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Anthropogenic Effects on Green Infrastructure Spatial Patterns in Kisangani City and Its Urban–Rural Gradient

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Abstract: Urban and peri-urban expansion significantly influences the spatial pattern of cities and surrounding zones. This study examines the spatial changes in green infrastructure components, specifically focusing on mature forests, short forests, and agricultural and grass lands from 1986 to 2021, using satellite imagery. Two landscape ecology indexes, 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 in a specific context of increasing urbanization and peri-urbanization in Kisangani city, DR Congo. The findings reveal a decline in both mature and short forests, respectively, from 1986 to 2021, and from 2006 to 2021 alongside a continuous expansion of agricultural and grass lands at the landscape scale. Moreover, the spatial pattern of mature and short forests exhibited significant variations across urban, peri-urban, and rural zones. In the context of 2021, in urban and peri-urban zones, mature forests account for less than 1% of the 2.25 km^2 plots, against more than 35% in certain 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 decline and fragmentation, particularly in urban and peri-urban zones, while agricultural and grass lands 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 highlight the need for urban planning in Kisangani to prioritize green infrastructure preservation, focusing on maintaining forest connectivity and preventing further fragmentation. Policies should promote sustainable land use in peri-urban zones to achieve a balance between urban expansion and the provision of essential ecosystem services, thereby enhancing long-term resilience.

Keywords: urbanization gradient; green infrastructure; spatial pattern; Kisangani

1. Introduction

The process of urbanization has rapidly occurred on a global scale over the past six decades [1,2]. In fact, in 1950, 70% of the world's population resided in rural areas, while less than one-third (30%) inhabited urban regions [1]. Since 2007, the global urban population has exceeded the global rural population [1] and is expected to remain the majority until 2050 [1–3], particularly in developing countries, which are projected to account for over 90% of the growth in global urban population between 2030 and 2050 [4,5].

Consequently, most cities are experiencing an increase in urbanized areas that is twice as fast as population growth [6]. In African cities, this accelerated urbanization is accompanied by a range of ecological challenges [1–7]. In certain cities, which are unplanned or poorly managed, urban expansion leads to rapid urban sprawl [5–8], pollution, environmental degradation, as well as unsustainable production and consumption models [5–7].

This model of urban expansion threatens to degrade urban green infrastructure [4–7] and has the potential to significantly increase carbon emissions [5].

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 [9,10]. These benefits may include absorbing, adapting, and transforming both sudden and chronic stresses in cities and improving air and water quality, mitigating the urban heat island effect, reducing flood risk, enhancing biodiversity, and providing recreational and cultural opportunities [11–18]. However, the profound transformations 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 [4,19]. Therefore, integrating sustainability into the urbanization process becomes imperative [20,21]. One of the solutions is to protect existing green infrastructure and strategically incorporate green spaces within built environments [7,22,23]. To this end, several research projects focus on understanding, among other things, the spatio-temporal changes in urban green infrastructure [24,25], their typology and specific composition [4–7], as well as the ecosystem services provided for the benefit of populations [12,22,26,27].

The city of Kisangani, located in the Democratic Republic of Congo (DRC), is experiencing rapid spatial expansion due to rapid demographic growth [28]. From 1987 to 2021, the city's urban core grew from 13.49 km^2 to 100.49 km^2, with an average annual rate of change estimated at 8.2% [8]. The rising demand for accommodation and social facilities in urban zones has resulted in significant expansion of peri-urban zones between 2010 and 2021 [8], a corollary of the decline in urban densities, now evident in most of the world's cities [6]. Despite significant urban and peri-urban expansion, the city of Kisangani remains deficient in scientific research focused on understanding the spatial dynamics of its green infrastructure. Indeed, in 2010, Bamba et al. [29] 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 [30]. 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 [7], which leads to the degradation of dense forest through the expansion of agricultural and built-up spaces. In this perspective, in 2014, Kadima et al. [31], mapped the different types of green spaces in the city of Kisangani from 1960 to 2010. However, this study is restricted to quantifying the number of green spaces with their spatial location, without examining their configuration and composition within the landscape. Furthermore, the effects of peri-urbanization in the conversion of these green spaces were not examined.

The present study aims to assess the impact of urbanization and peri-urbanization, currently observed in the city of Kisangani [8], on the spatial pattern of the green infrastructure, described in three components, including mature forests, short forests (which refers to secondary forests), agricultural and grass lands. In Kisangani city, these green space types provide essential ecosystem services, such as the absorption, adaptation to, and transformation of both acute and chronic stressors. Additionally, they play a crucial role in enhancing air and water quality, mitigating the urban heat island effect, reducing flood risks, promoting biodiversity, and offering recreational and cultural opportunities. Thus, these green spaces are integral components of the city's green infrastructure.

Therefore, this study addresses a key research gap concerning the lack of empirical data regarding the impacts of urbanization on green infrastructure in Kisangani, specifically regarding the spatial and temporal patterns of green spaces loss and fragmentation. While urbanization effects on green spaces have been widely studied in other regions, Kisangani's unique urban–rural gradient and its implications for green spaces cover and ecosystem services have not been adequately examined. This research provides essential insights into the ways urban expansion alters 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) in 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.

Therefore, at the landscape scale, we hypothesize that urban expansion in Kisangani from 1986 to 2021 has significantly impacted green infrastructure, particularly by reducing the proportion of mature and short forests while increasing the area of agricultural and grass lands. This expansion is expected to fragment the largest patches of mature and short forests, decreasing their size and altering spatial configuration.

Within the urban–rural gradient, we anticipate distinct variations in forests composition and configuration, with urban zones showing lower proportions and smaller patches than peri-urban and rural zones, largely due to intensive human activities. Agricultural and grass land areas are expected to vary similarly, with peri-urban zones showing larger, more continuous patches due to greater land availability and proximity to urban trade.

Over time, from 1986 to 2021, we predict a significant decline and fragmentation of mature and short forests across all zones due to less managed urban expansion [8–32], while agricultural and grass lands increase in peri-urban and rural areas. In urban zones specifically, agricultural and grass land areas are expected to decline and fragment over time as they are gradually converted into built-up areas.

2. Materials and Methods

2.1. Study Area

Covering 2947.9 km^2, the study area comprises six communes of Kisangani and a peripheral zone (Figure 1). Five of these six communes, Makiso, Mangobo, Kabondo, Tshopo, and Kisangani, are located on the right bank of the Congo River. Lubunga is the only commune on the left bank of the same river (Figure 1). Kisangani experiences an average annual rainfall of 1724 mm, based on data collected over a 50-year period (1956–2005), with an average annual temperature of 25.3 °C [33]. The monthly precipitation is greater than 60 mm [33]. These climatic data combined confer to the city of Kisangani an Af-type climate in line with Köppen's classification [33–35]. The population has increased significantly over time [8]. Estimated at 105,666 inhabitants in 1959 [36], demographic data from the National Institute of Statistics (INS) indicate that this population reached more than 2,184,096 inhabitants in 2021 [28]. The population represents several ethnic groups from different provinces of the Democratic Republic of Congo and neighbouring countries, and lives mainly from agriculture [37], commercial activities, and fishing.

2.2. Data and Methods

2.2.1. 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) sensors, with a spatial resolution of 30 m. Images with low cloud cover (<10%) were obtained, thus enabling analysis over a period of 35 years, with a 5-year time step. These satellite data were supplemented by 310 GPS surveys that provide detailed information on land use and land cover (Table 1).

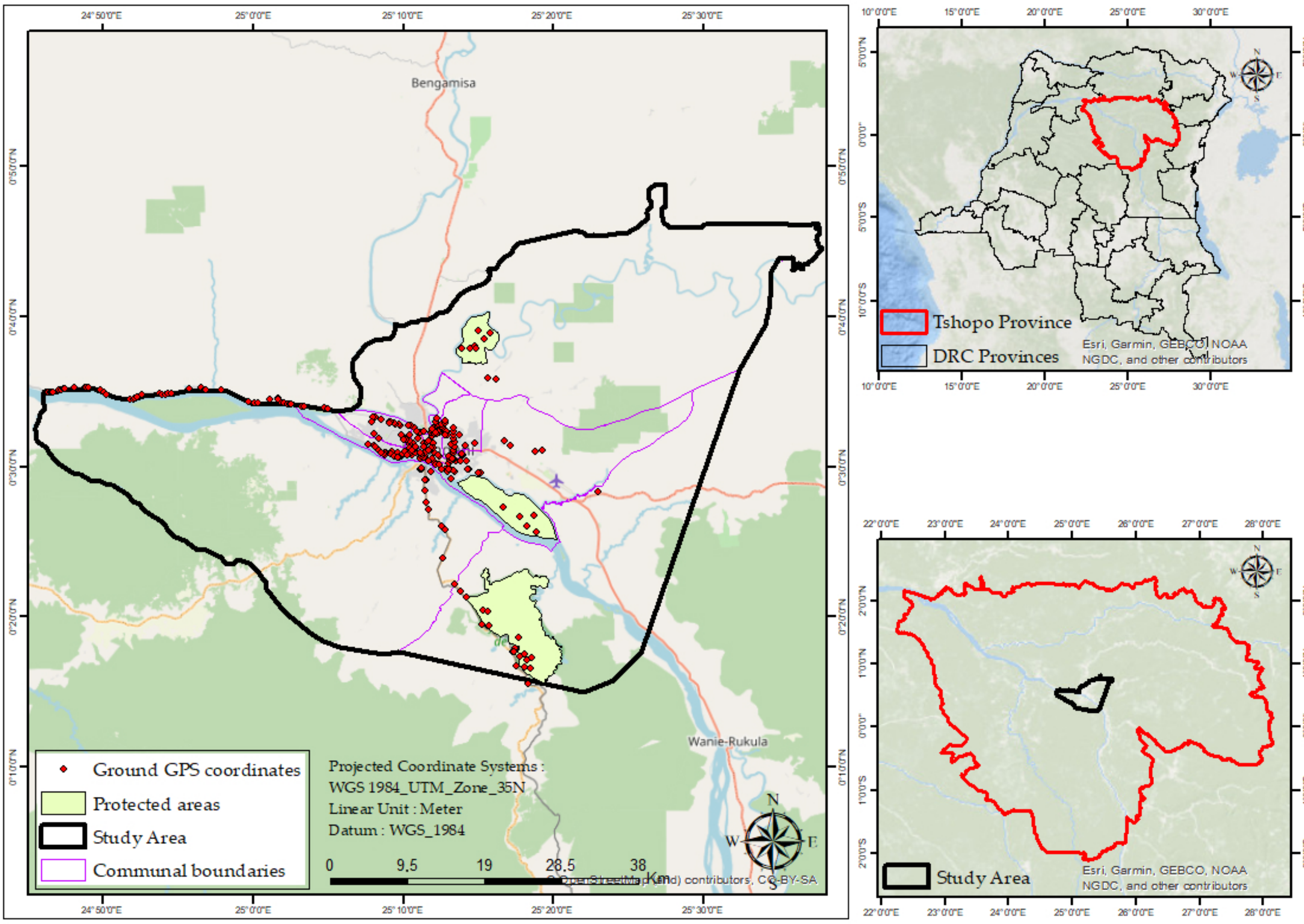


Figure 1. The geographical location of Kisangani and its periphery. Kisangani is divided into six communes and includes three protected areas on its periphery. The road network includes national and provincial roads.

Table 1. The characteristics of the data used.

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

The dates selected relate to different periods characterized by social and political changes expected to impact spatial landscape pattern. Indeed, 1986 is part of the 1980–90 decade affected by a national economic deficit. Confronted with this economic context, several companies decided to close down, including SOLBENA, ALIPOST (Postal Supply), INNOVATION, and PRODIMPEX, among others [38]. A total of 84 companies closed in 1989 [38], forcing the city's inhabitants to a high degree of dependence on agricultural activities. The period between 1991 and 1996 was part of a decade (1990 to 2000) of multiple confrontations between different armed groups [37–39], which forced a large part of the population to leave the urban centre for peripheral zones. In contrast, 2001 was marked by the return of stability after six days of armed confrontation in 2000 [37]. Furthermore, 2006 and 2011 were notable for the general elections, while 2016 coincides with the dismemberment of the DRC's provinces [40]. Finally, 2021 experienced significant demographic growth, with more than 2,000,000 people living in the city [28].

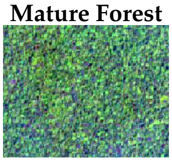
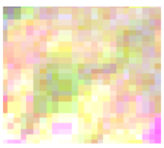
2.2.2. Satellite Data Pre-Processing

In order to minimize atmospheric effects and radiometric variations due to the difference between the Landsat sensors [41,42], surface reflectance (SR) images were used. The Landsat 4–5 TM and Landsat 7 ETM+ surface reflectance is generated using the Landsat Adaptive Ecosystem Disturbance Processing System (LEDAPS) algorithm, while the Landsat 8–9 OLI surface reflectance is obtained using the Land Surface Reflectance Code (LaSRC) [43,44]. These algorithms provide the images with optimal radiometric and spectral characteristics [45], thus allowing comparison between several images of the same region [44]. Using the Global Geodetic System (WGS-84), these images were resampled at the same 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 carried out for each date in order to better discriminate the types of land cover.

2.2.3. Supervised Classification of Satellite Images

The visual interpretation of color compositions generated by the combination of green, red, and near-infrared bands from Landsat imagery, creates a type of false-color representation that enhances the visibility of green spaces. This analysis was further supported by high spatial resolution images, particularly those sourced from Google Earth available in the Earth Engine, as well as Planet Scope images with a spatial resolution of 3 m, and the NDVI variation. These advanced imaging techniques facilitated the selection of training points for calibrating the supervised classification of the studied land cover types, including (1) mature forests, (2) short forests, and (3) agricultural and grass lands (Table 2). In this study, all other land cover types that are not part of the green infrastructure, in particular, built and bare soil as well as water, have been merged into the 'other' class. The use of high spatial resolution images enabled to overcome the confusion observed in the variation of NDVI values for mature forest and agricultural land. The Random Forest algorithm [46–48] was adopted to train supervised classification. In order to achieve optimum accuracy and performance, the number of decision trees was set at 100 for all the images analyzed. The advantage of this algorithm lies in its ability to generate several decision trees that independently analyze and assign the samples in their respective classes, and thus improve the classification performance [8,42].

Table 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, Gilbertiodendron dewevrei, as well as other species characteristic of wetlands.	0.74–0.82
Short Forest 	Forest types that succeed regeneration and constitute the transitional phase to the establishment of the mature forest (that refers to secondary forests). This type is characterized by the prevalence of heliophilous species.	0.80–0.87
Agricultural and Grass Land 	Land covered by agricultural 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

2.2.4. Assessment of Classification Accuracy

Classifications were evaluated through the global, user, and producer accuracy obtained from the confusion matrixes. During the field missions carried out in August 2022 and March 2023, 642 GPX control points were sampled, depending on the accessibility of the 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 [49]. For the reference classification (2021), four strata corresponding to the four types of land cover studied were formed. 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 grass land, 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 on the basis of archival imagery available in Google Earth Pro, supported by the unchanged landscape areas identified in the reference classification (2021). In order 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 forest in Hansen's classification as any pixel with 50% or more forest cover. The forest patch is then dominant in the pixel. Thus, for a forest pixel, any spatial change between 2000 and 2021, reducing the forest cover rate to less than 50%, was considered as a pixel transformed into non-forest, and inversely. Thus, a contingency table was produced, comparing the changes classified as forest and those classified as non-forest with the reference data. This table enabled to determine the user, producer and global accuracies, using Equations (1)–(3) from Ref. [50].

2.2.5. Delineation of Urban–Rural Gradient Zones

To delineate and classify the zones of the urbanization gradient, built-up areas, which represent one of the most precise, coherent, and dynamic morphological criteria [6,25], were analyzed. For each date, 1986–1991–1996–2001–2006–2011–2016 and 2021, analysis of satellite images enables the identification of built-up areas based on impermeable surfaces (pavements, rooftops, and compacted ground) [6–8]. Thus, an area is defined as urban when it comprises a majority of built-up pixels (exceeding 50%) within training zones of 250 m $\times$ 250 m [8]. Additionally, an area is categorized as peri-urban if the proportion of built-up pixels within a 250 m $\times$ 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 designated as rural when the 250 m $\times$ 250 m training zone is predominantly comprised of vegetation pixels [8].

2.2.6. 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 usually applied to analyze spatial patterns within the urban–rural gradient [51]. The first involves the implementation of a transect that extends from the urban centre to the rural periphery, in which spatial pattern indexes are analyzed [51,52]. The second methodology involves the use of buffer zones to compute indexes for a series of concentric zones surrounding the urban center [2,29,53]. In order to obtain a more complete and representative view of the spatial pattern within an urban–rural gradient and to better understand the complexity and variability of the studied landscape, for each zone of the urban–rural gradient, sampling plots were randomly selected in all directions (north, south, east, west, northeast, northwest, southeast, and southwest) (Figure 2). This approach enables us to include significant variations that may be perpendicular to a transect, including short-distance variations that can escape an approach based on concentric zones.

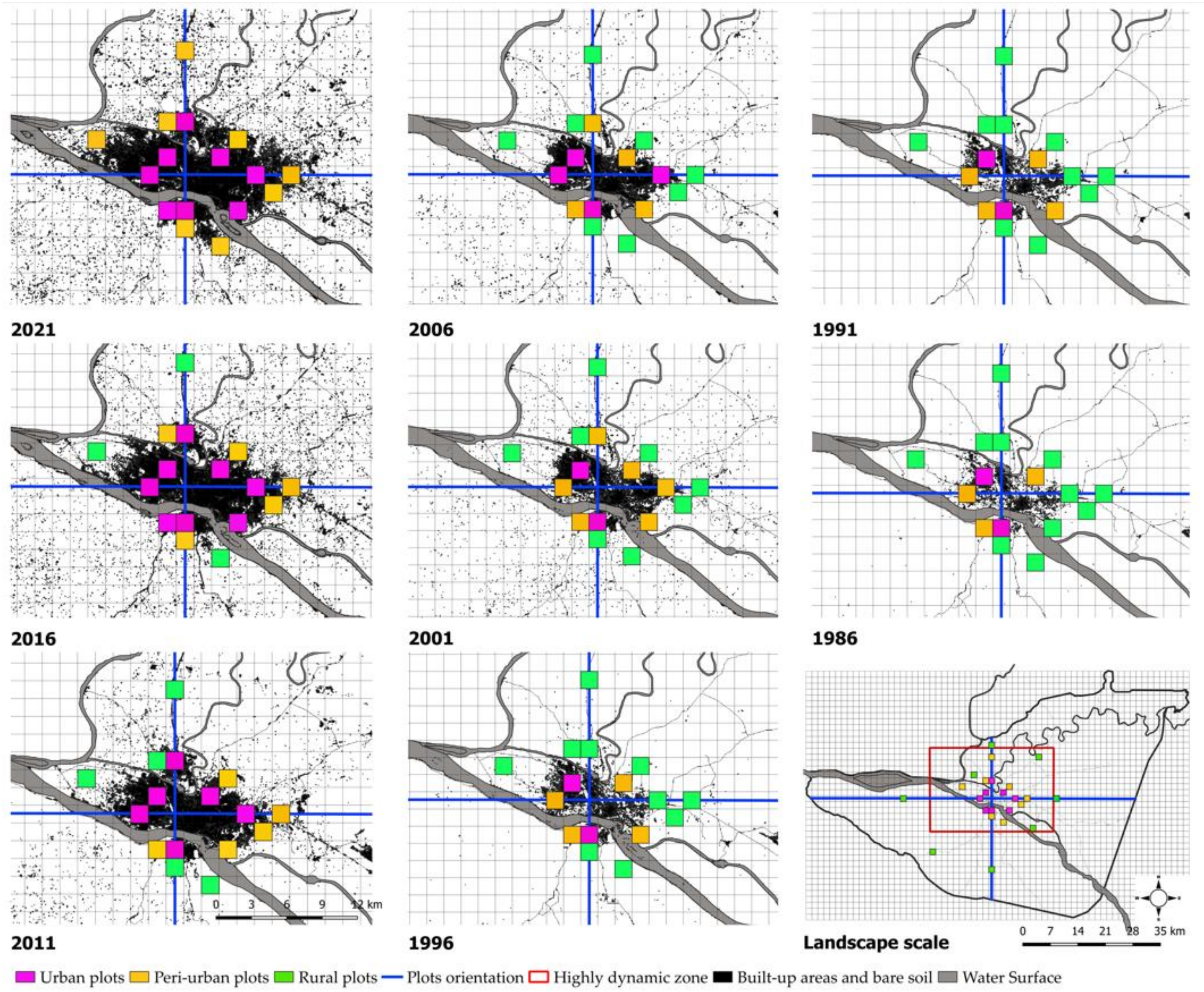


Figure 2. The sample plots in the urban–rural gradient randomly selected in the north, south, east, west, northeast, northwest, southeast, and southwest directions. The changes in the status of these plots over time, within the area outlined in red, highlight the dynamic nature of urban, peri-urban, and rural zones.

Indeed, 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 km^2), were randomly selected from each zone for the reference year (2021). The eight random plots, with sizes of 2.25 km^2, were adopted 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 chosen 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 urbanization's impacts on green infrastructure across the entire urban–rural gradient. However, it should be noted that the status of these observation plots has changed over time, reflecting the dynamics of urban, peri-urban, and rural zones.

For each plot analyzed, two landscape ecology indexes, the percentage of landscape (PLAND), and the largest patch index (LPI), were analyzed. This study selects PLAND and LPI because they provide complementary insights into landscape composition and configuration. PLAND quantifies the proportion of green infrastructure within the landscape, capturing overall extent, while LPI identifies the largest contiguous patch, reflecting connectivity and dominance. Together, these indices effectively capture both the amount and spatial structure of green infrastructure, making them well-suited for analyzing temporal and spatial changes in green infrastructure patterns. It is important to note that both indexes are sensitive to alterations in the landscape induced by human activities [54–56]. Therefore, the percentage of the landscape occupied by each green infrastructure component (Equation (1)) was quantified to verify the following: (i) the expected decline in both mature and short forest, alongside an expected increase in the proportion of agricultural and grass land 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 intensive human activities; and (iii) the higher proportions of agricultural and grass land expected in peri-urban zones than in urban and rural zones due to land availability and proximity to urban trade. Furthermore, the proportion covered by the largest patch (Equation (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.

$$\mathrm{PLAND} = \frac{\sum_{j=1}^{n} a_{\mathrm{ij}}}{A} \times 100 \tag{1}$$

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

$$\mathrm{LPI} = \frac{max_{j=1}^{n}\,(a_{ij})}{A} \times (100) \tag{2}$$

LPI = Largest Patch Index

For the reference year (2021), data relating to the composition (PLAND) and configuration (LPI) of green infrastructure components in the eight sample plots, categorized by zones along the urbanization gradient, initially asymmetric, were subjected to a logarithmic transformation to meet the normality assumption required for the ANOVA test. However, for previous years, the constant asymmetrical characteristics of the data, relating to the reduction in the number of urban and peri-urban plots over time (Figure 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 zone of the urbanization gradient. 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.

3. Results

3.1. Validation of Supervised Classifications and Mapping of Land Cover

The indicators derived from confusion matrixes, including user, producer, and overall accuracy, with values above 80% (Table 3), confirm a reliable level of land cover discrimination. Moreover, the comparison of our change map to the change map produced by Hansen [49] reveals that the local classification is slightly more representative and consistent with reference data than the global classification (Table 4). Visual interpretation of the land-use maps indicates a gradual expansion of agricultural areas in the landscape of

Kisangani. 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 3).

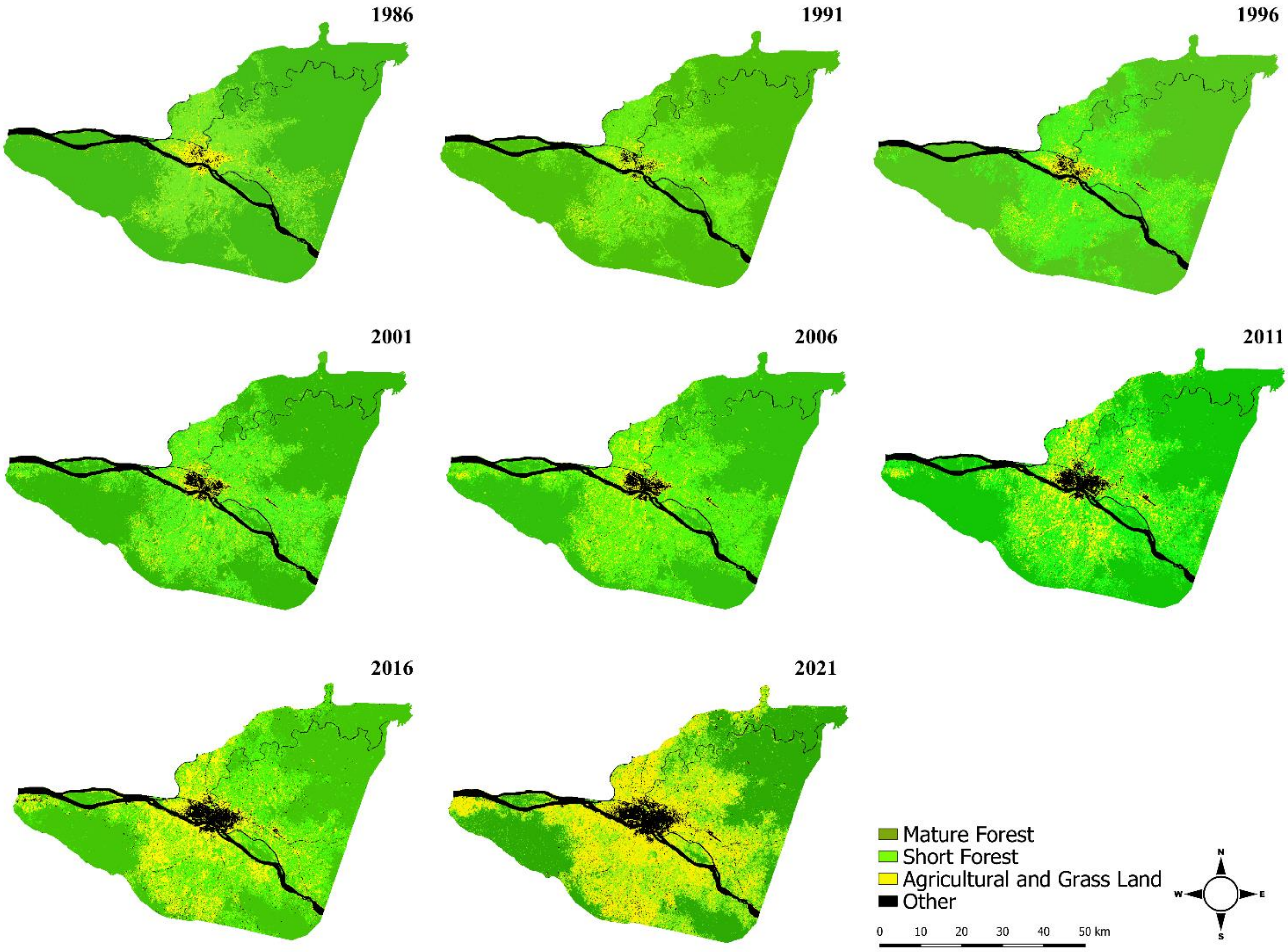


Figure 3. The mapping of green infrastructure components based on a supervised classification of Landsat images using the Random Forest algorithm. The expansion of agricultural and grass land is occurring alongside a decrease of mature and short forest.

Table 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 grass land; 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

Table 3. *Cont.*

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 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 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	

3.2. 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 4a). Specifically, an estimated total of 100,711.32 hectares 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 4b).

Conversely, at the landscape scale, the area of short forest increased by 9695.69 hectares from 1986 to 2021. However, the dynamics of short forests at the landscape level exhibited two primary trends (Figure 4a). From 1986 to 2006, the area of short forest increased by approximately 38,000 hectares, translating to an increase of more than 35% compared to the initial area. In contrast, from 2006 to 2021, short forests experienced a loss estimated at 28,000 hectares, reflecting a decrease of more than 29% relative to the area observed in 2006.

Additionally, a general trend towards a decrease in the proportion of the largest patches of both mature and short forest between 1986 and 2021 has been observed (Figure 4b). Notably, the largest patch of mature forest experienced a decrease of over 60% in area during this timeframe, while the largest patch of short forest experienced a staggering reduction of more than 84% (Figure 4b). The loss of both mature and short forest in recent years has been offset by the expansion of agricultural and grass land. Indeed, agricultural land has expanded, with a 7852.70 ha gain between 1986 and 2021. In 1986, agricultural and grass land constituted 4% of the landscape. By 2021, This land use type had risen to 32% (Figure 4a). This expansion of agricultural land has intensified over the periods 2011–2016 and 2016–2021. In fact, the proportion of agricultural land in the landscape increased from 14.2% to 20.6% between 2011 and 2021.

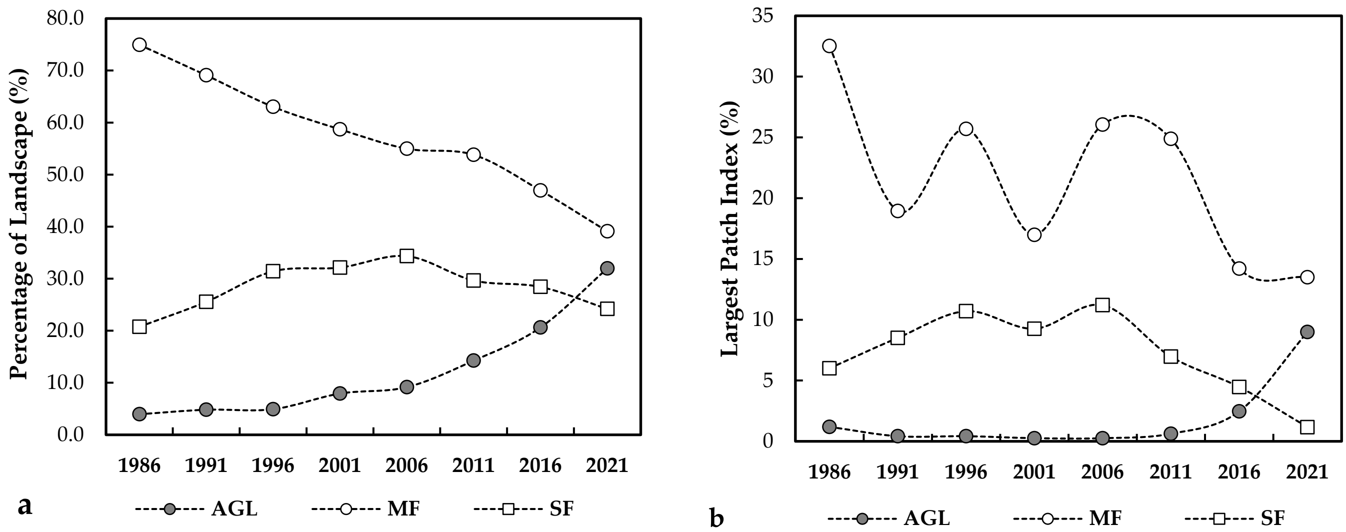


Figure 4. The spatial pattern of green infrastructure in the landscape of Kisangani. The landscape composition is illustrated in (**a**), and the spatial configuration in (**b**). Agricultural and grass land (AGL); mature forest (MF); short forest (SF). The results in this figure reveal a significant transformation in both the composition and spatial configuration of the green infrastructure.

3.3. The Spatial Pattern of Green Infrastructure Within the Urban–Rural Gradient

Within the urbanization gradient, as anticipated, the composition and configuration of mature and short forests are significantly different between urban, peri-urban, and rural zones of Kisangani according to the 2021 data (p-value < 0.05) (Figure 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(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(a_2)). Specifically, in plots measuring 2.25 km^2, mature forests typically account for less than 1% 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, typically characterized by heliophilous, fast-growing species, represents higher proportions in peri-urban zones than in urban zones. In certain 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(b_1)). In rural zones, short forests largely exceed the proportions observed in urban and peri-urban zones, with some plots showing coverage of over 65%. In terms of configuration, urban and peri-urban zones feature smaller patches than rural areas (Figure 5(b_2)). The last component of the green infrastructure, agricultural and grass land also demonstrates significant variation in both composition and configuration among urban, peri-urban, and rural zones (p-value < 0.05) (Figure 5(c_1,c_2)). Notably, peri-urban zones in Kisangani present a higher proportion of agricultural land, featuring larger patches than urban zones. In certain 2.25 km^2 plots within peri-urban zones, agricultural land comprises over 89%, with continuous patches exceeding 87%. By comparison, the highest proportion recorded in urban zones within similar plots is 41%. However, these findings reveal that the composition (proportions of agricultural land) and configuration (extent occupied by the largest patches) in peri-urban zones are not significantly different from those in rural zones (p-value > 0.05) (Figure 5(c_1,c_2)). This reflects the opportunities afforded by peri-urban and rural zones, especially in terms of the availability of land for agricultural use.

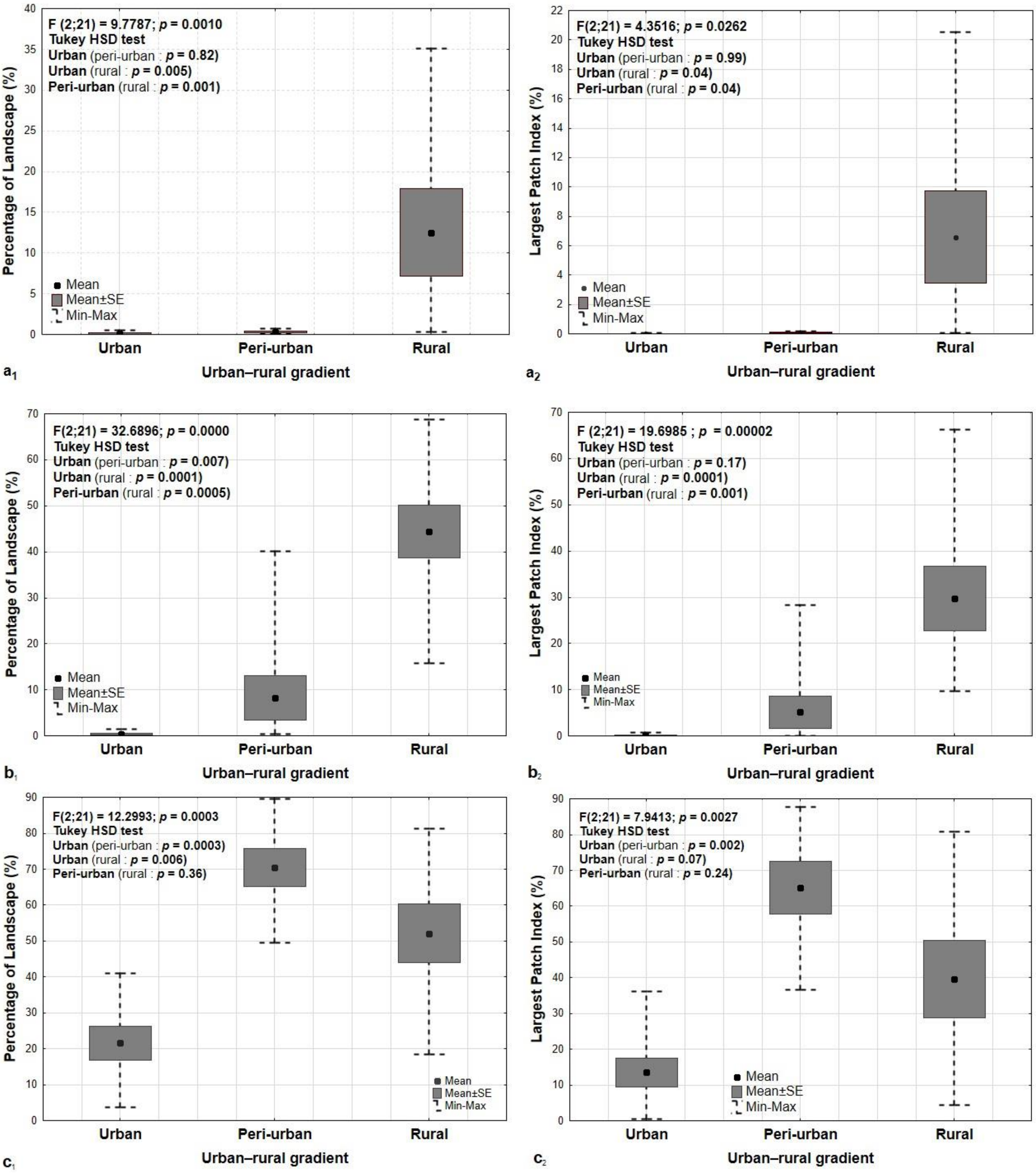


Figure 5. The spatial pattern of mature forests (a_1,a_2), short forests (b_1,b_2), agricultural and grass lands (c_1,c_2) within the urban–rural gradient using 2021 data. The standard error (SE) of the mean in this context is greater when the PLAND and/or LPI is highly variable within the urbanization gradient.

3.4. 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 decline and fragmentation respectively in their proportions and in the largest patches in urban, peri-urban, and rural areas (Figure 6). These changes in both composition and configuration are especially significant in urban and peri-urban zones (Figure 6(a_1,a_2,b_1,b_2)). Rural zones exhibit also a continuous decrease and a change respectively in the proportion and the spatial configuration (Figure 6(c_1,c_2)). However, these spatial changes are not statistically significant (p-value > 0.05). It should be noted that in 1996, mature forests underwent a restoration trend in urban and peri-urban areas.

Short forests, as well as mature forests, experience changes in their composition and configuration along the urban–rural gradient from 1986 to 2021 (Figure 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 significant fragmentation into larger patches (Figure 7(a_1,a_2)) despite a restoration trend 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 (Figure 7(b_1,b_2)). However, from 2011 to 2021, a consistent decline and increased fragmentation were observed in peri-urban areas. Rural zones also revealed no significant temporal effects (p-value > 0.05) regarding the changes in 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 (Figure 7(c_1,c_2)).

The results further indicate significant changes in the composition and configuration of agricultural and grass lands over time within urban, peri-urban, and rural zones (p-value < 0.05) (Figure 8). However, the trend of these changes varied depending on the zone. In urban zones, agricultural land experienced a significant decrease in its proportion, and a significant fragmentation of larger patches (p-value < 0.05) from 1986 to 2021 (Figure 8(a_1,a_2)). In contrast, the proportion of agricultural land in peri-urban areas remained relatively stable from 1986 to 2006. A sharp decline occurred between 2006 and 2011, followed by a significant increase from 2011 to 2021 (Figure 8(b_1,b_2)). Rural zones experienced a significant increase in agricultural land proportion, accompanied by a significant expansion of the largest patches (Figure 8(c_1,c_2)).

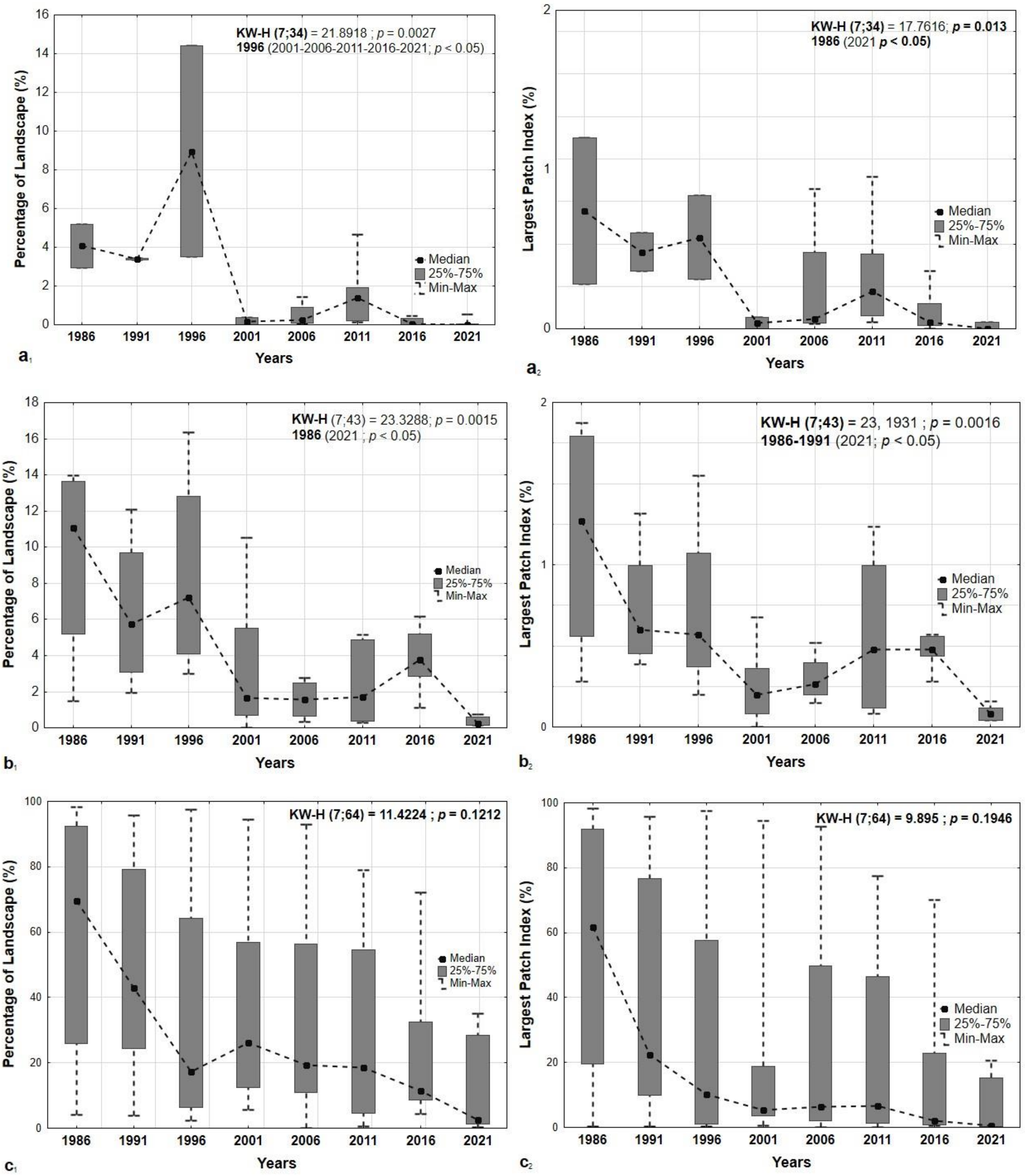


Figure 6. Temporal changes in the composition and the spatial configuration of mature forests in urban zones ($\mathbf{a_1}$,$\mathbf{a_2}$), peri-urban zones ($\mathbf{b_1}$,$\mathbf{b_2}$), and rural zones ($\mathbf{c_1}$,$\mathbf{c_2}$).

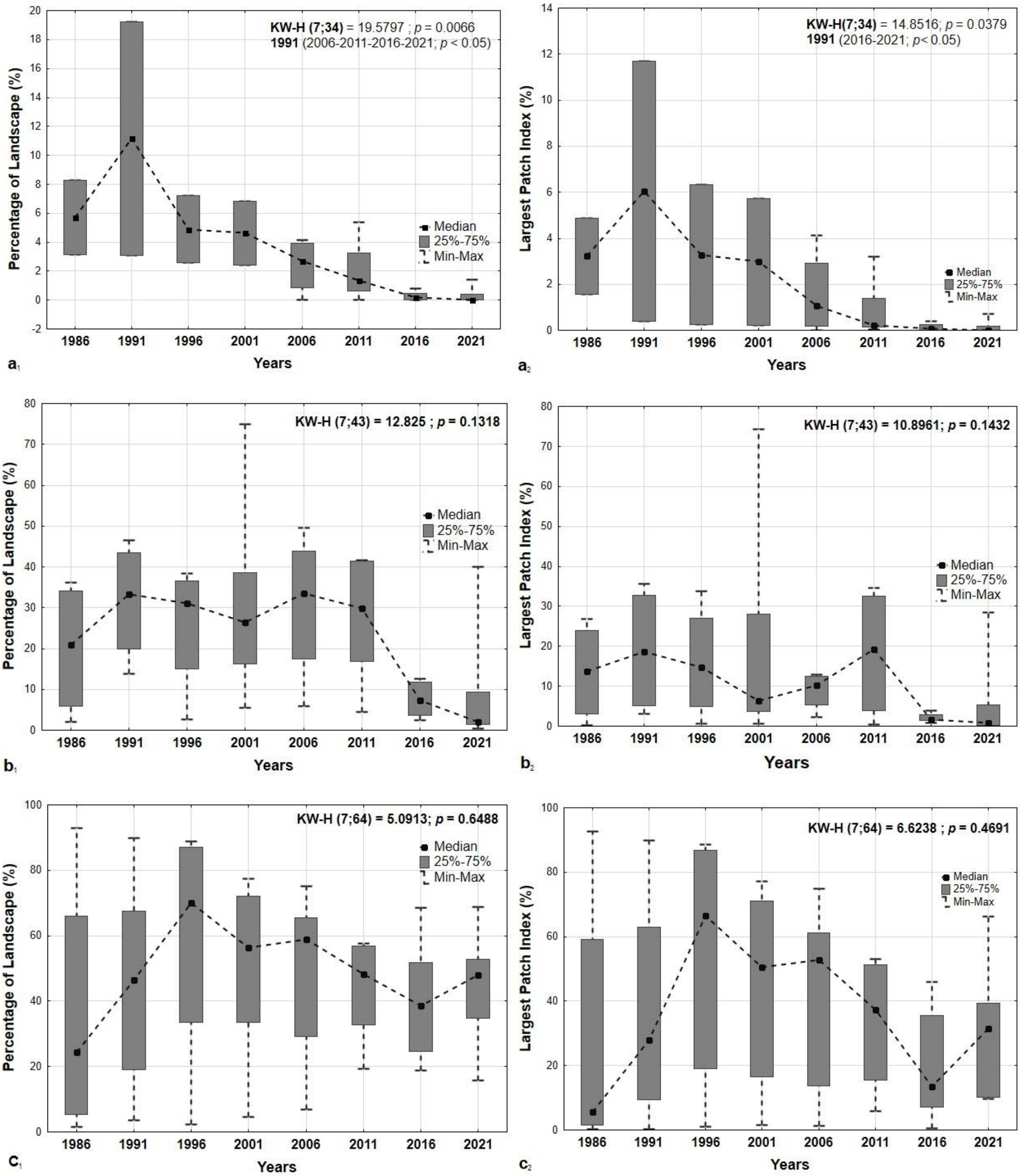


Figure 7. Temporal changes in the composition and the spatial configuration of short forests in urban zones ($\mathbf{a_1}$,$\mathbf{a_2}$), peri-urban zones ($\mathbf{b_1}$,$\mathbf{b_2}$), and rural zones ($\mathbf{c_1}$,$\mathbf{c_2}$).

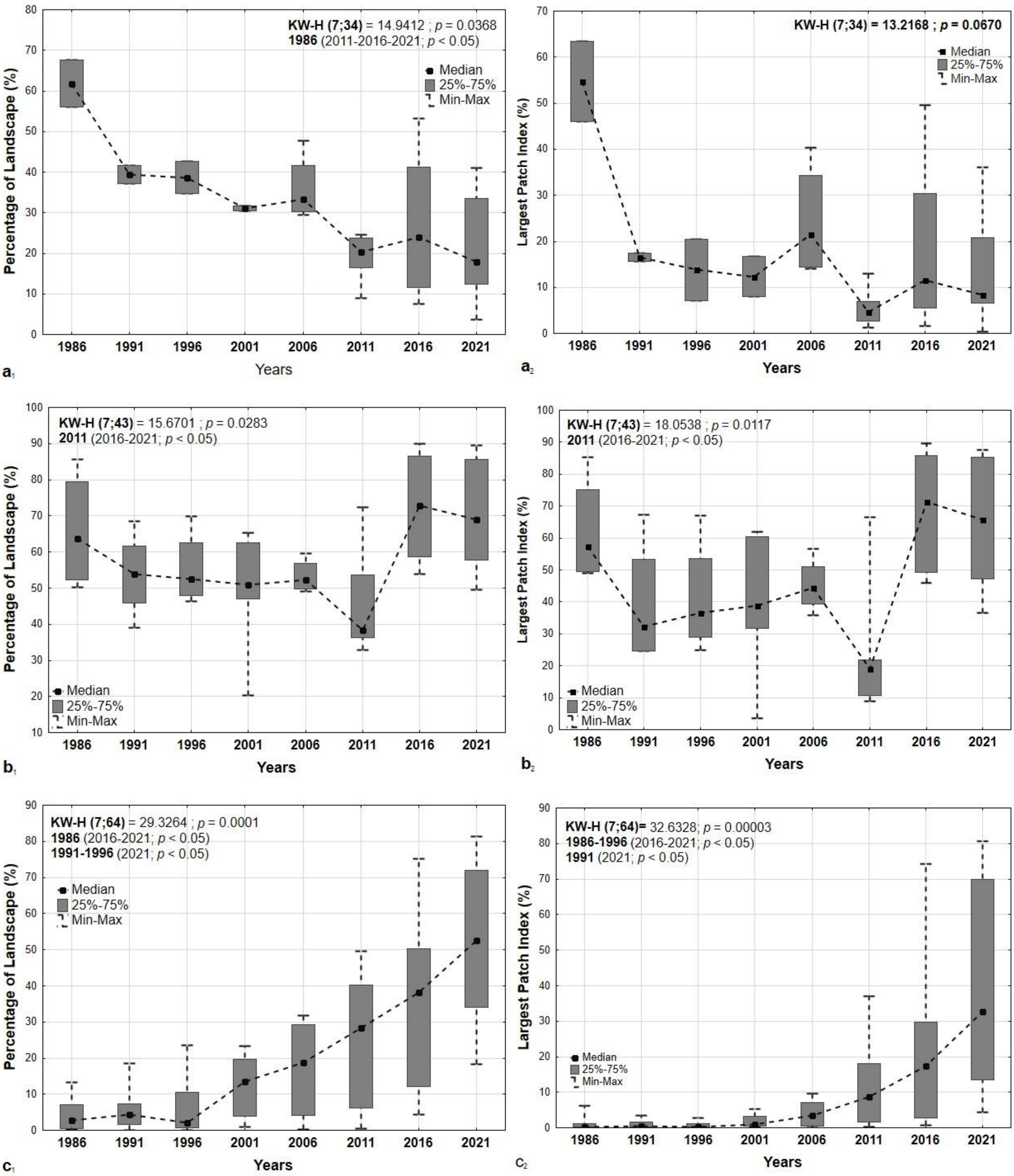


Figure 8. Temporal changes in the composition and the spatial configuration of agricultural and grass land in urban zones (**a_1**,**a_2**), peri-urban zones (**b_1**,**b_2**), and rural zones (**c_1**,**c_2**).

4. Discussion

4.1. Classifications and Analyses of the Green Infrastructure Spatial Patterns

Validation indicators, including user, producer, and global accuracy [50–57], supported by field data, attest the reliability of classification results. Furthermore, comparing the change map from 2001 to 2021 derived from the local classification to Hansen's global classification [49] enhances the credibility of the local classifications. In fact, 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 [57]. Furthermore, the criteria for forest cover on the Hansen map remain debatable. For the purposes of this study, 232 reference points were randomly selected and categorized into forest and non-forest areas. These data underwent quality control by overlaying them on high spatial resolution images (Planet Scope images with a 3 m spatial resolution) to ensure data quality. Additionally, in the Hansen map [49], a criterion of at least 50% overlap was used to determine a pixel as forest. Thus, forest is the dominant land cover within a pixel.

As no single index can provide a complete view of the landscape's complexity [54,55], the spatial pattern of the green infrastructure was assessed using two main indexes of composition (PLAND) and configuration (LPI). These metrics, which are often indicators of human impact on landscape morphology [54–56], revealed significant changes in the composition and configuration of mature forests, short forests, agricultural and grass lands in Kisangani and its urbanization gradient.

4.2. 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 [38] and armed conflicts [39], 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 the resolution of 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 [58]. 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 [28]. In tropical regions, the population growth increases the need for residential accommodation and agricultural land [8,24,59]. 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, similar to many other regions in the Democratic Republic of Congo, exhibits a low level of industrialization [60]. 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, previously vast and continuous, are increasingly fragmented into small patches. This steady fragmentation since 2011, due to agricultural expansion and forest exploitation, largely artisanal, 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 [25]. In the plain of Lubumbashi, from 2001 to 2011, the clear forests underwent significant degradation due to the development and expansion of other land uses, in particular, the bare soil habitat complex [61]. Furthermore, in the city of Lubumbashi, over the 25 years from 1989 to 2014, green space has decreased in all the city's communes [24]. In contrast to Lubumbashi, where various components included in the green infrastructure have decreased, in particular, 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 [24,25,59]. In the city of M'sila, Algeria, green infrastructure is constantly sacrificed for urban expansion [62]. In Kisangani, despite ineffective urban development policies [32], mature forests are heavily exploited for energy purposes. Indeed, wood remains the primary energy source for 90% of urban residents and some local industries [63]. Combined with slash-and-burn agriculture, wood-energy activities contribute to mature forest degradation [64]. These transformations lead to a loss of biodiversity and limit contact with nature [4,18,19].

4.3. 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). In fact, 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 [8,32], as well as the inadequacy of the current national urban development law in addressing contemporary urban development challenges [24,58]. 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 forest, coupled with significant 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 [65]. 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 agricultural land proportion between 1986 and 2001. However, the demographic boom from 2011 to 2021 [28], driven largely 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 landscape of Kisangani, land governance in both peri-urban and rural zones, largely characterized by a mixture of formal regulations and informal practices, provides local farmers with relatively easy access to land. Farmers frequently exploit the land according to local practices and customary agreements. These agricultural activities, dominant in peri-urban zones, ensure the population's food security in urban, peri-urban, and rural zones.

Nevertheless, in order to limit the steady degradation of both mature and short forests, urban planners should prioritize the integration of green infrastructure into urban development plans. Implementing zoning regulations that protect existing mature forests and creating green corridors to connect urban, peri-urban, and rural landscapes can facilitate ecological resilience. Moreover, promoting sustainable agricultural practices in peri-urban zones is essential, given that agricultural land constitutes over 89% of certain plots in these areas. Encouraging agroecological techniques and providing incentives for urban agriculture can help mitigate pressures on urban ecosystems while enhancing local food security. In addition, reforestation initiatives targeting urban areas should also be launched to restore short forests and improve urban biodiversity. Community tree planting programs, especially in underutilized spaces, can significantly increase forest cover, while collaboration with local NGOs and schools can foster community stewardship. Moreover, expanding and maintaining urban green spaces, such as parks and recreational areas, is vital for enhancing ecological functions and overall quality of life. Designing multifunctional spaces that incorporate native plant species and wildlife habitats, coupled with public awareness campaigns, can further support urban biodiversity in order to meet the current challenges of sustainable development [24,58].

Finally, strengthening policies for land use management is crucial. The significant changes in forest components and agricultural land distribution emphasize the need for comprehensive land use policies that prioritize green infrastructure conservation across urban, peri-urban, and rural settings. Developing a robust land use assessment framework will ensure policies remain adaptive to ongoing developments, while involving community stakeholders in the decision-making process will align land use policies with local ecological and social needs.

5. Conclusions

The green infrastructure components examined in the Kisangani landscape, including mature forests, short forests, agricultural and grass lands, underwent substantial spatial change from 1986 to 2021 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 forest in urban areas do not significantly 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 certain peri-urban plots compared to just 1.3% in urban and more than 65% in rural zones. Agricultural and grass lands vary significantly across the urban–rural gradient, covering over 89% of certain 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 significant in rural zones. Agricultural land, conversely, shows a significant decrease in their proportion and increased fragmentation of patches in urban zones, while significantly increasing in peri-urban and rural zones with 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 the promotion of ecological corridors, urban parks, and buffer zones, may mitigate some negative impacts. This balanced approach can better align urban growth and economic development with ecosystem service conservation across the urban–rural gradient.

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