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Influence of Urban Sprawl on Spatial-Temporal Changes Along Rupingazi Riverine Ecosystem, Embu County, Kenya

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Abstract

Urban sprawl refers to the unplanned expansion of urban areas, typically leading to inefficient land use and environmental degradation. This study analyzes the impact of urban sprawl on the Rupingazi River ecosystem between 1989 and 2019 using Landsat satellite imagery. Analysis of NDBI values revealed a consistent distinction between built-up and non-built-up areas, with built-up surfaces recording higher positive values across all periods. The findings show a significant transformation within Embu County. In 1989, non-built-up land and vegetation dominated the landscape at 4.7 km^2 (70.47%). By 1999, this declined to 4.46 km^2 (56.89%) as built-up areas expanded to 3.38 km^2 (43.11%). A critical shift occurred in 2009, when built-up areas (4.58 km^2; 51.93%) overtook natural cover (48.07%) for the first time. By 2019, urban surfaces reached 6.04 km2 (68.17%), leaving only 31.83% natural cover. These trends necessitate stricter zoning enforcement, riparian buffer protection, and compact development strategies. Urban planners must integrate geospatial monitoring to mitigate environmental pressure on the Rupingazi riverine ecosystem.

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Abstrak

Urban sprawl tidak terencana memicu penggunaan lahan tidak efisien dan degradasi lingkungan. Penelitian ini menganalisis dampak urban sprawl terhadap ekosistem Sungai Rupingazi antara tahun 1989 dan 2019 menggunakan citra satelit Landsat dan analisis geospasial. Hasil analisis nilai NDBI menunjukkan perbedaan konsisten antara area terbangun dan non-terbangun, di mana permukaan terbangun mencatat nilai positif yang lebih tinggi di semua periode. Ditemukan transformasi signifikan di Kotamadya Embu: Pada tahun 1989, lahan non-terbangun dan vegetasi mendominasi sebesar 4,7 km^2 (70,47%). Namun, pada tahun 1999, luasan ini menurun menjadi 4,46 km^2 (56,89%) seiring ekspansi area terbangun menjadi 3,38 km^2 (43,11%). Titik balik terjadi pada tahun 2009, di mana area terbangun (4,58 km^2; 51,93%) melampaui lahan vegetasi (48,07%) untuk pertama kalinya. Hingga 2019, area terbangun melonjak drastis menjadi 6,04 km^2 (68,17%). Tren ini memerlukan penegakan regulasi zonasi yang ketat, perlindungan penyangga riparian, dan strategi pembangunan kompak. Perencana kota harus mengintegrasikan alat pemantauan geospasial dalam pengambilan keputusan untuk melindungi ekosistem sungai Rupingazi.

INTRODUCTION

The unchecked expansion of urban areas exerts a significant influence on spatial–temporal changes by fragmenting natural landscapes, increasing impervious surfaces, and disrupting hydrological systems. Urban sprawl is a phenomenon that has significantly impacted social, economic, and natural environments over several decades (Zipperer et al., 2020). This process has been accelerated by rapid human population growth, with a sizeable proportion of people moving to urban areas. The world's population was approximately 1.6 billion in the year 1900, with only 13% of this population living in urban areas at that time. The world's urban population increased to about 50% by the year 2008, with close to 3.9 billion of the total population living in urban areas. According to the United Nations (2014), the urban population is expected to rise to 6.4 billion by the year 2050, representing 60% of the total world population. Most of this population increase is projected to occur in Asia and Africa (United Nations, 2014).

Murayama et al. (2021) employed multi-temporal GIS and remote sensing techniques to analyze urbanization trends in developing countries, illustrating how spatial patterns evolve and contribute to environmental degradation. Similarly, Mansour et al. (2023) used a GIS-based Markov Chain model combined with an Artificial Neural Network (ANN) to monitor urban sprawl in a coastal city, thereby forecasting future land-use dynamics. Their study highlighted the potential ecological risks of continued expansion. Collectively, these studies underscore the importance of integrating spatial metrics with temporal simulation tools to understand and predict how urban sprawl drives landscape transformation.

Building on these approaches, this study demonstrates the application of state of the art methods by integrating GIS and remote sensing to capture spatial–temporal dynamics. This approach reinforces the critical role of spatial–temporal analysis in understanding complex environmental and urban process relationships along the Rupingazi River.

Despite the growing body of literature on urban sprawl, notable research gaps persist. Most existing studies concentrate on large metropolitan cities, leaving smaller inland urban centers relatively underexplored. In addition, riverine ecosystems, despite their ecological sensitivity and importance to urban sustainability, are rarely examined as focal systems in sprawl analyses. Furthermore, only a few studies in Eastern Africa have employed the Normalized Difference Built-up Index (NDBI) to analyze the effects of urban sprawl. Therefore, the current study bridges these gaps by focusing on a medium-sized town, deviating from the norm of large metropolitan areas examined in previous studies. Additionally, this study employed the NDBI index, which has rarely been used in East African contexts to analyze urban sprawl. The study of the Rupingazi riverine ecosystem, located at the periphery of the town, further addresses a research gap, as previous studies have laid little emphasis on these ecosystems, even though they are often at the receiving end of urbanization impacts.

Previous studies revealed that rapid population growth and rural–urban migration increase the demand for housing, pushing development into peri-urban zones (Njiru, 2016; Maina & Waiganjo, 2024). Improvements in transport infrastructure, particularly the construction of new roads and highways, open previously inaccessible land to developers (Hassan et al., 2023), leading to encroachment of previously uninhabited land. Market forces, such as low land prices on urban fringes, housing shortages in urban cores, and speculative land markets, further encourage outward expansion, as households and developers seek cheaper plots and larger lots (Yiran et al., 2020; Hassan et al., 2023). Weak land use governance, inadequate zoning enforcement, and fragmented institutional coordination facilitate the emergence of informal and unplanned settlements on riparian and agricultural lands (Njiru, 2016; Yasin et al., 2021). Economic growth and rising incomes also influence residential preferences, favoring lower-density, single-use housing (Kim et al., 2020; Angel, 2023), while limited provision of core services in central areas or high central rents drives both public and private investment toward peri-urban locations (Omasire et al., 2020; Maina & Waiganjo, 2024), such as riparian ecosystems. Agricultural land conversion, often driven by both formal subdivision and informal occupation, remains a recurrent proximate cause of sprawl in many Kenyan and wider African contexts (Omasire et al., 2020; Maina & Waiganjo, 2024). Previous studies also noted that social factors, including perceptions of security, aspirations for home ownership, and cultural preferences for larger plots, when coupled with weak planning regulations, accelerate outward expansion (Hassan et al., 2023; Dadashpoor & Shahhossein, 2024).

The linkage between these urban sprawl drivers and riparian pressure along the Rupingazi River is consistent with findings from studies on Kenyan and East African urban river systems. For instance, Mwangi et al. (2016) revealed that rapid population growth, weak land-use control, and inadequate infrastructure provision often push informal settlements toward river corridors. Such expansion directly affects riparian zones through vegetation removal, waste dumping, and increased runoff, confirming that urban rivers frequently become focal points of informal development pressure in rapidly growing municipalities like Embu. Mwangi et al. (2016) findings are also consistent with observations made along the Rupingazi River, where numerous dumping sites and informal settlements were identified within the riverine ecosystem. The study noted that the proximity of the riverine ecosystem to the municipality places it at the receiving end of urban expansion impacts.

Rapid urban growth in Kenya has increasingly manifested as sprawling and uncoordinated expansion of urban areas into peri-urban and rural lands, resulting in profound land-use and environmental consequences. For instance, a previous study found that urban sprawl in Kenya is characterized by the conversion of agricultural land, the shrinkage of natural vegetative cover, and encroachment into conservation areas, largely driven by rising housing demand and inadequate land-use regulation (Maina & Waiganjo, 2024). A study in Eldoret Municipality revealed that built-up area expanded from approximately 5.38 km² in 1995 to 27.57 km² in 2017, while vegetation cover declined from 9.72% to 2.66%, reflecting unplanned land-use shifts typical of sprawling urban growth (Rotich & Opiyo, 2022). Additionally, it was revealed that 55% of prime agricultural land in Wote (Makueni County) had been converted due to sprawl, thereby exacerbating food security and land management challenges (Omasire et al., 2020). These dynamics highlight the pressing need for integrated land-use planning and strong development control, demonstrating how unchecked urbanization in Kenya can jeopardize sustainable development objectives, including riverine ecosystem resilience.

The Rupingazi riverine ecosystem has been experiencing significant challenges, as evidenced by numerous dumping sites, vegetation clearance, and increased infrastructure development along the river corridor (Kareithi, 2016; Bonareri, 2017; Nyaga, 2021). The study analyzed the influence of urban sprawl on the Rupingazi riverine ecosystem's spatial–temporal changes from 1989 to 2019. The policy recommendations derived from this study could help reduce the influence of urban sprawl on the Rupingazi riverine ecosystem in Embu County. This research has also contributed to the body of knowledge in urban geography, environmental science, hydrology, and urban planning.

The research objective was to analyze the influence of urban sprawl on the spatial–temporal changes of the Rupingazi riverine ecosystem. The study employed the NDBI based on Landsat satellite imagery. Overall, the study contributes empirical evidence of landscape transformation, establishing a crucial baseline for informed riverine ecosystem management and targeted conservation strategies within the ecosystem.

METHOD

Study Area

The study was conducted in the Rupingazi Riverine ecosystem within Embu Municipality, Embu County, Kenya. The area lies between latitudes 0°32 ´ 24″ and 0°32 ´ 46″ South and longitudes 37°27 ´ 01″ and 37°27 ´ 31″ East (Figure 1). Embu Conty covers an approximate area of 80 km² and is located about 120–150 km northeast of Nairobi. Embu County is situated east of Mount Kenya, whose southern slopes form part of the county boundary. The county is bordered by Tharaka Nithi County to the north and Kirinyaga County to the east.

Embu Municipality is located within the highlands of Mount Kenya at approximately 0.537° S latitude and 37.458° E longitude. The area is drained by two permanent rivers, River Rupingazi and River Kapingazi, which play a significant role in supporting local ecosystems and livelihoods. Mount Kenya is the most prominent physical feature in the region, and Embu Municipality is the eighth-largest municipality in Kenya.

The municipality has experienced rapid population growth, with a population of 64,970 recorded in 2019 and a projected population of 75,711 by 2027 (Kenya National Bureau of Statistics, 2019). The population is predominantly composed of the Embu community, alongside other ethnic groups including Kikuyu, Kamba, and Ameru. The area experiences a bimodal rainfall pattern, with long rains occurring from March to June and short rains from October to December. The mean annual rainfall is approximately 1,499 mm. July is typically the coldest month, while September records the highest temperatures.

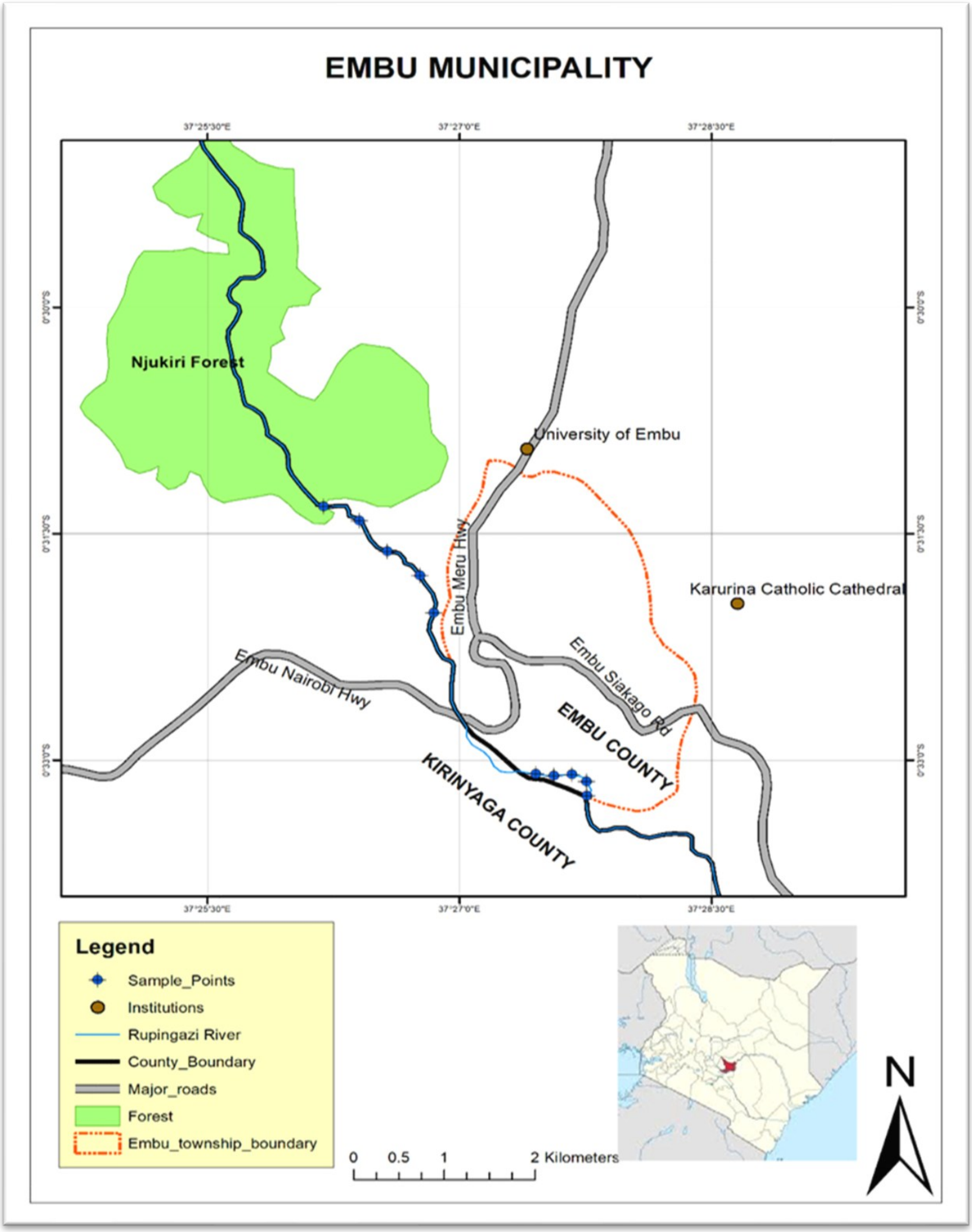

Figure 1. Map of Embu Municipality

Research Design

This study examined the complex relationship between urban sprawl and the Rupingazi Riverine ecosystem in Embu Municipality, Kenya. A spatial–temporal descriptive research design was adopted, as it enables systematic description and comparison of spatial variations and temporal trends in the expansion of built-up areas without manipulating study variables. The analysis covered 30 years, allowing for the assessment of long-term urban growth trajectories. The pixel served as the spatial unit of analysis within Embu Municipality, facilitating detailed spatial characterization of land-use and land-cover changes. Primary data were obtained from GIS-based satellite imagery and processed using remote sensing techniques, including the NDBI, to consistently quantify and map spatial–temporal changes in built-up areas across the study period.

Data Source

The Embu Municipality land use plan was obtained from the Embu Physical and Urban Planning Office. Multi-temporal Landsat satellite imagery with a spatial resolution of 30 m was acquired for the years 1989, 1999, 2009, and 2019, all corresponding to Path 168 and Row 060. The dataset comprised Landsat 4–5 Thematic Mapper (TM) scenes for 1989 (05/01/1989), 1999 (20/02/1999), and 2009 (15/07/2009), and a Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) scene for 2019 (29/09/2019). These images provided a consistent three-decade temporal record suitable for long-term urban change detection. The selected years coincided with national population census periods, given that population growth is a key driver of urban sprawl.

Image Preprocessing

Image preprocessing was conducted to ensure spectral consistency and comparability across sensors and time periods. This included radiometric calibration, atmospheric correction using the Dark Object Subtraction (DOS) method, geometric correction, and cloud masking. Cloud masking involved the removal or replacement of cloud-contaminated pixels where necessary. This approach aligns with McFeeters (1996), who demonstrated that the Normalized Difference Water Index enhances the detection and masking of water bodies and clouds, thereby preventing their misclassification as built-up areas in NDBI-based analyses. Following preprocessing, the images were clipped to the Embu Municipality boundary and a 30-m buffer zone along the Rupingazi River to focus the analysis on areas directly influenced by urban expansion within the riverine ecosystem.

Data Analysis

The NDBI (Zha et al., 2003) was employed to quantify and map the spatial extent of built-up areas within the Rupingazi riverine ecosystem over the study period. After preprocessing, the Shortwave Infrared (SWIR) and Near Infrared (NIR) bands were extracted from each temporal dataset and used to compute NDBI according to the standard Equation 1:

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \tag{1}$$

where $NDBI$ is Normalized Difference Built-Up Index, $SWIR$ is Shortwave Infrared band (Landsat 4–5 TM: Band 5, and Landsat 8 OLI: Band 6), and NIR is the Near Infrared band (Landsat 4–5 TM: Band 4, and Landsat 8 OLI: Band 5).

The computation was performed in ArcGIS using pixel-wise raster calculations to generate continuous NDBI layers for each reference year. Pixel values greater than zero were classified as built-up surfaces due to higher reflectance in the SWIR band, while negative values represented non-built-up areas such as vegetation, water bodies, and bare soil. A threshold-based classification approach was applied to categorize the landscape into built-up and non-built-up classes, and classification accuracy was assessed using overall accuracy (OA), kappa coefficient (k), user accuracy (UA), and producer accuracy (PA) test.

Temporal change detection analysis was subsequently conducted to quantify the dynamics of built-up area expansion and its encroachment toward the riparian reserve. Spatial overlay analyses were used to evaluate the extent to which urban sprawl altered the Rupingazi riverine ecosystem over time. The land-use classification scheme is presented in Table 1.

Table 1. Description of the various land use categories in the study area

ID	Land Use Categories	Description
A	Built-up	Settlements, paved roads, and industrial facilities within the municipality.
B	Non-built-up	Bare land, water, and recreational activities.
C	Vegetation	Other land uses include urban farming and plant species.

RESULT AND DISCUSSION

Accuracy Assessment

Map accuracy testing is a crucial step in remote sensing analysis to ensure the reliability of land cover and land use classification results. Accuracy evaluation is necessary to assess the extent to which the resulting classification classes represent actual conditions on the ground, ensuring that the spatial and temporal analysis results can be scientifically validated. In this study, accuracy testing was conducted on all classification maps from 1989, 1999, 2009, and 2019 to ensure consistency and validity of the long-term change analysis results.

Classification accuracy is derived from several key indicators: UA, PA, OA, and the Kappa coefficient. UA measures the reliability of a class from the perspective of the map user, while PA indicates the classification's success in representing the reference class. OA provides an overview of overall classification accuracy, while the Kappa coefficient measures the level of agreement between the classification results and the reference data, considering the possibility of random fit. The accuracy test results for each observation for 1989, 1999, 2009, and 2019 period, respectively are presented in Table 2.

Table 2. Accuracy assessment for classification

Year	Built-up PA (%)	Built-up UA (%)	Non-Built &Vegetation PA (%)	Non-Built &Vegetation UA (%)	OA (%)	*k*
1989	78.60	76.40	85.90	84.10	81.50	0.67
1999	81.40	79.60	86.70	85.20	83.90	0.72
2009	85.20	83.90	87.40	86	86.30	0.79
2019	88.70	87.20	89.30	88.10	88.40	0.83

The accuracy assessment results in Table 2 revealed a steady improvement in classification accuracy of the choropleth maps from 1989 to 2019. In 1989, the overall accuracy (81.50%) and Kappa coefficient (0.67) indicated a substantial level of agreement, suggesting that the classification was generally reliable though affected by moderate commission and omission errors. Both producers' and User's Accuracies for built-up and non- built-up areas were above 75%, reflecting satisfactory class separability despite sensor and mapping limitations. By 1999, marginal increases were observed across all accuracy indices, with OA rising to 83.90% and Kappa to 0.72, implying improved classification consistency and reduced misclassification, particularly within built-up and non-built-up areas.

The 2009 and 2019 maps show significant enhancements, with OA values of 86.30% and 88.40% and corresponding Kappa values of 0.79 and 0.83, denoting high reliability and near-perfect agreement. This progression illustrates technological advancements in image processing, classification algorithms, and the availability of higher-resolution data. As noted by Gomez et al. (2016), the integration of machine learning and improved spatial resolution has fundamentally enhanced the capacity to distinguish complex land cover features, thereby reducing misclassification risks that were prevalent in earlier satellite missions (Chander et al., 2009).

Land Use Land Cover Change

Land use and land cover changes in Embu District were analyzed to determine the dynamics of regional development. This analysis was based on the NDBI value, which is used to distinguish built-up and non-built-up areas dominated by vegetation. The results of the analysis are presented as the area and percentage of each land use category across all observation years. Table 3 illustrates the increasing and decreasing trends in built-up and non-built-up areas in the study area.

Table 3. LULC Change in Embu Municipality Between 1989 to 2019

Years	Land Use Categories	NDBI Range	Area (km²)	Area (%)
1989	Non-Built-up	-0.32- -0.08	4.70	70.47
	Vegetation	-0.079-0.042		
	Built-up	0.043-0.3	1.97	29.53
1999	Non-Built-up	-0.2- -0.071	4.46	56.89
	Vegetation	-0.07- -0.01		
	Built-up	-0.009-0.1	3.38	43.11
2009	Non-Built-up	-0.39-0.045	3.74	48.07
	Vegetation	0.046-0.17		
	Built-up	0.18-0.52	4.58	51.93
2019	Non-Built-up	-0.24- -0.04	2.82	31.83
	Vegetation	-0.04-0.03		
	Built-up	0.03-0.16	6.04	68.17

The information presented in Table 3 revealed that, between 1989 to 2019, the NDBI range for built-up areas has shown a consistent increase, indicating urban sprawl. In 1989, built-up areas had a relatively narrow NDBI range (0.043 to 0.3), suggesting limited and scattered built-up areas. By 1999, although the lower bound slightly declined to -0.009, the upper limit remained modest at 0.1, pointing to a slow initial urban growth phase. A major shift was observed in 2009, where the range expanded dramatically (0.18 to 0.52). The increased range indicated accelerated urban sprawl. The study observed an increase in built-up area from 3.38 km^2 in 2009 to 6.04 km^2 in 2019. The spatial extent of non-built-up areas has generally declined over time, as reflected by the shifting NDBI ranges. In 1989, the values ranged widely from -0.32 to -0.08, suggesting expansive open spaces, bare land, or natural ground. By 1999, the range had already narrowed (-0.2 to -0.071), implying a conversion of some of these lands into built-up areas.

The decline in NDBI range between 2009 and 2019 may be attributed to spatial planning reforms, following the introduction of county governments in Kenya in 2013 under the new constitutional dispensation of 2010. Republic of Kenya (2011) required all urban areas to have spatial plans to regulate urban development. This could possibly be the reasons behind the reduction of NDBI between 2009 to 2019. This reflected renewed growth, possibly due to urban sprawl. The study attributed the projected increase in NDBI by 2019 to a reduction in the development space within the municipality. This would make the developers look for more spaces along the riverine ecosystem, hence an increase in the NDBI range. This trend reflected increasing pressure on the riverine ecosystem due to population growth and economic activities.

The observed increased urban sprawl on the Rupingazi riverine ecosystem had some profound implications on the ecosystem; an increase in NDBI indicated vegetation loss, which directly affected flora and fauna dependent on the riverine ecosystem. The riverine vegetation stabilizes riverbanks; thus its removal accelerates river erosion. This led to increased sediment loads in the river. Reduced tree cover resulted in higher local temperatures (urban heat island effect).

Higher NDBI observed in this study implied more concrete, thus may have reduced rainwater infiltration and increased stormwater discharge into the river Rupingazi. Increased urban sprawl may have contributed to more thus degrading water quality. Impervious surfaces in Embu municipality may also have reduced groundwater recharge, potentially lowering baseflows in the Rupingazi River, especially during dry seasons. Urban sprawl fragments the riverine ecosystem, which may isolate species. The riverine ecosystem may also lose its capacity to provide clean water, carbon sequestration, and flood regulation. Degraded riverine ecosystems may reduce recreational activities along the Rupingazi riverine. Restoring the degraded Rupingazi riverine ecosystem may be associated with cost implications to the county government of Embu.

To enhance the visualization of the influence of urban sprawl on the Rupingazi riverine ecosystem, NDBI indices were used to extract choropleth maps. The information was presented in Figures 2 to 5.

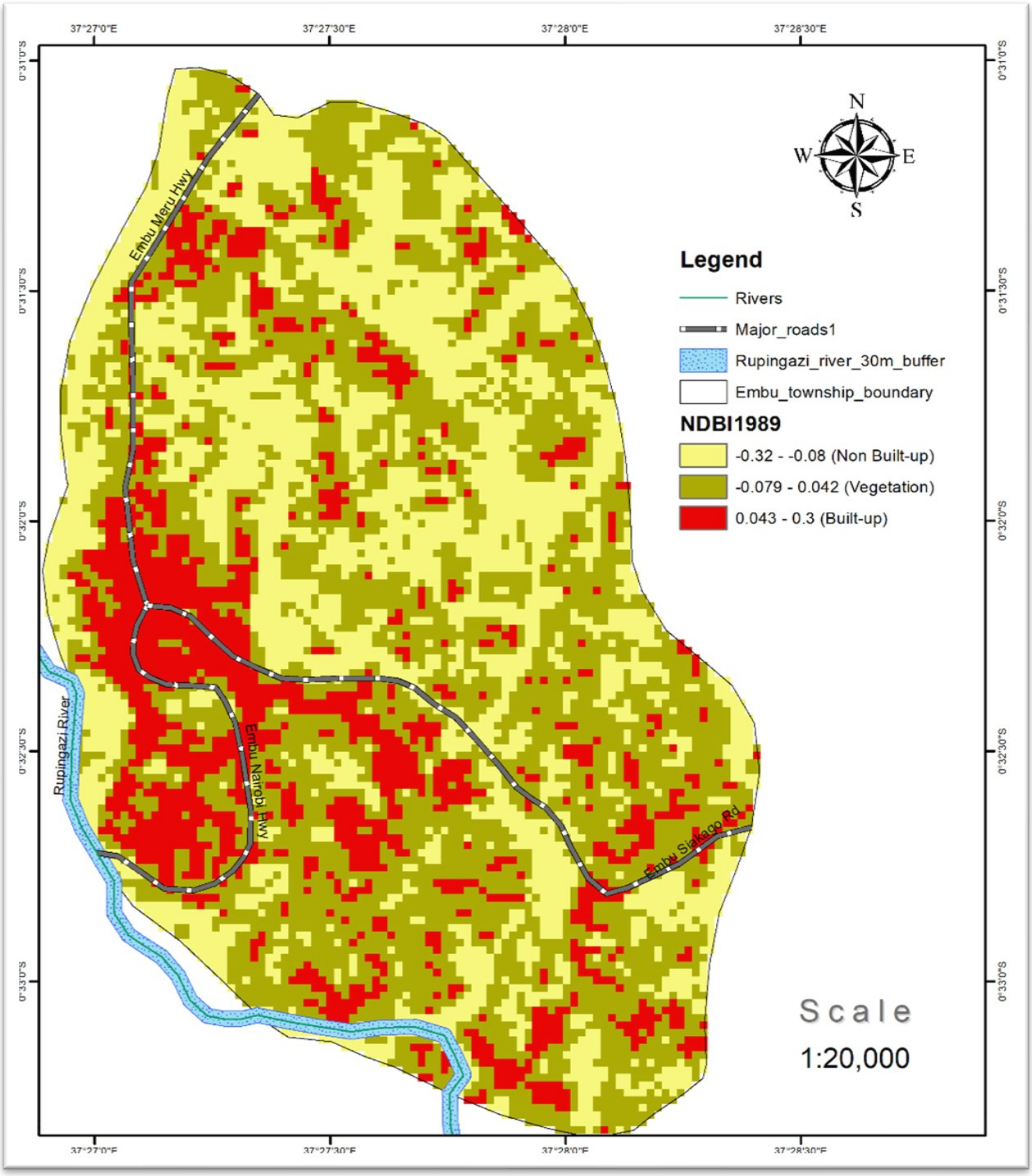

Figure 2. Map of NDBI for 1989

In 1989, the Rupingazi riverine ecosystem showed relatively low built-up areas (Figure 2), indicating limited urban development and a predominantly natural landscape. This can be visualized from the choropleth map as shown by the yellow colour covering most sections of the river Rupingazi ecosystem with minimal patches of maroon. The river sections were largely undisturbed, with dense vegetation cover and minimal built-up structures. This suggested that human activity and infrastructural expansion had not yet significantly influenced the riverine ecosystem, allowing the ecosystem to maintain its ecological integrity. The low urbanization levels during this period likely supported biodiversity and stable hydrological processes, reflecting a time before major urban sprawl emerged in the region. The information presented in Figure 3 shows the NDBI Choropleth Map in 1999.

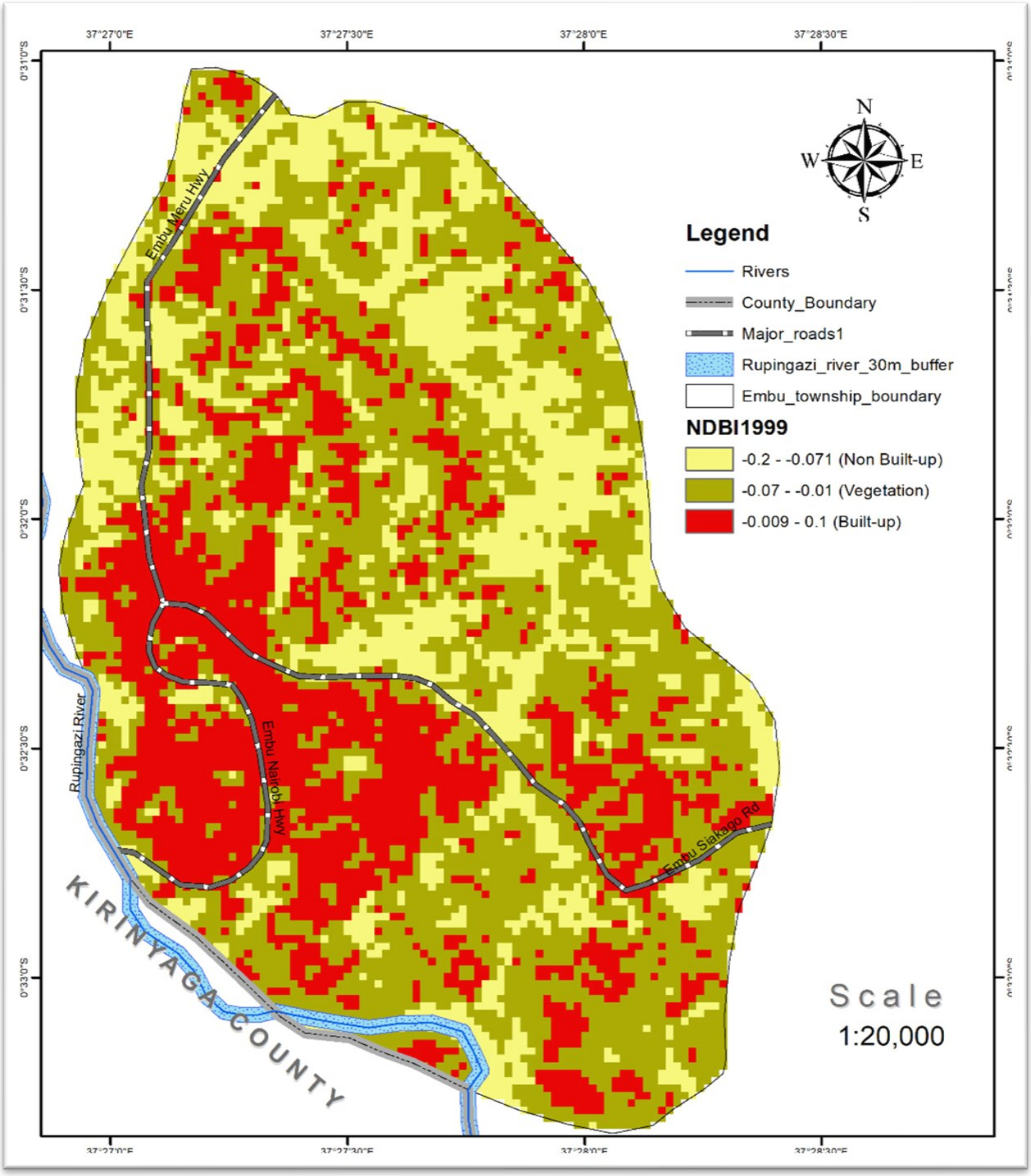

Figure 3. Map of NDBI for 1999

By 1999, a slight but noticeable rise in built-up areas along the river Rupingazi marked the initial stages of urban sprawl along the Rupingazi riverine ecosystem (Figure 3). This was evidenced by noticeable increased traces of maroon colour along a few sections of the Rupingazi riverine ecosystem. The maroon colour along sections of the Rupingazi riverine ecosystem implied a slight increase in levels of urban sprawl. This shift suggested early land-use changes, likely driven by population growth and the beginnings of infrastructural development. This can be traced from the choropleth maps by increased patches of maroon color on the map between 1989 and 1999. The encroachment of built-up areas signaled a transition toward increasing urban sprawl influence. The gradual urban sprawl during this decade may have been linked to economic activities and rural-urban migration, setting the stage for more rapid expansion in subsequent years. The information presented in Figure 4 shows the NDBI Map in 2009.

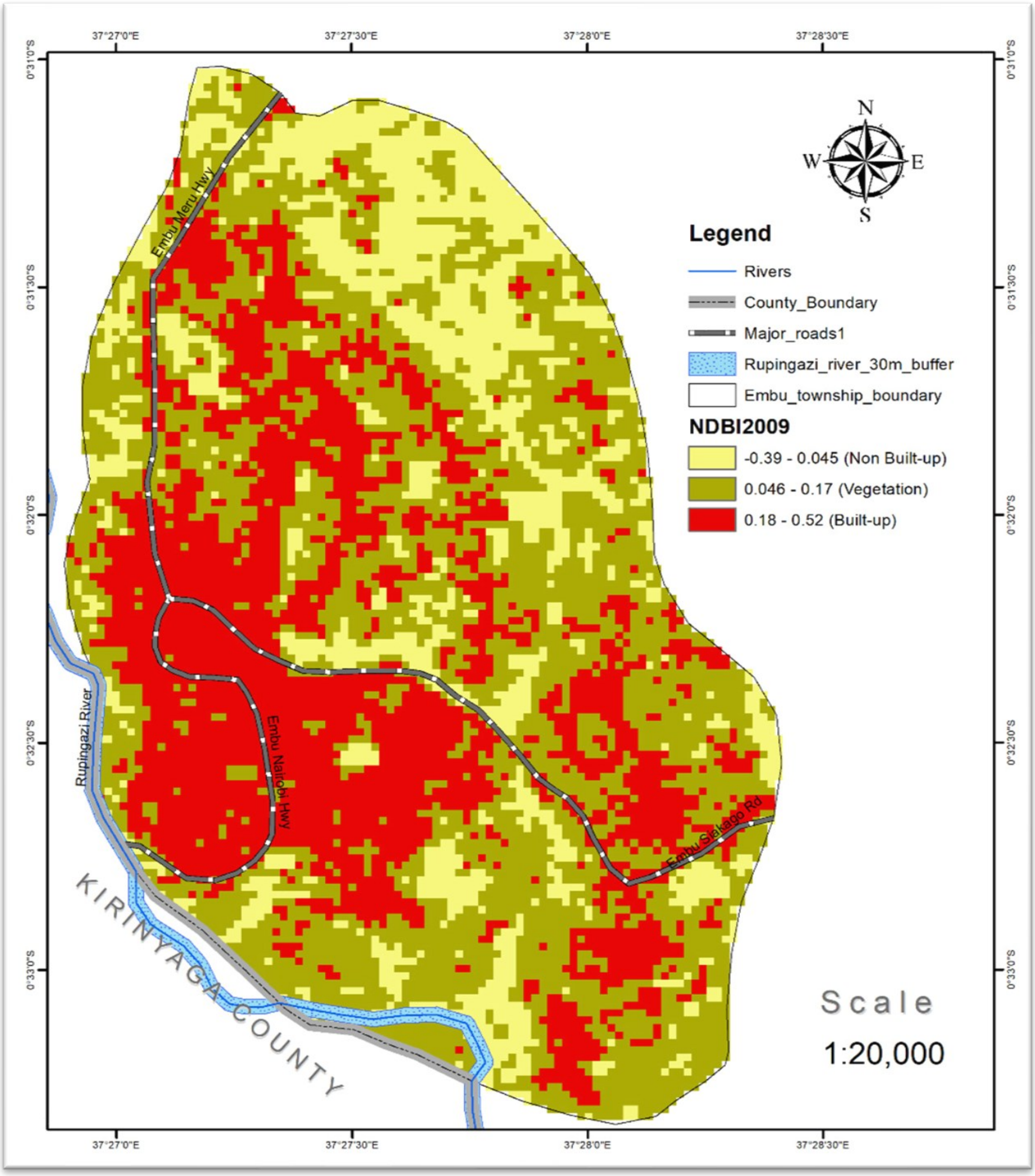

Figure 4. Map of NDBI for 2009

The year 2009 revealed a significant increase in built-up areas along the river Rupingazi, highlighting accelerated urban sprawl and substantial vegetation loss along the Rupingazi riverine ecosystem (Figure 4). This is visualized from the map with increased patches of maroon colour along the Rupingazi riverine ecosystem. The maroon colour patches can be observed nearing Rupingazi riverine ecosystem as an indication of increased Embu urban sprawl. In Kenyan history, the period between 2002 and onwards marked a strong political and economic revolution in Kenya. There was an improvement in the Kenyan economy that may have increased the people's income making them to shift from rural areas to urban areas such as Embu municipality. This period likely coincided with intensified development pressures, including housing demands and commercial activities. The expansion of built-up areas encroached the Rupingazi riverine ecosystem, thus reducing its green cover. The noticeable increased urban

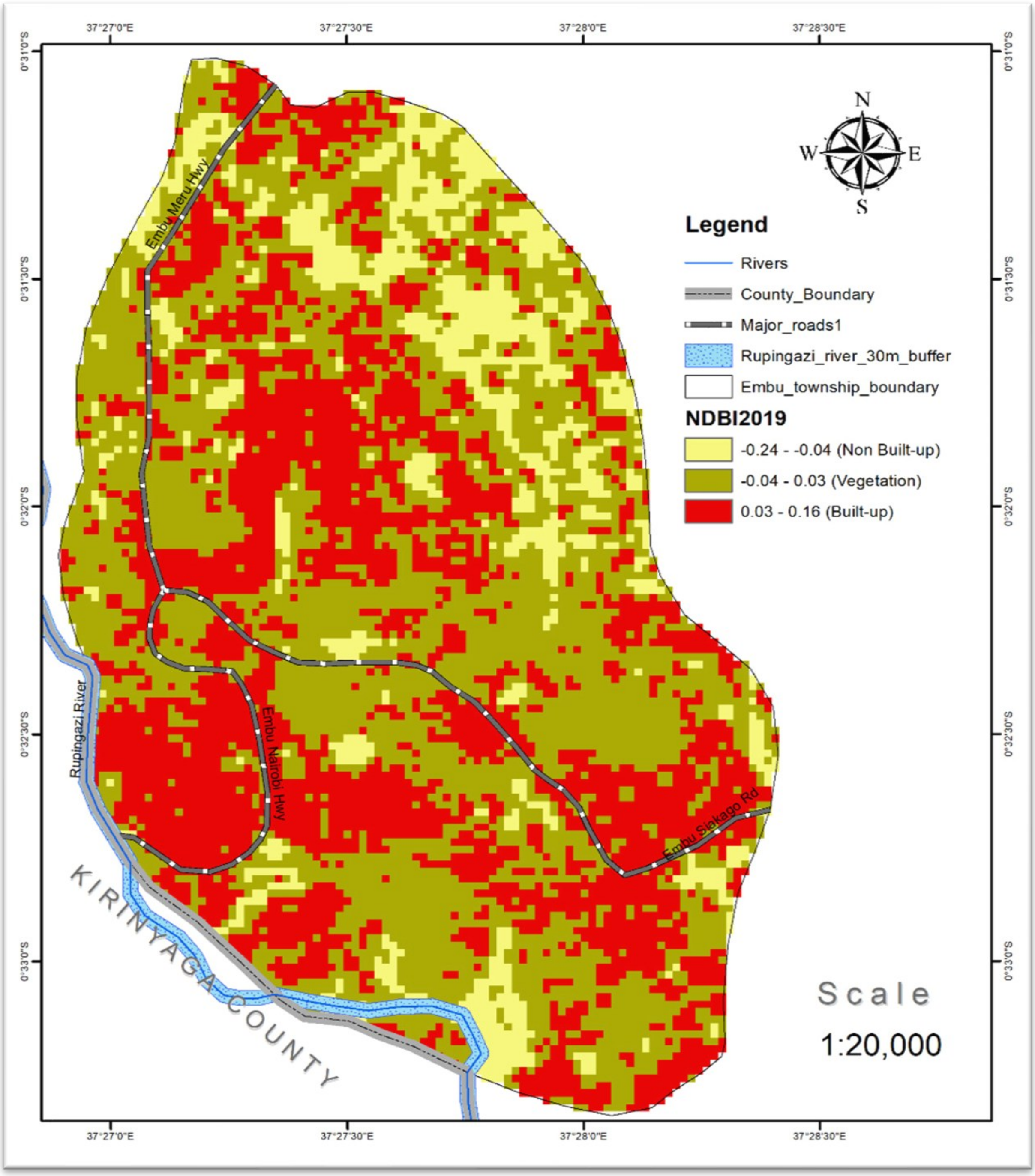

Figure 5. Map of NDBI for 2019

sprawl along Rupingazi riverine ecosystem underscores the ecological consequences of unchecked urban sprawl, raising concerns about long-term sustainability of the Rupingazi riverine ecosystem. The information presented in Figure 5 shows NDBI map in 2019.

By the year 2019, urban sprawl had intensified dramatically, with more built-up expansion along the Rupingazi riverine ecosystem. This is clearly shown in Figure 5 by increased patches of maroon color along the Rupingazi riverine ecosystem compared to the year 2009. The increased density of maroon color implies an increased rate of urban sprawl. This period was particularly significant in Kenya as it followed Kenya's devolved governance system (post-2013), which spurred population growth in Embu Municipality. Increased administrative and economic activities by the Embu County government exacerbated pressure on natural resources, leading to further riverine encroachment. The study findings highlight how policy shifts and urban sprawl trends can accelerate riverine ecosystem degradation, emphasizing the need for stricter enforcement of riverine ecosystem protection

These study findings were consistent with previous global studies; a study on the impact of urban expansion on riparian vegetation in Kenyan river basins using remote sensing revealed a strong negative correlation (r =0.87) between NDBI and NDVI along the river Nairobi (Mundia & Aniya, 2005). Bonareri (2017) found a P-value of 0.01 (< 0.05) between NDBI and NDVI, confirming a statistical significance between the two urbanization and vegetation. A study on monitoring urban land use and land cover changes in South-East Asia found a correlation between -0.75 and -0.92, showing that riverine ecosystems were highly vulnerable to the influence of urbanization (Samek et al., 2012).

The NDBI results for Embu Municipality between 1989 and 2019 revealed a clear and progressive increase in built-up intensity, consistent with findings from previous global and regional studies that used NDBI to monitor urban expansion. The study observed that NDBI values rose from 0.043–0.30 in 1989 to 0.18–0.52 in 2009, reflecting a marked intensification of urban sprawl, similar to the pattern reported by Eyoh & Ekpa (2019), who found a substantial increase in built-up area in Uyo from 6.76% in 1986 to 44.04% in 2018 based on rising NDBI values. The study also shows a narrowing distinction between non-built-up and built-up NDBI in 1999, which mirrors observations by Arif & Toersilawati (2024) in Sleman, where transitional zones exhibited fluctuating NDBI due to land conversion from vegetation to built-up surfaces. The notable rise in 2009 built-up values (0.18–0.52) corresponds to trends observed in studies from Kathmandu by Bhomi et al. (2024), where increased NDBI was associated with accelerated urbanization and reduced vegetative cover.

Previous studies across the globe have demonstrated that indices such as NDBI are reliable for analyzing the impacts of urban sprawl on riparian and peri-urban ecosystems. Zha et al. (2003) showed that NDBI consistently produced higher positive values in built-up surfaces, while natural vegetated areas remained in negative ranges. Similar findings were observed by Mhangara et al. (2024) in South Africa, who observed a strong upward trend in NDBI values in rapidly expanding cities and linked this rise to the conversion of riparian vegetation into residential and commercial land uses. In Ghana, Gyile et al. (2025) found that built-up expansion identified through NDBI corresponded with significant declines in NDVI. This mirrors the current study that noted a strong negative correlation of 0.98 between NDBI and NDVI. Likewise, Mugambi et al. (2022) used NDVI–NDBI integration to demonstrate riparian degradation along Kenyan river corridors driven by unregulated settlement growth.

Limitations of the study

The analysis primarily relied on Landsat satellite imagery with a spatial resolution of 30 m. While Landsat provides an essential long-term temporal archive for monitoring urban expansion, its moderate spatial resolution presents inherent challenges in detecting fine-scale environmental changes.

Weng (2012) emphasized that 30 m pixels often struggle to distinguish complex urban features, such as small residential buildings, narrow transport networks, and fragmented land parcels. In the context of the Rupingazi riverine ecosystem, this leads to the mixed pixel problem, where a single 30 m × 30 m area integrates diverse spectral signatures from water, riparian vegetation, and man-made structures. As noted by Small (2006), this moderate resolution tends to smooth or blur small-scale land cover variations. This blurring effect is particularly critical in riparian corridors where development is often linear and narrow; if a built-up feature does not occupy a significant portion of the 900 m^2 pixel area, its spectral signal may be overwhelmed by the surrounding vegetation, leading to an underestimation of human encroachment.

Furthermore, the reliance on the NDBI introduces specific spectral uncertainties. Zha et al. (2003), the pioneers of this index, acknowledged that NDBI can suffer from spectral confusion, particularly between built-up areas and bare soil or fallow lands, due to their overlapping reflectance patterns in the SWIR and NIR bands. In a dynamic ecosystem like the Rupingazi, where vegetation clearance (as noted by Kitur et al., 2017) often leaves exposed soil before actual construction begins, the NDBI might misidentify these cleared areas.

This limitation implies that the study may capture the result of urbanization (large built-up clusters) but potentially misses the process of degradation (fine-scale clearing and fragmented informal settlements). Consequently, the actual intensity of urban pressure on the riparian buffer may be higher than what is spectrally detectable at a 30 m scale, suggesting that the reported results represent a conservative estimate of the total ecosystem disturbance.

CONCLUSION

The study analysed the influence of urban sprawl on spatial-temporal changes along Rupingazi riverine ecosystem using NDVI. The findings revealed that urban sprawl had significantly reshaped the Rupingazi riverine ecosystem, with Landsat-derived NDBI values clearly showing a steady expansion of built-up areas and a corresponding decline in natural land. The sharp rise in built-up reflectance, particularly from 2009 onward, indicated intensified urban growth and increasing pressure on riparian environment. These findings highlight the urgent need for stricter enforcement of zoning regulations, enhanced protection of riparian buffers, and adoption of sustainable urban planning strategies to curb further ecological degradation. Further studies should complement NDBI with additional remote-sensing indices and higher-resolution data to improve the accuracy of ecosystem change detection.

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Author Contributions

Conceptualization: JR, MNj; writing-original draft: JR, MNj; methodology: JR, MNj; analysis: JR; visualization: JR, MNj; writing-review and editing: MNk.

Declaration of Competing Interests

The authors declare no conflict of interest

Data Availability Statement

The data used in this study is available to the corresponding author.

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