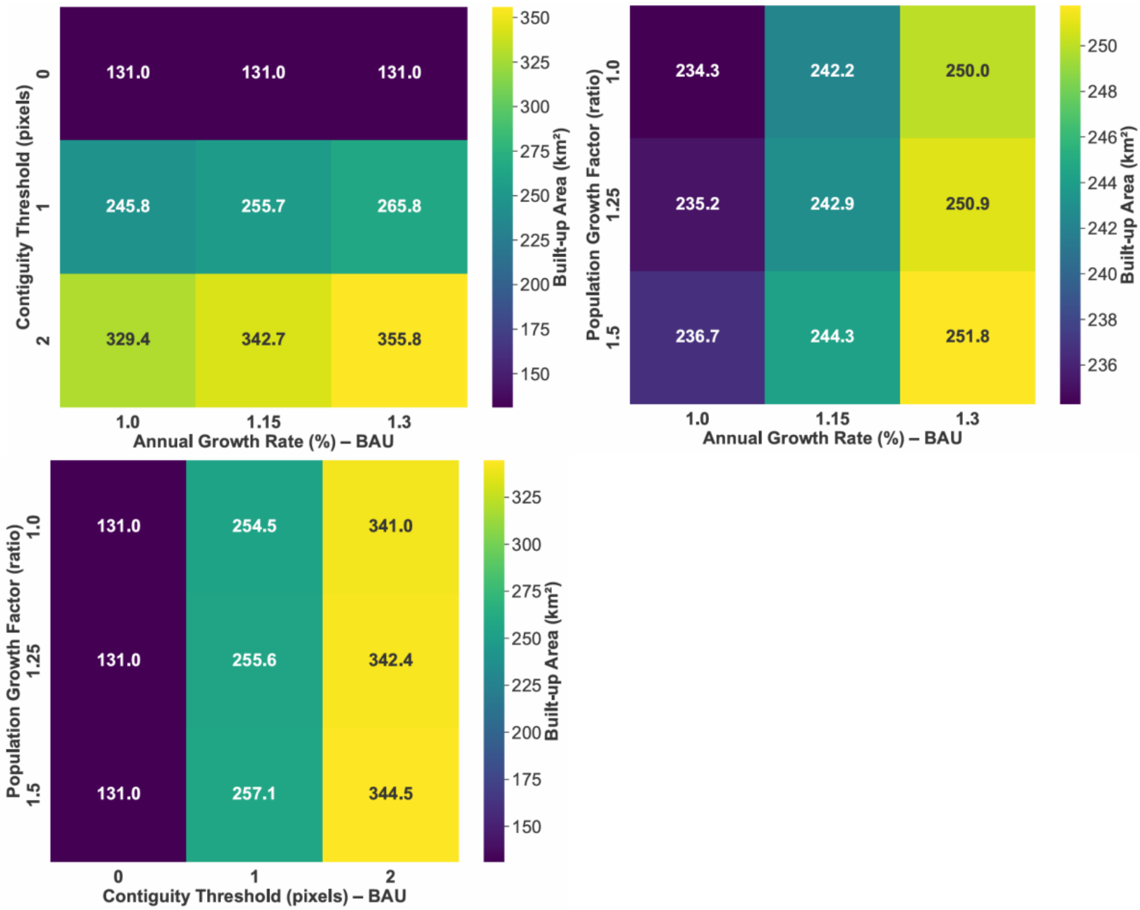


Figure 8.12. Sensitivity of built-up area expansion from 2024 to 2060 to key parameters under the BAU Scenario. Built-up area is most strongly driven by the contiguity of existing urban pixels, which amplifies the effects of demographic growth and spatial expansion rates; low contiguity limits urban propagation, whereas higher contiguity triggers substantial increases in built-up surfaces through enhanced parameter interactions.

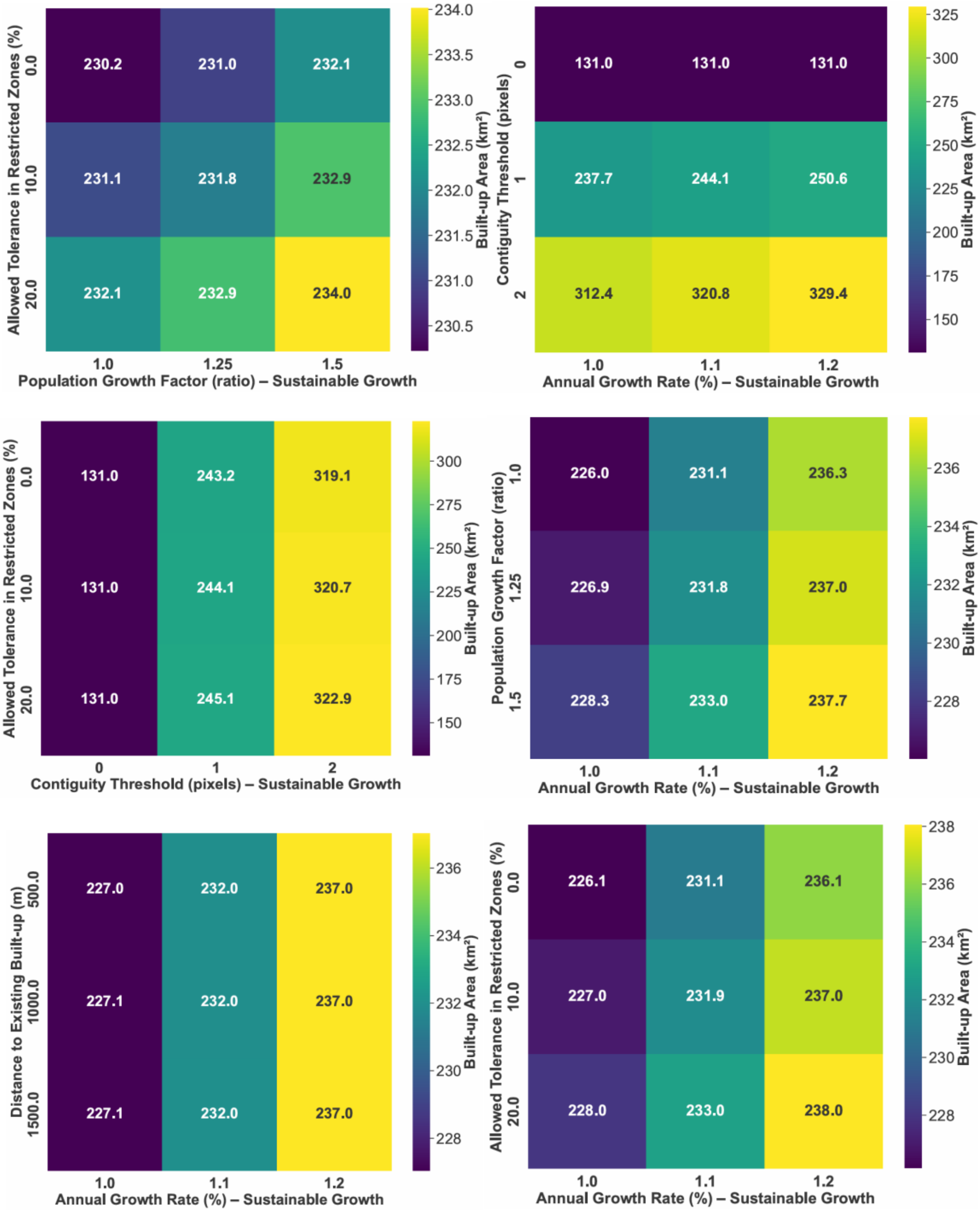


Figure 8.13. Sensitivity of built-up area expansion from 2024 to 2060 to key parameters under the Sustainable Growth Scenario.

8.8. Discussion

8.8.1. Methodological insights into urban growth modeling

The methodological framework employed in this study combines technical innovation with conceptual grounding, offering clear advantages over conventional land-use and land-cover change (LULCC) models. The use of a U-Net deep learning architecture (Ronneberger et al., 2015; Shojaei et al., 2022), trained on multi-temporal built-up data and supplemented with spatially explicit explanatory variables, enabled the model to capture both fine-scale spatial dependencies and broader contextual patterns of urbanization. Unlike classical CA models, which rely on transition rules, most of which defined in linear form and often fail to represent local heterogeneity in land use dynamics, often characterized by nonlinearity, complexity, emergence, and self-organization (Kamusoko & Gamba, 2015; Feng & Tong, 2018; Bhusal et al., 2024), deep learning architectures, such as U-Net, can directly learn complex spatial dependencies from data while preserving pixel-level detail in predictions (Bhusal et al., 2024). Several methodological refinements further enhanced model performance. The informed patch extraction strategy addressed class imbalance by ensuring adequate representation of change pixels, while the structuring of inputs into a multidimensional data cube integrated key drivers of urban growth, including density, accessibility, and topography, into the prediction process. These design choices increased robustness despite limited training data, and contributed to the model's reasonably good accuracy (FoM = 0.54)(García-Álvarez et al., 2022; Pontius et al., 2008). Nonetheless, limitations remain, notably the dependence on high-quality data and the difficulty of predicting rare or dispersed urban changes, which partially constrained sensitivity to fragmented dynamics.

A distinctive contribution of this study is the integration of scenario development under a choralogical framework. By contrasting a Business-as-Usual (BAU) pathway, a compact Sustainable Urbanization scenario, and a Hybrid Sustainable Growth scenario, the model moves beyond simple trend extrapolation to explore policy-relevant urban futures. Grounded in the recognition of land as a finite resource, choralogy offers a rationale for limiting sprawl and promoting compact, efficient, and ecologically sustainable development. The Sustainable Urbanization scenario enforces a strict 1 km threshold from existing built-up areas, combined with the full exclusion of urban green belts and waterways, demonstrating how spatial constraints can promote contiguous, sustainable urban growth. The Hybrid Sustainable Growth scenario, in contrast, adopts a more flexible approach, allowing expansion into a broader radius around existing built-up areas and incorporating local socio-economic factors, such as proximity to agricultural lands and road networks. This scenario reflects real-world pressures on land use while still partially preserving ecological and green spaces, offering a pragmatic balance between conservation and realistic urban expansion.

Together, these three scenarios illustrate the spectrum of possible urban futures in Kisangani, highlighting how choralogical principles can guide both strict and flexible strategies for sustainable land management and urban planning.

8.8.2. Urban growth dynamics under alternative scenarios

The comparison between the Business-as-Usual (BAU), Sustainable Growth, and Hybrid Sustainable Growth scenarios highlights contrasting patterns of urban expansion and land consumption in Kisangani. Under the BAU scenario, urban growth is widely dispersed, gradually encroaching into non-built areas, and producing numerous small, scattered patches that lead to pronounced urban sprawl. In contrast, the Sustainable Growth Scenario promotes densification around existing urban cores, preserves larger non-built patches, and consolidates the urban form over time, demonstrating the potential of strict spatial constraints to guide sustainable urban development. The Hybrid Sustainable Growth scenario exhibits an intermediate pattern between these two extremes. While built-up areas expand beyond the strict 1 km threshold of the Sustainable scenario, the expansion is more controlled than in BAU. Peripheral patches are moderately sized, and some green and non-built-up areas are partially preserved, reflecting both ecological concerns and local socio-economic pressures, such as proximity to agricultural lands and road networks. This scenario, therefore, represents a pragmatic balance between realistic urban growth and sustainable land management, capturing the influence of socio-spatial dynamics on urban expansion.

Linking these results to the United Nations Sustainable Development Goals (SDGs), the Sustainable and Hybrid scenarios contribute directly to SDG 11 on sustainable cities and communities, by promoting compact urban growth, preserving undeveloped land, and enhancing the efficiency and resilience of urban systems (United Nations, 2015b). The Hybrid scenario demonstrates how flexible, context-aware planning can achieve sustainability outcomes comparable to those under strict constraints while better reflecting local realities.

The compact city model has been widely recognized for its benefits in mitigating urban sprawl and promoting sustainable urban development. Dieleman & Wegener (2004) showed that policies encouraging higher urban densities can reduce the environmental pressures associated with dispersed urban growth. Building on sustainable urbanism theory, compact urban forms advocate higher densities, mixed land uses, and controlled expansion, thereby enhancing livability, resource efficiency, and urban resilience (Lehmann, 2016; Zapata Campos et al., 2022). In addition, compact forms can positively influence physical health and social interactions when higher densities are accompanied by mixed land uses, accessible public transport, limited car dependency, green spaces, and social equity (Mouratidis, 2019). However, in the African context, where cities experience rapid demographic growth and significant expansion of informal settlements, the strict compact city model faces limitations. These conditions necessitate an adaptive, hybrid approach that maintains the core advantages of compact urbanism while integrating peripheral areas through thoughtful spatial planning. The Hybrid scenario illustrates that such an approach can deliver environmental, social, and functional benefits without excluding urban fringes, making it better suited to the dynamic realities of African cities.

Applying sustainable urban development models in Congolese cities, particularly in Kisangani, requires addressing significant institutional and planning challenges. Urban areas in the Democratic Republic of Congo often face outdated or poorly implemented master plans, weak enforcement of urban planning regulations, and a lack of coordination among stakeholders (UN-Habitat, 2015; Useni et al., 2017; Sambieni, 2019; Balandi et al., 2023). In this context, compact city principles, higher densities, mixed land uses, and controlled expansion can only be practical if supported by institutional reforms and inclusive governance. State institutions, political actors, and local authorities play a critical role in updating and enforcing planning instruments, while academic researchers and urban professionals provide the evidence base and technical expertise to adapt these strategies to local conditions.

This contribution entails both producing reliable data and designing context-sensitive solutions. On one hand, spatial analyses of socio-economic surveys and environmental assessments reveal the actual dynamics of demographic growth and ecological pressures. On the other hand, technical expertise enables the translation of this knowledge into actionable instruments, such as updated master plans, sustainable mobility systems, land-use control mechanisms, and participatory planning approaches. By adopting a hybrid urban development model, Kisangani can combine the benefits of compact city principles, such as mixed land uses and controlled urban expansion, with the flexibility to accommodate peripheral areas and informal settlements. This approach ensures that urban planning is not purely theoretical but is tailored to the city's specific social, economic, and environmental challenges. The hybrid model may allow for sustainable urban growth that preserves livability, enhances resource efficiency, supports resilience, and maintains connectivity across urban, peri-urban, and rural zones.

For Kisangani, applying these models means not only limiting urban sprawl and ecological impacts (Balandi et al., 2023; Balandi et al., 2024; Balandi et al., 2025) but also ensuring that higher densities are coupled with investments in public transport, green spaces, and basic infrastructure. The Hybrid Sustainable Growth scenario demonstrates that practical, context-aware strategies can achieve these objectives even when strict spatial constraints are relaxed, allowing for moderate peripheral growth while preserving key ecological and socio-economic functions. Ultimately, the success of sustainable urbanization in Kisangani hinges on the collective commitment of policymakers, institutions, and the research community to translate theoretical models into actionable, locally adapted policies.

Notably, the sensitivity analysis highlights that even the two extreme scenarios, BAU and Sustainable Growth, are not rigid; their outcomes can vary significantly depending on local spatial configurations, demographic pressures, and parameter interactions. This nuance underscores that urban trajectories are context-dependent, and that scenario outcomes should be interpreted as flexible representations reflecting a range of plausible futures rather than fixed predictions.

8.9. Conclusion

This study investigated the dynamics of urban expansion in Kisangani, Democratic Republic of the Congo, by contrasting a Business-as-Usual (BAU) trajectory with two alternative pathways: a Sustainable Growth and a Hybrid Sustainable Growth scenario, both inspired by the discipline of Choralogy, which emphasizes the responsible management of land as a finite and vulnerable resource. Building on a combination of historical Landsat data, spatial explanatory variables, and a modified U-Net model, the analysis reveals that urban growth in Kisangani has historically followed an outward-sprawl pattern, with limited regard for planning instruments or ecological constraints.

Projections under the BAU scenario suggest this trend will continue, with a dispersed pattern of built-up pixels progressively encroaching on non-built areas, thereby intensifying environmental pressures at the urban fringe. In contrast, the Sustainable Growth Scenario spatially preserves non-built zones by promoting a more compact and contiguous form of urbanization. While total built-up area grows faster under BAU, the largest built-up patch expands more under the Sustainable Scenario, particularly after 2045, reflecting the consolidation of urban form through spatial constraints such as proximity thresholds and green belt exclusion zones. The Hybrid Sustainable Growth scenario demonstrates an intermediate yet insightful pattern. Although it allows some peripheral expansion beyond the strict 1km threshold of the Sustainable Growth, it maintains a relatively compact urban core while preserving key non-built areas, especially those aligned with ecological corridors and agricultural lands. This balanced outcome illustrates how moderate spatial constraints can reconcile development needs with land conservation, offering a more flexible and context-sensitive model of sustainable urban growth. The hybrid pathway thus reflects a realistic compromise between strict sustainability principles and the socio-economic dynamics that shape urban growth in rapidly developing contexts such as Kisangani.

Overall, these results highlight the potential of spatially explicit planning strategies to mitigate sprawl, enhance land-use efficiency, and preserve ecological functions along the urban-rural gradient. They also demonstrate that sustainability is not a binary outcome, but a spectrum, where adaptive and hybrid approaches may offer viable solutions in cities facing institutional and economic constraints.

Beyond its methodological framework, this research highlights the urgent need to re-examine urban planning practices in Kisangani and other Congolese cities. This can be operationalized through systematic audits of existing urban plans, GIS-based mapping to monitor urban expansion, participatory workshops with municipal authorities, community groups, and NGOs, and the development of prospective planning scenarios that assess environmental, social, and economic impacts. Based on these analyses, recommendations can be formulated to adjust zoning regulations, integrate green infrastructure, and enhance governance mechanisms, thereby ensuring urban planning is both adaptive and responsive to local realities.

Chapter 9

General discussion

9.1. Methodological approaches

The methodological approach adopted in this thesis integrates spatial analysis, remote sensing, and prospective modelling to capture the complexity of urban dynamics in Kisangani and their associated ecological impacts. The combination of these tools enabled the characterization, quantification, and anticipation of urbanization processes in a context of limited urban planning control. This section, therefore, outlines the main methodological choices that structure the scientific approach, from the processing and integration of satellite data to the simulation of urban expansion trajectories. It also highlights the innovations implemented to adapt existing approaches to the local realities of the Kisangani landscape, while underscoring their contribution to a better understanding of the spatial transformations observed along the urbanization gradient.

9.1.1. Processing and integration of satellite data: strengths and limitations

This thesis used a complementary approach to processing and integrating satellite data, relying on multiple data sources and scales of analysis. Combining images from multisource optical sensors (Sentinel-2, SPOT, Landsat, and MODIS) with field surveys and derived products, such as the Global Human Settlement Layer (GHSL) datasets from the Joint Research Center (European Commission, 2023), enabled the construction of a coherent analytical framework, both temporally and spatially. This multi-sensor approach provided a key methodological foundation for analyzing urban growth, the evolution of green infrastructure, the ecological integrity of forest landscapes, urban thermal dynamics, and the prospective simulation of Kisangani's expansion.

Landsat images, used consistently for nearly four decades, provided essential temporal continuity for tracking long-term changes in urban and forest landscapes. The surface reflectance products processed with the LEDAPS and LaSRC algorithms (Sayler & Zanter, 2021; Sayler & Zanter, 2023), minimised radiometric and atmospheric variations between sensors (Roy et al., 2016), thereby ensuring the comparability of the time series. Higher-resolution images, such as those from Sentinel-2 and SPOT, enabled finer discrimination of urban, peri-urban, and rural areas, strengthening the accuracy of analyses across the urbanization gradient and of the spatial pattern of Kisangani city. Finally, the use of MODIS data, despite its coarser spatial resolution (1000 m), proved particularly relevant for studying the urban heat island phenomenon due to the high acquisition frequency and stability of derived thermal products (Lu et al., 2018; Wan, 2013).

A robust set of field and validation data reinforced this multi-sensor integration. Across all studies conducted, more than 600 GPS records were collected within the urban centre of Kisangani, in its periphery (Masako and Mbiye), and in remote rural zones (Yoko and Yangambi), supporting validation of the classifications, while very-high-resolution images from PlanetScope and Google Earth enabled visual and spatial consistency checks. Demographic data from the National Institute of Statistics of Kisangani (INS, 2022), spatialized demographic data at 1-km resolution from GHSL

(European Commission, 2023), and topographic and morphological variables from the Shuttle Radar Topography Mission (SRTM) and ALOS World 3D enriched the spatial analysis. They helped relate observed dynamics to structural determinants of Kisangani's urban development.

Although the selection and integration of data were conducted rigorously, specific potential sources of uncertainty, inherent primarily to the nature and diversity of the datasets employed, deserve attention. These limitations mainly concern inter-sensor consistency and the quality of reference data and were addressed through specific procedures to mitigate their effects and preserve the robustness of the results. Radiometric and geometric differences between sensors were considered; the systematic use of surface reflectance products processed via the LEDAPS and LaSRC algorithms (Sayler & Zanter, 2021; Sayler & Zanter, 2023), ensured radiometric homogeneity and reduced inter-sensor discrepancies.

Limitations related to the quality and representativeness of reference data constitute another critical aspect. As emphasized by Foody (2013) and Olofsson et al. (2014), the reliability of classifications depends closely on the accuracy of the validation samples, their spatial distribution, and their alignment with the diversity of land-cover classes. In this thesis, such risks were mitigated through a balanced selection of reference points across the urbanization gradient: within the urban area of Kisangani, in peripheral zones (Masako and Mbiye), and in more remote rural areas (Yoko and Yangambi), thereby covering all identified landscape contexts. Moreover, comparison of our classifications with those produced at the global scale, such as the revised classification of Hansen (2013), strengthened the reliability of our results, as reflected by the high accuracies obtained (Table 5.4).

Nevertheless, in the supervised classifications, the most significant commission errors were observed for short forest in 1991 (18.39%) and agricultural and grassland in 2016 (19.59%), indicating an overestimation of these classes. These confusions likely result from spectral similarities between short forest formations and herbaceous or agricultural cover, as well as from heterogeneity in landscape mosaics. More limited commission errors were also observed for mature forest in 2021 (4.35%) and for built-up and bare soil areas (3.75%), suggesting a more pronounced distinction between these classes during classification. Regarding omission errors, the highest values were recorded for short forest in 1996 (14.99%) and for agricultural and grassland in 2006 (14.02%), indicating that a substantial proportion of pixels belonging to these classes was not correctly identified. These omissions reflect an under-representation of the relevant surfaces, often linked to internal spectral variability or mixing with other land-cover types. Lower omission errors were noted for built-up and bare soil areas in 1996 (6.18%) and for mature forest in 2016 (0.9%), indicating better detection of these classes on those dates. Overall, the observed commission and omission errors highlight the limitations in discriminating certain vegetation classes, particularly in ecological transition zones where spectral signatures frequently overlap.

It is also important to note that some of the global datasets used, particularly the GHSL products, rely partly on interpolation, which may introduce uncertainty in rapidly changing urban areas. To verify the reliability of these estimates, particularly those for building volume derived from GHSL, independent assessments were conducted using OpenStreetMap building footprints and AW3D30 (Digital Surface Model) and SRTM30 (Digital Terrain Model) data. The absence of statistically significant differences between the GHSL-derived estimates and those obtained through this comparative approach confirms the coherence and reliability of the GHSL data for Kisangani and supports their integration into spatial analyses.

Overall, the satellite data processing and integration approach adopted in this thesis demonstrates the value of combining multisensor spatial observations, field data, and globally derived products to analyze urban and environmental dynamics. By integrating the temporal continuity of Landsat series, the spatial precision of Sentinel-2 and SPOT, the temporal regularity of MODIS, and the descriptive richness of GHSL datasets, this strategy overcame the limitations inherent to each source. It enabled a coherent, robust, and reproducible interpretation of spatial transformations in Kisangani. Radiometric corrections, cross-validation against GPS field surveys, and comparisons of global datasets with local estimates helped control for potential biases and ensure the reliability of the results. This integrated approach thus provides a solid scientific foundation for understanding the interactions among urban expansion, the spatial patterns of natural and semi-natural components, and thermal dynamics, while offering a methodological framework that is transferable to other urban contexts.

9.1.2. Analysis of urbanization gradient zones: strengths and limitations

The definition and delimitation of urbanization gradient zones constitute a central methodological issue in studies of urban spatial dynamics. As highlighted by Angel et al. (2010) and Wolman et al. (2005), the main difficulty lies in defining precise, coherent boundaries for these zones. Administrative boundaries, often used in classical approaches, are inadequate in this context because they may be modified arbitrarily and frequently encompass heterogeneous territories where highly urbanized areas coexist with predominantly rural zones (Angel et al., 2010). Consequently, adopting an analytical framework based on morphological and functional criteria emerges as a more robust and representative alternative for capturing the spatial reality of rapidly expanding African cities. It is within this perspective that the classification method for urbanization gradient zones was applied, developed from the decision model of André et al. (2014), based on morphological characteristics, particularly density, dominance, and continuity of built-up areas (Salomon et al., 2022; Sambieni et al., 2019). The simplicity of implementation justifies this methodological choice, the model's reproducibility, and its ability to adapt to contexts characterized by complex landscape mosaics, such as that of Kisangani.

In this approach, the delimitation of urbanization gradient zones relies on a combination of morphological criteria applied at a supra-parcel scale (André et al., 2014). However, this thesis additionally incorporates population density, known to decrease globally from urban to rural areas (Angel et al., 2007; Clark, 1951) as an additional indicator to refine the understanding and classification of the gradient zones.

Thus, a zone is considered urban when it exhibits dominance and continuity of built-up areas, meaning that more than 50% of the pixels within the 250 m × 250 m grid cell are built-up, in an area where population density exceeds 100 inhabitants/km². This threshold corresponds to the minimum density observed in the zones contiguous to Kisangani's city center in 2020. A zone is classified as peri-urban when the proportion of built-up pixels is less than or equal to 50%, reflecting a fragmented, discontinuous structure, generally associated with human densities similar to or slightly below the urban threshold. Finally, a zone is considered rural when the 250 m × 250 m grid cell is dominated by vegetation, and population density remains below 100 inhabitants/km². This hierarchy, based on built-up dominance and population density, enables coherent characterization of spatial transitions between continuous urban fabrics, expanding mixed zones, and rural landscapes.

The relevance of the urbanization gradient as an analytical framework lies in its capacity to represent the continuity of spatial and functional transitions between the city and the countryside, whereas traditional zonal approaches often impose arbitrary discontinuities. It enables understanding of the city not as an isolated entity but as a spatial system that is gradually expanding and characterized by continuous interactions among urban, peri-urban, and rural components. In Kisangani, this gradient-based interpretation is particularly well-suited to describing the polycentric structure and pronounced spatial heterogeneity, in which dispersed settlements, agricultural spaces, and forest fragments coexist. It therefore provides a deeper understanding of the dynamics of urban expansion and their effects on the landscape's ecological and functional configuration.

However, the robustness of this approach depends on the quality and resolution of the data used. Morphological criteria can be difficult to apply consistently when image spatial resolution is insufficient to capture fine built-up discontinuities. In this dissertation, the use of high-resolution images from Sentinel-2 and SPOT sensors addressed this limitation by facilitating discrimination of built surfaces at the supra-parcel scale and improving classification accuracy. Furthermore, the availability of spatialized population data at 1-kilometer resolution contributed to refining the delineation of these zones. These methodological precautions ensured the reliability of the classification and minimized the risks of confusion between gradient zones.

Finally, scale effects and model transferability are essential elements for interpreting and generalizing the results. The thresholds of density or built-up dominance used to define gradient zones should not be considered universal: they depend closely on urban morphology, topographic conditions, and the level of urbanization formalization in each city. The approach proposed for Kisangani should therefore be regarded as an adaptable analytical framework rather than a fixed model.

Its value lies less in establishing absolute thresholds than in the conceptual and operational coherence it provides. By combining morphological and demographic criteria, this method offers a robust and transferable analytical framework that captures the complexity of urban-rural transitions and supports temporal and interurban comparisons in African contexts experiencing rapid urbanization.

9.1.3. Analysis of urban de-densification and the spatial pattern of green infrastructure components

Understanding urban de-densification traditionally relies on analyzing variations in population density over built-up surfaces (Angel et al., 2010; Cortinovis et al., 2022). In this thesis, this classical approach was adapted by developing spatial indices specifically designed to quantify urban de-densification in a context where detailed and accurate demographic data are limited. These indices are based on spatial characteristics often induced by urban de-densification. Indeed, classical methods highlight the phenomenon of decreasing density when the expansion of built-up areas exceeds population growth, reflecting the emergence of sparsely populated, dispersed (Angel et al., 2010; European Environment Agency, 2006) and hybrid areas known as peri-urban zones (Bogaert & Halleux, 2015). In other words, the emergence of peri-urban zones constitutes a spatial expression of urban de-densification. Thus, the ratio of peri-urban to urban zones and the peri-urban fraction (Equations 4.1 and 4.2) enable characterization of trends in urban de-densification in contexts where population censuses are unavailable, as is the case in most countries of the global south. These indices offer an indirect spatial insight into urban de-densification, independent of spatialized population data.

The analysis of the spatial pattern of green infrastructure components was conducted in parallel to characterize their composition and spatial configuration across the urbanization gradient. Two classical approaches are generally used to analyze spatial patterns along the urban-rural gradient: the transect-based approach extending from the urban center toward the periphery (Junxiang et al., 2013; Schneider et al., 2005), and the approach based on concentric buffer zones around the city center (Bamba et al., 2010; Seto & Fragkias, 2005; Useni et al., 2018). However, these methods have limitations in capturing the complexity and heterogeneity of urban landscapes, particularly in polycentric cities or those whose morphology is constrained by infrastructure and natural features. To overcome these limitations, this thesis adopted a randomized approach, using observation plots distributed in all directions around the urban center (north, south, east, west, and intermediate directions) to cover the three zones of the urbanization gradient. This method provides a more representative and nuanced interpretation of landscape pattern by accounting for spatial variability in all directions. Unlike approaches based on transects or concentric buffer zones, which prioritize radial progression and risk overlooking lateral contrasts, particularly those related to the orientation of road axes, topographic constraints, or local land use dynamics, the use of random plots ensures homogeneous, balanced coverage of the landscape. This spatial arrangement captures variations occurring perpendicular to urban growth axes, as well as short-distance discontinuities, which are often overlooked in classical approaches.

9.1.4. Modeling and simulation of urban trajectories: strengths and limitations

Prospective modeling of urban expansion represents a decisive step toward understanding possible landscape transformation trajectories and anticipating their environmental and functional implications. Traditionally, land-use change models rely on statistical approaches or cellular automata (CA), in which transitions between classes are governed by explicit rules calibrated from historical data (Kamusoko & Gamba, 2015; Pontius et al., 2008). These approaches have enabled significant progress in representing urban dynamics, but their ability to capture emerging complexity, non-linearity, and context-dependent variability in spatial processes remains limited (Bhusal et al., 2024; Feng & Tong, 2018). CA models exhibit significant sensitivity to the selection of indicators and parameters. These are often based on simplifying assumptions that fail to accurately reflect the morphological and socio-economic diversity of tropical cities.

In this context, the deep learning-based approach implemented in this thesis constitutes a methodological leap in urban modeling. Indeed, the use of a U-Net architecture adapted for land-use change prediction makes it possible to integrate both local dependencies (related to built-up configuration) and contextual influences (linked to local socio-economic realities) (Ronneberger et al., 2015; Shojaei et al., 2022). This approach provides a more realistic and dynamic representation of urbanization processes, particularly relevant in a context such as Kisangani, where urban growth unfolds in a heterogeneous and often unplanned manner (UN-Habitat, 2015). By combining explicit variables such as local urban density, road proximity, distance to agricultural areas, topography, and population density, the model captures the spatial-organization logic that underlies human settlement choices. This approach moves beyond a purely morphological understanding toward a functional interpretation of the drivers of urban expansion.

However, integrating a reflection grounded in choralogy beyond the technical dimension broadens the interpretative scope of urban simulation. Proposed by de Bogaert (Bogaert et al., 2015), choralogy, a term derived from the Greek words "chôra" (meaning space or territory) and "logos" (science), is proposed as the science of spaces, conceived not as mere areas to be occupied, but as environments that serve ecological functions, social values, and economic uses. It views territory as a system of cohabitation, in which each natural, built, or agricultural element contributes to a collective spatial organization subject to sustainability constraints. In other words, choralogy encourages considering land as a finite and fragile resource whose management must balance human pressures with the environment's ecological and functional capacities.

In urban modeling, this proposed discipline offers a relevant conceptual framework for linking expansion dynamics to principles of spatial coherence, compactness, and ecological continuity. The scenarios simulated in this dissertation, namely the Business-as-Usual (BAU) scenario, the Sustainable Growth scenario, and the Hybrid Sustainable Growth scenario, reflect this choralogical perspective in different ways. Thus, the BAU scenario, which extrapolates historical trends without spatial constraints, illustrates an unregulated trajectory in which land-use dynamics disregard territorial equilibria, leading to increased fragmentation and degradation of ecological continuities. In contrast, the sustainable growth scenario involves compact, contiguous urbanization strictly confined to a 1 km perimeter around existing built-up areas. This scenario completely excludes green belts from any conversion process. It prioritizes spatial cohesion and the preservation of landscape structures as foundations of territorial sustainability. However, its applicability in many African contexts remains limited, as rapidly growing cities, driven by strong demographic pressure, often face institutional constraints, weak enforcement capacities, and significant informal urban expansion, which can challenge the strict implementation of such controlled development frameworks.

The hybrid sustainable growth scenario provides a more contextualized translation of these principles. By allowing controlled development yearly within a 2-km radius around existing built-up areas and assigning a relatively high probability of urbanization to patches near agricultural zones and roads, this scenario integrates the socio-economic realities of Kisangani, particularly land-use pressure and dependence on road infrastructure, while maintaining minimal spatial continuity. Thus, chorology is not confined to a normative approach to planning; it offers an analytical framework that links urban morphology, socio-spatial interactions, and ecological sustainability. By anchoring growth scenarios in these principles, prospective modeling does more than predict where the city will expand; it also considers how that expansion occurs and the associated spatial costs. This approach paves the way for a holistic understanding of the territory, in which the city and its surroundings interact and evolve within a network of mutual dependencies.

Although the scenarios provide contrasted and coherent representations of potential urbanization trajectories in Kisangani, they remain simplifications of a complex reality. The Business-as-Usual (BAU) scenario, based on linear extrapolation of past trends, does not fully account for potential shifts induced by policy interventions, emerging socio-economic dynamics, or recent land-tenure changes. Yet, sensitivity analysis reveals that the model is not insensitive: the spatial configuration of existing built-up areas, particularly contiguity, strongly mediates the impact of demographic growth and annual spatial expansion rates. While these factors alone produce modest changes, their combined influence becomes pronounced in areas with higher contiguity, highlighting that even under BAU assumptions, local spatial structures can amplify urban expansion.

In the Sustainable Growth scenario, stringent spatial constraints, such as the 1-km buffer and green belt regulations, moderate overall expansion and reduce sensitivity. Nevertheless, contiguity remains a key driver, and its increase enhances the effects of demographic pressure, spatial growth, and tolerance parameters. This demonstrates that, even under restrictive planning, clustered built-up areas can facilitate further urbanization once critical spatial thresholds are reached. The Hybrid scenario, positioned between BAU and Sustainable Growth, integrates local realities more effectively but remains dependent on probabilistic and weighting assumptions, whose reliability hinges on the quality of input data and the stability of factors. Overall, these scenarios should be interpreted as exploratory representations rather than precise predictions. Notably, the sensitivity analysis nuances previous perceptions of model rigidity: it shows that urban expansion responds opportunistically to spatial and demographic conditions, revealing complex interactions that inform the potential for both peripheral growth and compact development under contrasting planning regimes.

9.2. Integrated discussion of the results

9.2.1. Validation of the hypotheses and coherence of the dynamics

The multi-temporal analysis conducted in Axis 1 of this thesis highlights a progressive transformation of the Kisangani landscape toward an increasingly urbanized configuration, reflecting a profound reorganization of the city's spatial and functional structures. Over time, Kisangani's urban space has expanded, encroaching upon peripheral fringes and giving rise to a mosaic of peri-urban zones whose morphology combines urban features with rural legacies. This evolution, observable between 1987 and 2021, reflects a dual process of expansion and spatial consolidation, in which phases of diffusion, marked by the emergence of new, isolated urban patches, alternate with phases of coalescence characterized by the merging of built-up cores. Furthermore, the temporal analysis of the trend toward de-densification observed in other cities (Angel et al., 2010), confirms that, in Kisangani, the overall trend (1987-2021) remains one of continuous densification of the urban fabric, despite a marked de-densification between 2010 and 2021. Thus, the observed persistent densification may partly explain the limited occurrence of de-densification patterns in Kisangani's urban areas.

Furthermore, this apparent paradox between continued densification and emerging de-densification can be better understood when considering the internal dynamics of a rapidly growing intermediate city such as Kisangani. The filling of interstitial spaces within the urban core suggests an ongoing process of consolidation, where vacant or underused plots are progressively occupied, thereby maintaining a global trend of densification. At the same time, the observed de-densification between 2010 and 2021 may reflect a relative redistribution of urban growth toward peripheral zones, including areas such as Mutumbe and Cimesta, where spatial expansion is more pronounced. These dual dynamic highlights a transitional urban phase, typical of cities that have not yet reached saturation.

However, the interpretation of densification and de-densification processes should be considered in light of the scope and nature of the indicators used. In this study, these spatial metrics effectively capture key dimensions of urban density such as the urban footprint (total contiguous built-up area of the city), the residential share (proportion of urban land allocated to residential use), and plot coverage (proportion of residential plots covered by buildings), which are directly observable from spatial data (Angel et al., 2021). By contrast, other important determinants of urban density, typically derived from census data and architectural information, are not directly accounted for. These include total population within the urban footprint, building height (average number of residential floors), floor plan efficiency (share of floor area used for living space), occupancy rate (share of housing units that are occupied), and persons per dwelling unit (Angel et al., 2021). As a result, while spatial indicators provide robust and consistent insights into the morphological evolution of the urban fabric, they represent only part of the broader set of processes shaping urban density. Nevertheless, in data-scarce contexts, these indicators remain indispensable proxies, playing a crucial role in understanding and interpreting densification and de-densification processes, and providing a consistent, operational basis for analyzing urban dynamics and informing planning decisions, particularly in rapidly growing cities such as Kisangani.

This dual process of densification and de-densification is accompanied by a significant degradation of green infrastructure components, reflecting the growing influence of urban and demographic dynamics on natural and semi-natural ecosystems. As built-up areas spread along the urbanization gradient, vegetative structures that previously ensured ecological and climatic regulation become increasingly fragmented and impoverished. The results relating to the dynamics of green infrastructure components, presented in Axis 2 of the thesis, show that between 1986 and 2021, Kisangani lost more than 47% of its mature forests, while degraded or secondary forests and agricultural lands expanded considerably, rising from 4% to more than 32% of the landscape. Along the urban-rural gradient, the distribution of green infrastructure components reveals considerable spatial heterogeneity. Mature forests remain highly fragmented in urban and peri-urban areas, where they cover less than 1% of the 2.25 km² plots, whereas in rural areas they exceed 35%. Short forests and agricultural lands, meanwhile, show extensive expansion in peri-urban and rural areas, indicating a decline of mature forest formations in favor of agricultural and herbaceous mosaics. This rapid shift reflects both demographic growth and the economic dependence of households on agriculture and fuelwood, the primary energy source for more than 90% of urban residents (Schure et al., 2013). This dynamic is common to many cities in sub-Saharan Africa (Diallo et al., 2020; Sambieni, 2019), is accompanied in Kisangani by particularly severe degradation of mature forests, once vast and continuous and now fragmented into isolated patches.

The intensification of these processes of artificialization has thus led to a progressive loss of ecological connectivity and an increase in edge effects in the peripheral forest landscapes of Kisangani, as revealed by the fragmentation and edge-effect analyses conducted in Axis 3 of this thesis. This fragmentation is both spatial and functional. Spatially, it manifests as a drastic reduction in contiguous forest areas, particularly in the Masako and Mbiye landscapes in the immediate vicinity of Kisangani's urban area. Analyses show that since 2016, forest patches in these two landscapes have practically lost their interior zones, with the interior-to-edge ratio (I/E) tending toward zero for all distances considered (50 m to 200 m). In other words, these forest fragments no longer possess a stable ecological core: the entire cover is exposed to edge effects, with altered ecological conditions. The observed forest fragmentation is not limited to a loss of area; it also disrupts spatial interactions among ecological mosaics. The multiplication of roads, scattered dwellings, and cultivated fields increases the discontinuity of the vegetative cover. This loss of connectivity is particularly concerning in Masako and Mbiye, where the relationship between forest patch size and edge-effect intensity is weak (low R^2). Surface temperature (LST) variations are therefore weakly correlated with fragment size, indicating that degradation has a deep impact on the remaining forest patches. This finding reveals a thermal homogenization of the forest landscape under anthropogenic influence, characterized by the predominance of border microclimates at the expense of stable interior conditions. Such exposure to edge effects is an indicator of advanced degradation: it undermines ecosystem functioning (Fahrig, 2009; Laurance et al., 2007) and disrupts the structure of faunal and floral communities (Dantas et al., 2016; Iyongo, 2013; Meniko et al., 2020). Under these conditions, the ecological resilience of the remaining fragments weakens, and their carbon sequestration capacity decreases, reducing the contribution of these forests to regional climate regulation.

In contrast, the Yangambi landscape retains a relatively intact structure: the low exposure of forests to edge effects, even 200 m from the border, indicates better ecological integrity, supported by coordinated management among research, conservation, and sustainable development stakeholders. This comparison highlights the dependence of ecological stability on institutional and community-based mechanisms of territorial governance.

The observed transformations in the components of urban green infrastructure and peripheral forest landscapes have directly affected Kisangani's urban microclimate, particularly by intensifying urban heat islands (UHIs). Between 2000 and 2024, the area covered by moderate UHIs ($0.1 < UHI < 0.2$) increased more than twofold, growing from 16 km² to 38 km², while the area covered by high UHIs ($0.2 < UHI \leq 0.3$) grew from 9 km² to 19 km². These results highlight the interconnectedness of urban dynamics, ecological degradation, and thermal regimes. The progressive disappearance of forests and the fragmentation of habitats not only compromise biodiversity and ecosystem resilience (Laurance et al., 2007), but also amplify microclimatic constraints, worsening urban living conditions (air quality, thermal comfort, public health) (Candra et al., 2016; Martínez et al., 2004).

9.2.2. Processes and explanatory mechanisms

The sequential urbanization dynamics observed in Kisangani, a model described by Dietzel et al. (2005), correspond to a model of urbanization occurring in successive waves rather than through simultaneous growth, as observed in other urban contexts. Unlike Lubumbashi, where diffusion and coalescence coexist (Useni et al., 2018), Kisangani exhibits temporally differentiated phases. In Kisangani, this alternation between diffusion and coalescence appears to stem from local drivers.

It should be noted that, historically, Kisangani's urban expansion was initially influenced by the Catholic Church's missionary strategy, which favored establishing religious sites at considerable distances from inhabited urban cores (V. Mbatu, personal communication, April 2023). These missions, which gradually became service and settlement hubs, contributed to the emergence of new peripheral centralities. In parallel, the location of major parastatal enterprises, particularly the Kisangani Textile Company, Bralima, SNCC, and the National Electricity Company, helped structure the development of satellite residential neighborhoods around their industrial sites. This sectoral distribution explains the dispersed built-up patches observed in historical imagery, notably in 1987 imagery.

Furthermore, periods of political instability and armed conflict between 1990 and 2000 (Koluwa, 2020), also reshaped the city's trajectory. Peripheral areas, which became refuge zones, experienced rapid densification, while post-conflict economic recovery encouraged private-sector investment in interstitial areas, initiating a phase of urban aggregation. From a demographic perspective, Kisangani's urban expansion reflects a continental trend of rapid urban population growth. As in many sub-Saharan African cities, large-scale rural-urban migration, driven by the economic opportunities and better living conditions, exerts sustained pressure on urban land (Canning et al., 2016; Mercandalli & Losch, 2018). Central areas, particularly the commune of Makiso, concentrate most administrative, economic, and logistical functions, exerting a substantial pull on populations and activities. This concentration, also observed in major Congolese cities such as Kinshasa and Lubumbashi (Delbart & Wolff, 2002; Useni et al., 2018), illustrates the persistence of functional centralization inherited from colonial and postcolonial administrative structures.

However, precarious socio-economic conditions and the high cost of housing in central communes often push large segments of the population toward peripheral, still-rural margins where land remains more accessible (Useni et al., 2018). The result is diffuse, often unplanned urbanization characterized by discontinuous extensions and low-density built forms, consistent with the European Environment Agency's observations on non-compact urban forms (European Environment Agency, 2006). In Kisangani, this mode of urban expansion is also explained by the weakness of planning instruments and urban governance and is strongly shaped by underlying socio-spatial and land tenure dynamics. This is reflected in a duality of land access systems, where formal regulatory frameworks coexist with informal and customary arrangements that govern a large share of urban land transactions (Monga Ngonga et al., 2020). This duality fuels competition for space, as land acquisition is driven simultaneously by official procedures and by negotiated or customary practices, often lacking clear coordination. Rapid demographic growth sustained rural-urban migration, and household fragmentation further intensified demand for residential plots, while land is increasingly perceived as both a social necessity and a secure economic asset, encouraging early occupation and speculative holding of available land. These dynamics are particularly pronounced in peripheral areas, where weaker institutional control facilitates informal expansion, but they also extend toward central zones under strong socio-economic pressure. Combined with weak enforcement of urban planning regulations and persistent governance gaps, this land tenure duality emerges as a key driver shaping both densification and spatial expansion processes observed in Kisangani. The repeated failure to implement the 1978, 2008, and 2010 development plans (UN-Habitat, 2015), combined with insufficient institutional control over land, has favored spontaneous urbanization, often occurring outside any regulatory framework. This governance deficit has led to fragmentation of the urban space, a progressive loss of natural and semi-natural ecosystems, and a decline in landscape coherence.

The emergence of dense architectural configurations, particularly in the city center, where hotels and commercial complexes are being developed, creates an “urban canyon” effect (Arnfield, 2003), trapping heat, limiting ventilation, and promoting nocturnal thermal retention (Oke, 2002; Stewart & Oke, 2012). This spatial configuration, combined with the drastic reduction in vegetative cover, reflects a negative synergy between artificialization and the degradation of ecological functions and services. Consequently, these factors drive a gradual increase in surface temperatures. The growing correlation between Building Volume Density (BVD) and surface temperature demonstrates the amplifying role of urban morphology.

Beyond the urban core of Kisangani, the conversion of forests and agricultural zones into bare or built-up land in peri-urban areas reduces evapotranspiration capacity and locally amplifies warming. This process generates thermal gradients that extend toward rural areas through convection (Omidvar et al., 2020; Zhang et al., 2022), indicating a peripheral expansion of the heat island phenomenon in Kisangani. Thermal intensification in Kisangani is therefore not solely due to dense urbanization but results from a continuous chain of thermal disturbances along the urban-rural gradient, directly linked to landscape fragmentation and vegetation loss.

Given this dual ecological and thermal vulnerability, urban planning must integrate the restoration and protection of green infrastructure as central levers for adaptation. The establishment of vegetated buffer zones between built-up cores and forest fragments, as well as the creation of ecological corridors connecting urban, peri-urban, and rural zones, can mitigate edge effects and restore ecological continuity. These strategies are modeled and simulated in this thesis through three distinct scenarios.

9.2.3. Urban futures of Kisangani: scenarios and trajectories

The previous section highlighted the extent of ecological degradation and microclimatic disturbances generated by the rapid artificialization of the Kisangani landscape. Unplanned urban expansion has fragmented landscape continuities, accelerated the loss of vegetated surfaces, and consequently intensified thermal contrasts across the urbanization gradient, revealing increasing vulnerability within Kisangani’s socio-ecological system. These disruptions highlight the importance of prospective modeling as a tool for predicting future trends and identifying ways to make urban growth more sustainable. The analysis of urban development scenarios for Kisangani by 2060 thus enables the integration of current expansion dynamics with ecological and climatic resilience requirements while accounting for context-specific local constraints.

This forward-looking approach enabled assessment of the potential trajectories of Kisangani’s urban landscape under three contrasting scenarios: Business-as-Usual (BAU) (Morales et al., 2025; Tang et al., 2024), Sustainable Growth, and Hybrid Sustainable Growth. These simulations highlight profoundly different patterns of spatial growth, reflecting land-use logics with distinct ecological and socio-economic implications. Under the BAU scenario, urban growth remains largely diffuse and poorly controlled. Built-up areas expand in a fragmented manner across the periphery, gradually encroaching on undeveloped lands and generating a mosaic of small, dispersed patches. This type of expansion intensifies the consumption of agricultural and forested lands, multiplies ecological discontinuities, and promotes the proliferation of areas with high thermal exposure (Dwivedi & Khire, 2018; Jato-espino, 2019). The spatial configuration resulting from this scenario reproduces current trends of sprawl and fragmentation, with cumulative effects on ecological connectivity and urban thermal comfort.

Conversely, the Sustainable Growth scenario prioritizes compact urbanization, based on densification around existing cores and the preservation of extensive undeveloped areas. This spatial configuration tends to consolidate the urban form and reduce pressure on natural spaces. Peripheral green and agricultural areas are better preserved, and that may enable ecological continuity and more effective microclimatic regulation. This scenario illustrates the potential of rigorous urban planning to steer spatial development toward more sustainable forms, consistent with ecological resilience and the reduction of urban heat islands.

The Hybrid Sustainable Growth scenario represents an intermediate position between the two previous ones. Although built-up expansion exceeds the strict thresholds of the sustainable scenario, it remains more controlled than in the BAU. Peripheral areas retain undeveloped fragments of varying ecological value, and urban extensions are organized along structural axes linked to road networks and agricultural zones. This scenario reflects a realistic compromise between urban growth imperatives and the preservation of ecological functions, integrating local socio-economic constraints, particularly land pressure, the need for land access, and proximity to agricultural activities. From this perspective, the hybrid scenario appears as a pragmatic pathway for Kisangani: it shows that more sustainable forms of urbanization can be achieved without resorting to absolute restrictions, provided that development is guided by integrated spatial planning. This model aligns with the principles of compact urban development, widely recognized in the scientific literature for their capacity to limit urban sprawl and enhance urban resilience. By promoting functional diversity, controlled density, and rational land use, compact development optimizes infrastructure, reduces energy costs, and improves the quality of the living environment (Dieleman & Wegener, 2004; Lehmann, 2016; Zapata Campos et al., 2022). Moreover, it directly contributes to achieving the Sustainable Development Goals (SDGs), particularly SDG 11 on sustainable cities and communities, by promoting balanced and inclusive growth models (United Nations, 2015).

However, applying these prospective scenarios in the Congolese context, particularly in Kisangani, raises significant institutional and governance challenges. Existing urban plans are often outdated or poorly enforced, and coordination among public, private, and community actors remains insufficient (Monga Ngonga et al., 2020; UN-Habitat, 2015). In this framework, hybrid city models can deliver their intended outcomes only if accompanied by institutional reform, strengthened territorial governance, and enhanced participation by local stakeholders. State and municipal institutions must update planning instruments and ensure their enforcement, while researchers, urban planners, and civil society actors contribute the knowledge and tools needed to design solutions adapted to local realities. The success of this transition, therefore, depends on the capacity to translate scientific knowledge into operational instruments that integrate spatial data, technical expertise, and inclusive decision-making processes. On the one hand, environmental and socio-economic analyses help elucidate pressures on natural resources and growth dynamics; on the other hand, integrating these analyses into revised planning schemes, sustainable mobility systems, land-use control mechanisms, and participatory planning approaches ensures their effective implementation.

Thus, the hybrid scenario is not limited to a morphological compromise between compactness and expansion: it opens the way toward an ecosystem-based approach to urban development, in which the restoration of ecological continuities, density management, and thermal regulation become the foundations of a sustainable spatial and climatic equilibrium. This vision invites a rethinking of the city not merely as a space of growth, but as a living system capable of integrating production, mobility, housing, and the environment within a dynamic of co-evolution.

9.3. Theoretical, methodological, and practical implications

Beyond the specific results obtained, this thesis presents several significant implications for the understanding, analysis, and management of urban dynamics in rapidly expanding tropical cities. It primarily offers an integrated interpretation of the spatial, ecological, and microclimatic transformations associated with urbanization by articulating remote sensing, landscape ecology, and prospective modeling within a systemic framework. This interdisciplinary approach contributes to a better understanding of the complex interactions between urban expansion, ecological degradation, and thermal alteration. It opens the way to a renewed interpretation of trajectories of artificialization in tropical contexts. Theoretically, it enriches scientific reflection on territorial sustainability by highlighting the need to articulate spatial, environmental, and social dimensions within a single analytical system.

From a methodological perspective, the thesis proposes several noteworthy advances. It integrates population density as a complementary variable in delineating and mapping the urbanization gradient, alongside morphological criteria. This approach enhances the distinction between urban, peri-urban, and rural areas by capturing the decline in density from the urban core to the peripheries and providing a more representative account of the city's spatial structure. The thesis also develops original spatial indices, such as the peri-urban/urban ratio and the peri-urban fraction, that allow quantification of urban de-densification through spatial analysis, even in the absence of precise demographic data. These indicators thus provide a direct and reproducible interpretation of built-up dispersion dynamics. Furthermore, the analysis of landscape spatial patterns relies on a random-sampling framework that spans the entire urbanization gradient. This methodological choice enables better capture of local discontinuities, lateral variations, and the spatial heterogeneity of urban and peri-urban landscapes, leading to a finer and more realistic representation of landscape structures. Finally, the thesis introduces an original integration of prospective modeling within a reflection inspired by choralogy. The simulation of three contrasting scenarios, Business-as-Usual, sustainable, and hybrid, makes it possible to explore differentiated urban trajectories according to territorial and ecological constraints.

On a practical level, the research provides valuable insights for urban planning and sustainable management of tropical territories. The simulated scenarios serve as decision-support tools that enable the anticipation of the effects of urban expansion on ecological structures and guide spatial planning policies. The sustainable urbanization scenario, by promoting compact, space-efficient growth, demonstrates the feasibility of a balanced approach to managing development and environmental preservation. The hybrid scenario, more flexible and grounded in local realities, offers a realistic alternative reconciling socio-economic imperatives with the partial conservation of green infrastructure. Together, these theoretical, methodological, and practical contributions strengthen analytical and operational capacities to address the challenges of tropical urbanization and provide a scientific framework that is transferable to other urban contexts experiencing similar dynamics.

Chapter 10

General conclusion and perspectives

10.1. General conclusion

This thesis pursued a dual objective: on the one hand, to deepen understanding of the spatial, ecological, and microclimatic transformations induced by urban growth in Kisangani; and, on the other hand, to assess urban development models that support more sustainable urbanization in Kisangani. To address this dual purpose, the thesis was structured around five complementary axes forming an integrated approach. The first axis aimed to quantify and characterize the city's spatial growth to determine whether it follows a process of urban dedensification, as observed in most cities globally, and to assess its implications for the landscape's spatial pattern. The second axis examined the effects of this expansion on the composition and configuration of green infrastructure by identifying differentiated dynamics across urban, peri-urban, and rural zones. The third axis focused on forest fragmentation and edge effects to measure how the reduction and discontinuity of forest patches alter microclimatic balances in the peripheral forested landscapes of Kisangani. The fourth axis explored the dynamics of urban heat islands through a spatiotemporal analysis of land surface temperature and the interactions between building volume density, vegetation cover, and urban expansion. Finally, the fifth axis enabled the modeling of prospective trajectories of urban growth under three scenarios, Business-as-Usual, Sustainable Growth, and Hybrid Sustainable Growth, to evaluate planning options most favorable to environmental sustainability and spatial coherence in the urban development of Kisangani.

Within this framework, the diachronic analysis of Kisangani's spatial dynamics first revealed a particularly rapid urban and peri-urban expansion over the past three decades. Between 1987 and 2021, the urban core expanded from 13.49 km² to 100.49 km², representing a more than sevenfold increase in urban area and corresponding to an average annual growth rate of 8.2%. This evolution reflects a dual process of spatial expansion and consolidation, in which phases of diffusion, marked by the emergence of new isolated urban patches, alternate with phases of coalescence. The temporal analysis of urban de-densification suggests that, despite significant peri-urbanization between 2010 and 2021, the overall trend in Kisangani appears to remain one of persistent densification, which may currently limit the extent of urban de-densification. In contrast to the de-densification observed in other cities, this pattern may indicate the particularity of Kisangani's spatial structure, potentially influenced by land constraints, patterns of spontaneous settlement, and the limited effectiveness of spatial planning and regulation. However, the interpretation of densification and de-densification processes should be considered in light of the scope and nature of the indicators used, as they are derived primarily from indirect spatial indicators due to the lack of demographic data.

The observed spatial expansion was accompanied by profound transformations in green infrastructure components across the urbanization gradient, reflecting the growing influence of urban and demographic dynamics on natural and semi-natural ecosystems. The results show that between 1986 and 2021, Kisangani lost more than 47% of its mature forests, while degraded or secondary forests and agricultural land expanded substantially, increasing from 4% to over 32% of the landscape. This rapid transformation reflects both demographic growth and the population's economic dependence on agriculture and fuelwood, the primary energy source for more than 90% of Kisangani's urban population.

These trends are also expressed through the dynamics of forest fragmentation in the peripheral landscapes of Kisangani, particularly within the forest complexes of Masako, Mbiye, Yoko, and Yangambi. Spatially, this fragmentation has led to a drastic reduction in the number of contiguous forest patches, particularly in the Masako and Mbiye landscapes near Kisangani's urban area. Analyses show that since 2016, the forest patches in these two landscapes have almost completely lost their interior zones, with the interior/edge ratio (I/E) approaching zero for all ecological distances (50 m to 200 m). In other words, these forest fragments no longer possess a stable ecological core: the entire cover is exposed to edge effects, with altered ecological conditions. This forest fragmentation has also led to a decline in connectivity between ecological mosaics, which is particularly concerning in Masako and Mbiye, where the relationship between patch size and edge-effect intensity is weak (low R^2). Variations in land surface temperature (LST) are therefore only weakly correlated with patch size, indicating that degradation has a deep impact on the remaining forest fragments. This finding reveals a thermal homogenization of the forest landscape under anthropogenic influence, characterized by the predominance of edge microclimates over stable interior conditions. In contrast, the Yangambi landscape retains a relatively stable ecological structure, demonstrating that integrated and coordinated management can preserve the ecological resilience of peri-urban and rural landscapes.

These transformations observed in urban green infrastructure components and peripheral forested landscapes have had direct repercussions on Kisangani's urban microclimate, particularly by intensifying Urban Heat Islands (UHI). Between 2000 and 2024, the extent of moderate UHI ($0.1 < UHI < 0.2$) more than doubled, increasing from 16 km² to 38 km², while high UHI ($0.2 < UHI \leq 0.3$) expanded from 9 km² to 19 km² (Figure 7.5). These trends reveal a gradual increase in land surface temperature linked to the progression of land artificialization and the densification of built-up areas. The growing correlation between Building Volume Density (BVD) and land surface temperature confirms the cumulative effect of urban morphology on local thermal regimes.

The results thus highlight the interdependence between urban dynamics, ecological degradation, and local thermal regimes in Kisangani. Confronted with this dual ecological and thermal vulnerability, prospective modeling has emerged as an essential tool for anticipating future trajectories and identifying leverage points to reorient Kisangani's urban growth towards more sustainable forms. Accordingly, the potential evolution of Kisangani's urban landscape was assessed under three scenarios: Business-as-usual (BAU), sustainable growth, and hybrid sustainable growth. These simulations revealed deeply contrasting spatial growth patterns, reflecting land-use logics with distinct ecological and socio-economic implications. Under the BAU scenario, urban growth remains largely diffuse and uncontrolled. Built-up areas expand in a fragmented manner along the periphery, progressively encroaching on non-built spaces and generating a mosaic of small, scattered patches. The Sustainable Growth scenario favors compact urbanization through densification around existing cores and the preservation of large undeveloped areas. This spatial configuration tends to consolidate the urban form and reduce pressure on natural spaces. Peripheral green and agricultural areas are better preserved. This scenario illustrates the potential of rigorous urban planning to guide spatial development toward more sustainable forms. The Hybrid Sustainable Growth scenario lies midway between the two preceding ones. Although built-up expansion exceeds the strict thresholds of the sustainable scenario, it remains more controlled than in the BAU scenario. Peripheral areas retain non-built fragments of varying ecological importance, and urban extensions are organized along structuring axes connected to road networks and agricultural areas. This scenario represents a realistic compromise between urban growth imperatives and the preservation of ecological functions, integrating local socio-economic constraints, notably land pressure, access-to-land needs, and the proximity of agricultural activities.

Notably, the sensitivity analysis highlights that even the two extreme scenarios, BAU and Sustainable Growth, are not rigid; their outcomes can vary significantly depending on local spatial configurations, demographic pressures, and parameter interactions. This nuance underscores that urban trajectories are context-dependent and that scenario outcomes should be interpreted as flexible representations reflecting a range of plausible futures rather than fixed predictions.

Beyond these results, the thesis provides several significant conceptual and methodological contributions. Theoretically, it renews the understanding of tropical urban dynamics by situating them within a systemic perspective in which space, nature, and the urban climate interact closely. It also applies the notion of choralogy to urban modeling, using it as an integrative framework to rethink spatial interactions across territorial scales. Methodologically, the research innovates by developing urban dedensification indices (such as the peri-urban/urban ratio and the peri-urban fraction) and by integrating population density into the mapping of the urbanization gradient, thus offering relevant tools for understanding spatial dynamics.

In practice, this thesis highlights the need for renewed territorial governance grounded in integrated spatial planning and improved coordination among public, private, and community actors. The success of compact or hybrid city models depends on effectively updating urban plans, strengthening institutional capacities, and fostering local ownership of spatial decision-support tools. The results demonstrate that urban sustainability cannot be achieved without a close articulation between scientific knowledge, operational planning, and participatory governance.

10.2.Recommendations

For decision-makers, urban governance should prioritize a phased and strategic approach to integrated spatial planning that incorporates lessons from urban expansion and the loss of green space. In the short term, the Hybrid Sustainable Growth scenario should be adopted as a reference framework to guide immediate policy actions. This includes updating zoning regulations to better control urban expansion, identifying and protecting critical peri-urban agricultural and green areas, strengthening inter-agency coordination, and introducing rapid monitoring tools based on key indicators such as vegetation cover and urban density. In the medium term, efforts should focus on consolidating these measures by developing ecological corridors, strengthening institutional capacities, and implementing adaptive planning approaches that respond to evolving urban dynamics. In the long term, the objective should be to institutionalize a flexible and sustainable urban planning model that ensures territorial resilience while maintaining a balance between socio-economic development and ecological preservation.

For local stakeholders and communities, active engagement in urban planning and green space management should be encouraged through a progressive timeline. In the short term, communities should be mobilized to participate in participatory zoning processes, urban gardening projects, and tree planting initiatives, while awareness campaigns highlight the importance of green spaces for urban resilience. In the medium term, these efforts should evolve into more structured programs supporting sustainable peri-urban agriculture, backed by training, incentives, and collaboration with local NGOs. Community-based management of green spaces should also be strengthened to ensure continuity and effectiveness. In the long term, the goal is to foster strong local ownership and long-term stewardship of urban ecosystems, enabling communities to play a central role in sustaining socio-ecological balance and embedding a lasting culture of environmental responsibility.

For scientists and researchers, a similar phased approach is essential to ensure that knowledge production effectively supports sustainable urban development. In the short term, research should expand beyond forested peripheries to include urban cores and peri-urban areas, focusing on urban morphology, microclimatic conditions, and human well-being, and establishing monitoring systems for urban heat islands and vegetation dynamics. In the medium term, efforts should concentrate on developing and refining decision-support tools, such as dedensification indices and integrated urban gradients, while strengthening collaboration with policymakers and local communities to ensure that scientific outputs are actionable and relevant. In the long term (8-20 years), research should contribute to the development of integrated urban modeling systems and long-term socio-environmental monitoring frameworks, ultimately positioning science as a central pillar of adaptive, evidence-based urban governance.

10.3.Perspectives

The identified limitations open several ways for future research. Indeed, it would be relevant to deepen the analysis of the interactions among urban morphology, quality of life, and climate vulnerability by integrating detailed socio-economic indicators and mobility data. Moreover, developing participatory modeling tools that engage local stakeholders in scenario simulations would strengthen the research's operational and transformative dimensions. Finally, comparing Kisangani's urban trajectories with those of other tropical cities in Central Africa would provide a solid basis for assessing the transferability of the urban models.

In addition to these directions, future research would greatly benefit from the increasing availability of radar remote sensing data, particularly Synthetic Aperture Radar (SAR), which offers significant advantages for both urban and environmental studies. Unlike optical imagery, radar data enables consistent monitoring regardless of cloud cover, which is particularly valuable in tropical regions. Importantly, its capacity to capture three-dimensional structural information enables more detailed characterization of urban morphology, including building height, vertical density, and spatial compactness, thereby improving understanding of densification and vertical growth processes within cities. In parallel, radar-based approaches also provide powerful tools for analyzing surrounding forest ecosystems, as they can estimate forest structure, biomass, and canopy height dynamics. This dual applicability makes radar data especially relevant for studying coupled urban-forest systems, such as those surrounding Kisangani, where urban expansion and forest degradation are tightly interconnected. By integrating radar-derived 3D information, future studies could therefore better capture the vertical dimension of both urban growth and forest dynamics, leading to more comprehensive assessments of land-use change and environmental sustainability.

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Appendix

Appendix

Appendix 1. Scientific publications produced during the PhD: 2022–2025

1. **Balandi, J. B.,** Meniko, J.-P. P. T. H., Sambieni, K. R., Sikuzani, Y. U., Bastin, J.-F., Musavandalo, C. M., Besisa, T.N., Elangilangi, J. M., Selemani, T. M., Mweru, J. M., & Bogaert, J. (2023). Urban Sprawl and Changes in Landscape Patterns: The Case of Kisangani City and Its Periphery (DR Congo). Land 2023, 12(11), 2066: https://doi.org/10.3390/land12112066
   This article belongs to the Special Issue **Recent Progress in Urbanisation Dynamics Research II**
2. **Balandi, J. B.,** Meniko, J.-P. P. T. H., Sambieni, K. R., Sikuzani, Y. U., Bastin, J.-F., Musavandalo, C. M., Besisa, T.N., Jesuka, R., Sodalo, C., Mukubu, L.P., & Bogaert, J. (2023). Anthropogenic Effects on Green Infrastructure Spatial Patterns in Kisangani City and Its Urban–Rural Gradient (DR Congo). Land 2024, 13(11), 1794 : https://doi.org/10.3390/land13111794
   This article belongs to the Special Issue **Managing Urban Green Infrastructure and Ecosystem Services**
3. **Balandi, J. B.,** Selemani, T. M., Meniko, J.-P. P. T. H., Sambieni, K. R., Sikuzani, Y. U., Bastin, J.-F., Tshomba, P. W., Elangilangi, J. M., Mobunda, J.T., Agassounon, B.M., & Bogaert, J. (2025). Spatiotemporal analysis of urban heat islands in Kisangani city using MODIS imagery: exploring interactions with urban-rural gradient, building volume density, and vegetation effects. Climate 2025, 13(5), 89: https://doi.org/10.3390/cli13050089
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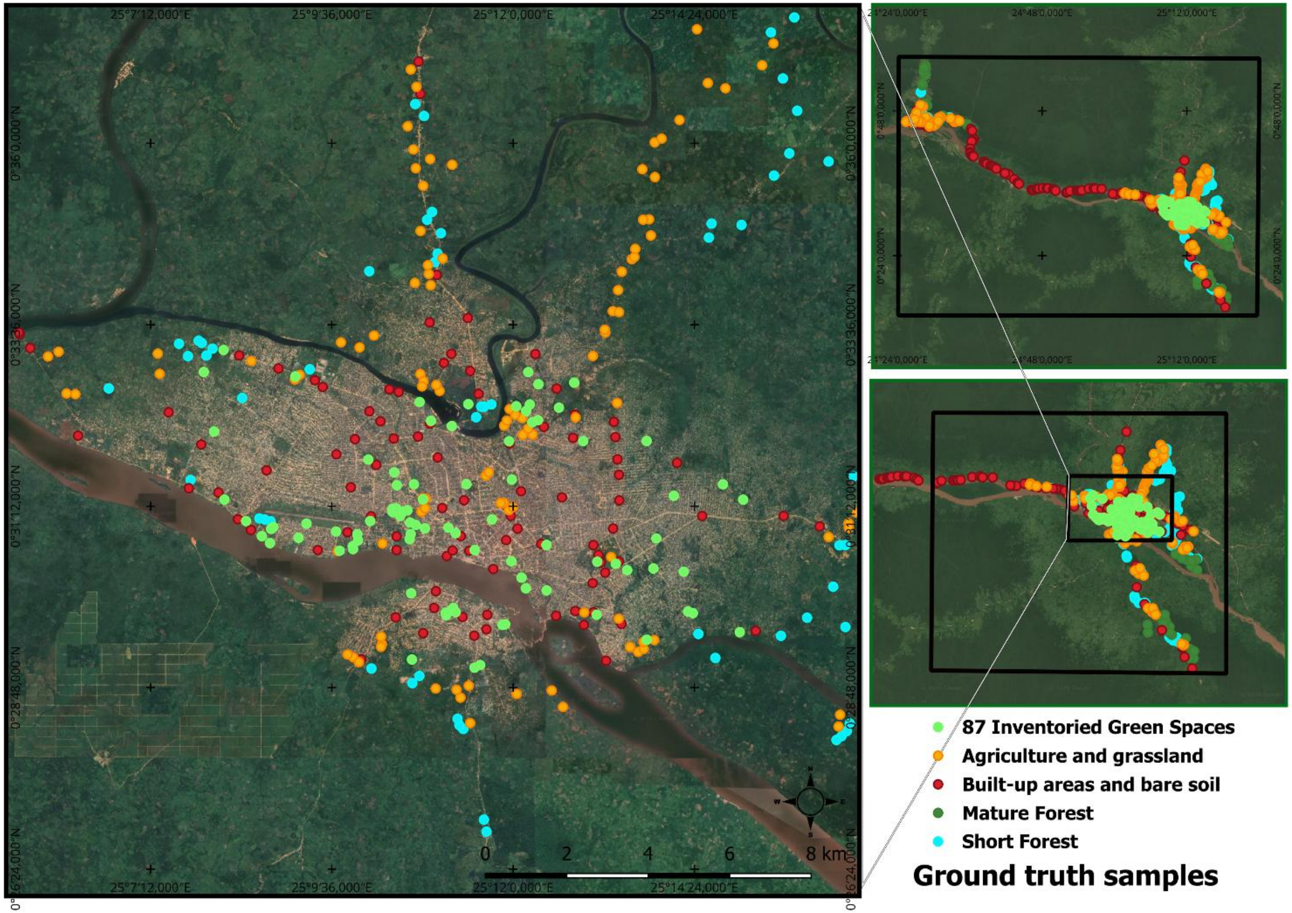
Appendix 2. The validation of land cover classifications. HAL corresponds to the Human-Altered Landscape; UA is the user's accuracy; PA is the producer accuracy; OGV corresponds to the Old-Growth Vegetation; WS is the water surface; OA is the overall accuracy.

Yangambi									
HAL	**1986**	**1991**	**1996**	**2001**	**2006**	**2011**	**2016**	**2021**	**2024**
UA	99.5	99.9	99.8	98.2	99.6	99.8	100	100	99.9
PA	99.4	98.2	99.6	99.1	99.5	99.7	99.2	96.5	97.9
OGV	**1986**	**1991**	**1996**	**2001**	**2006**	**2011**	**2016**	**2021**	**2024**
UA	98.9	89.7	98.6	99.7	93.2	91.3	99.8	99.6	99.3
PA	97.8	83.8	84.2	95.2	91.7	88.1	95.3	84.9	98.3
WS	**1986**	**1991**	**1996**	**2001**	**2006**	**2011**	**2016**	**2021**	**2024**
UA	100	100	100	100	100	99.8	100	100	100
PA	100	99.8	100	99.9	100	99.7	100	99.9	99.8
OA	99.4	96.3	97.4	98.8	98.7	98.1	98.2	96.1	97.1
Yoko									
HAL	**1986**	**1991**	**1996**	**2001**	**2006**	**2011**	**2016**	**2021**	**2024**
UA	99.4	97.9	99.3	98.2	99.3	97.8	100	97.6	97.5
PA	98.7	98.5	98.5	98.5	98.4	98.4	98.2	100	99.8
OGV	**1986**	**1991**	**1996**	**2001**	**2006**	**2011**	**2016**	**2021**	**2024**
UA	98.7	90.8	91.7	94.5	92.8	92.9	99.5	96.8	98.6
PA	98.9	84.1	85.2	92.5	87.5	85.5	92.5	91.8	98.5
WS	**1986**	**1991**	**1996**	**2001**	**2006**	**2011**	**2016**	**2021**	**2024**
UA	99.9	100	99.7	99.8	98.8	100	100	100	100
PA	99.8	99.8	99.6	98.7	99.8	99.8	99.9	99.7	99.7
OA	99.3	96.3	97.1	98.4	97.3	97.2	98.8	97.4	98.0
Masako -Mbiye (Single area)									
HAL	**1986**	**1991**	**1996**	**2001**	**2006**	**2011**	**2016**	**2021**	**2024**
UA	97.5	98.9	97.4	98.1	98.4	96.9	99.8	98.6	96.6
PA	96.7	97.6	99.7	99.7	99.5	97.5	98.7	99.7	98.9
OGV	**1986**	**1991**	**1996**	**2001**	**2006**	**2011**	**2016**	**2021**	**2024**
UA	97.8	85.9	86.8	95.5	88.8	84.8	93.9	86.9	97.3
PA	96.9	91.1	92.3	93.5	93.5	90.5	99.4	92.8	98.6
WS	**1986**	**1991**	**1996**	**2001**	**2006**	**2011**	**2016**	**2021**	**2024**
UA	98.9	100	98.6	98.8	98.7	100	100	100	100
PA	99.8	99.8	97.7	98.7	99.9	99.9	99.6	96.7	98.7
OA	98.3	96.4	96.5	98.8	98.4	96.3	98.2	96.4	98.9

Appendix 3.



25°7'12,000"E
25°9'36,000"E
25°12'0,000"E
25°14'24,000"E
0°36'0,000"N
0°33'36,000"N
0°31'12,000"N
0°28'48,000"N
0°26'24,000"N
0 2 4 6 8 km
24°24'0,000"E
24°48'0,000"E
25°12'0,000"E
0°48'0,000"N
0°24'0,000"N
87 Inventoried Green Spaces
Agriculture and grassland
Built-up areas and bare soil
Mature Forest
Short Forest
Ground truth samples

Appendix

Appendix 4. Demographic dynamics in the city of Kisangani, 1990–2021

République démocratique du Congo
Ministère du Plan
INSTITUT NATIONAL DE LA STATISTIQUE

INS

Direction Provinciale
KISANGANI

POPULATION DE LA VILLE DE KISANGANI REPARTIE PAR SEXE DE 1990 A 2021

ENTITES ADMINISTRATIVES	1990			1991			1992			1993			1994		
	H	F	T	H	F	T	H	F	T	H	F	T	H	F	T
Ville de Kisangani	232 037	205 768	437 805	244 103	216 468	460 571	256 552	227 508	484 060	269 379	238 884	508 263	282 848	250 828	533 676
1. Lubunga	47 256	41 906	89 162	49 703	44 076	93 779	52 248	46 334	98 582	54 861	48 651	103 512	57 604	51 083	108 687
2. Makiso	23 138	20 519	43 657	24 332	21 578	45 910	25 583	22 686	48 269	26 862	23 821	50 683	28 205	25 012	53 217
3. Mangobo	49 240	43 665	92 905	51 792	45 928	97 720	54 442	48 278	102 720	57 163	50 693	107 856	60 022	53 227	113 249
4. Tshopo	45 477	40 329	85 806	47 883	42 462	90 345	50 282	44 590	94 872	52 796	46 819	99 615	55 436	49 160	104 596
5. Kabondo	45 764	40 583	86 347	48 135	42 686	90 821	50 599	44 871	95 470	53 129	47 114	100 243	55 785	49 470	105 255
6. Kisangani	21 162	18 766	39 928	22 258	19 738	41 996	23 398	20 749	44 147	24 568	21 786	46 354	25 796	22 876	48 672

ENTITES ADMINISTRATIVES	1995			1996			1997			1998			1999		
	H	F	T	H	F	T	H	F	T	H	F	T	H	F	T
Ville de Kisangani	303 321	268 982	572 303	318 488	282 431	600 919	334 412	296 553	630 965	351 153	311 382	662 535	368 689	326 950	695 639
1. Lubunga	61 760	54 768	116 528	64 862	57 520	122 382	68 091	60 382	128 473	71 515	63 401	134 916	75 070	66 571	141 641
2. Makiso	30 244	26 821	57 065	31 759	28 163	59 922	33 345	29 570	62 915	35 016	31 049	66 065	36 763	32 601	69 364
3. Mangobo	64 354	57 068	121 422	67 585	59 933	127 518	70 950	62 918	133 868	74 516	66 064	140 580	78 223	69 367	147 590
4. Tshopo	59 499	52 763	112 262	62 421	55 354	117 775	65 597	58 171	123 768	68 823	61 080	129 903	72 321	64 134	136 455
5. Kabondo	59 811	53 040	112 851	62 814	55 703	118 517	65 942	58 477	124 419	69 257	61 401	130 658	72 701	64 471	137 172
6. Kisangani	27 653	24 522	52 175	29 047	25 758	54 805	30 487	27 035	57 522	32 026	28 387	60 413	33 611	29 806	63 417

Appendix

ENTITES ADMINISTRATIVES	2000			2001			2002			2003			2004		
	H	F	T	H	F	T	H	F	T	H	F	T	H	F	T
Ville de Kisangani	391 224	346 936	738 160	410 355	363 900	774 255	406 023	406 944	812 967	426 325	427 285	853 610	450 305	468 683	918 988
1. Lubunga	79 575	70 567	150 142	83 554	74 095	157 649	83 392	82 139	165 531	87 562	86 246	173 808	91 862	95 612	187 474
2. Makiso	38 969	34 558	73 527	40 916	36 284	77 200	42 230	38 830	81 060	44 342	40 771	85 113	45 031	46 868	91 899
3. Mangobo	82 917	73 530	156 447	87 063	77 206	164 269	85 718	86 764	172 482	90 004	91 102	181 106	95 464	99 360	194 824
4. Tshopo	76 661	67 983	144 644	80 494	71 382	151 876	79 164	80 306	159 470	83 122	84 322	167 444	88 260	91 862	180 122
5. Kabondo	77 064	68 340	145 404	80 917	71 757	152 674	79 232	81 076	160 308	83 194	85 123	168 317	88 710	92 331	181 041
6. Kisangani	36 038	31 958	67 996	37 411	33 176	70 587	36 287	37 829	74 116	38 101	39 721	77 822	40 978	42 650	83 628

ENTITES ADMINISTRATIVES	2005			2006			2007			2008			2009		
	H	F	T	H	F	T	H	F	T	H	F	T	H	F	T
Ville de Kisangani	490 223	477 570	967 793	515 960	502 442	1 018 602	543 047	529 031	1 072 078	571 287	556 541	1 127 828	600 998	585 481	1 186 479
1. Lubunga	102 401	90 805	193 206	107 777	95 572	203 349	113 435	100 590	214 025	119 334	105 821	225 155	125 541	111 323	236 864
2. Makiso	49 000	56 572	105 572	51 573	59 542	111 115	54 281	62 668	116 949	57 104	65 927	123 031	60 073	69 356	129 429
3. Mangobo	99 522	100 419	199 941	104 747	105 691	210 438	110 246	111 240	221 486	115 979	117 024	233 003	122 010	123 109	245 119
4. Tshopo	103 497	93 239	196 736	108 931	98 134	207 065	114 650	103 286	217 936	120 612	108 657	229 269	126 885	114 306	241 191
5. Kabondo	93 189	93 063	186 252	98 081	97 749	196 030	103 230	103 091	206 321	108 598	108 452	217 050	114 246	114 092	228 338
6. Kisangani	42 614	43 472	86 086	44 851	45 754	90 605	47 205	48 156	95 361	49 660	50 660	100 320	52 243	53 295	105 538

Appendix

ENTITES ADMINISTRATIVES	2010			2011			2012			2013			2014		
	H	F	T	H	F	T	H	F	T	H	F	T	H	F	T
Ville de Kisangani	632 251	615 927	1 248 178	663 862	646 725	1 310 587	697 057	679 060	1 376 117	731 911	713 012	1 444 923	770 701	750 803	1 521 504
1. Lubunga	132 069	117 112	249 181	138 672	122 968	261 640	145 606	129 116	274 722	152 886	135 572	288 458	160 989	142 757	303 746
2. Makiso	63 197	72 963	136 160	66 357	76 611	142 968	69 675	80 442	150 117	73 159	84 464	157 623	77 036	88 941	165 977
3. Mangobo	128 355	129 511	257 866	134 772	135 987	270 759	141 512	142 786	284 298	148 588	149 925	298 513	156 463	157 871	314 334
4. Tshopo	133 483	120 250	253 733	140 157	126 263	266 420	147 165	132 576	279 741	154 523	139 205	293 728	162 713	146 583	309 296
5. Kabondo	120 187	120 025	240 212	126 196	126 027	252 223	132 506	132 328	264 834	139 131	138 944	278 075	146 505	146 308	292 813
6. Kisangani	54 960	56 066	111 026	57 708	58 869	116 577	60 593	61 812	122 405	63 624	64 902	128 526	66 995	68 343	135 338

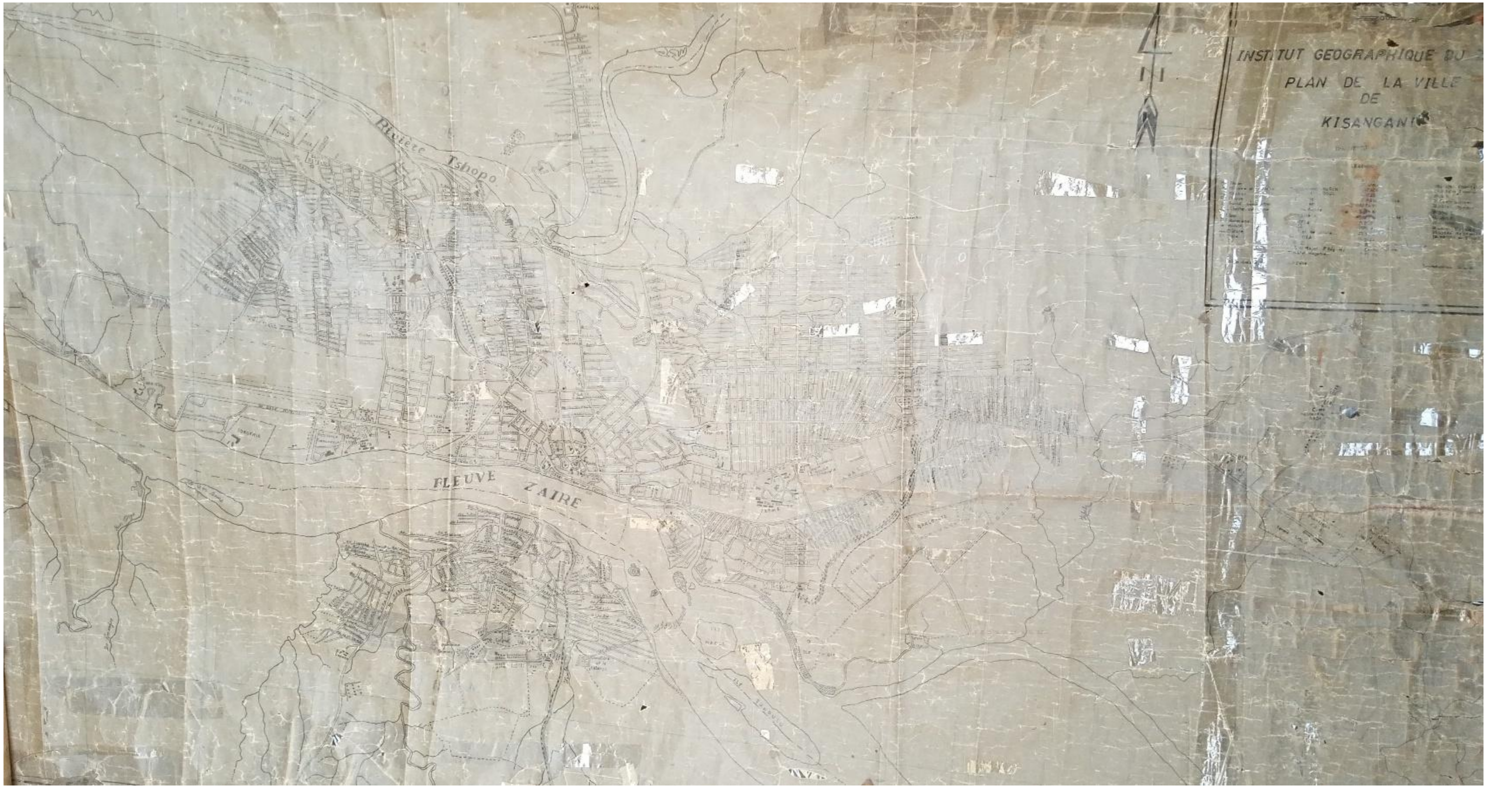
ENTITES ADMINISTRATIVES	2015			2016			2017			2018			2019		
	H	F	T	H	F	T	H	F	T	H	F	T	H	F	T
Ville de Kisangani	811 549	790 595	1 602 144	854 561	832 497	1 687 058	899 853	876 619	1 776 472	947 545	923 080	1 870 625	997 764	972 004	1 969 768
1. Lubunga	169 521	150 323	319 844	178 506	158 290	336 796	187 967	166 679	354 646	197 929	175 513	373 442	208 419	184 816	393 235
2. Makiso	81 119	93 655	174 774	85 418	98 619	184 037	89 945	103 846	193 791	94 712	109 350	204 062	99 732	115 145	214 877
3. Mangobo	164 756	166 238	330 994	173 488	175 049	348 537	182 683	184 327	367 010	192 365	194 096	386 461	202 560	204 383	406 943
4. Tshopo	171 337	154 352	325 689	180 418	162 533	342 951	189 980	171 147	361 127	200 049	180 218	380 267	210 652	189 770	400 422
5. Kabondo	154 270	154 062	308 332	162 446	162 227	324 673	171 056	170 825	341 881	180 122	179 879	360 001	189 668	189 412	379 080
6. Kisangani	70 546	71 965	142 511	74 285	75 779	150 064	78 222	79 795	158 017	82 368	84 024	166 392	86 733	88 478	175 211

Appendix

ENTITES ADMINISTRATIVES	2020			2021		
	H	F	T	H	F	T
Ville de Kisangani	**1 050 646**	**1 023 520**	**2 074 166**	**1 106 330**	**1 077 766**	**2 184 096**
1. Lubunga	219 465	194 611	**414 076**	231 097	204 925	**436 022**
2. Makiso	105 018	121 248	**226 266**	110 584	127 674	**238 258**
3. Mangobo	213 296	215 215	**428 511**	224 601	226 621	**451 222**
4. Tshopo	221 817	199 828	**421 645**	233 573	210 419	**443 992**
5. Kabondo	199 720	199 451	**399 171**	210 305	210 022	**420 327**
6. Kisangani	91 330	93 167	**184 497**	96 170	98 105	**194 275**

Source: Projections de la Direction Provinciale de l'I.N.S/Ex.Province Orientale

Appendix 5. Map of Kisangani during the Republic of Zaire period (Geographical Institute of the Congo, 2022)



Appendix