



Research Articles

Built-up expansion and urban land use trade-offs in peri-urban Cotonou (Benin), West Africa: A scenario-based remote sensing approach

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ARTICLE INFO

Keywords:

Urban spatial growth
Vegetation loss
Remote sensing
Scenario modeling
Land Change Modeler
Sustainable planning
Cotonou

ABSTRACT

In sub-Saharan Africa, understanding how urban land use and land cover (LULC) are changing is key to assessing the vulnerability of peri-urban ecosystems and improving spatial planning strategies. This study analyzes the dynamics of built-up expansion and associated land use trade-offs in the municipalities surrounding Cotonou, Benin, from 2002 to 2023, and simulates urban spatial growth trajectories to 2050 under three contrasting development scenarios. Multispectral Landsat imagery was classified using the Random Forest algorithm, and scenario-based projections were generated through the Land Change Modeler (LCM) in TerrSet. Classification accuracies were high ($Kappa > 0.98$), ensuring the reliability of results. Over the two-decade period, built-up/bare soil areas expanded by 12 %, while vegetation and others areas declined by 11.8 %, reflecting a moderate diffusion pattern and medium-speed urban spatial growth. Scenario projections indicate continued land conversion under the Rapid Economic Growth and Current Trend scenarios, primarily at the expense of vegetated areas. In contrast, the Green-city scenario highlights the potential for reversing land degradation through reforestation and spatial containment. These findings reveal critical trade-offs between development and environmental conservation, and demonstrate the value of scenario-based remote sensing approaches for guiding sustainable urban planning in rapidly transforming urban fringes of coastal West Africa.

Introduction

Urban land use and land cover (LULC) dynamics are among the most significant anthropogenic transformations reshaping socio-ecological systems across the globe. These spatiotemporal changes are driven by the interplay of socio-economic forces and natural factors, as LULC change is both a cause and consequence of human activity and biophysical processes [33,72]. Over the past century, socio-economic, demographic, and technological changes have dramatically altered natural landscapes[27,56]. In particular, rapid urban expansion, fueled by population growth and economic development, exerts increasing pressure on agricultural lands and natural ecosystems. This pressure is

especially evident in peri-urban areas, which serve as transitional zones between rural and urban systems and are increasingly subject to unregulated land conversion and the loss of ecological habitats[5].

While urbanization is often associated with improved economic opportunities and infrastructure development[19,57], its unintended environmental consequences are increasingly concerning. Urban land transformation contributes to extreme weather events such as flash floods[40]and intensification of urban heatwaves[64], largely driven by vegetation loss and the proliferation of impervious surfaces. These impacts underscore the importance of conceptualizing cities not merely as built environments but as complex socio-ecological systems[12], where human-nature interactions must be fully integrated into land use

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<https://doi.org/10.1016/j.cacint.2025.100263>

Received 3 July 2025; Received in revised form 12 September 2025; Accepted 5 November 2025

Available online 9 November 2025

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planning and governance frameworks.

Globally, urban areas are home to more than half of the world's population, with this number expected to grow steadily in the coming decades. According to the World Cities Report, 7.8 billion people now live in urban areas, with projections indicating an increase to 9.7 billion by 2050[60]. The majority of this growth is expected to occur in developing countries, particularly in sub-Saharan Africa, which alone will account for a significant portion of the additional 2.5 billion urban residents projected by 2050. This urban demographic explosion is particularly evident in peri-urban zones of rapidly growing African cities, which often lack the institutional capacity and regulatory frameworks to manage expansion sustainably.

In West Africa, this trend is particularly pronounced along urban fringes where formal and informal development patterns intersect [63,65]. Peri-urban landscapes are rapidly transforming, characterized by fragmented urban sprawl and the encroachment of built-up areas onto ecologically sensitive zones. Such transformations have been widely documented, highlighting spatial and demographic reconfigurations in peri-urban environments[28,41].

In Benin, peri-urban municipalities surrounding Cotonou (Abomey-Calavi, Sèmè-Podji, and Ouidah) are undergoing intense urban transformation. These municipalities now form a contiguous urban agglomeration with Cotonou, functioning as residential suburbs due to the city's overcrowding and unplanned spatial growth[31]. As available land within Cotonou becomes increasingly scarce, these municipalities have absorbed much of the region's urban expansion, often without adequate planning, resulting in significant land degradation and fragmentation of natural landscapes. Urban growth has extended across the entire peri-urban municipalities of Cotonou, accompanied by a drastic reduction in vegetation cover. Despite these developments, limited research has investigated the spatiotemporal dynamics of LULC change in these municipalities. In particular, few studies have explored spatial growth patterns, quantified urban expansion, or modeled future land use trajectories based on alternative development scenarios.

Advances in remote sensing (RS) and geographic information systems (GIS) now provide robust tools to monitor, analyze, and simulate land use transformations. Recent studies have demonstrated the value of these technologies in delivering spatially explicit evidence for informed urban decision-making[9,17,35,62]. Machine learning algorithms, such as Random Forest, have proven effective in classifying multispectral satellite imagery for LULC change detection. Furthermore, dynamic modeling platforms like the Land Change Modeler (LCM) in TerrSet offer powerful capabilities to simulate future land transitions under various development trajectories.

Despite the availability of such tools, there remains a methodological and analytical gap in their application to peri-urban contexts in West Africa. In particular, the integration of LULC classification with scenario-based modeling remains underutilized, especially in examining long-term implications of current development pathways. This is further compounded by known limitations of spatial models related to simulation methods, data availability, and the complexity of land use processes [29,44]. Nevertheless, as[3] note, these models offer significant potential to formalize territorial change processes and identify areas with a high likelihood of transformation.

This study aims to address these knowledge gaps by analyzing the spatiotemporal dynamics of urban expansion in the peri-urban municipalities of Cotonou between 2002 and 2023, and projecting LULC change to 2050 under three alternative development scenarios. We apply supervised classification of multispectral Landsat imagery using the Random Forest algorithm and simulate spatial transitions using LCM in TerrSet under a Current Trend, Rapid Economic Growth, and Green-city scenario. Our central hypothesis is that these peri-urban municipalities are experiencing rapid and unplanned urban expansion, and that the Rapid Economic Growth and Current Trend scenarios will lead to significantly higher urban land cover by 2050 compared to the Green-city scenario, which emphasizes ecological sustainability and spatial

containment.

Materials and methods

Study area description

This study focuses on the coastal municipalities of Ouidah, Abomey-Calavi (in atlantic departments), and Sèmè-Podji (in ouémé departments), located in southern Benin between latitudes 6°18'-6°44'N and longitudes 1°56'-2°44'E (Fig. 1). This study focuses primarily on three municipalities surrounding Cotonou, while two others, which are predominantly lacustrine and rural (Fig. 1), are not analyzed in detail. These three peri-urban municipalities play a central role as transition zones between Cotonou and the surrounding regions. Nevertheless, the geospatial analyses conducted here (classification and modeling) encompass the broader landscape of all five municipalities around Cotonou, thereby providing a more suitable framework to capture local/regional dynamics as well as urban–rural interactions across the continuum. These areas, positioned on the outskirts of Cotonou, the country's largest economic hub, are undergoing rapid urban expansion[31]. This growth is largely driven by the overpopulation[31]and spatial saturation of Cotonou[13], which has spurred the development of a conurbation with its neighboring municipalities[20]. The resulting urban sprawl is largely unregulated, leading to environmental degradation and challenges to sustainable land management[14]. The demographic shift is notable: while Cotonou's population growth has slowed, nearby municipalities like Abomey-Calavi, Ouidah, and Sèmè-Podji have absorbed much of the regional population increase, becoming commuter towns. The Atlantic and Ouémé departments are expected to become the most populated in Benin by 2030.

Data, tools, and image classification

To monitor the spatial urban growth of peri-urban municipalities around Cotonou over time, satellite imagery was subjected to supervised classification using the Random Forest (RF) algorithm[45,51,71]. This was performed on the Google Earth Engine (GEE) platform to map land use and land cover (LULC) change for the years 2002, 2013, and 2023 (Fig. 2). The images used were acquired from the Landsat 7 and 8 sensors, specifically the Enhanced Thematic Mapper Plus (ETM +) and the Operational Land Imager and Thermal Infrared Sensor (OLI-TIRS), respectively. Landsat images with 30 m resolution were acquired in the dry season (December-January) (Table 2).

Although the initial objective was to analyze urban dynamics over the last three decades (1990–2020), the years 2002, 2013, and 2023 were ultimately selected. This choice was based on the availability of cloud-free, high-quality imagery with good visual rendering. Additionally, these years correspond to national census periods in Benin, specifically the third, fourth, and fifth General Population and Housing Censuses (RGPH 3, 4, and 5). The year 2002 was chosen as the base year, as it marks the beginning of large-scale migration from Cotonou to neighbouring municipalities and the implementation of major government infrastructure projects [13]. A total of 450 geographical points have been used for testing the accuracy of the maps produced. For each map, different confusion matrices were produced (Appendix A) to validate the accuracy of the LULC classification. Analysis of the multi-date LULC classification results (Fig. 2 and Table 1) shows that the overall classification accuracies for 2002, 2013, and 2023 are 99.74 %, 99.44 %, and 99.15 %, respectively. The Kappa coefficients for these classifications are 0.99, 0.99, and 0.98, respectively. According to standard interpretation indices[52], these LULC maps are considered highly reliable[15,54]. (table A1 in appendix A).

The future projection of urban spatial expansion was carried out through a geospatial simulation of LULC in the study area by the year 2050, using the LCM within the TerrSet software[42,49]. This modeling was based on the classified land cover maps derived from satellite

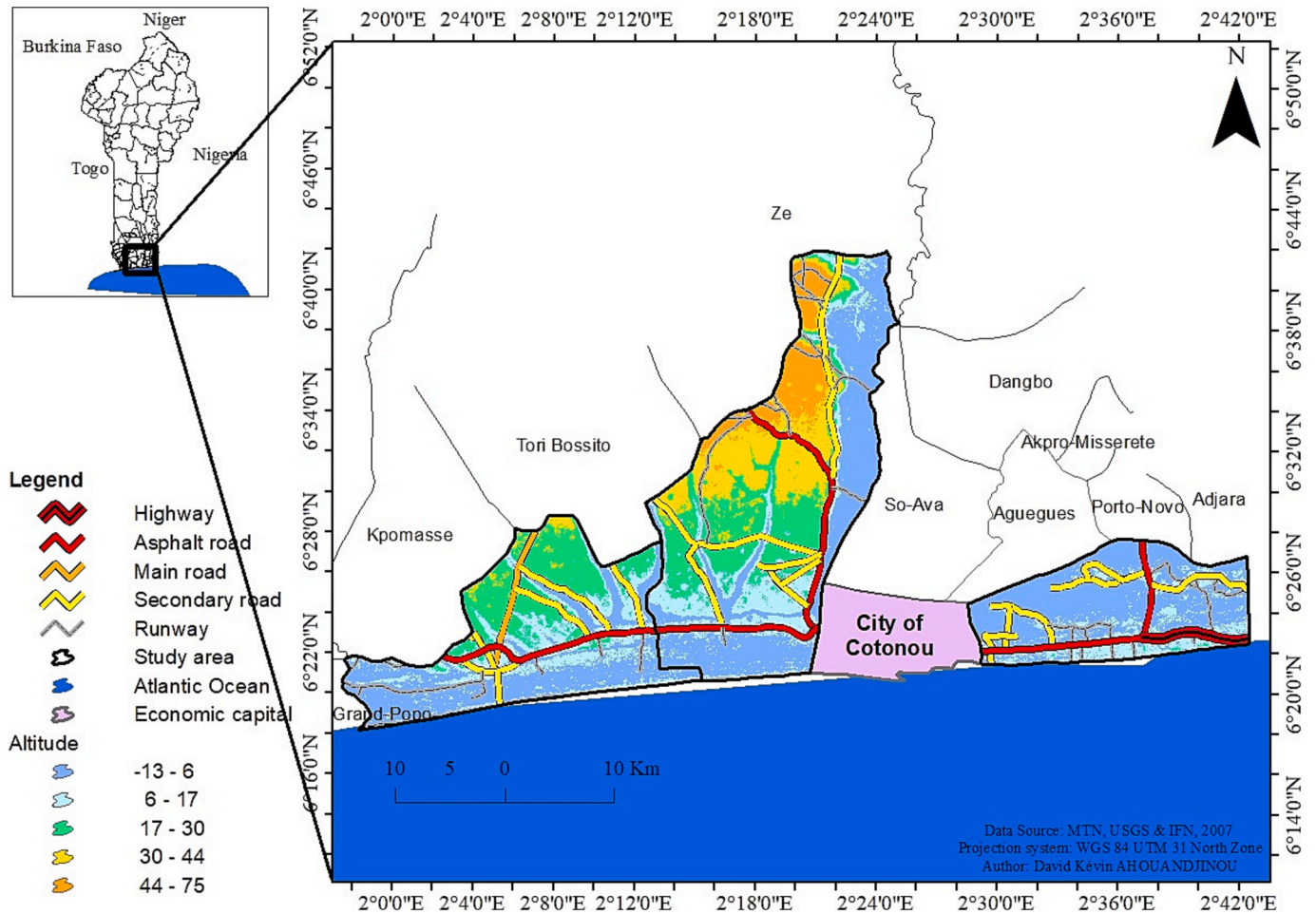


Fig. 1. Map of study area, illustrating of the peri-urban municipalities around Cotonou.

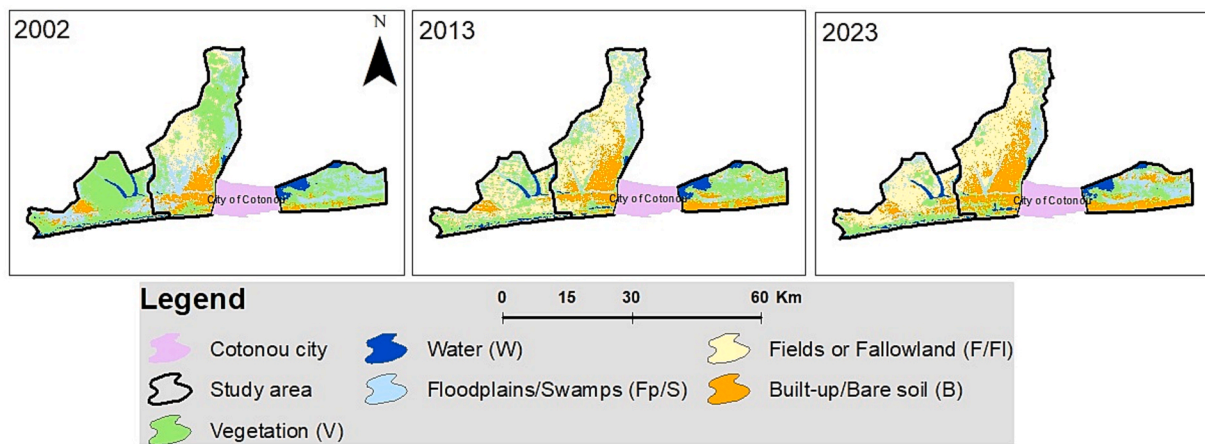


Fig. 2. LULC maps for 2002, 2013, and 2023. Expansion of built-up/bare soil and fields/fallowland in the southern Benin, classified by the Random Forest algorithm.

imagery, combined with auxiliary spatial data (Table 3) [2,3]. The input datasets included three classified LULC maps (2002, 2013, and 2023), slope, elevation, population density (2020), soil type, distance to fields/fallowland, distance to roads, and distance to built-up/bare soil areas. In addition, the spatial preprocessing analyses applied to those explanatory variables mainly involve harmonizing projection systems and making atmospheric and/or radiometric corrections necessary to ensure optimal data quality, followed by estimating the slope from the DEM and generating buffer zones for distance variables.

Characterizing the model of urban spatial expansion in the peri-urban municipalities around Cotonou

The characterization of urban spatial expansion was based on a combination of spatiotemporal analyses of land use, identification of spatial transformation processes, and assessment of the intensity of urban growth. First, a diachronic analysis of LULC change[54] was conducted to quantify the evolution of built-up/bare soil areas and to identify general trends in urban expansion[7,61]. Changes in area and

Table 1
Trends in the proportions of LULC class from 2002 to 2023.

LULC class	2002		2013		2023	
	area (ha)	%	area (ha)	%	area (ha)	%
Built-up/bare soil	11,195	10.8	17,309	16.7	23,715	22.8
Water	5031	4.8	5312	5.1	4689	4.5
Floodplains/ swamps	23,370	22.5	13,717	13.2	13,574	13.1
Fields/fallowland	13,693	13.2	35,070	33.8	38,980	37.6
Vegetation	50,517	48.7	32,364	31.2	22,848	22.0

% = Proportion

Table 2
Characteristics of the satellites images used.

Years	Acquisition dates	Satellites	Space versions	Bands used
2002	2002-01-15 to 2002-12-29	Landsat 7	ETM+	5, 4 and 2 of 30 m resolution
2013	2013-01-05 to 2013-12-15			
2023	2023-01-01 to 2023-01-15	Landsat 8	OLI-2; TIRS-2	6, 5 and 3 of 30 m resolution

OLI-TIR: Operational Land Imager and Thermal Infrared Sensor; ETM+: Enhanced Thematic Mapper Plus.

Table 3
List of influencing factors (used in this study) exploring the dynamics of land use changes in the peri-urban area of Cotonou.

Factor Category	Variable or data	Preprocessing	Sources
Land use and land cover change	Land use and land cover classes	Spatial analysis – LULC map of 2002, 2013, and 2023 with Landsat images [3]	Image Google Earth Engine [59]
Proximity factors	Distance to fields/fallow land	Spatial analysis – Estimation from the 2023 LULC maps with the Landsat 8 image	Image Google Earth Engine [59]
	Distance to built-up/bare soil	Spatial analysis – Estimation from the 2023 LULC maps with the Landsat 8 image	Image Google Earth Engine [55]
Transport	Distance to roads	Spatial analysis – Buffers zone creation [38]	Shapefile[48]
Geophysicalfactors	Slope	Spatial analysis – Image SRTM 1 Arc-Second Global DEM [38]	USGS[47]
	Elevation	Image SRTM 1 Arc-Second Global DEM[55]	USGS[47]
	Soil type	Spatial analysis – Buffers zone creation [55]	Shapefile[48]
Demographic factor	Population density	Estimates of number of people per grid square (persons/km ²)[38]	World Population [66]

proportions of land cover classes were assessed, with a particular focus on vegetation loss. Second, spatial transformation processes associated with urban expansion were examined using the decision tree approach proposed by[10]. This method evaluates changes in key landscape configuration metrics, such as the number of patches, total area, and total perimeter[8,11]. The mode of urban growth (diffusion or coalescence) was identified by analyzing changes in the number of built-up/bare soil patches relative to their total area in the landscape [18,61]. Finally, the Urban Expansion Intensity Index (*UEII*) was calculated to

quantify the intensity of urban growth [1,30,50]. The index was computed both for the entire study area and for each individual municipality. *UEII* classifies urban expansion intensity into several categories (very slow, slow, medium-speed, high-speed, and very high-speed) and is calculated using the formula:

$$UEII_i = \frac{ULA_{t_2} - ULA_{t_1}}{TLA_i \times \Delta t} \times 100$$

Where *UEII_i* is Urban Expansion Intensity Index of unit *i*; *ULA_{t₂}* and *ULA_{t₁}* are the areas of urban built-up land of unit *i* at times *t₂* and *t₁*, respectively; *TLA_i* is the total land area within the study area *i* and Δt is the study time period (i.e., *t₂* and *t₁*). According to[1], *UEII* reflects the future direction and the potential of urban expansions as well as compares speed or intensity of urban land-use change in different periods. The following indices were designed as a benchmark for interpreting *UEII* output values. This ranges from < 0.28 (very slow expansion), 0.28–0.59 (slow expansion), 0.59–1.05 (medium-speed expansion), 1.05–1.92 (high-speed expansion), and > 1.92 (very high-speed expansion)[1].

Geoprospective modeling of urban spatial expansion to 2050

To produce predictive LULC change, the land cover maps from 2002 and 2013 were used as the base and calibration years, respectively, to simulate LULC change for the year 2023. The result was validated using the actual classified map of 2023[2,3]. The LCM in TerrSet was employed for this modeling due to its versatility and ability to simulate various land cover change scenarios by manipulating model inputs[3]. Historical land cover changes from 2002 to 2013 were analyzed in terms of gains, losses, net change, and class-level contributions (especially

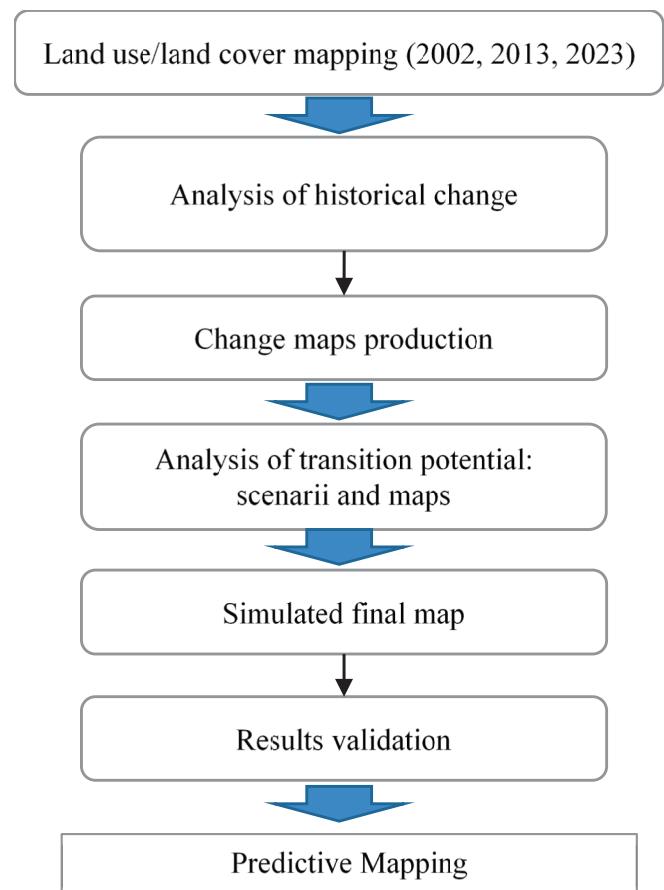


Fig. 3. Methodology for modeling and simulating the LULC map.

vegetation) to the expansion of built-up/bare soil, and fields/fallowlands. The Fig. 3 illustrates the major steps involved in the modeling process.

Analysis of historical changes and transition potential

The quantification of LCLU changes between 2002 and 2013 was carried out through two complementary approaches: an analysis of gains and losses, and an assessment of net changes and the contribution of vegetation to the expansion of anthropogenic classes (built-up/bare soil area, and fields/fallowland). The analysis of potential transitions served as a foundational step in designing future land use scenarios. It helped identify the specific land cover transitions to be incorporated into each scenario. Two major categories of transitions were considered anthropogenic (conversion of natural to human-modified land) and reforestation (reversion to vegetated land cover). Table 4 summarizes the key transition types used in the modeling, while Fig. 4 presents the historical change analysis highlighting the dominant transformation trends observed in the study area.

Geoprospective scenarios for spatial modeling

Three different simulation scenarios [2,55] were developed to project the future expansion of built-up/bare soil by 2050.

• **Scenario 1: Current Trends (CT) by 2050**

This scenario, assumes the continuation of existing land use trends without the implementation of new economic or environmental land use policies. Future land use patterns are projected to follow trajectories observed in the past and recent years (2002–2023), based on socio-economic drivers such as population and economic growth.

• **Scenario 2: Rapid Economic Growth (REG) by 2050**

In the REG scenario, both demographic and economic growth are expected to accelerate significantly. Government subsidies for agriculture are projected to increase, resulting in the expansion of cultivated lands. Industrialization and the development of hotels and restaurants will intensify. However, there will be no effective policies to protect natural resources, leading to their continuous degradation or disappearance.

• **Scenario 3: Green-city by 2050**

This scenario is inspired by the Coordinated Environmental Sustainability scenario. It envisions the development of urban green spaces and the establishment of protected areas (urban forestry). The main objective is to preserve existing vegetation by promoting sustainable agriculture and the development of green infrastructure. Environmental legislation and government incentives will support agroforestry and reforestation efforts, thereby reducing deforestation. Agricultural activities will continue with environmentally friendly practices, while economic and demographic growth and urbanization proceed at a

Table 4
Transitions specified for prospective scenarios by type.

Transition types	Transitions used	Scenarios
Anthropic pressure	<ul style="list-style-type: none"> Vegetation to Fields/fallowland Vegetation to Built-up/bare soil Fields/fallowland to Built-up/bare soil 	Current Trends (CT) and Rapid Economic Growth (REG)
Reforestation	<ul style="list-style-type: none"> Fields/fallowland to Vegetation Built-up/bare soil to Fields/fallowland 	Green-city

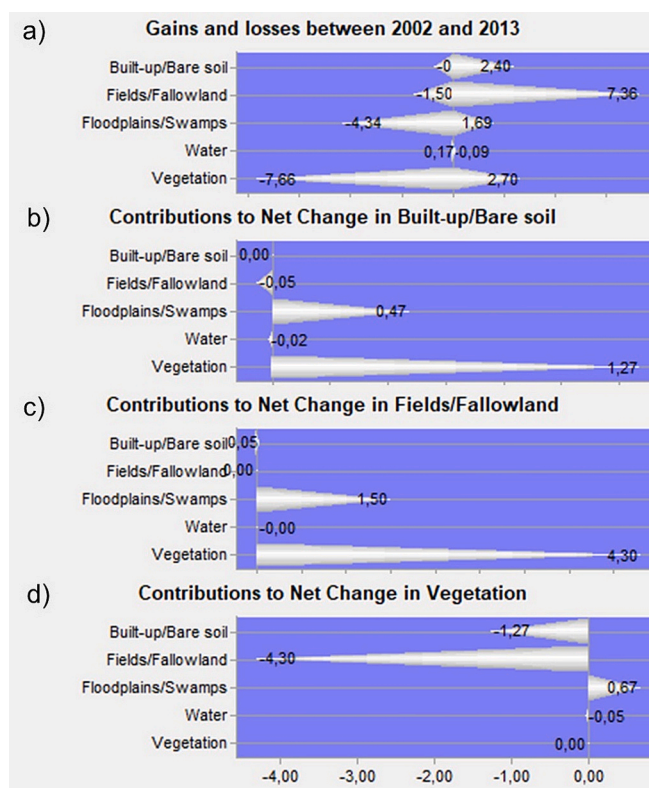


Fig. 4. Analysis of historical changes.

moderate pace. This scenario aligns with the principles of sustainable agriculture and green cities, consistent with the Sustainable Development Goals (SDGs).

Definition and analysis of explanatory variables of land use change

Depending on the types of LULC transitions considered for each scenario, explanatory variables were selected using Cramer’s V coefficient and general calibration analysis (Table 5). For each scenario, the main transitions were subdivided into specific sub-models to identify the driving factors (i.e., explanatory variables). For all scenarios, key

Table 5
Significant values of Kramer’s coefficient and general calibration analysis of explanatory variables (used in this study) for land use categories in peri-urban area of Cotonou..

Model	Cramer’s V	Accuracy (%)	Skill measure	Influence order	
With all variables	Index value	P value	53.50	0.41	N/A
Var. Population density constant	0.3492	0.00	26.97	0.08	2
Var. Slope constant	0.3282	0.01	53.42	0.41	6
Var. Distance to fields/fallowland constant	0.3266	0.02	53.00	0.41	3
Var. Distance to built-up/bare soil constant	0.3338	0.03	53.14	0.41	4
Var. Elevation constant	0.2632	0.04	20.78	0.00	1 (most influential)
Var. Distance to roads constant	0.2561	0.05	53.14	0.41	5
Var. Soil type constant	0.4016	0.06	53.52	0.41	7 (least influential)

variables included the distance to roads, agricultural areas, and built-up/bare soil (appendix B). Additional variables such as slope, elevation, and population density were also integrated (appendix B). In the CT scenario, no modifications were made to the transition probabilities observed in the historical change analysis. In contrast, for the Green-city scenario, the transition probabilities from vegetation to fields/fallowland or built-up/bare soil were reduced to reflect conservation efforts. Conversely, these probabilities were increased under the REG scenario to simulate the pressure of rapid development. The performance of the simulation sub-models was evaluated using a calibration process based on a multilayer perceptron (MLP) artificial neural network. After 10,000 iterations, the overall accuracy was 53.5 % for the anthropogenic degradation sub-model and 59.7 % for the reforestation sub-model, indicating acceptable performance levels. Model validation was conducted using two approaches. First, a visual comparison through photo-interpretation between the predicted LULC map for 2023 and the actual classified map for the same year. Second, a statistical comparison of proportional trends using the chi-square test [49] to assess whether there was a significant difference between the predicted and actual maps. All statistical tests were conducted at the 5 % significance level.

Results

Characterization of the urban spatial expansion pattern in peri-urban municipalities around Cotonou

Spatiotemporal evolution of built-up/bare soil (2002–2023)

The diachronic analysis of LULC between 2002 and 2023 reveals a significant expansion of built-up/bare soil areas in the peri-urban municipalities around Cotonou (Fig. 5). This expansion is marked by a 12 % increase in built-up/bare soil, growing from 11,195 ha in 2002 to 23,715 ha in 2023 (Table 6). Conversely, there has been an 11.8 % decline in vegetation and other over the same period, with these areas shrinking from 87,580 ha in 2002 to 75,402 ha in 2023. Although water bodies have remained relatively stable in spatial extent (Fig. 5), a slight increase of 0.3 % was observed between 2002 and 2013, followed by a decrease of 0.6 % from 2013 to 2023 (Table 6), indicating a more subtle yet ongoing transformation dynamic.

Spatial transformation processes and urban growth modes

The spatial expansion model of built-up/bare soil is primarily characterized by the creation of new patches of built-up/bare soil as the main spatial transformation process (Table 7). Between 2002 and 2023, these areas experienced a continuous appearance of new patches. Moreover, the expansion has largely occurred through a diffusive growth pattern, with new patches emerging scattered across the landscape rather than through the merging of existing ones (Table 7). This indicates that urban spatial expansion in the outskirts of Cotonou predominantly follows a

Table 6

Changes in the proportions of land use and land cover classes. In this table, we use the term “Other” to refer to all classes of “vegetation, floodplains/swamps, and fields/fallowland” in order to show the expansion of built-up/bare soil in the landscape.

Land use/land cover class	2002		2013		2023	
	area (ha)	%	area (ha)	%	area (ha)	%
Built-up/bare soil	11,195	10.8	17,309	16.7	23,715	22.8
Water	5031	4.8	5312	5.1	4689	4.5
Others	87,580	84.4	81,152	78.2	75,402	72.6

Caption: % = Proportion, and in this table, we use the term “Other” to refer to all classes of “vegetation, floodplains/swamps, and fields/fallowland” in order to show the expansion of built-up/bare soil in the landscape.

Table 7

Spatial transformation processes and urban spatial growth modes of built-up/bare soil from 2002 to 2023.

Spatial transformation type	2002–2013	2013–2023
Spatial transformation processes	Creation	Creation
Mode of urban spatial growth	Diffusion	Diffusion

diffusion-based growth model, where new developments spread outward in a fragmented and dispersed manner.

Intensity and nature of urban spatial expansion from 2002 to 2023

The analysis of the Urban Expansion Intensity Index (UEII) reveals that the intensity of built-up/bare soil expansion across the peri-urban municipalities around Cotonou shifted from a slow expansion between 2002 and 2013 to a medium-speed expansion between 2013 and 2023 (Table 8). However, this pattern of expansion varies significantly from

Table 8

Urban Expansion Intensity Index (UEII) values and characterization of built-up/bare soil expansion intensity.

Periods	Landscape of peri-urban Cotonou	Peri-urban municipalities around Cotonou		
		Ouidah	Abomey-Calavi	Sèmè-Podji
2002–2013	0.54(slow expansion)	0.00(very slow expansion)	0.60 (medium-speed expansion)	1.05 (medium-speed expansion)
2013–2023	0.62(medium-speed expansion)	0.41(slow expansion)	0.71 (medium-speed expansion)	0.76 (medium-speed expansion)

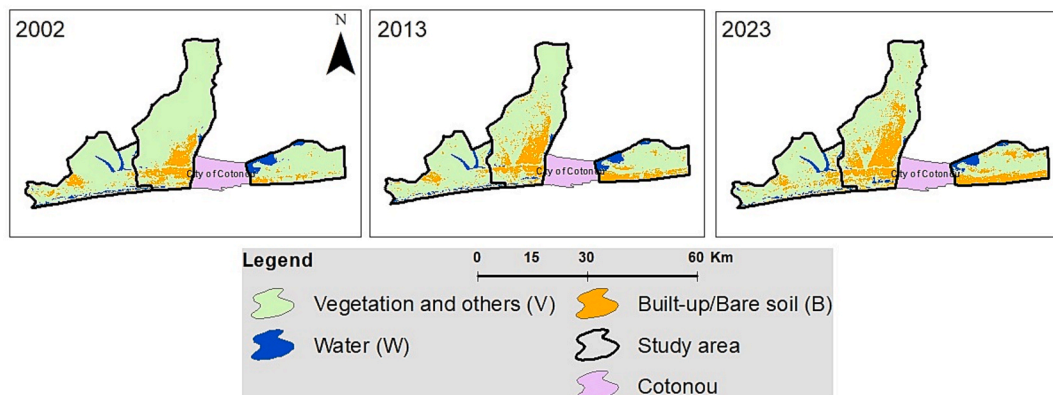


Fig. 5. Multi-date mapping of urban spatial expansion in 2002, 2013 and 2023.

one municipality to another. Specifically, the municipalities of Abomey-Calavi and Sèmè-Podji experienced a medium-speed expansion of built-up/bare soil area throughout the 2002–2023 period. In contrast, the municipality of Ouidah evolved from a state of very slow expansion between 2002 and 2013 to a slow expansion between 2013 and 2023.

Geospective modeling of urban spatial expansion in the peri-urban municipalities around Cotonou

Validation of the prediction model

To ensure accurate predictions of LULC in the Cotonou's peri-urban municipalities by 2050, validation of the prediction model was essential (Fig. 6). The results indicate no significant difference ($p > 0.05$) between the proportions of land cover classes simulated for 2023 and those obtained from the actual 2023 classification, thereby confirming the robustness of the model (Fig. 7). However, with the exception of water bodies, all other LULC showed slight differences in the proportional values between the simulated and classified 2023 maps. Additionally, a visual comparison of the two maps demonstrates a strong spatial agreement between the simulated and observed land cover patterns (Fig. 6).

Land use projection scenarios for 2050

The prospective modeling based on three geospatial scenarios reveals distinct trajectories of land use change by 2050 (Fig. 8). The generated maps display a spatial distribution that is consistent with the historical trends observed between 2002 and 2023, both in terms of land cover changes and class distribution. Furthermore, the extent of water bodies remains virtually unchanged across all three scenarios between 2023 and 2050 (Table 9). However, statistically significant differences in land cover proportions are observed among the three scenarios ($p = 0.00$, Fig. 8). Built-up/bare soil areas and fields/fallowland are projected to increase considerably, with the most pronounced growth occurring under the REG (Rapid Economic Growth) scenario compared to the CT (Current Trends) scenario. In contrast, the Green-city scenario, governed by environmentally conservative policies, shows a more balanced co-dominance among built-up/bare soil, vegetation, and fields/fallowland classes in 2050.

The REG scenario appears to be the most severe, projecting a 15.1 % loss of vegetation, compared to an 11.2 % reduction under the CT scenario, relative to the 2023 baseline. Under REG, built-up/bare soil and fields/fallowland areas are expected to increase sharply, by 8.8 % and 13 %, respectively, highlighting the rapid expansion and associated decline in vegetation cover.

In the CT scenario, a more moderate increase is observed: 4.8 % in built-up/bare soil and 13.1 % in fields/fallowlands. By contrast, the Green-city scenario shows a slight increase in built-up/bare soil by 0.8 % and a substantial 11.7 % gain in vegetation in 2050. However, floodplains/swamps and fields/fallowlands are projected to decline by 6.7 %

and 5.7 %, respectively. This is attributed to the transformation of older fallowlands and the reforestation of certain areas, such as young plantations from 2023, within the simulation model.

Discussion

Methodological approach for modeling and simulation

In a context of rapid and poorly planned urban growth, understanding urban spatial dynamics and their prospective simulation is essential. Our analysis combined spatial transformation processes[10], the typology of urban growth[36], and the Urban Expansion Intensity Index (UEII)[1,50], ensuring a robust characterization of urban spatial dynamics. These analyses helped identify the nature of changes in the landscape, quantify the speed of urban expansion, and characterize the mode (diffusion or coalescence) of urban spatial growth.

Regarding the modeling, among the many existing geospatial prediction tools, CA-Markov and LCM[22] are widely discussed for their ability to simulate spatiotemporal dynamics of urbanization. However, other tools may be more suitable and specialized for exploring future urban expansion dynamics. According to[3], the NEDUM-2D, SLEUTH, and LCM models are the most appropriate, and their complementarity allows for more accurate simulations of urban sprawl, as demonstrated in comparative studies. Nevertheless, the selection of a modeling tool must be guided by rigorous criteria and appropriate methods[42]. Based on our study objectives, the phenomena to be simulated, and the model functionalities, the LCM model, previously used in Benin by[2] and[49], was selected for this research. The use of this model requires land cover maps from two prior periods (2002 and 2013 in this study) relative to the target year[3,42]. A third map serves as the reference for model validation (2023 in our case). The comparison between simulated and classified LULC proportions for 2023[2,49], showed that the LCM model accurately reproduced the future urbanization changes around Cotonou.

An important limitation of this study lies in the moderate accuracy of the Multi-Layer Perceptron (MLP) sub-model used in the LCM (53.5–59.7 %). Although modest, this accuracy is consistent with other applications conducted in data-scarce contexts[2,49] and remains useful for identifying general spatial trends rather than precise quantitative forecasts. In this sense, the model's results remain highly relevant for land use planning, where detecting broad trajectories is often more valuable than obtaining exact values[38]. The limited performance is largely explained by the absence of dynamic socio-economic variables such as demographic growth, migration flows, and land tenure changes [6]. Previous studies have emphasized that excluding such evolving drivers (land tenure regimes, agricultural prices, subsidies, and population dynamics) can bias the accuracy of land use simulation models [21,68]. However, the lack of validated methods for spatializing these variables in West Africa remains a major challenge. Therefore, our study relied on a set of static and dynamic predictors (land cover at different

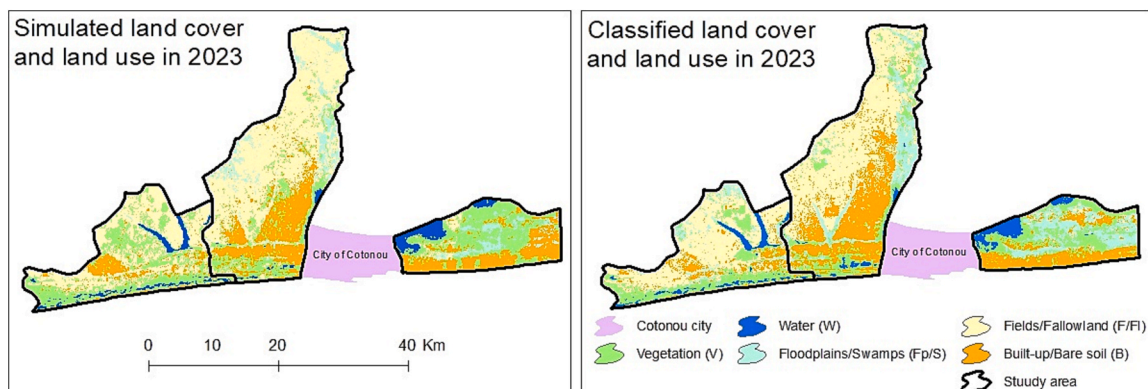


Fig. 6. Classified map and simulated map in 2023 for model validation.

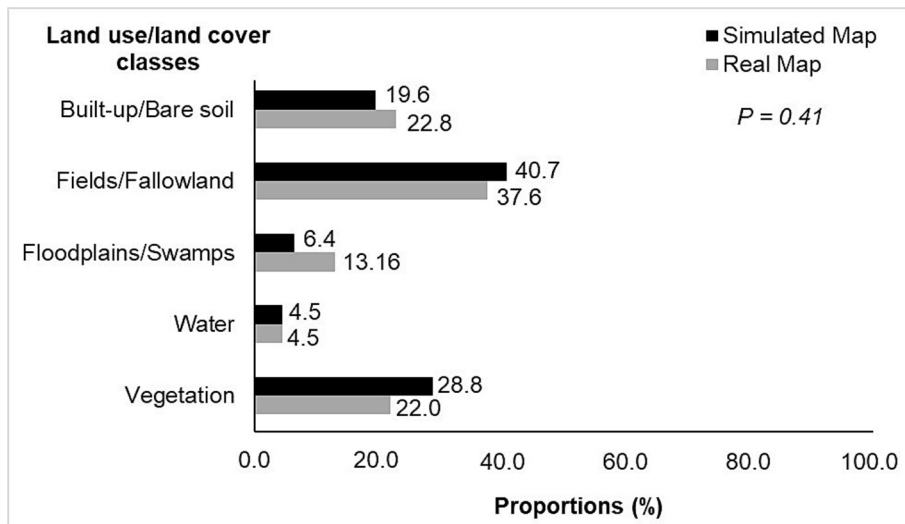


Fig. 7. Proportion of LULC classes in simulated and classified maps.

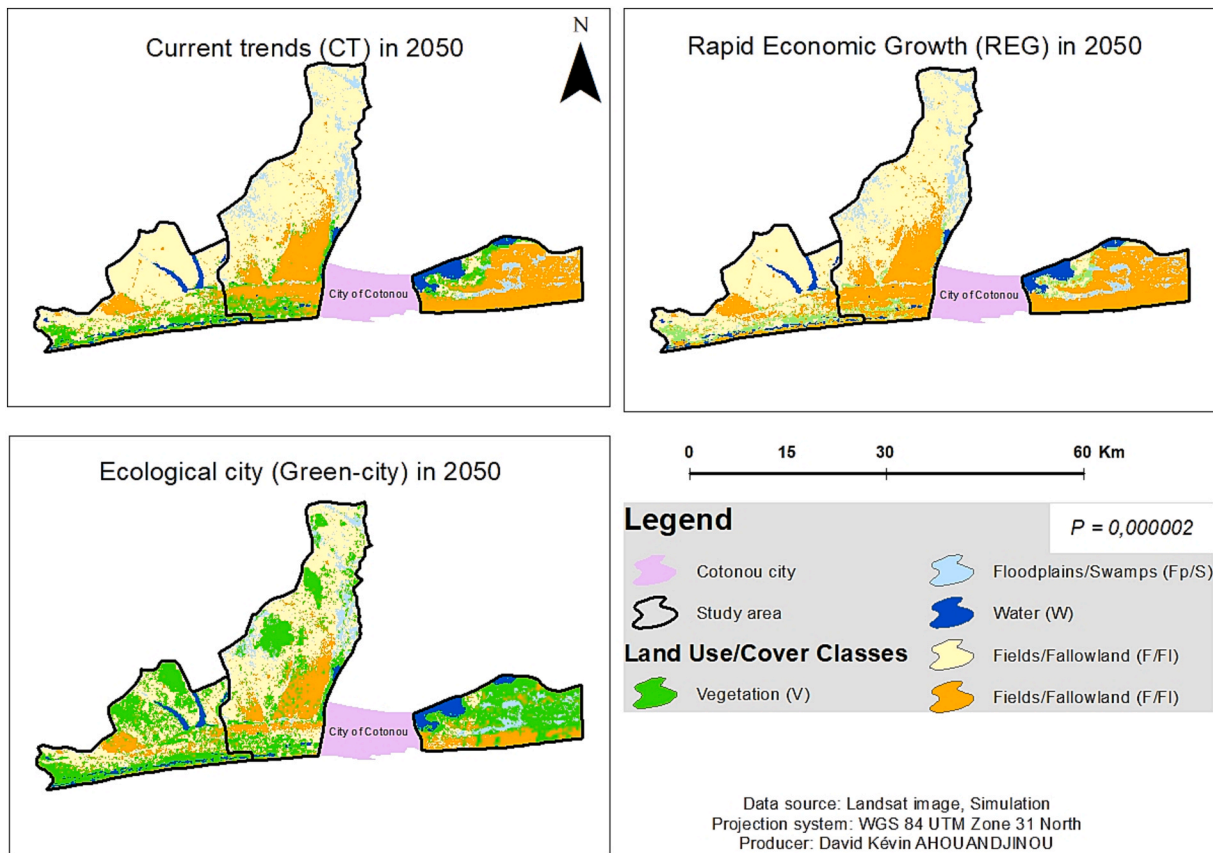


Fig. 8. Predictive LULC maps by scenario.

dates, slope, elevation, population density, soil type, distance to fields/fallow lands, distance to roads, and distance to built-up/bare soil areas), which are identified in the literature [4,38] as key determinants of land use change [23]. Their explanatory power was systematically assessed using Cramer’s V and the calibration procedures embedded in LCM, ensuring robustness.

Visual validation through photo-interpretation revealed some discrepancies in the representation of floodplains/swamps, reflecting the complexity of peri-urban dynamics [12,67]. Although the model slightly underestimated floodplains/swamps in 2023, it successfully captured

the accelerated evolution of all LULC units. This observation is consistent with other studies that highlight difficulties in using multitemporal images to map dynamic urban changes, especially due to mixed pixels and spectral confusion [46,70]. This may be due to the difficulties of representing the hydrological and ecological heterogeneity of peri-urban systems using only optical remote sensing. Our multi-temporal remote sensing approach reflects the methodological rigor described by [53], who documented landscape evolution over several decades in MENA cities such as Luxor and Amman using similar techniques. The integration of hydrological and ecological data could therefore improve

Table 9
Trends in LULC class proportions by scenario.

Land use/land cover class	2023		CT in 2050		REG in 2050		Green-city in 2050	
	area (ha)	%	area (ha)	%	area (ha)	%	area (ha)	%
Built-up/bare soil	23,715	22.8	28,624	27.6	32,767	31.6	24,361	23.5
Water	4689	4.5	4643	4.5	4643	4.5	4643	4.5
Floodplains/swamps	13,574	13.1	6646	6.4	6646	6.4	6646	6.4
Fields/fallowland	38,980	37.6	52,596	50.7	52,454	50.6	33,073	31.9
Vegetation	22,848	22.0	11,194	10.8	7194	6.9	34,979	33.7

% = Proportion.

the representation of floodplains/swamps. Another limitation concerns model validation. Indeed, although our study did not compare its results with those obtained using CA-Markov, SLEUTH, or DINAMICA, these approaches remain relevant. In particular, CA-Markov could provide a complementary perspective on transition probabilities and strengthen the robustness of long-term projections, as demonstrated by comparative studies[32,35]. As for the SLEUTH model, it does not allow for the effective integration of social and environmental factors[24]. However, the modeling approach (LCM) we used remains pertinent because it integrates a dimension of complementarity with Markov chains. Specifically, in LCM modeling, the Markov chain is used to determine the volume and transition probabilities between land use classes, while the MLP identifies the explanatory drivers and spatializes these transitions, thus ensuring a projection that is both quantitative and spatially explicit [43]. Accordingly, CA-Markov, DINAMICA, and LCM all use a Markov matrix to calculate the amount of change for each transition, yielding comparable results[43]. Moreover, LCM has a rigid structure that makes it difficult to alter the model's behavior[43], which nevertheless constitutes an advantage for building sub-models, as illustrated in our scenario analysis. Consequently, this combined MLP-Markov approach presents strong potential for forecasting urban growth, particularly in West African contexts marked by severe satellite data constraints, where the adoption of deep learning approaches remains limited[68]. In sum, despite the moderate MLP accuracy and the absence of complementary validation, our projections remain robust and policy-relevant, providing reliable insights into spatial dynamics and supporting evidence-based land use planning. Nevertheless, future research should combine multiple modeling approaches to reduce uncertainty and assess the sensitivity of projections to model choice.

Characterization of the urban spatial expansion model in the Cotonou's peri-urban municipalities

The analysis of spatial dynamics over the 2002–2023 period reveals a marked trend of urbanization in the peri-urban municipalities around Cotonou. Built-up/bare soils area increased by 12 %, while vegetated areas and other LULC classes declined by 11.8 %. Trends of spatial regression have been reported by several authors in Benin[2,21,49], across Africa[7,61], and globally[16,34,37,58]. This development likely reflects increasing land pressure linked to urban expansion and the progressive reduction of natural or low-anthropized areas. Indeed, the expansion of built-up/bare soils is primarily driven by demographic growth [39], informal settlements along road corridors, and housing demand associated with Cotonou's economic centrality. The regression of vegetated areas is mainly explained by the conversion of fields/fallow land, fuelwood harvesting, and peri-urban construction[21]. The reduction of floodplains/swamps reflects both uncontrolled encroachment by human settlements and weak enforcement of urban planning regulations[39,49]. Moreover, the observed urban spatial growth model is mainly characterized by peripheral diffusion, marked by the emergence of new, discontinuous patches of built-up/bare soils. This pattern has also been reported by[61] and[7] in their studies on urban spatial growth in the cities of Lubumbashi and Kisangani, respectively, in the DR of Congo. This process illustrates a gradual sprawl of the city toward

the peripheries, where new urban developments take the form of isolated patches that tend to agglomerate over time, as demonstrated by [18]. According to these authors, urban spatial growth first occurs through diffusion of built-up/bare soils, followed by their coalescence over time. Thus, coalescence represents a final state of urban spatial growth that alternates with diffusion as an initial state[18]. This suggests that coalescence may dominate the future expansion dynamics of the complex formed by the peri-urban municipalities around Cotonou.

Moreover, the diffusion-based growth observed in this study often results from unplanned or weakly structured urbanization, frequently driven by informal LULC dynamics. At the territorial scale of the municipalities complex formed by Abomey-Calavi, Sèmè-Podji, and Ouidah, the expansion of built-up/bare soil area followed a pattern of slow expansion between 2002 and 2013, and medium-speed expansion between 2013 and 2023, reflecting moderate but continuous growth. However, a municipal-level analysis reveals significant differences in the expansion of built-up/bare soil area. The municipalities of Abomey-Calavi and Sèmè-Podji exhibit a medium-speed expansion model, indicating an intensification of urban dynamics over the past two decades. These two municipalities play a central role in redistributing the urban pressure from Cotonou, due to their immediate proximity and increasing residential appeal. In contrast, the municipality of Ouidah shows a more nuanced evolution. Between 2002 and 2013, expansion was of the very slow type, reflecting marginal urbanization during that period. However, the subsequent period (2013–2023) reveals an acceleration toward a slow expansion pattern, suggesting the beginning of a more sustained urban dynamic, likely linked to recent development projects and improved transportation infrastructure connecting Ouidah to the Cotonou metropolitan area. These results confirm that urban expansion in the peri-urban municipalities around Cotonou is not homogeneous. It follows differentiated territorial logics, influenced by local socioeconomic, infrastructural, and political factors. These differentiated dynamics set the stage for our scenario-based simulations, which provide insights into possible future trajectories of urbanization in peri-urban Cotonou.

Urbanization modeling in the peri-urban municipalities around Cotonou

The results of the future LULC projections for the Cotonou's peri-urban municipalities reveal different spatial configurations in 2050, depending on the geospatial scenarios employed. Overall, vegetated areas are projected to decrease by 11.2 % and 15.1 % under the CT and REG scenarios, respectively, in 2050. This reduction leads to an increase in built-up/bare soil areas (4.8 % under CT and 8.8 % under REG) and fields/fallowlands (13.1 % under CT and 13 % under REG). Similar patterns have been reported by other authors following geospatial projections in several municipalities from northern to southern Benin [2,21,69]. Our results also align with those of[55] in the Punjab province of Pakistan and[25] in the Senegal River basin. According to[21], approximately 70 % of Abomey-Calavi's area will be occupied by human settlements in 2025 at the expense of agricultural and vegetated spaces. The comparatively higher rate of built-up area in their study may result from differences in the size of the study areas and the urban construction potential of each municipality. Abomey-Calavi is characterized by

ferallitic soils, which are more suitable for construction, whereas the other municipalities around Cotonou mostly have hydromorphic soils that are less favorable for building. Additionally, Abomey-Calavi shares the Godomey district with Cotonou, which facilitates migratory flows linked to economic dynamics between the two urban centers. Furthermore, some disparities were observed between the results of [49] in the RB-BVO and those of our study. According to their projections, RB-BVO will be slightly dominated by spontaneous vegetation formations, with co-dominance of floodplains/swamps and fields/fallowlands in 2035.

However, under the Green-city scenario, the ecological potential around Cotonou offers the prospect of a return to greener landscapes by 2050. Sustainable land use planning inherently integrates an ecological dimension, and our predictive mapping suggests that vegetation could dominate future landscapes, with co-dominance of built-up/bare soil areas and fields/fallow lands. Nevertheless, potential overestimations of vegetation, particularly in floodplains/swamps such as in Sèmè-Podji, highlight the need to integrate demographic data [6,21] and hydrological dynamics into scenario design. Indeed, the accuracy of these predictive models depends closely on the quality and availability of data [68]. The limitations of remote sensing in distinguishing wetland vegetation from terrestrial vegetation [4] in coastal areas further reinforce the need for cautious interpretation of the results. The dynamics observed in our peri-urban Cotonou case also reflect those found in other urban contexts in the MENA region [53], confirming the regional relevance of diffusion-coalescence-based urban growth models. The Green-city scenario also resonates with the principles of agroecological self-organization and polycentric governance observed in MENA settings, where community-based land stewardship contributes to sustainable territorial transitions [26].

Despite these challenges, the Green-city scenario presents an optimistic and politically relevant vision. Its success depends on strong political will [23], effective community engagement, and the mobilization of financial mechanisms. Concrete measures include government incentives for agroforestry, the promotion of urban and peri-urban agriculture, mandatory tree planting by residents, and legal protection of urban green spaces. These actions are consistent with Benin's National Forest Policy for 2040 [74], which aims at restoration, conservation, and sustainable land management, as well as with the Agenda 2030 [73] framework for climate resilience. Integrating urban forestry into national spatial planning would thus align local initiatives with broader strategic goals. This scenario should therefore be considered a normative pathway that highlights the transformative potential of ecological restoration and sustainable agriculture when incorporated into urban planning [38]. If effectively implemented, the Green-city scenario could reverse the degradation trends projected under the CT and REG scenarios and contribute significantly to achieving the Sustainable Development Goals (SDGs) in Benin's coastal region. Then, such integrative approaches are not only critical for Benin but also resonate with broader global agendas for sustainable and climate-resilient urbanization.

Policy implications for natural resource protection in peri-urban Cotonou

Based on scenario projections, clear policy directions emerge for peri-urban Cotonou. Under the CT and REG scenarios, the projected decline of vegetation and expansion of built-up and fields/fallowlands highlight the urgent need to regulate settlement growth. This requires zoning plans that restrict construction in floodplains/swamps while channeling urban expansion toward less fragile areas. In contrast, the Green-city scenario illustrates the socio-ecological benefits of embedding green infrastructure, urban agriculture, and agroforestry within municipal development strategies. Integrating such practices into local planning aligns with polycentric governance models, where empowered communities drive agroecological transitions [26]. Effective implementation of this vision demands spatially explicit measures [23], including the delineation of urban forest reserves, designation of ecological corridors, and enforcement of tree-cover protection within

new residential developments. Rapid demographic growth must also be incorporated into zoning strategies, as it drives natural area loss and informal settlements. Thus, zoning should define settlement boundaries, economic centers, administrative areas, agro-economic activity zones, and sustainable mobility corridors, while ensuring the valorization of natural areas. To reduce rural–urban migration pressures, socio-economic opportunities and improved service infrastructure in rural regions are essential. At the political level, integration must be aligned with Benin's National Forest Policy 2040 [74] and the Agenda 2030 [73] framework, ensuring that peri-urban planning advances climate resilience and sustainable land management. Civic reforestation programs, supported by fiscal incentives and community monitoring, can further strengthen local ownership. Overall, embedding the Green-city approach into spatial regulations provides a concrete pathway to reverse degradation trends and safeguard natural resources in Cotonou's rapidly urbanizing coastal landscape.

Conclusion

This study characterized the dynamics of urban spatial expansion and simulated future land use and land cover changes up to 2050 under three distinct development scenarios in the peri-urban municipalities of Cotonou. The results reveal a marked expansion of built-up/bare soil areas, particularly under the Rapid Economic Growth (REG) scenario, which appears especially detrimental to vegetation cover compared to the Current Trend (CT) scenario. In contrast, the Green-city scenario illustrates a more sustainable trajectory, showing the potential for vegetation recovery and controlled urban expansion. While these projections offer useful foresight, they remain dependent on assumptions and methodological constraints, including the exclusion of dynamic variables such as population growth, land tenure changes, or governance shifts. Future studies that incorporate these dynamic factors and validate projections against real-world trends will further improve the robustness of scenario-based modeling. Despite these limitations, the present findings provide a valuable decision-support tool for land use planners and policymakers, supporting the formulation of more resilient and sustainable urban development strategies in the Cotonou metropolitan region.

CRedit authorship contribution statement

Sèdjro David Igor Thierry Kévin Ahouandjinou: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Carlo Sodalo:** Writing – review & editing, Visualization, Validation, Methodology. **Raoul Kouagou Sambieni:** Writing – review & editing, Visualization, Validation, Supervision, Conceptualization, Methodology. **Abdel Aziz Osseni:** Visualization, Validation, Methodology, Writing – review & editing. **Arcadius Yves Justin Akossou:** Visualization, Validation, Supervision, Methodology, Conceptualization, Writing – review & editing. **Jan Bogaert:** Visualization, Validation, Supervision, Conceptualization, Methodology, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors would like to thank the Ecole Régionale Post-Universitaire d'Aménagement et Gestion Intégrés des Forêts et Territoires Tropicaux (ERAIFT), UNESCO-MAB and ERAIFT's donors, in this case the European Union through AGRINATURA, for their financial and

material support.

Ethical statement

This scientific article does not involve any studies conducted by the authors that include human participants, animals, or plants. The authors confirm that all sources cited in this review have been properly acknowledged and referenced. There are no conflicts of interest related to this work. The authors have adhered to ethical standards in scientific publishing, including avoiding plagiarism and respecting intellectual property rights.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.cacint.2025.100263>.

Data availability

Data will be made available on request.

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