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Non-linear Urban Expansion and Ecological Collapse: Evidence from a Polarized Urban–Rural Gradient in Bukavu (DR Congo)

Emery Akonkwa Shabani

emeryshaban@gmail.com

Université Officielle de Bukavu (UOB)

Nadege Cizungu Cirezi

Ecole Régionale Post-Universitaire d'Aménagement et de Gestion Intégrée des Territoires tropicaux (ERAIFT)

Serge Mugisho Mukotanyi

Université Catholique de Bukavu (UCB)

Eliel Chirongozi Mutabesha

Ecole Régionale Post-Universitaire d'Aménagement et de Gestion Intégrée des Territoires tropicaux (ERAIFT)

Guillaine Busime Baharanyi

Université Catholique de Bukavu (UCB)

Médard Mpanda Mukenza

TERRA Research and Teaching Center, Université de Liege

Joël Mobunda Tiko

Ecole Régionale Post-Universitaire d'Aménagement et de Gestion Intégrée des Territoires tropicaux (ERAIFT)

Julien Bwazani Balandi

Ecole Régionale Post-Universitaire d'Aménagement et de Gestion Intégrée des Territoires tropicaux (ERAIFT)

Jan Bogaert

TERRA Research and Teaching Center, Université de Liege

Yannick Useni Sikuzani

Université de Lubumbashi

Research Article

Keywords: Urban–rural gradient, Ecosystem degradation, Remote sensing, Landscape metrics, Unplanned urbanization, Ecological resilience

Posted Date: May 28th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9587284/v1

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Additional Declarations: No competing interests reported.

Abstract

Peri-urbanization is a major driver of landscape transformation and ecosystem degradation through habitat fragmentation, vegetation loss, and land artificialization, particularly along urban–rural gradients where anthropogenic pressures are highly concentrated. This study analyzes the trajectories and mechanisms of ecological change induced by peri-urban expansion over a twenty-year period (2005–2024) in Bukavu, eastern Democratic Republic of the Congo, a rapidly growing city characterized by intense demographic pressure and largely unplanned urban development. The research aims to analyze how urban dynamics restructure landscape patterns and degrade ecosystems along a polarized urban–rural gradient by integrating urban morphology, biophysical indicators, and spatial transformation processes. Methodologically, the study adopts an integrative framework combining: (i) the delineation of the urban–rural gradient based on Morphological Urbanization Status, (ii) multi-temporal analysis of Landsat imagery (2005, 2011, 2017, 2024) using spectral indices, (iii) quantification of landscape structure through FRAGSTATS metrics, and (iv) identification of spatial transformation processes via a decision-tree approach. The results reveal rapid and spatially polarized urban expansion. Built-up areas nearly doubled between 2005 and 2024 (14.7 to 27.5 km²; +87%), while dense vegetation declined sharply (15.1 to 4.1 km²; −73%). Landscape structure evolved toward marked homogenization, with increasing dominance of built-up land (PLAND: 33% to 69.4%), high aggregation of artificial surfaces (COHESION > 99%), and rising contagion (11.9 to 52.3). Peri-urban areas concentrate the most critical processes, including habitat dissection, declining vegetation indices, and accelerated loss of ecological functionality. This study contributes urban ecological research by proposing a mechanistic interpretation of ecosystem degradation in unplanned cities of the Global South. It shows that ecological decline is structured by spatial polarization and sequential land-cover transitions, highlighting peri-urban areas as critical zones of ecological vulnerability. These findings underscore the urgent need to integrate landscape structure and transitional zones into urban planning to enhance resilience and biodiversity conservation in rapidly expanding tropical cities.

1. Introduction

Rapid urbanization has emerged as one of the most powerful drivers of socio-ecological transformation worldwide. In the Global South, and particularly in Sub-Saharan Africa, this process is characterized by accelerated urban growth that is largely unplanned, spatially extensive, and predominantly driven by horizontal expansion into peri-urban areas[1]. Such forms of urbanization are consistently associated with extensive land artificialization, habitat fragmentation, biodiversity loss, and the progressive degradation of ecosystem services, ultimately undermining the resilience of urban systems[2].

Within this context, the urban–rural gradient has become a central analytical framework in urban ecology and landscape ecology. It conceptualizes ecological transformations as a continuum of decreasing anthropogenic pressures from urban cores toward rural peripheries[3]. Empirical studies conducted in cities of Europe and North America have shown that such gradients are typically associated with

relatively predictable ecological trajectories, including declining biodiversity, simplification of landscape structure, and reduced ecological connectivity as urbanization intensifies[2].

However, the applicability of these models to rapidly growing African cities remains highly problematic. Unlike Global North contexts, African cities often evolve under conditions of weak institutional control, informal land tenure systems, limited urban planning, and intense demographic pressure[4]. Under such conditions, the urban–rural gradient tends to be neither continuous nor stable, but rather discontinuous, spatially fragmented, and strongly polarized, reflecting complex and often unpredictable socio-spatial dynamics[5].

From a methodological perspective, existing approaches remain insufficient to capture these dynamics in an integrated manner. Remote sensing techniques effectively document land-use and land-cover changes but often fail to explain the underlying spatial mechanisms driving ecological degradation[6]. Landscape metrics provide quantitative measures of fragmentation and homogenization, yet are frequently used in a descriptive manner without explicit linkage to the urban morphological processes that generate them[7]. Conversely, urban morphological approaches capture the spatial organization of built environments but remain largely disconnected from their ecological implications[8].

As a result, a major analytical gap persists: the lack of an integrated framework capable of simultaneously linking urban form, biophysical vegetation dynamics, and landscape transformation processes, particularly in contexts of unplanned urbanization. While ecological degradation is widely documented, it is rarely explained in terms of its spatial logic and underlying mechanisms[9]. Addressing this gap requires moving beyond descriptive analyses toward process-based interpretations of how urban expansion structurally reorganizes ecological systems. In rapidly urbanizing African cities, these transformations are not only accelerated but also non-linear, threshold-driven, and spatially discontinuous, challenging conventional gradient-based models derived from the Global North.

Analyzing the ecological impacts of peri-urbanization therefore requires integrative approaches capable of articulating urban morphology, biophysical dynamics, and landscape structure. The urban–rural gradient provides a critical analytical framework for capturing the spatial distribution of anthropogenic pressures beyond administrative boundaries. Multi-temporal remote sensing enables the reconstruction of long-term trajectories of urban expansion and ecological degradation, while landscape ecology metrics offer insights into structural transformations, including fragmentation, homogenization, and loss of connectivity. When combined within a mechanistic interpretative framework, these approaches enable a shift from describing patterns to understanding the processes through which peri-urbanization drives ecological degradation.

The city of Bukavu, located in the eastern Democratic Republic of Congo, provides a particularly relevant case study. It is experiencing rapid demographic growth driven by both rural migration and conflict-induced displacement[10], within a context of largely unplanned urban expansion, strong land pressure, and weak territorial governance[11]. Bukavu exhibits a highly contrasted urban–rural gradient: the central communes of Ibanda and Kadutu are characterized by near-continuous artificialization, while the

peripheral commune of Bagira retains a partially preserved vegetated matrix, functioning as a residual ecological reservoir[12]. This configuration is further shaped by steep topography, which amplifies the environmental consequences of deforestation, including erosion, runoff, and landslide risks. Moreover, the proximity of the Kahuzi-Biega National Park, a UNESCO World Heritage Site, adds a critical regional dimension to the socio-ecological implications of urban expansion[13].

This study contributes to urban ecology and landscape science in three key ways. First, it demonstrates that urban–rural gradients in unplanned cities are not continuous but highly polarized and spatially fragmented, leading to non-linear ecological responses. Second, it identifies a sequential mechanism of ecosystem degradation, in which dense vegetation is progressively fragmented, transitions into herbaceous cover, and is ultimately replaced by built-up areas. Third, it proposes an integrated analytical framework combining urban morphology, spectral indices, and landscape metrics to capture both structural and functional dimensions of ecological change.

Focusing on the period 2005–2024, this study captures a critical phase in the urban evolution of Bukavu, marked by accelerated spatial expansion and rapid contraction of vegetated habitats. It aims to analyze and explain the effects of peri-urbanization on ecosystem degradation along the urban–rural gradient. Specifically, the objectives are to: (i) characterize the structure and polarization of the urban–rural gradient, (ii) quantify spatio-temporal trajectories of land-cover transformation, and (iii) identify dominant landscape processes driving fragmentation, homogenization, and loss of ecological connectivity. This study tests the following hypotheses: (1) the urban–rural gradient is not continuous but spatially polarized, resulting in non-linear variations of spectral indices, with NDVI and GEMI decreasing sharply and NDBI increasing disproportionately across transition zones; (2) ecosystem degradation follows a sequential land-cover transition pathway, characterized by the progressive conversion of dense vegetation into herbaceous cover and subsequently into built-up areas, detectable through changes in PLAND, NP, and transition matrices; (3) urban expansion induces a dual spatial process combining aggregation of built-up areas (increase in PLAND and COHESION, decrease in NP) and fragmentation of vegetated classes (decrease in PLAND, increase in NP), particularly in peri-urban zones; (4) increasing urbanization leads to a significant decline in ecological connectivity, reflected by decreasing COHESION and increasing CONTAG values, indicating progressive landscape homogenization; (5) peri-urban areas exhibit the highest rates of ecological degradation, characterized by intermediate NDVI/GEMI values, increasing NDBI, and peak fragmentation metrics, indicating their role as critical transition zones. This study adopts a multi-method approach to capture complementary dimensions of urban ecological transformation, combining morphological classification, spectral indices, and landscape metrics to link spatial form, ecological condition, and transformation processes.

2. Materials and methods

2.1. Study area

The city of Bukavu (Fig. 1), located in eastern Democratic Republic of the Congo along the southwestern shore of Lake Kivu, covers approximately 60 km² and is administratively divided into three communes—Ibanda, Kadutu, and Bagira—displaying contrasting spatial structures shaped by rapid and largely unplanned urban expansion[1]. Bukavu is characterized by a steep and highly dissected topography, composed of hillslopes and valleys that increase exposure to erosion, surface runoff, and landslides. The tropical highland climate (1,300–1,500 mm annual rainfall; mean temperature ~ 20–22°C) has historically supported dense vegetation, which is now increasingly degraded under urban pressure[14]. The city has experienced rapid demographic growth, with a population exceeding one million inhabitants, driven by rural migration and conflict-related displacement. This growth occurs in a context of limited planning and weak governance, leading to predominantly informal and spatially heterogeneous urban expansion[15]. The spatial organization of Bukavu reflects a strongly polarized urban–rural gradient, with densely built and highly artificialized central areas (Ibanda and Kadutu) contrasting with more fragmented and partially vegetated peri-urban zones (Bagira). These peri-urban areas represent critical transition spaces where land-use conversion and ecological degradation are particularly intense. Overall, Bukavu provides a relevant case study for analyzing the interactions between unplanned urbanization, landscape transformation, and ecological degradation in rapidly growing cities of the Global South.

2.2. Materials and methods

2.2.1. Data

The analysis is based on a multi-temporal series of Landsat imagery covering the city of Bukavu, derived from Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and Landsat 8 Operational Land Imager (OLI) sensors. Four key dates were selected—2005 and 2011 (Landsat 7 ETM+), and 2017 and 2024 (Landsat 8 OLI)—to capture major phases of recent urban expansion. Landsat imagery, with a spatial resolution of 30 m and broad spectral coverage from the visible to the mid-infrared, provides a robust framework for diachronic analysis of land-use and land-cover dynamics at the urban scale[16]. The selected dates reflect both methodological consistency and key stages in the urbanization trajectory. The year 2005 corresponds to a post-conflict recovery phase marked by renewed urban growth, while 2011 and 2017 represent intermediate stages characterized by progressive consolidation and outward expansion of built-up areas. The year 2024 provides a recent reference state, capturing an advanced stage of peri-urbanization and enabling the assessment of cumulative ecological transformations over nearly two decades. All images were acquired during the dry season to minimize phenological variability and ensure spectral comparability across dates[17]. The temporal continuity and radiometric consistency of the Landsat archive provide a reliable basis for analyzing long-term urban dynamics and associated ecological degradation processes[15].

2.2.2. Image preprocessing

Preprocessing was conducted using the Google Earth Engine (GEE), selected for its capacity to handle large satellite archives while ensuring the reproducibility and standardization of multi-temporal

processing workflows[17]. This choice is particularly appropriate for diachronic analyses requiring consistent and scalable data processing. Landsat images were atmospherically corrected using the LEDAPS algorithm for Landsat 7 ETM + and LaSRC for Landsat 8 OLI. These methods were selected due to their robustness in converting top-of-atmosphere reflectance into surface reflectance, ensuring comparability across sensors and acquisition dates[18].

To ensure inter-sensor consistency between Landsat 7 ETM + and Landsat 8 OLI, surface reflectance products from Collection 2 Level 2 were systematically used. In addition, all images were selected from the dry season to minimize phenological variability. This approach follows standard radiometric normalization practices[15]. No explicit bandpass adjustment coefficients were applied; however, the combination of atmospheric correction, seasonal consistency, and quality masking ensures a satisfactory level of spectral comparability for multi-temporal analysis.

The images were subsequently georeferenced and radiometrically harmonized following standard NASA protocols to ensure interannual consistency, which is essential for reliable temporal analysis[15]. Cloud and shadow pixels were identified and masked using the quality assessment (QA) bands embedded in Landsat products, reducing atmospheric noise and improving the reliability of spectral signatures[19]. This preprocessing workflow ensures that observed spatial and temporal variations primarily reflect actual changes in land cover rather than artifacts related to atmospheric conditions, acquisition geometry, or sensor differences[20]. However, the 30 m spatial resolution of Landsat imagery may limit the detection of fine-scale urban structures and small vegetation patches, particularly in highly heterogeneous peri-urban environments.

2.2.3. Delineation of the urban–rural gradient (MUS)

The urban–rural gradient was defined using Morphological Urbanization Status (MUS), allowing the characterization of the spatial structure of urbanization independently of administrative boundaries. This methodological choice is justified by the fact that, in contexts of unplanned urban growth, administrative units often fail to reflect the functional organization of urban space. The study area was subdivided into a regular grid of 250 × 200 m (5 ha), within which the proportions of built-up areas, open spaces, and vegetation cover were estimated through visual interpretation of high-resolution imagery from Google Earth[21]. The use of high-resolution imagery complements medium-resolution satellite data and improves the accuracy of morphological characterization.

The selection of this spatial unit represents a compromise between spatial resolution and statistical robustness [22]. Smaller grid sizes tend to generate excessive local variability, while larger units may obscure transition zones, which are critical for analyzing urban–rural gradients. Each grid cell was classified into three morphological categories—urban, peri-urban, or rural. The classification was validated using a stratified sample of approximately 90 grid cells, verified through field observations conducted in 2024, ensuring the consistency and reliability of the gradient definition.

For each grid cell, three coefficients were calculated:

α = (built-up area / total cell area) × 100

β = (herbaceous vegetation area / total cell area) × 100

γ = (dense vegetation area / total cell area) × 100

Based on these coefficients, each cell was classified as follows:

- - Urban: α > 50%
- - Peri-urban: α between 20% and 50%
- - Rural: α < 20%

To reduce subjectivity inherent to visual interpretation, classification thresholds were standardized and applied consistently across all grid cells. The calculated coefficients (α, β, γ) were then aggregated at the neighborhood level to produce the values presented in Table 1, allowing a quantitative characterization of the urban–rural gradient.

2.2.4. Multi-temporal land-use/land-cover mapping

Land-use and land-cover (LULC) maps were generated for the four dates using a supervised classification based on the Random Forest algorithm implemented in Google Earth Engine. Classification was performed independently for each date (2005, 2011, 2017, and 2024), resulting in four distinct Random Forest models to account for temporal variability in spectral signatures and sensor differences.This algorithm was selected due to its robustness in handling complex spectral environments, such as tropical urban landscapes characterized by high spatial heterogeneity and non-linear spectral responses[23]. Three land-use/land cover classes were defined: (i) dense vegetation (tree and shrub formations), (ii) herbaceous vegetation (grasslands, fallows, and low crops), and (iii) built-up areas (impervious surfaces and infrastructure). Training samples for historical dates (2005, 2011, and 2017) were generated through retrospective visual interpretation of high-resolution imagery available in the Google Earth archive, combined with the identification of temporally stable land-cover areas. Field observations conducted in 2024 were used to validate class definitions and improve classification consistency, rather than directly train earlier models.This simplified classification scheme was deliberately adopted to reduce classification uncertainty while maintaining ecological relevance, particularly in distinguishing high-value ecosystems, transitional land-cover types, and artificial surfaces.

The Random Forest model was parameterized with approximately 100 trees to ensure stability, while overfitting was controlled through out-of-bag (OOB) error estimation[24]. Classification accuracy was assessed using confusion matrices based on independent validation samples. Overall accuracy, Kappa coefficient, and class-specific producer and user accuracies were calculated[25]. Accuracy values consistently exceeded 85–90%, indicating that the resulting maps are sufficiently reliable for analyzing spatio-temporal dynamics of urbanization and ecological degradation.

2.2.5. Reproducibility and analytical consistency

All processing steps were implemented using standardized workflows within a cloud-based environment, ensuring full reproducibility and consistency across temporal datasets. Landsat data were accessed from Collection 2 Level 2 datasets, specifically LANDSAT/LE07/C02/T1_L2 for Landsat 7 ETM + and LANDSAT/LC08/C02/T1_L2 for Landsat 8 OLI. This approach enhances the transferability of the methodology to other rapidly urbanizing contexts. Furthermore, the methodological framework was designed to support explicit hypothesis testing. The integration of spectral indices (NDVI, GEMI, NDBI), used to characterize vegetation condition and artificialization, with landscape metrics (PLAND, NP, COHESION, CONTAG), used to quantify spatial structure, enables a direct linkage between observed patterns and underlying processes of fragmentation, aggregation, and ecological degradation along the urban–rural gradient.

Random Forest hyperparameters and sampling procedures are explicitly defined to ensure reproducibility. The full processing workflow implemented in Google Earth Engine can be made available upon request.

2.2.6. Spectral indices and ecological assessment

To quantify ecological conditions and urban-induced transformations, three spectral indices were computed: NDVI, GEMI, and NDBI.

The Normalized Difference Vegetation Index (NDVI) was calculated as:

$$\mathrm{NDVI} = \frac{(\mathrm{NIR} - \mathrm{RED})}{(\mathrm{NIR} + \mathrm{RED})}$$

where NIR and RED correspond to near-infrared and red reflectance, respectively. NDVI exploits the strong reflectance of healthy vegetation in the near-infrared domain and its absorption in the red domain due to chlorophyll activity. High NDVI values indicate dense and functional vegetation, while low or negative values correspond to degraded vegetation, bare soil, or artificial surfaces, making NDVI a sensitive indicator of vegetation loss associated with urban expansion[26].

The Global Environmental Monitoring Index (GEMI) was computed as:

$$\mathrm{GEMI} = \frac{\eta\ (1 - 0{,}25\eta\ ) - (\mathrm{RED} - 0{,}125)}{(1 - \mathrm{RED})}$$

with η = [2(NIR² − RED²) + 1.5NIR + 0.5RED] / (NIR + RED + 0.5).

GEMI introduces a non-linear transformation of spectral reflectance designed to reduce soil background effects and atmospheric noise. It improves the detection of intermediate and degraded vegetation states, particularly in heterogeneous environments where vegetation, bare soil, and transitional land covers coexist, as typically observed in peri-urban areas[27].

The Normalized Difference Built-up Index (NDBI) was calculated as:

$$\mathrm{NDBI} = \frac{(\mathrm{SWIR} - \mathrm{NIR})}{(\mathrm{SWIR} + \mathrm{NIR})}$$

where SWIR corresponds to shortwave infrared reflectance. Built-up and impervious surfaces exhibit higher reflectance in the SWIR domain compared to NIR, resulting in positive NDBI values, whereas vegetated areas typically yield negative values. NDBI therefore provides a direct proxy for land artificialization and urban expansion processes[28].

The combined behavior of NDVI, GEMI, and NDBI reflects a structured and sequential process of urban-driven ecological transformation. High NDVI and low NDBI values characterize dense and functional vegetation, whereas progressive degradation is marked by decreasing NDVI and intermediate GEMI values, indicative of mixed or transitional vegetation states. In advanced stages of urbanization, both NDVI and GEMI decline, while NDBI increases, reflecting the dominance and consolidation of built-up surfaces. These indices therefore capture complementary and interrelated dimensions of ecological change, linking vegetation decline, transitional degradation, and land artificialization. Their joint variation enables the identification of sequential and non-linear land-cover transitions along the urban–rural gradient, where ecological shifts are most pronounced. To ensure spatial comparability, index values were aggregated at the neighborhood level and across Morphological Urbanization Status (MUS) classes, allowing direct assessment of the relationship between ecological condition and urbanization intensity, and supporting hypothesis testing on spatial patterns of ecological vulnerability[29].

2.2.7. Quantification of landscape structure

Landscape structure was quantified using spatial metrics computed with FRAGSTATS (version 4.2), based on LULC maps derived from Landsat classifications. For each date, a set of metrics was calculated to characterize both landscape composition and spatial configuration. This approach enables moving beyond a purely surface-based analysis to examine how urbanization restructures the landscape mosaic[8]. The selected metrics were chosen for their direct relevance to the study hypotheses on fragmentation, homogenization, and loss of ecological connectivity. The proportion of landscape occupied by each class (PLAND) provides a synthetic measure of artificialization and habitat regression[30].

Metrics such as the number of patches (NP), patch density (PD), and shape complexity (e.g., LSI) were used to assess fragmentation, dissection, and geometric simplification of habitats[31].

Connectivity and cohesion metrics, including COHESION and CONTAG, were selected to evaluate the functional continuity of habitats and the degree of aggregation of built-up areas, which are central to understanding ecological resilience under urban expansion[32]. Additionally, Shannon and Simpson diversity indices were used to quantify landscape heterogeneity and detect trends toward homogenization. All metrics were calculated for each date and, when relevant, stratified along the urban–rural gradient. This design allows direct testing of whether increasing urbanization is associated

with declining ecological cohesion, increased fragmentation, and progressive simplification of landscape structure, in line with the study hypotheses.

2.2.8. Land-use transitions and underlying ecological processes

Land-use dynamics were analyzed by comparing transitions between classes for each time interval (2005–2011, 2011–2017, 2017–2024) using transition matrices derived from Landsat classifications. However, transition matrices and landscape metrics alone do not allow for the unambiguous identification of underlying ecological processes. To address this limitation, the decision-tree model proposed by Bogaert [33]was used as a mechanistic interpretative framework.

This model classifies landscape transformation trajectories based on the combined evolution of three key parameters: (i) total class area, (ii) number of patches, and (iii) patch perimeter. Based on these parameters, several processes can be identified. A simultaneous decrease in area and number of patches indicates suppression, corresponding to the loss of ecological units. A decrease in area combined with an increase in the number of patches reflects fragmentation of previously continuous habitats. Conversely, an increase in area associated with a reduction in patch number indicates aggregation, typically linked to the consolidation of built-up areas. Dissection is characterized by increasing geometric complexity without major variation in patch number. This framework enables moving from a descriptive analysis of land-cover change to a process-based interpretation of how peri-urbanization drives ecological degradation along the urban–rural gradient.

2.2.9. Methodological integration framework

The combination of methods used in this study is designed to capture complementary dimensions of urban ecological transformation. The Morphological Urbanization Status (MUS) provides the spatial structure of urbanization along the gradient. Spectral indices (NDVI, GEMI, NDBI) characterize ecological conditions and vegetation dynamics. Landscape metrics quantify structural changes such as fragmentation and aggregation, while transition matrices reveal temporal dynamics of land conversion. This integrated framework enables linking spatial patterns to underlying ecological processes, allowing a mechanistic interpretation of urban-driven ecosystem degradation.

3. Results

3.1. Morphological structure of the urban–rural gradient

Figure 2 illustrates the spatial structure of the urban–rural gradient by mapping the distribution of Morphological Urbanization Status (MUS) classes across Bukavu. It reveals a marked spatial polarization, with highly urbanized and spatially continuous built-up areas concentrated in the central communes of Ibanda and Kadutu, in contrast to the more heterogeneous and vegetation-dominated peri-urban and rural patterns observed in Bagira. This spatial representation emphasizes the organization

and spatial continuity of urbanization processes, highlighting the existence of distinct morphological zones and transitional interfaces. In contrast, Fig. 3 provides a quantitative characterization of this spatial structure by analyzing the distribution of grid cells across MUS classes. Rather than mapping spatial patterns, it measures the relative dominance and proportion of each morphological category within communes. This quantitative perspective confirms and refines the spatial patterns identified in Fig. 2, demonstrating that the gradient is not continuous but strongly imbalanced, with a clear dominance of urban classes in central areas and peri-urban/rural classes in peripheral zones. Together, Figs. 2 and 3 provide complementary but distinct analytical insights: Fig. 2 captures the spatial configuration and organization of the gradient, while Fig. 3 quantifies its internal structure and degree of polarization. Their combined interpretation supports the conclusion that the urban–rural gradient in Bukavu is discontinuous, spatially fragmented, and characterized by abrupt transitions rather than gradual change.

Quantitative results (Table 1) reinforce this pattern. Ibanda displays high urbanization coefficients (α), particularly in Ndendere (α = 83.46), Nyalukemba (α = 71.32), and Panzi (α = 68.70), indicating dense and continuous built-up structures. Similarly, Kadutu presents extreme levels of urbanization, with fully urbanized neighborhoods such as Cimpunda, Kasali, and Mosala (α = 100), as well as Nyamugo (α = 88.88). These values reflect compact and saturated urban forms, associated with intense spatial pressure and the near-complete disappearance of vegetated areas. In contrast, Bagira exhibits a more heterogeneous morphological configuration. Neighborhoods such as Cahi (β = 75.75) and Kasha (γ = 59.13) are dominated by peri-urban and rural characteristics, indicating the persistence of open and vegetated spaces. These areas function as transitional buffers, mediating the shift between densely urbanized cores and less developed peripheries. However, the coexistence of highly urbanized neighborhoods (e.g., Lumumba and Nyakavogo) within Bagira reveals a fragmented and uneven pattern of urban expansion. Overall, this morphological structure demonstrates that urbanization in Bukavu is spatially concentrated and discontinuous, producing a polarized gradient that directly shapes ecological dynamics. Highly urbanized central areas concentrate anthropogenic pressure, while peri-urban zones—particularly in Bagira—emerge as critical areas of vulnerability, where ongoing urban expansion is likely to drive accelerated habitat fragmentation and vegetation loss. The coefficients presented in Table 1 are derived from the MUS classification described in the Methods section.

Table 1
Quantitative characterization of the urban–rural gradient using neighborhood-level urbanization coefficients (α, β, γ) in Bukavu. Coefficients α, β, and γ represent the percentage of built-up area, herbaceous vegetation, and dense vegetation respectively within each neighborhood.

Municipality	Neighborhoods	α	B	γ	Morphology statut
Ibanda	Ndendere	83.46	16.53	0.00	Urban
	Nyalukemba	71.32	17.48	11.18	Urban
	Panzi	68.70	20.61	10.68	Urban
Bagira	Cahi	24.24	75.75	0.00	Peri-urban
	Kasha	20.86	20.00	59.13	Peri-urban
	Lumumba	62.50	30.35	7.10	Urban
	Nyakavogo	53.84	27.29	18.46	Urban
Kadutu	Cimpunda	100.00	0.00	0.00	Urban
	Kajangu	78.94	21.05	0.00	Urban
	Kasali	100.00	0.00	0.00	Urban
	Mosala	100.00	0.00	0.00	Urban
	Nkafu	71.01	20.28	8.69	Urban
	Nyakaliba	58.49	33.96	7.54	Urban
	Nyamugo	88.88	11.11	0.00	Urban

3.2. Spatio-temporal dynamics of land-use/land cover

Figure 4 illustrates the spatio-temporal evolution of land use in the city of Bukavu between 2005 and 2024, revealing a rapid and cumulative urbanization trajectory. In 2005, the landscape was characterized by a relatively balanced mosaic, where built-up areas coexisted with significant extents of dense and herbaceous vegetation, particularly in peripheral zones. Between 2005 and 2011, built-up expansion intensified markedly, primarily radiating from central urban cores at the expense of vegetated areas. This phase corresponds to the consolidation of existing urban structures and the initial fragmentation of natural habitats.

By 2017, urban expansion became more diffuse, extending toward peripheral areas. During this period, dense vegetation was increasingly reduced to isolated fragments, indicating a progressive loss of ecological continuity. By 2024, the landscape is largely dominated by artificial surfaces, while dense vegetation persists only as highly fragmented and residual patches. Herbaceous vegetation remains primarily in discontinuous patches, suggesting its transitional role prior to conversion into built-up areas.

Overall, this sequence reflects a transition from a heterogeneous landscape mosaic to a homogenized urban matrix dominated by artificial surfaces. This pattern is consistent with a process of predominantly horizontal and unplanned urban expansion, structured by continuous outward growth, leading to habitat fragmentation, vegetation loss, and functional degradation of urban and peri-urban ecosystems.

The transition matrix (Table 2) provides a quantitative assessment of these dynamics, highlighting a clear and sustained process of land artificialization between 2005 and 2024. The proportion of built-up areas increased continuously, from 33.00% (2005–2011) to 53.45% (2011–2017), then 55.53% (2017–2024), reaching 68.42% in 2024, corresponding to a net gain of + 35.42% over the entire period. In contrast, dense vegetation experienced a sharp decline, decreasing from 33.93% to 10.98%, then 8.83%, and ultimately 2.73% in 2024, representing a cumulative loss of − 31.20%. Herbaceous vegetation exhibited an intermediate trajectory, remaining relatively stable until 2017 (around 35.7%), before declining to 27.54% in 2024, indicating increased vulnerability during the most recent phase of urban expansion. Diagonal values of the transition matrix indicate strong persistence of built-up areas, increasing from 30.17% to 47.14% and then 51.14%, confirming the largely irreversible nature of land artificialization. In contrast, the persistence of dense vegetation declined sharply (from 8.45% to 1.76%), reflecting its decreasing resilience under urban pressure. Herbaceous vegetation maintained relatively high stability until 2017, before declining, reinforcing its transitional character. Off-diagonal values reveal dominant conversion processes. Across all periods, the conversion of dense vegetation into built-up areas constitutes the primary transition, particularly pronounced between 2005 and 2011 (12.86%). The conversion of herbaceous vegetation into built-up areas intensifies significantly during 2017–2024 (15.64%), confirming its role as an intermediate stage in the urbanization process. Reverse transitions from built-up areas to vegetation remain marginal, indicating a strongly unidirectional dynamic dominated by urban expansion.

Taken together, these results reveal a cumulative trajectory of ecological degradation driven by sequential land-cover conversion. The stability and expansion of built-up areas, combined with the progressive collapse of dense vegetation and the transitional role of herbaceous vegetation, indicate a structured transformation process rather than random change. This pattern supports the hypothesis of a sequential and non-linear urbanization process, in which natural habitats are first fragmented, then replaced by intermediate vegetation states, and ultimately converted into artificial surfaces. Such dynamics highlight the critical role of peri-urban areas as zones of accelerated transformation, where the most significant ecological shifts occur. Overall, the observed transitions reflect a predominantly unplanned urban expansion process, characterized by directional and cumulative land conversion, with major implications for habitat fragmentation, ecological connectivity loss, and long-term degradation of urban and peri-urban ecosystems.

Table 2
Land-use/land-cover transition matrix (%) highlighting sequential land conversion processes and the expansion of built-up areas in Bukavu (2005–2024). Percentage values is calculated based on a constant total area of 44.25 km². Accordingly, 1% corresponds to approximately 0.44 km².

Area (%)					
Years	**Classes**	**Built up areas**	**Dense vegetation**	**Herbeceous vegetation**	**TOTAL**
2005–2011	Built up areas	**30.17**	0.23	2.60	33.00
	Dense vegetation	12.86	**8.45**	12.61	33.93
	Herbeceous vegetation	10.42	2.26	**20.41**	33.07
	TOTAL	53.45	10.98	35.70	100.00
2011–2017	Area (%)				
	Built up areas	**47.14**	0.07	6.28	53.45
	Dense vegetation	0.63	**6.31**	4.05	10.98
	Herbeceous vegetation	7.77	2.44	**25.49**	35.70
	TOTAL	55.53	8.83	35.82	100.00
2017–2024	Area (%)				
	Built up areas	**51.14**	0.18	4.00	55.53
	Dense vegetation	1.63	**1.76**	4.56	8.83
	Herbeceous vegetation	15.64	0.79	**19.00**	35.82
	TOTAL	68.42	2.73	27.54	100.00

3.3. Spectral evidence of ecological degradation

The spatial distribution of spectral indices reveals a clear and structured pattern of ecological degradation across Bukavu (Fig. 5). NDVI values are consistently low to very low in the central communes of Ibanda and Kadutu, indicating a dominance of artificial surfaces and reduced vegetation biomass. In contrast, higher NDVI values are primarily observed in Bagira and peripheral areas, reflecting the persistence of denser and more functional vegetation. This spatial pattern confirms that vegetation decline is strongly correlated with the intensity of urbanization.

The GEMI index exhibits a similar spatial structure but provides a more refined discrimination of degraded and mixed vegetation areas. By partially correcting soil background effects, GEMI highlights transitional zones where vegetation persists in fragmented or degraded forms, particularly in peri-urban areas. These zones largely correspond to areas undergoing conversion to built-up land. The convergence

between NDVI and GEMI confirms that vegetation loss is not diffuse but spatially organized along a strongly polarized urban–rural gradient. It also underscores the critical role of peri-urban areas as zones of ecological vulnerability, where vegetation degradation precedes and accompanies urban expansion.

NDBI values further reinforce this interpretation. High values are concentrated in Ibanda and Kadutu, reflecting dense and spatially continuous built-up areas characteristic of consolidated urban cores. Lower values dominate in Bagira, although intermediate values reveal emerging built-up patches, indicative of fragmented and ongoing urban expansion. Importantly, the transition between high and low NDBI values is abrupt rather than gradual, confirming the presence of a strongly polarized urban–rural gradient. This pattern indicates that urban expansion is structured through peripheral extension rather than continuous diffusion, reinforcing the role of peri-urban zones as active fronts of ecological transformation. These spectral patterns are consistent with the fragmentation and aggregation processes identified through landscape metrics, confirming the structural reorganization of the landscape.

3.4. Evolution of landscape diversity, homogenization and spatial transformation process

Landscape diversity indices reveal a progressive shift from a heterogeneous to a structurally simplified system (Table 5). In 2005, relatively high SHDI (~ 1.0) and SIDI (~ 0.7) values indicate a balanced and heterogeneous landscape, where built-up areas, dense vegetation, and herbaceous vegetation coexist in comparable proportions. Between 2005 and 2011, both indices decline (SHDI ~ 0.9; SIDI ~ 0.6), reflecting a loss of diversity associated with the rapid expansion of built-up areas at the expense of dense vegetation. Between 2011 and 2017, these indices remain relatively stable, suggesting a temporary stabilization of landscape diversity. However, this apparent stability is driven by the persistence of herbaceous vegetation, which partially compensates for the decline in dense vegetation. By 2024, SHDI returns to values close to 1.0, while SIDI remains low (~ 0.6). This divergence indicates a structurally present but functionally imbalanced diversity: although multiple classes remain, the landscape is increasingly dominated by built-up areas, while dense vegetation becomes marginal. Thus, SHDI alone masks a loss of effective ecological diversity, which is better captured by SIDI. Overall, these results indicate a transition toward a homogenized landscape dominated by artificial surfaces, accompanied by a decline in ecological resilience.

Table 5
Accuracy assessment of supervised land-use classification based on Landsat imagery (2005–2024): overall accuracy and Kappa coefficients.

Year	2005	2011	2017	2024
Overall accuracy	92.10	91.10	95.10	95.10
Kappa	88.10	86.50	92.70	92.50

The analysis of spatial metrics reveals distinct transformation trajectories for each land-cover class (Table 3). Built-up areas evolve primarily through aggregation between 2005 and 2017, as indicated by increasing PLAND and decreasing NP, reflecting the aggregation of urban patches. Between 2017 and 2024, this pattern shifts toward a process of creation, with simultaneous increases in PLAND and NP, indicating the emergence of new built-up patches and more diffuse urban expansion characteristic of advanced peri-urbanization. Dense vegetation is dominated by a suppression (attrition) process between 2005 and 2017, marked by a simultaneous decrease in PLAND and NP, indicating the progressive disappearance of vegetated units. Between 2017 and 2024, this dynamic transitions toward fragmentation, with a strong decline in PLAND combined with an increase in NP, reflecting the disintegration of residual patches into smaller and more isolated units. Herbaceous vegetation follows an intermediate trajectory. It initially undergoes aggregation (2005–2011), followed by creation (2011–2017), indicating the emergence of transitional vegetation patches. Between 2017 and 2024, it experiences attrition, reflecting its progressive conversion into built-up areas. These trajectories confirm a sequential transformation process, characterized by the collapse of dense vegetation, the temporary persistence of herbaceous cover, and its eventual conversion into artificial surfaces. These structural transformations explain the spatial patterns observed in spectral indices, particularly the decline in NDVI and the increase in NDBI in peri-urban areas.

Table 3
Temporal dynamics of land-use composition and landscape diversity indices indicating progressive ecological simplification in Bukavu (2005–2024)

Composition						
Years	**Land-use/land cover**	**PLAND**	**NP**	**PD**	**SHIDI**	**SIDI**
2005	Built up areas	33.00	547.00	12.30	1.00	0.70
	Dense vegetation	33.90	979.00	22.10		
	Herbeceous vegetation	33.10	680.00	15.30		
2011	Built up areas	53.40	334.00	7.50	0.90	0.60
	Dense vegetation	11.00	656.00	14.80		
	Herbeceous vegetation	35.60	500.00	11.20		
2017	Built up areas	55.40	254.00	5.70	0.90	0.60
	Dense vegetation	8.90	453.00	10.20		
	Herbeceous vegetation	35.70	503.00	11.30		
2024	Built up areas	69.40	355.00	1.90	1.00	0.60
	Dense vegetation	2.80	506.00	3.30		
	Herbeceous vegetation	27.80	202.00	4.70		

3.5. Configuration and connectivity of landscape structure

For built-up areas, the continuous decrease in LSI between 2005 and 2017 indicates a simplification of patch shapes associated with aggregation processes. This trend reverses in 2024, with a sharp increase in LSI (41.6), reflecting geometric complexity typical of diffuse and irregular peri-urban expansion. The strong decline in IJI (96.3 to 26.4) indicates reduced interspersion with other classes, while COHESION reaches near-maximum values (99.9), confirming strong spatial connectivity of built-up areas. Dense vegetation shows the opposite pattern, with decreasing LSI and a sharp decline in COHESION, indicating loss of structural complexity and ecological connectivity. This configuration is typical of landscapes undergoing attrition followed by residual fragmentation. Herbaceous vegetation exhibits increasing geometric complexity (LSI up to 70.4), combined with decreasing IJI, reflecting spatial dissection and reduced interaction with other classes. Despite high COHESION values, these patches remain structurally vulnerable, confirming their transitional role. At the landscape level, the strong increase in CONTAG (11.9 to 52.3) indicates progressive homogenization, driven by the dominance of built-up areas (Table 4).

Taken together, these results reveal a cumulative and spatially structured trajectory of ecological degradation. Urbanization in Bukavu is characterized by the consolidation and subsequent diffusion of built-up areas, the progressive collapse and fragmentation of dense vegetation, and the transitional role of herbaceous vegetation. This process leads to increasing landscape homogenization, loss of ecological connectivity, and reduced socio-ecological resilience, confirming that peri-urbanization acts as a key driver of non-linear and irreversible ecological transformation.

Table 4
Temporal evolution of landscape configuration metrics revealing fragmentation processes and urban consolidation in Bukavu (2005–2024)

Configuration					
Years	Land-use/land cover	LSI	IJI	COHESION	CONTAG
2005	Built-up areas	27.7	96.3	98.8	11.9
	Dense vegetation	52.6	125.3	95.9	
	Herbeceous vegetation	39.3	90.0	98.0	
2011	Built-up areas	20.3	57.0	99.2	28.3
	Dense vegetation	32.5	106.8	84.6	
	Herbeceous vegetation	37.2	115.7	99.0	
2017	Built-up areas	17.7	54.8	99.4	32.9
	Dense vegetation	28.7	101.6	84.4	
	Herbeceous vegetation	32.0	113.8	98.9	
2024	Built-up areas	41.6	26.4	99.9	52.3
	Dense vegetation	26.2	118.6	89.2	
	Herbeceous vegetation	70.4	56.1	99.1	

4. Discussion

4.1. Main findings: a polarized and non-linear model of urban ecological transformation

The combined use of morphological, spectral, and spatial metrics is essential to capture the multi-dimensional nature of urban ecological transformation, which cannot be adequately explained by a single methodological approach. The results of this study provide converging evidence that urbanization in Bukavu does not conform to the classical representation of a gradual and continuous urban–rural gradient, but instead follows a polarized, discontinuous, and process-driven trajectory. This finding directly challenges the dominant framework in urban ecology, which conceptualizes urban gradients as smooth transitions of decreasing anthropogenic pressure from the urban core to rural peripheries[3]. In Bukavu, the gradient is neither continuous nor stable; rather, it is structured by abrupt spatial discontinuities, with highly artificialized cores coexisting alongside fragmented and rapidly transforming peri-urban zones. This pattern aligns more closely with recent theoretical perspectives emphasizing non-linearity and spatial heterogeneity in urban systems, particularly in contexts of rapid and unplanned growth [9].

The integration of land-use dynamics, spectral indices, and landscape metrics reveals that this spatial polarization is not merely morphological but reflects a deeper reorganization of ecological processes. The strong and persistent increase in built-up areas, coupled with the near-collapse of dense vegetation, indicates that land-use change follows a cumulative and largely irreversible trajectory, consistent with global observations of urban expansion[5]. However, beyond this general trend, the results highlight a structured sequence of transformation, in which dense vegetation is progressively fragmented, replaced by herbaceous cover, and ultimately converted into artificial surfaces.

This sequential dynamic is particularly significant because it moves beyond descriptive land-cover change and provides evidence for a mechanistic pathway of ecological degradation. While similar processes have been suggested in land-change science[34], they are rarely demonstrated with such clarity in rapidly urbanizing African contexts. The role of herbaceous vegetation as an intermediate and transitional state is especially noteworthy, as it acts as a buffer phase that temporarily absorbs urban pressure before being converted, a pattern consistent with recent findings by Yuh et al.[35], but still underexplored in urban ecology.

The spatial distribution of spectral indices further reinforces this interpretation. The combined analysis of NDVI, GEMI, and NDBI demonstrates that ecological degradation is not spatially diffuse but strongly structured along the gradient, with the most pronounced changes occurring in peri-urban zones. Importantly, the transitions observed are not gradual but exhibit threshold-like behavior, where relatively stable vegetated systems rapidly shift toward degraded or artificial states once a certain level of urban pressure is reached. This supports the hypothesis of non-linear ecological responses to urbanization, a concept increasingly emphasized in the study of complex socio-ecological systems [9].

Landscape metrics provide an additional layer of interpretation by revealing how these transformations are organized spatially. The observed shift from aggregation to diffusion in built-up areas indicates a transition from compact urban growth to dispersed peri-urban expansion, reflecting a change in the underlying mechanisms of urbanization. At the same time, the sharp decline in cohesion and continuity of vegetated areas confirms a progressive loss of ecological connectivity, consistent with the well-documented effects of habitat fragmentation[36].

A key insight emerging from the combined analysis of SHDI and SIDI is that landscape change in Bukavu involves not only a reduction in diversity but also a functional reconfiguration of diversity. While the persistence of multiple land-cover classes may suggest a relatively high level of heterogeneity, the increasing dominance of built-up areas results in a functional homogenization of the landscape, where ecological processes are increasingly constrained. This distinction between structural and functional diversity is critical, as it highlights the limitations of relying on single metrics to assess ecological change.

Taken together, these results support the interpretation that urbanization in Bukavu operates as a process of spatial and ecological reorganization, rather than simple land conversion. It is characterized by (i) strong spatial polarization, (ii) sequential transformation of land-cover classes, and (iii) non-linear

ecological responses, particularly in peri-urban zones. These findings contribute to a growing body of research suggesting that rapidly expanding cities—especially in the Global South—should be understood as complex adaptive systems, where urban growth, landscape structure, and ecological processes are tightly interlinked and evolve through discontinuous and often irreversible transitions[9].

4.2. Implications for socio-ecological sustainability and urban planning

The results highlight that the socio-ecological trajectory of Bukavu is not only shaped by rapid urban growth, but by the spatial configuration and sequencing of that growth, which together determine the intensity and distribution of ecological degradation.

A key implication is that peri-urban areas—particularly in Bagira—should be considered priority zones for intervention, rather than residual spaces awaiting urbanization. The results show that these areas concentrate the most critical transformations: fragmentation of dense vegetation, proliferation of transitional herbaceous cover, and subsequent conversion into built-up land. This confirms that peri-urban zones are not passive margins, but active frontiers of socio-ecological change, where early-stage interventions could significantly alter long-term trajectories.

In the specific context of Bukavu, this vulnerability is amplified by the city's steep topography and high rainfall regime, which increase exposure to erosion, landslides, and runoff. The observed loss of vegetation cover in these zones is therefore not only an ecological issue but a major risk factor for urban resilience, as vegetation plays a key role in slope stabilization and hydrological regulation[37] [38]. This suggests that land-use planning cannot be decoupled from risk management, and that preserving vegetated areas in peri-urban slopes should be treated as a critical infrastructure function, rather than a secondary environmental concern.

The identification of a sequential land conversion process (dense vegetation → herbaceous cover → built-up areas) also provides actionable insights for planning. Herbaceous areas, often perceived as low-value or transitional land, emerge here as strategic intervention points, where land-use trajectories remain reversible. Protecting or regulating these areas could interrupt the conversion chain and delay or prevent irreversible artificialization. This finding challenges conventional planning approaches that prioritize only high-value ecosystems, and instead argues for a process-oriented approach to land management, targeting intermediate stages of transformation.

More broadly, the results reveal that urban expansion in Bukavu is predominantly horizontal, opportunistic, and weakly regulated, leading to a spatially fragmented and inefficient urban structure. This pattern reinforces land consumption, accelerates ecological degradation, and increases infrastructure costs, consistent with findings in other cities of the Global South[1].In this context, promoting controlled densification strategies in already urbanized areas (Ibanda and Kadutu) could reduce pressure on peri-urban ecosystems while improving spatial efficiency. However, such strategies

must be adapted to local constraints, including informal land tenure systems and limited governance capacity.

From an ecological perspective, the observed increase in landscape homogenization and loss of connectivity suggests that the city is moving toward a functionally simplified system, with reduced resilience to environmental stress. This has direct implications for ecosystem services, including water regulation, soil stability, and climate moderation [39][40].Integrating green infrastructure networks—such as corridors, buffer zones, and protected patches—into urban planning could help restore connectivity and mitigate some of these impacts. Importantly, such interventions should prioritize spatial continuity rather than isolated green spaces, as connectivity is critical for maintaining ecological function[36].

At a more conceptual level, the results suggest that sustainable urban planning in rapidly growing cities like Bukavu cannot rely on static zoning approaches. Instead, it requires a dynamic, gradient-based framework, capable of identifying where and how transformations occur along the urban–rural continuum. This implies shifting from a reactive model of urban management to a predictive and process-based approach, where planning decisions are informed by the mechanisms of land-use change and ecological degradation identified in this study.

Finally, these findings highlight the importance of integrating socio-economic drivers—such as population growth, migration, and land markets—into ecological analyses. Without addressing these underlying drivers, spatial planning interventions are likely to remain limited in effectiveness. In this sense, the study reinforces the need for integrated socio-ecological governance frameworks, capable of simultaneously addressing urban growth, environmental sustainability, and social equity.

4.3. Methodological limitations and future research directions

Despite its robustness, this study presents several limitations that should be acknowledged. First, the use of Landsat imagery with a spatial resolution of 30 m may limit the detection of fine-scale urban features and small vegetation patches, particularly in highly heterogeneous peri-urban environments. This may lead to an underestimation of micro-scale fragmentation and ecological variability. Second, the classification scheme, although ecologically relevant, relies on a simplified categorization of land-use classes. While this choice improves classification accuracy and interpretability, it may mask more subtle ecological gradients, particularly within vegetation types. Third, the analysis is primarily based on remote sensing and spatial metrics, which capture structural patterns but only indirectly reflect ecological processes. Integrating field-based ecological data (e.g., biodiversity, soil quality, or hydrological indicators) would provide a more comprehensive understanding of ecosystem functioning.

In addition, the use of four independent Random Forest models (one per date) implies that four distinct decision boundaries are generated in spectral space. As a result, inter-classifier uncertainty may arise and should be explicitly acknowledged, as differences between classifications may partly reflect model variability rather than only real land-cover change.

Furthermore, field validation was conducted only for the year 2024. Consequently, the absence of contemporaneous ground-truth data for earlier dates (2005 and 2011) represents a limitation, as classification accuracy for these periods relies on retrospective interpretation rather than direct field verification. This may introduce additional uncertainty in the temporal consistency of the results.

Future research should therefore focus on multi-scale and multi-source approaches, combining high-resolution imagery, field observations, and socio-economic data to better capture the complexity of urban socio-ecological systems. In particular, the integration of temporal modeling and scenario analysis could help identify potential tipping points and inform sustainable urban planning strategies. Additionally, extending this analytical framework to other cities in Sub-Saharan Africa would allow for comparative analysis and contribute to the development of generalized models of urban ecological transformation in rapidly growing regions.

5. Conclusion

This study investigated the effects of peri-urbanization on ecological degradation along the urban–rural gradient in Bukavu, based on an integrated framework combining multi-temporal Landsat imagery, spectral indices (NDVI, GEMI, NDBI), and landscape metrics. The results confirm the central hypothesis that unplanned urban expansion is a major driver of ecological degradation but refine it by demonstrating that this process is not gradual. Instead, urbanization follows a polarized and non-linear trajectory, structured by abrupt spatial discontinuities and concentrated in peri-urban areas. The study further validates the hypothesis of a sequential transformation process, where dense vegetation is fragmented, replaced by herbaceous cover, and ultimately converted into built-up areas. These findings highlight that ecological degradation is both structural and functional, involving vegetation loss, habitat fragmentation, and declining connectivity. In the specific context of Bukavu—characterized by steep topography and high environmental sensitivity—peri-urban zones emerge as critical areas where urban expansion directly amplifies ecological vulnerability and environmental risks. Methodologically, the integration of remote sensing, spectral indicators, and landscape metrics proves effective for capturing both spatial patterns and underlying processes of urban ecological change. However, the use of 30 m resolution data and simplified land-use classes may underestimate fine-scale heterogeneity and local ecological dynamics. From a planning perspective, the results emphasize the need to prioritize peri-urban areas, regulate horizontal expansion, and preserve vegetated spaces as key components of urban resilience. Future research should integrate higher-resolution data, field-based ecological indicators, and comparative analyses across cities to better capture thresholds and generalize the observed transformation processes. Overall, the study demonstrates that in rapidly growing cities, ecological degradation is not simply a by-product of urban growth, but a spatially structured and process-driven transformation, requiring integrated and context-specific planning approaches.

Declarations

Acknowledgements

We thank the Regional Postgraduate School for Integrated Management of Tropical Forests and Territories (ERAIFT) for its support in developing its systems approach.

We thank the anonymous reviewers and editors for their suggestions and constructive comments, which helped improve the quality of this manuscript. We would like to express our sincere gratitude to Aganze badesire Lebon,Mwale wa kila Bienvenu,Yedidya Musanganya Elikya and others collaborators like Mahasha Ga-Cubaka Pascal ,Namegabe Muchanga Leroi and Kamala Maghaviro Georges.

Author contribution

Emery Akonkwa Shabani : conceptualization,curation, methodology, Formal analysis, writing, Nadege Cizungu Cirezi : data curation,writing review,Serge Mugisho Mukotanyi : Investigation, data curation,writing review: Writing review, Eliel Chirongozi Mutabesha : writing review, Guillaine Busime Baharanyi : writing review, Médard Mpanda Mukenza: writing review, Joel Mobunda Tiko : writing review, Julien Bwazani Balandi: writing review, Jan Bogaert : writing review, Yannick Useni Sikuzani : supervision and writing original

Fundings

Notapplicable

Data availability

The authors want to declare that they can submit the data at whatever time based on your request. The data used for the current study are available from the corresponding author on reasonable request.

Ethics approval and consent to participate

Notapplicable

Consent to publish

Notapplicable

Clinical Trial Number

Notapplicable

Data citation in references

Not applicable

Competing interests

Not applicable

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Figures

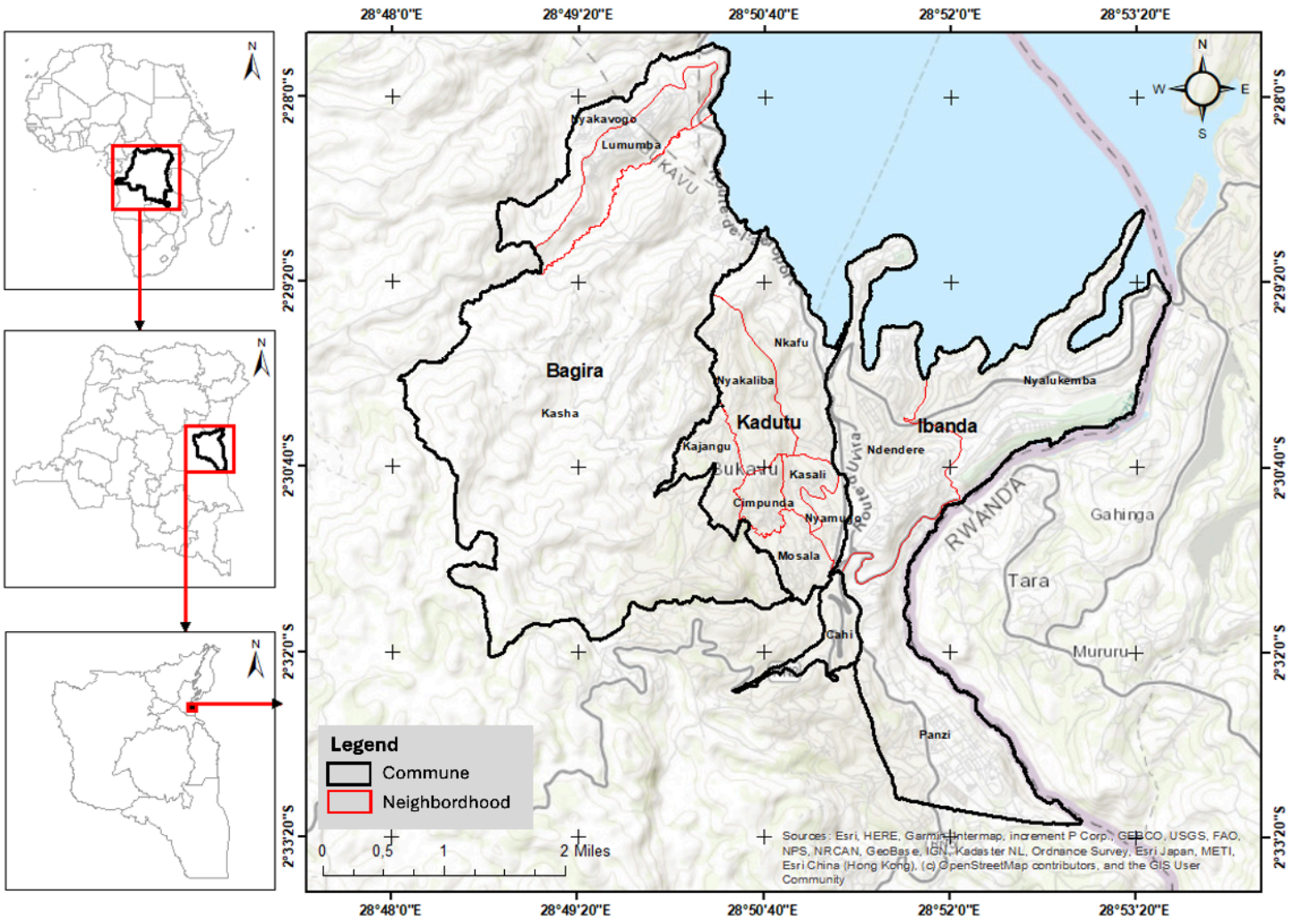


Figure 1

Geographic setting and spatial organization of Bukavu, illustrating administrative structure and urban configuration within the Lake Kivu region (DR Congo).

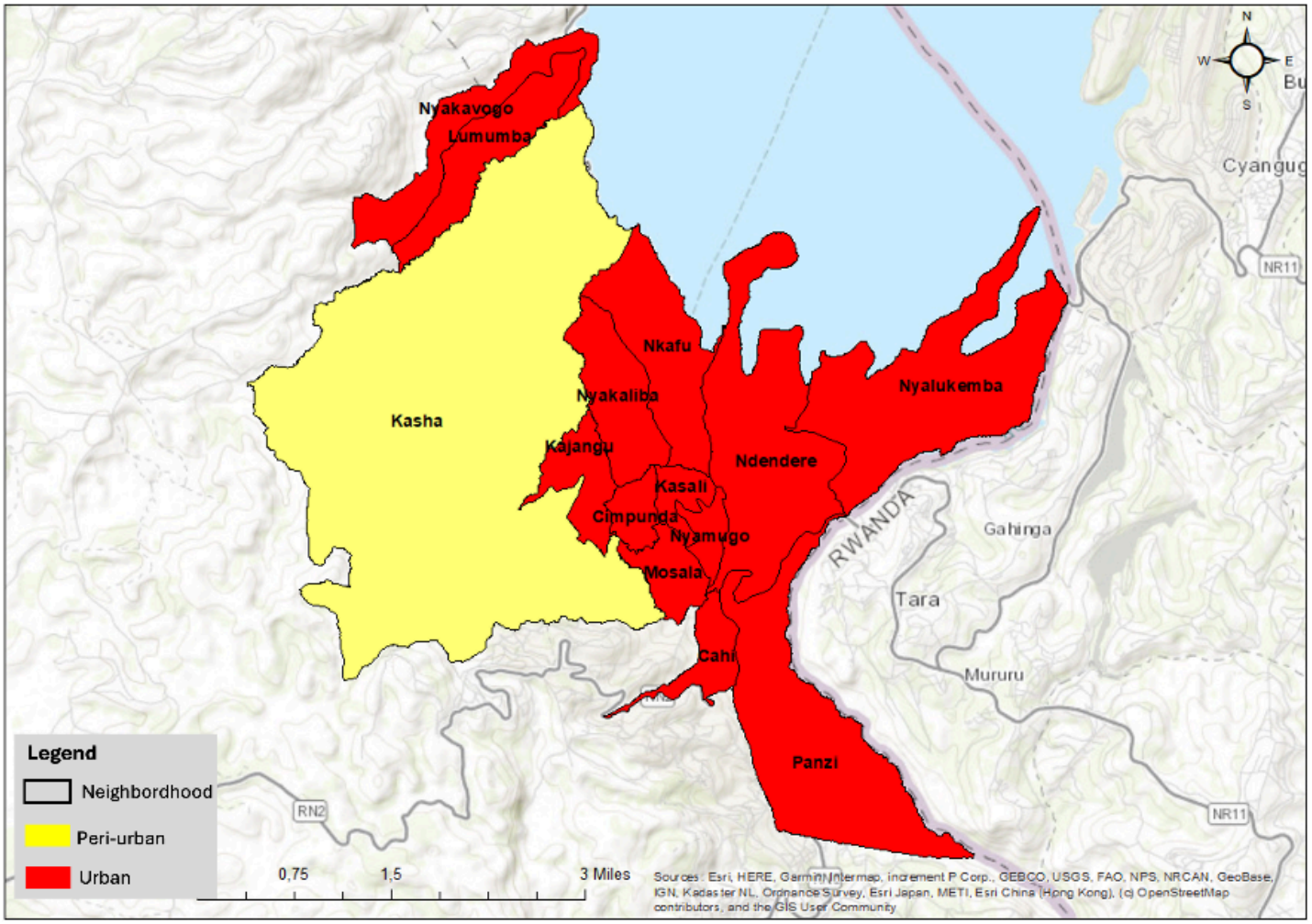


Figure 2

Spatial delineation of the urban–rural gradient based on Morphological Urbanization Status (MUS), derived from grid-based classification using built-up, herbaceous, and dense vegetation proportions.

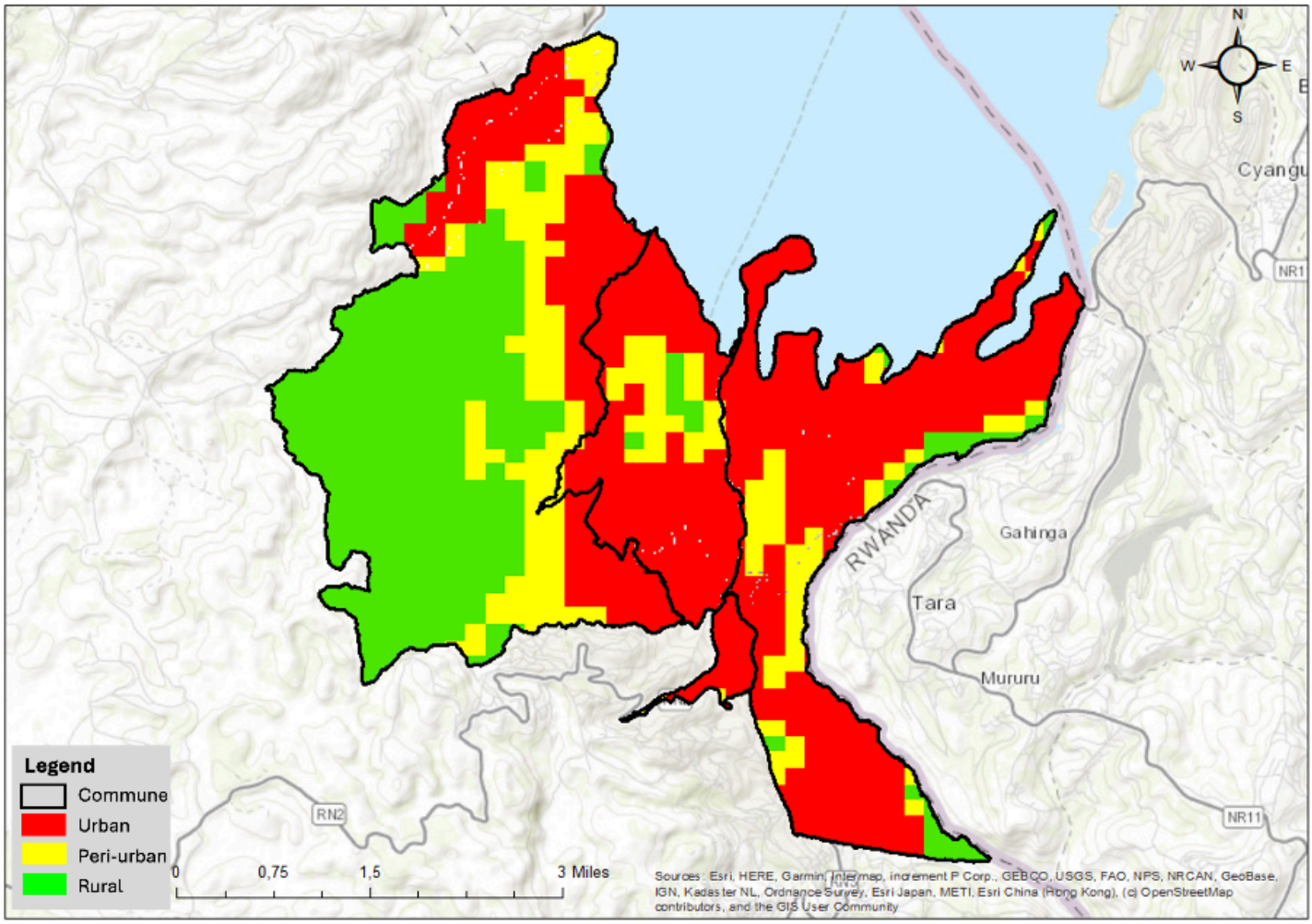


Figure 3

Distribution of grid cells across urban, peri-urban, and rural classes based on MUS classification thresholds.

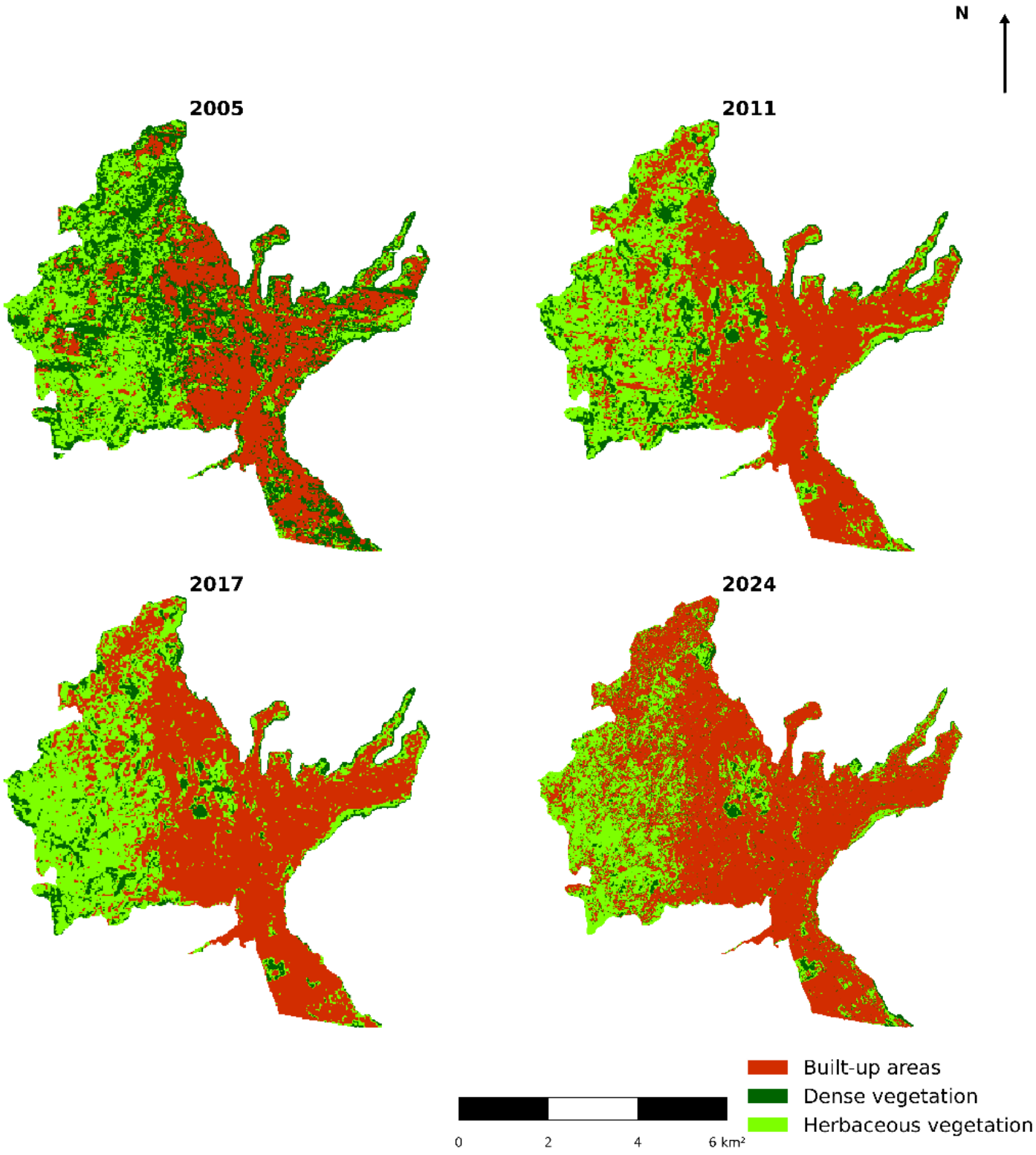


Figure 4

Spatio-temporal dynamics of land-use/land-cover change showing rapid urban expansion and progressive vegetation decline in Bukavu (2005–2024).

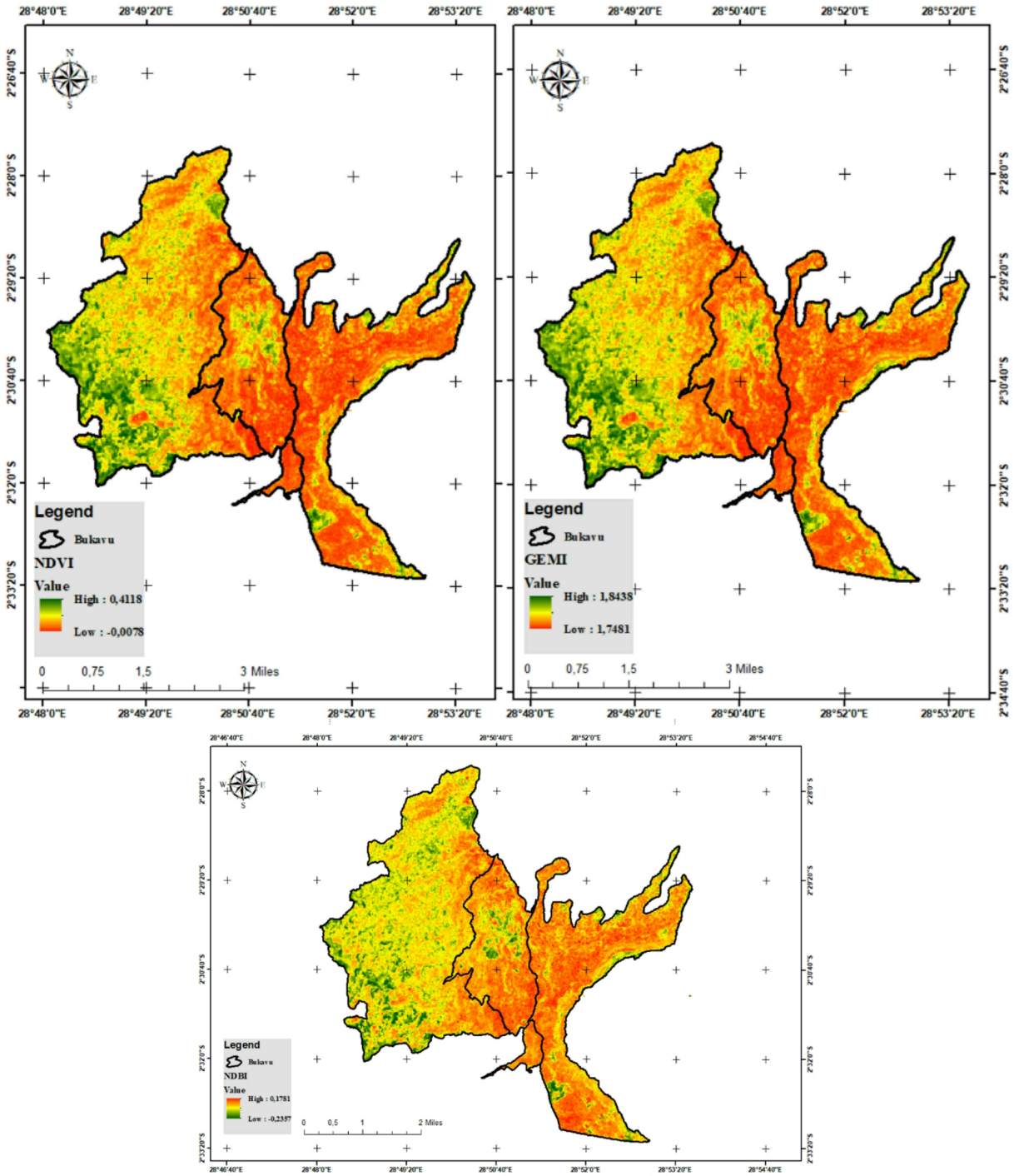


Figure 5

Spatial patterns of NDVI, GEMI, and NDBI illustrating ecological degradation and urban expansion along the urban–rural gradient in Bukavu