

Spatiotemporal dynamics of land use / land cover and woodland transformation in Bolgatanga, Ghana

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Research Article

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Abstract

Sub-Saharan Africa has the fastest population growth in the world with over 1.25 billion people with an annual growth rate of near 2.4% to 2.5%, this growth is accompanied high urban expansion and increased demand for land for farming at the expense of natural vegetations. This study examines the dynamics of land use/land cover (LULC) changes and woodland transformation in the Bolgatanga Municipality of Ghana, from 2002 to 2022, using multi-temporal Landsat satellite imagery and machine learning techniques. Employing a Random Forest classifier, six LULC classes; built-up, close woodland, open woodland, agricultural land, bare land, and water bodies were mapped to assess spatial and temporal transformations. Results reveal significant shifts: agricultural land expanded by 5.6% from 26.3% to 32%, built-up areas more than doubled increasing from 9.7% to 20.3%, and combined woodland cover declined by 18.9 percentage points from 58% to 39.1%. Normalized Difference Vegetation Index (NDVI) distribution showed maximum lower values in 2022, broadly consistent with the observed decline in classified woodland cover. The overall classification accuracy increased from 88.5% in 2002 to 96.9% in 2022, although class-specific accuracy varied particularly for built-up and water body classes. The findings of this study reveal a substantial landscape transformation associated with urban expansion, agricultural growth and woodland-cover change in the semi-arid savannah ecosystems. These findings underscore the urgency of integrated land-use planning and climate-resilient policies to balance urbanization with environmental sustainability in rapidly developing regions.

INTRODUCTION

Land use and land cover (LULC) change is one of the most visible expressions of human interaction with the environment, and its consequences are especially pronounced in semi-arid environments, where vegetation is already under natural moisture stress and land-cover/socio-economic interactions can rapidly degrade landscape structure [1]. In such settings, small additional pressures from human activity can tip ecosystems toward degradation more quickly than in wetter regions, since large-scale cropland expansion driven by growing demand for food and fuel is a documented driver of forest and natural-vegetation degradation across Sub-Saharan Africa, including in northern Ghana specifically [2], a pattern reported in a systematic review identifying population growth and agricultural-frontier expansion as the major drivers of this process region-wide [3]. Some semi-arid West African cities such as Damaturu in Nigeria have demonstrated similar traits where land use change monitors patterns of agricultural growth and urban expansion along side built-up area expanding at 4.5 to 5.3% annually [4].

Similarly in Ghana, urban expansion and agricultural transformation has been documented extensively as major drivers of LULC change in Ghana. According to [5], land areas previously used for agricultural activities in the Bolgatanga Municipality have been converted into residential and commercial infrastructural development due to population growth. More broadly, a similar study conducted a national assessment of land cover in Ghana across some selected regions over a 24 year period, the findings reported uneven transformation of agricultural land with gains and losses in farmlands associated to competing urban and agricultural pressures across regions with Oti region experiencing

the highest loss of approximately 947.83km² of farm lands over the study period, in contrast built area grew extensively nationwide at an average of 1,492.31 km² [6]. Comparable trends of farmland and settlement expansion at the expense of forest and water bodies have also been reported in the Upper Denkyira East District [7].

Beyond urban and agricultural expansion, woodland and vegetation degradation remains a persistent concern in Ghana's savanna and transitional zones, where tree and shrub cover is being progressively lost or thinned rather than fully cleared. In the Upper East Region, closed forests and grasslands have declined while open, degraded vegetation classes such as shrublands and bushes have expanded [8], a pattern indicating gradual degradation rather than abrupt deforestation. At a wider regional scale, an intensity analysis of land-cover change across Ghana's Northern, Upper East, and Upper West regions found that gains in cropland and tree cover during 1992–2015 came disproportionately at the expense of semi-arid shrubland, pointing to a slow erosion of natural vegetation cover even where forest area appeared to increase locally with most gains in arable land and tree/forest cover shown to have come at the cost of semi-arid shrublands during both study periods [9].

Landsat imagery remains the primary data source for monitoring these changes over multi-decadal timeframes, owing to its free availability and long historical archive stretching back to 1972, a data policy shift that substantially expanded its scientific use once opened to free public access in 2008[10]. Numerous LULC studies in Ghana have relied on multi-date Landsat classification to reconstruct land cover trajectories, typically applying supervised classification methods to time series of Landsat scenes to detect change between distinct time steps, as seen in analyses of the Tano River Basin[11], the Bosomkese forest reserve [12]. Among classification methods, the Random Forest algorithm has become increasingly preferred for LULC mapping because of its robustness to noisy training data and its ability to handle multiple input variables simultaneously without becoming overly sensitive to overfitting [13], [14] as demonstrated in a study that applied Random Forest classification to Landsat imagery to map more detailed urban land-use and change categories than are typically achievable with Landsat data alone [15]. This growing preference for Random Forest reflects a broader shift in the LULC literature toward machine-learning classifiers over traditional methods such as maximum likelihood classification, owing to their generally higher classification accuracy in comparative studies [16], [17] though the margin over maximum likelihood is not universal, a few comparative studies have found support vector machines or other classifiers performing comparably or better depending on the landscape and data used[18], so this should be framed as a general tendency rather than an absolute rule. Within Ghana specifically, LULC change in the northern regions has received particular research attention because of the area's semi-arid Sudanian climate and its vulnerability to both climatic stress and land pressure. The intensity analysis of Northern, Upper East, and Upper West regions found that the rate of land change was higher between 1992 and 2003 than between 2003 and 2015, with cropland expansion consistently occurring at the expense of natural shrubland and woodland cover [9]. These findings reinforce the need for continued, spatially explicit monitoring of vegetation and land cover change in northern Ghana's

semi-arid landscapes, using consistent, well-documented remote sensing methods capable of capturing both gradual degradation and abrupt land conversion over time.

Despite increasing evidence of urban expansion and land cover change in northern Ghana, there is relatively limited attention given to long term transition pathways among woodland, agricultural and built-up with the Bolgatanga municipality. This study therefore assesses the spatiotemporal LULC dynamics between 2002 and 2022 using multi-temporal Landsat imagery random forest classification. Specifically, this study quantifies major changes in LULC classes, identifies dominant landcover transition pathways, evaluates classification accuracy and examines associated spatial patterns of NDVI. The study contributes spatially explicit evidence of woodland transformation and agricultural expansion in a semi-arid Ghanaian landscape.

Study Area

The Bolgatanga Municipality previously known as Bolgatanga District was upgraded to the status of a Municipality in 2004 by Legislative Instrument (LI) 1797 (2004). Figure 1 shows the administrative boundary of the Municipality, which is located in the centre of the Upper East Region. Geographically, it lies between approximately 10° 42' 54" and 10° 37' 54" North of the Equator, and between 0° 51' 36" and – 1° 1' 12" West of the Prime Meridian, as depicted in Fig. 1. Bolgatanga Municipality is bordered to the north by the Bongo District, South and East by the Talensi and Bolga East Districts, respectively, and to the west by the Kassena-Nankana Municipality (see Fig. 1).

According to the Ghana Statistical Service (GSS), the population of the municipal was approximately 131,550 in 2010 and increased to 139,864 in 2021 [19]. Geographically, Bolgatanga is located in the savannah zone of Ghana, characterized by its dry, hot climate and low annual rainfall. The town is surrounded by hills, with its natural vegetation being that of the savannah woodland, characterized by short, scattered, drought-resistant trees and grass that gets burnt by bushfires or scorched by the sun during the long dry season.

Bolgatanga experiences a tropical savannah climate with two distinct seasons: rainy and dry. The rainy season usually starts in June and ends in October, with an average annual rainfall of about 800 mm. The dry season, which begins in November and ends in March, is characterized by hot and dry weather with little to no rainfall. The temperature in Bolgatanga ranges between 27°C and 34°C, with the hottest months being March and April. Agriculture is the main economic activity in Bolgatanga, with farming being the main occupation for most of the population. Crops such as millet, sorghum, and groundnuts, being the main staples, are cultivated within the city's surrounding areas. The most common economic fruit trees are the shea, dawadawa, baobab and acacia.

MATERIALS AND METHODS

Data Acquisition

Satellite data were collected for this study, this data included satellite imagery using Landsat Enhanced Thematic Mapper L1 (ETM+) of a 30m-by-30m spatial resolution. The a 2-decade period data was collected represented by three observation years at ten-year interval (satellite image description, Table 1). Cloud-free Landsat satellite images were captured from the USGS Earth Explorer website (<http://earthexplorer.usgs.gov>) for 2002, 2012 and 2022 to monitor the changes in land cover over time. Using a spatiotemporal stratified random sampling, a Garmin GPS device 66s was used to capture coordinates of pre-determined land cover samples for 2022, historic data on the other hand was acquired using the time-travel protocol on google earth pro for 2002 and 2012 to aid in training the dataset for image classification and validation. A minimum of 50 ground truth points of each land use class was acquired for the image validation, totaling 300 ground truth points for each year.

Table 1
Satellite image features and acquisition date

Satellite	Level	Sensor	No. of Bands	Paths/Rows	Spatial Resolution	Cloud Cover	Image Date
Landsat 7	L1TP	ETM+	9	194/053	30m*30m	10.00%	2002/10/30
Landsat 7	L1TP	ETM+	9	194/053	30m*30m	10.00%	2012/11/10
Landsat 8	L1TP	OLI	11	194/053	30m*30m	10.00%	2022/10/29
Source: US Geological Survey							

Treatment of Landsat 7 SLC-off imagery

The satellite imagery collected for 2012 from the Landsat 7 ETM+ contained SLC-off gaps, these gaps were corrected in the QGIS 3.24.1 platform by using the fill gap tool, this process filled missing pixels from the scene using the gap fill data provided during extraction from the USGS explorer platform, the entire scene was further masked to study area before subsequent training/validation was conducted.

Image preprocessing

Several pre-processing procedures were carried out in the study. The first was to conduct radiometric calibration, the essence of this calibration was to remove distortion in data capturing through factors such as the sun’s angle and instrument effect. The images were subsequently stacked to generate composite images using the ArcGIS 10.8 software. Three composite images were generated for 2002, 2012 and 2022. Since the composited images were more extensive than the study area, the QGIS 3.24.1 mask-to-layer tool was used to extract a subset image that matched the region of interest (AOI). This process was performed using a polygon shapefile of the Bolgatanga Municipality.

Table 2
Description of land cover classes used for the study (IPCC, 2022)

CODE	LULC CLASS	DESCRIPTION
1	Built Environment	Including all other forms of urban features such as residential, commercial, administrative, road, transportation and industry
2	Close Woodland	Natural woody vegetation with canopy cover ranging between 35% to 75% and canopy height exceeding 2.5 metres.
3	Open Woodland	Natural woody vegetation with canopy cover ranging between 10% to 35% and canopy height exceeding 2.5 metres.
4	Agricultural Land	This includes arable and tillable land, rice fields, and agroforestry systems which fall below the thresholds used for the Savannah woodland category as well as temporary fallow land.
5	Bare lands	untarred road, footpath and exposed land surface.
6	Water Bodies	including dugouts, streams, dams, rivers and ponds

Image classification

Supervised classification using Random Forest (RF) classifier in QGIS 3.24.1 was applied for the image classification. The random forests algorithm (RFA) is a machine learning technique that is increasingly being used for image classification [20]. RFA is good in handling outliers and noisier datasets; has a higher accuracy than other popular classifiers[21], [22]. This method is therefore most suitable for this study, the landcover types for classification included Close woodland, Open woodland, Built-up, Water, Bare land, and Agricultural land (see Table 2). 70% of the 300 training points acquired per year were used to train the Random Forest algorithm within QGIS 3.24.1 using the semi-automatic classification plugin, enabling the classification of pixels based on their probability of belonging to specific land cover class (Table 2) following the classification scheme [23].

A site-specific accuracy assessment was conducted with the remaining 30% of training points per year using Erdas Imaging 2014 to measure the accuracy of the results in order to determine the overall agreement between processed classification and ground-truthing data using the confusion matrix, The confusion matrix generated several measurements of quality, including overall accuracy, producer accuracy (PA), user accuracy (UA), and Kappa coefficient. This assessment approach assesses the correlation between satellite image classification and ground reference samples acquired [24]. The basis of selection was to confirm that features appearing in the satellite images genuinely reflect what is on the ground.

Post Classification Change Detection

The land use/land cover change was computed using a post classification cross tabulation, this process utilizes the independently classified LULC maps for 2002,2012 and 2022, overlays them to generate

cross tabulation matrices. Each matrix quantified the initial LULC class to a subsequent class. Areas that transitioned into other LULC classes were calculated in hectares and expressed in percentages of the relevant reference area. This approach enabled identification of dominant conversion pathways among woodland, agricultural, built-up, bare land and water body classes.

Normalized Difference Vegetation Index

Normalized Difference Vegetation Index (NDVI) is a widely used remote sensing metric that provides valuable insights into the health and abundance of vegetation. The NDVI for the study was computed for three time points, 30 October 2002 and 10 November 2012 for Landsat 7ETM+ while 29 October 2022 was computed for Landsat 8 OLI in QGIS 3.24.1 using the raster calculator tool with the following formulae:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

and the resulting image was used to assess the vegetation index of the Municipality descriptively and provide complementary information on vegetation conditions and spatial patterns.

RESULTS AND DISCUSSION

Land Use/Land Cover dynamics of Bolgatanga Municipality from 2002 to 2022

The classification accuracy was assessed using 50 reference points per class summing to 300 points per study year, Table 3 presents results of confusion matrix for land use/cover classifications for 2002, 2012 and 2022, the assessment demonstrates strong reliability, with the overall accuracy increasing from 88% in 2002 to 96% in 2022, while kappa increased from 0.70 to 0.90. This aligns closely to a study by [25]. Notwithstanding class level accuracy varied substantially among LULC categories and years. Close and open woodland achieved consistently high producer and user accuracies in 2002 and 2012. In 2022 however, built-up recorded a producer accuracy of 32.5% despite a user accuracy of 70%, indicating substantial omission and potential confusion of spectral similarities of some classes.

Table 3
Accuracy assessment results for the various land use/cover maps.

LULC Classes	2002		2012		2022	
	PA	UA	PA	UA	PA	UA
Built-Up	63.2	86.6	76.1	88.3	32.5	70
Close Woodland	99.5	89.7	97.9	97.1	100	98.5
Open Woodland	89.7	97.1	100	97.1	100	100
Agricultural Land	71.9	42.8	98.5	58.9	100	98.5
Bare Lands	44.2	71.9	58.9	42.8	100	98.5
Water Body	9	100	15.1	100	97.5	91
Overall Accuracy	88.5		91.5		96.9	
Kappa coefficient	0.7		0.8		0.9	

The LULC trajectory of Bolgatanga Municipality between 2002 and 2022 reveals a consistent and accelerating decline in natural woodland, absorbed almost entirely by two competing land uses: agricultural expansion and urban built-up growth. Clear-cut patterns are observed when open and close wood lands are observed jointly rather than separately, a combined woodland cover declined from 58.0% in 2002 to 49.5% in 2012 and to 39.1% by 2022, indicating a net loss of nearly 19 percentage points over two decades. Over the same period, built-up area more than doubled from 9.7% to 20.3%, similarly on the other hand, agricultural land rose from 26.3% to 32.0%. Together, these two classes absorbed almost all of the land vacated by woodland loss, positioning population growth and its associated urban and agricultural land demand as the principal drivers of land cover change in the municipality.

In 2002, open woodland (37.6%) dominated the southwestern zone of the municipality, this may be linked to limited interference with the vegetation cover. Built-up areas at this stage were modest (9.7%) and clustered around the municipal core, reflecting the early-stage urbanization typical of regional capitals in northern Ghana before the acceleration of rural-urban migration [26], [27].

By 2012, the picture shifts: closed woodland briefly rose to 29.5%, overtaking open woodland (20.0%). This is not necessarily a conservation success, rather it more plausibly reflects a transitional degradation pathway, in which disturbed open woodland regenerates into denser, shrubbier secondary growth before eventual clearance, this pattern has been documented in comparable West African savannah systems undergoing agricultural and settlement pressure [9]. Built-up land grew to 14.1%, and agricultural land held roughly steady (25.1%), suggesting that in this middle period, expansion pressure was still primarily absorbing degraded and marginal land rather than displacing intact woodland outright.

It is worth noting that, the 2012–2022 interval is where the woodland-to-agriculture/built-up conversion becomes most pronounced. Closed woodland collapsed from 29.5% to 15.8%, and open woodland made only a partial recovery to 23.3% representing a net woodland loss that coincides almost exactly with the combined gains in agricultural land (+ 6.9 points) and built-up area (+ 6.2 points) over the same decade. This is consistent with findings from Bolgatanga itself, where rising urban populations have been shown to directly displace surrounding farmland and, by extension, the natural vegetation at the agricultural frontier, as urban residential and commercial development expropriates land originally zoned for agriculture[5]. The mechanism is twofold: population growth increases direct demand for residential and commercial land[28], while simultaneously increasing demand for food production, pushing farming into previously wooded margins[5]. Both processes draw down the same finite woodland stock, explaining why open and closed woodland decline in tandem with built-up and agricultural growth rather than independently of one another.

This dual-pressure pattern mirrors dynamics observed elsewhere in Ghana's urbanizing secondary cities, where unplanned peri-urban growth outpaces formal planning frameworks and encroaches directly into surrounding natural land cover[29], this challenge is further compounded by weak enforcement of land-use zoning under Ghana's national spatial development framework [30]. At a broader scale, the rate of woodland loss recorded here is not unusual as it sits within global patterns of tropical and sub-tropical forest and woodland conversion to agriculture and settlement documented by [12], reinforcing that Bolgatanga's experience is a local instance of a well-established regional and global land-conversion pathway rather than an anomaly.

Taken together, these results support the study's central argument that, population growth in Bolgatanga Municipality has driven simultaneous urban and agricultural expansion, and both have converged on the same resource the municipality's open and closed woodland as their primary land bank. Without targeted land-use planning that channels future growth toward already-degraded or bare land rather than remaining woodland, the observed trajectory suggests continued woodland loss is likely to persist.

Land Use/Cover Transition of Bolgatanga Municipality from 2002 to 2022

The land use land cover transitions between 2002 and 2022 as illustrated in Fig. 4 and detailed in Table 4, revealed significant transformations in land cover classes across varied categories. The findings indicated a notable conversion of 13.16% of open woodland to closed woodland, while 52.71% of close wood land was transformed to open wood land and this contrasting transitions between open and close woodland indicate changes in vegetation structure or density. These transitions may reflect shifts in disturbance regimes, climate factors and land management practices within the Municipality [31], more notably 27.90% and 21.09% of open and close woodland transitioned to agricultural land respectively, this could be triggered by high demand for land for farming activities as the population increases [32], similarly, bare land lost 42.11% to agricultural activities. A study conducted by [33] emphasizes that understanding these dynamics is crucial for effective land management and policy formulation. The

relationship between land use change and environmental consequences is profound, as changes can affect biodiversity, carbon storage, and hydrological cycles. The comprehensive exploration of land use dynamics not only aids in recognizing local transformations but also contributes to broader ecological studies aimed at assessing impacts on climate change and resource management [34]. The ongoing evaluation of land use changes, therefore, remains vital for informing sustainable land management strategies in response to both anthropogenic pressures and ecological needs.

Table 4
LULC transition matrix in percentage for 2002 to 2022

From ↓ / To →	Built-Up	Close Woodland	Open Woodland	Agricultural Land	Bare Land	Water Body
Built-Up	26.16	3.67	21.94	45.77	2.42	0.04
Close Woodland	8.30	16.94	52.71	21.09	0.83	0.12
Open Woodland	12.40	13.16	45.26	27.90	1.25	0.04
Agricultural Land	17.85	8.65	34.72	36.92	1.83	0.03
Bare Land	22.26	5.76	27.46	42.11	2.35	0.05
Water Body	6.29	30.90	20.50	6.69	0.99	34.63

LULC Change Differences from 2002 to 2022

The change differences in the land use/cover presents dynamic shifts of landuse/covers, the analysis from 2002 to 2022 is statistically represented in Fig. 3, 5 and Table 5, indicating notable changes in the landscape. Built-up land increased by 10.6 percentage points increasing its area to 6626 ha from 3175 ha in 2002, this increase may be attributed to population growth and urban expansion, this trend closely aligns with a study Kumasi, reporting rapid urbanization due to population growth [35], similarly [36] reported fragmentation and vegetation loss attributed to urban expansion. Close and open woodland exhibited a marginal and notable changes of -4.6% and – 14.3% respectively in 2022, implying potential deforestation or land-use changes. Agricultural land on the other hand surged by 5.6% covering 10407 ha at the expense of other land use/covers, this corresponds with the increase in built up areas indicating population growth and in effect the high demand for food[37]. Bare land and water bodies witnessed slight increase 2.6% and 0.1% in 2022 respectively.

Table 5
Land use / cover total change difference from 2002 to 2022

LULC Class	2002 area (ha)	2002 (%)	2022 area(ha)	2022 (%)	Change Percentage Points
Built-Up	3175	9.7	6626	20.3	10.6
Close Woodland	6635	20.4	5133	15.8	-4.6
Open Woodland	12245	37.6	7593	23.3	-14.3
Agricultural Land	8567	26.3	10407	32.0	5.6
Bare Land	1938	6.0	2783	8.5	2.6
Water Body	9	0.0	27	0.1	0.1

Source: Field Survey, 2024

Normalized Difference Vegetation Index (NDVI) 2002 and 2022

The NDVI (Normalized Difference Vegetation Index) results from Bolgatanga Municipality over the period from 2002 to 2022 as illustrated in Fig. 7 closely align with observed land use and cover dynamics, revealing significant ecological trends such as the decline of woodlands, agricultural expansion, and a decrease in bare land areas. In 2002, the NDVI range was between -0.47 and 0.30 , indicative of moderate vegetation vigor, primarily comprising open and closed woodlands, alongside substantial non-vegetated areas, notably bare land and dry soils. This is consistent with land classification data that shows woodlands constituted 58% of land coverage while seasonal agricultural lands made up 26.3% [38]. The negative NDVI values, particularly reaching -0.47 , generally correspond to water or non-vegetated surfaces, although mixed pixels may produce intermediate values. By 2022, the NDVI range had narrowed to -0.08 to 0.14 , indicating a reduction in vegetation density across the landscape, alongside a less pronounced appearance of bare land. The decline in maximum NDVI values from 0.30 to 0.14 corroborates the observed loss of woodland areas, where combined woodland cover decreased from 58% to 39.1%. This substantial decline is attributed to ongoing deforestation and fragmentation processes, a trend observed in other regions facing similar anthropogenic pressures [39]. Moreover, the escalation of agricultural land use to 32% by 2022 indicates a more consistent land use pattern that diminishes seasonal bareness, mirroring findings from a study in Ethiopia, which also reported significant shifts in vegetation productivity relative to agricultural expansions [40]. Similarly, the NDVI trends reflect challenges in differentiating built-up areas from bare land, as urban expansion recorded at 20.3% by 2022 complicates vegetation analysis by introducing mixed pixels with low vegetation signals.

This scenario is consistent with findings reported by [27], highlighting that urban sprawl significantly impacts NDVI readings due to the conversion of vegetated areas to built-up structures. Despite these challenges, NDVI serves as a crucial ecological indicator, elucidating the ongoing transformation from

heterogeneous woodlands to a more homogenized agro-urban landscape. This aligns with the broader understanding of how land use changes can dramatically alter ecological systems and affect the availability of ecosystem services that are vital for sustainability and community resilience in the face of climate variability [41]

CONCLUSION AND RECOMMENDATION

This study underscores the profound transformation of land use/cover (LULC) in Bolgatanga Municipality, Ghana, between 2002 and 2022, associated with rapid urbanization, agricultural expansion, and woodland cover transformation. Remote sensing analyses revealed that built-up areas more than doubled from 9.7% to 20.3%, a 5.6% expansion of agricultural land, and an 18.9% decline in combined woodland cover from 58.0% to 39.1%. NDVI trends further corroborated ecological stress, with NDVI values similarly showed a decline in the maximum observed vegetation signal, which is broadly consistent with the reduction in classified woodland cover. These shifts reflect the interplay of population growth, climate variability, and unplanned urban sprawl, exacerbating risks to biodiversity, soil health, and ecosystem services in this semi-arid savannah region. While classification accuracy improved over time (96.9% overall accuracy in 2022), challenges in mapping fragmented urban features highlight the need for advanced methodologies in heterogeneous landscapes.

The study recommends that, zoning enforcement should Prioritize areas where built-up expansion intersects remaining woodland and other environmentally sensitive land cover units while promoting agroforestry, drought-resistant crops, and soil conservation techniques to mitigate land degradation caused by expanding farmlands. Strengthen extension services to support smallholder farmers in adopting sustainable practices.

Declarations

Ethical Approval

Not applicable

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Data Availability

The Landsat satellite imagery utilized for this study is publicly available through the United States Geological Survey Earth Resources Observation and Science Center. The derived LULC classification and validation data sets generated are available with corresponding author upon reasonable request

Author Contribution

Conceptualization, methodology, data curation, formal analysis visualization and writing of the original manuscript were carried out by Mr. Perry Demobayine Gandaa.

Conflict of Interest

The authors declare no conflicts of interest.

Consent to Publish declaration

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Figures

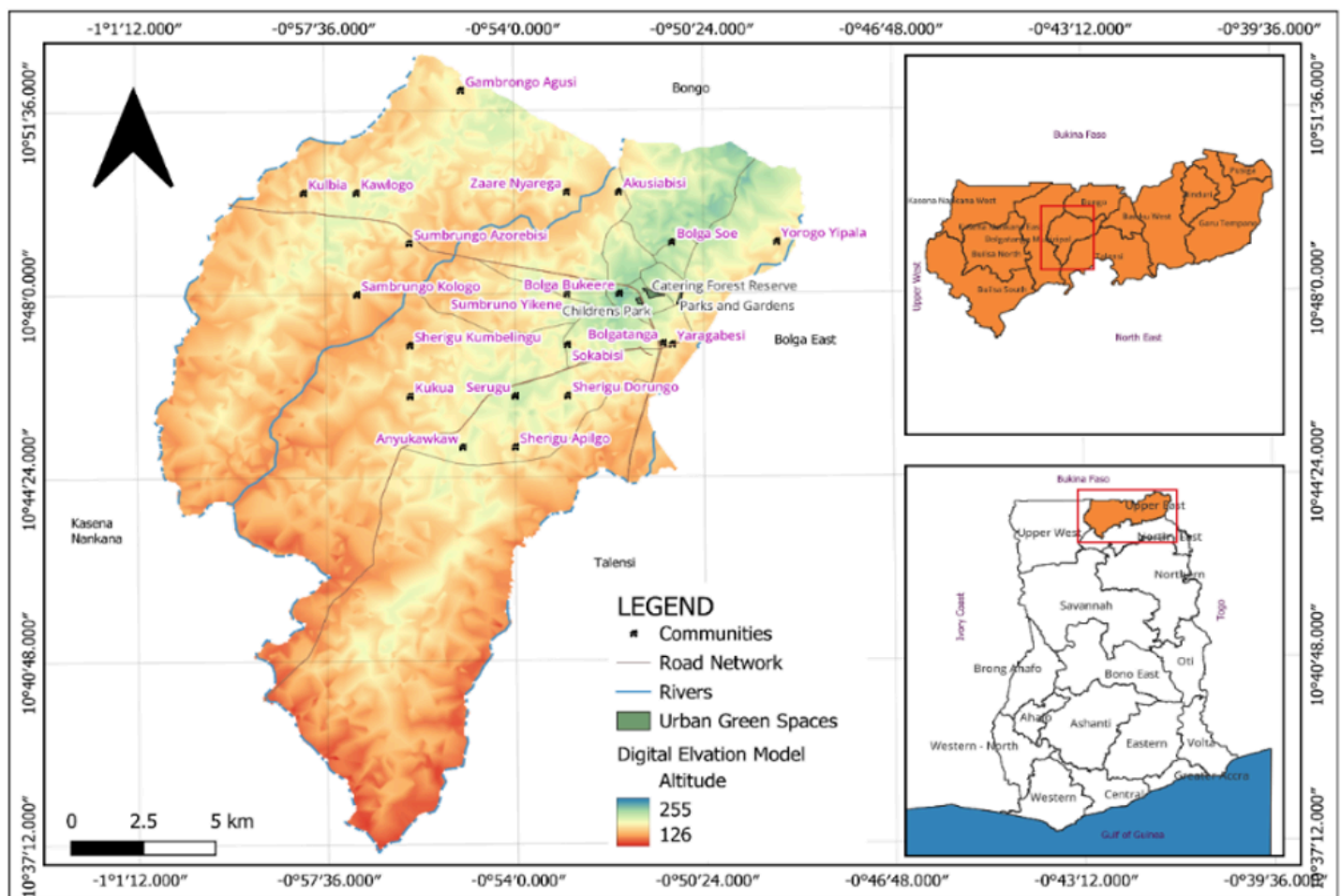


Figure 1

Study Area map of Bolgatanga Municipal

Source: Author's Construct

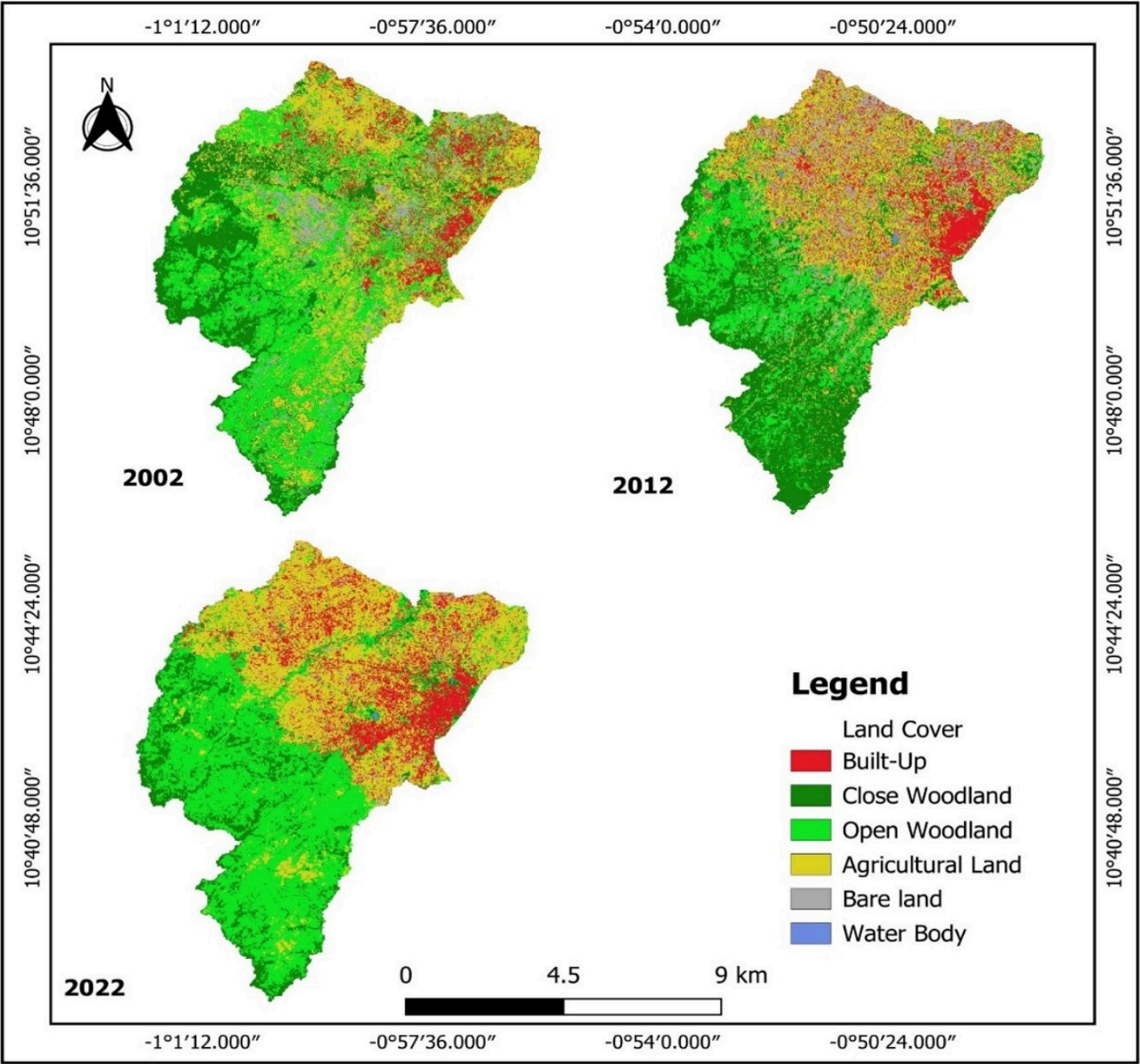


Figure 2

Composite LULC maps of Bolgatanga Municipality for 2002, 2012, and 2022.

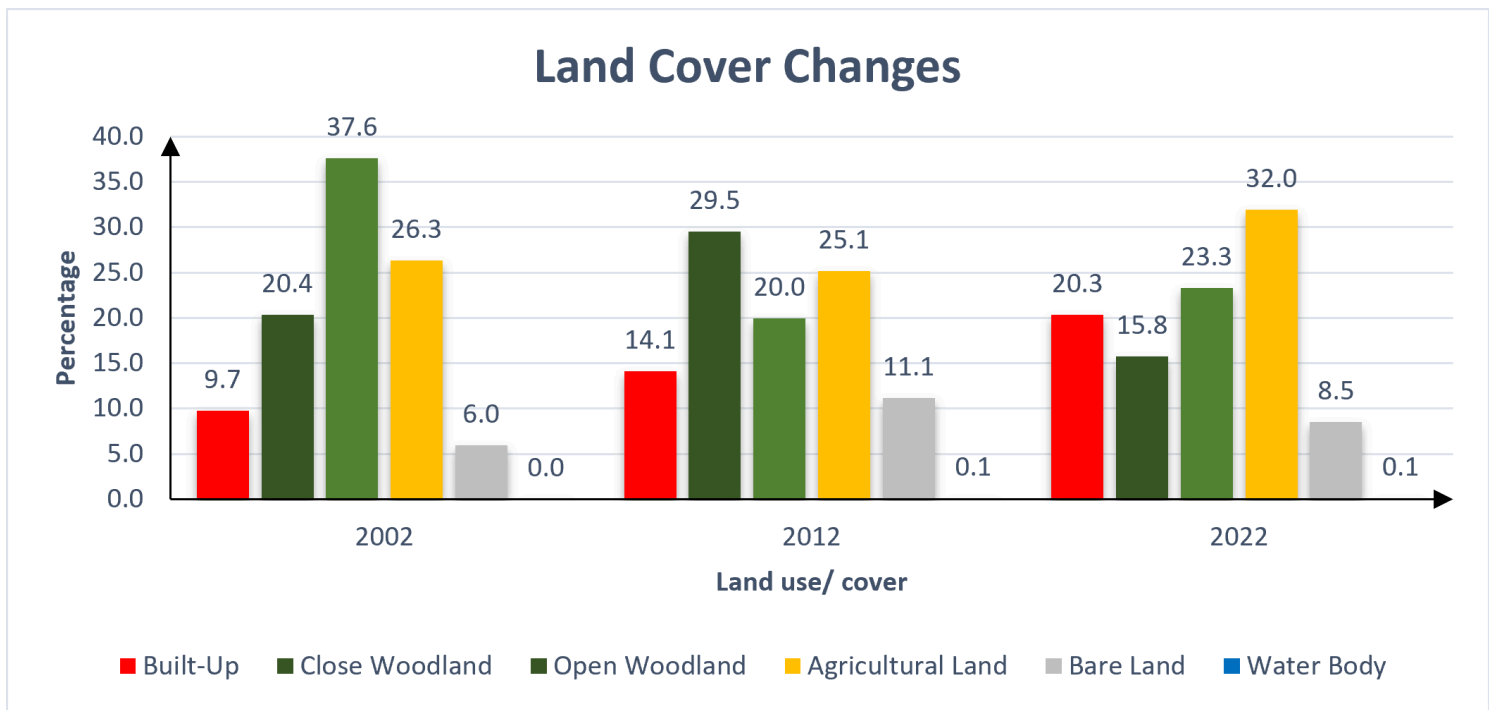


Figure 3

Percentage Distribution of LULC classes in Bolgatanga Municipality, 2002, 2012, and 2022.

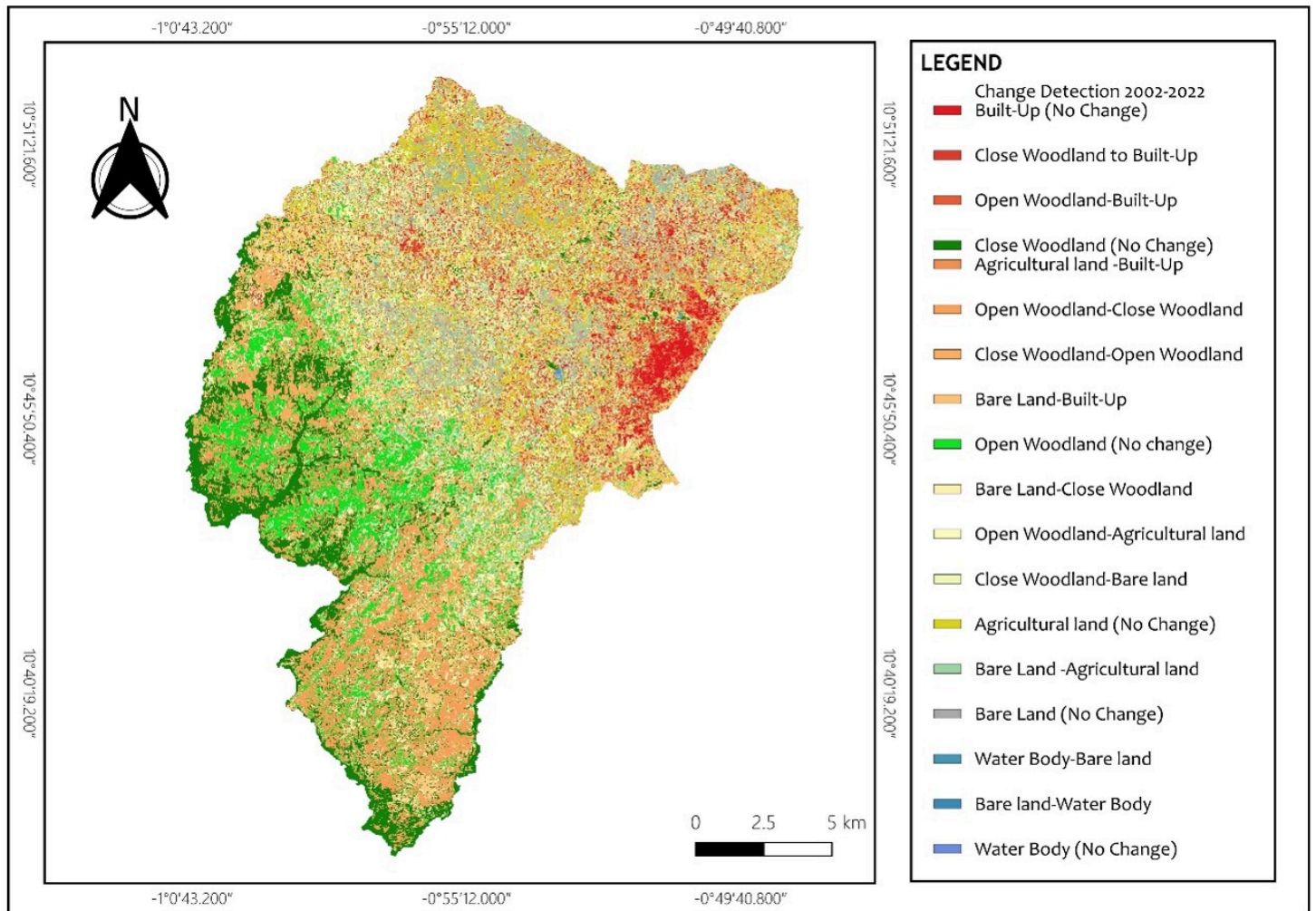


Figure 4

Land Use/Cover transition for 2002 to 2022 in the Bolgatanga Municipality

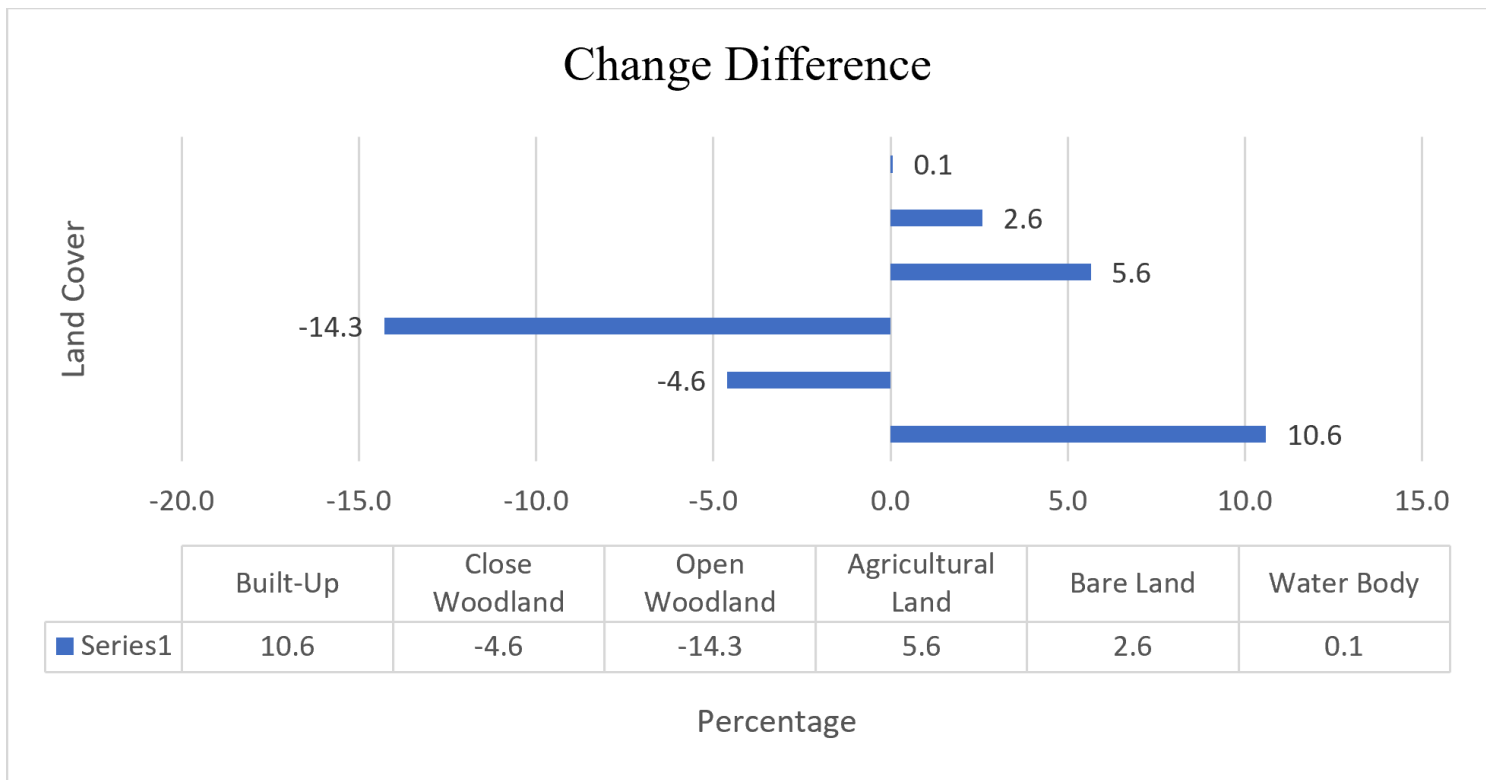


Figure 5

LULC Percentage change in Bolgatanga Municipality between 2002 and 2022

Source: Authors' analysis of Landsat imagery, 2024

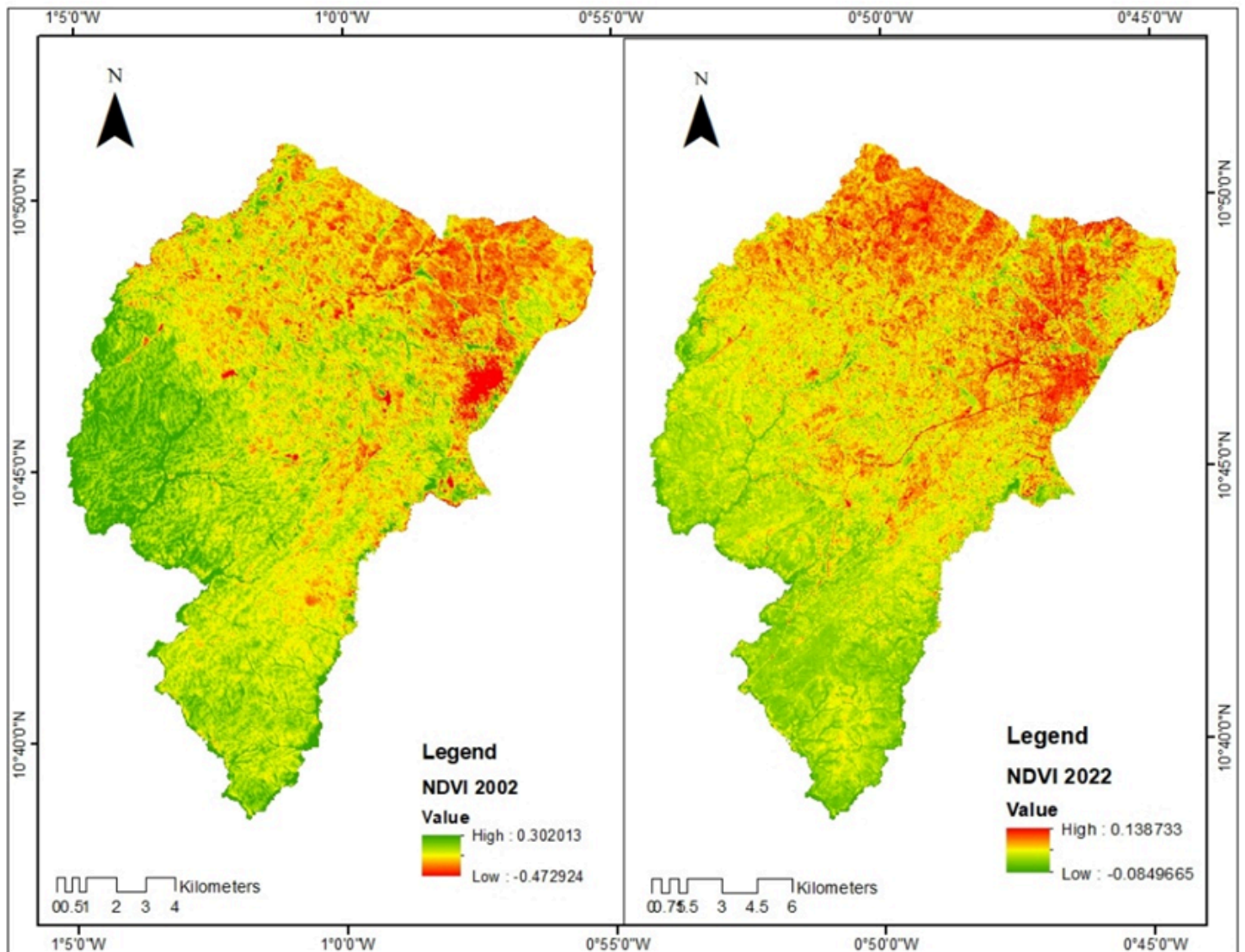


Figure 6

NDVI distribution for Bolgatanga Municipality in 2002 and 2022