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Michael Batame and Kingsley Kanjin *

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Towards Sustainable Forest Management: Assessing and Predicting Landuse/cover Change on Forest Landscape and Estimating its Impact on Forest Health in Southeast Georgia, USA

Michael Batame [1] and Kingsley Kanjin [2,*]

[1] Warnell School of Forestry and Natural Resources, University of Georgia, Athens, GA 30602, USA
[2] Toledo Metropolitan Area Council of Government (TMACOG), OH, 43604, USA
* Correspondence: kanjinkingley3@gmail.com; Tel.: +1(419)-932-1884

Abstract: The conversion of LULC classes into other types is occurring at a faster rate globally including United States. Many studies have examined the drivers and causes of LULC changes, particularly, in northeast Georgia and Atlanta in the United States, while the case of southeast Georgia remains unstudied. Thus, this study filled the gap by quantifying and predicting the impact of LULC change on forestlands and how these LULC changes have affected forest health. The study used Landsat images, including 2005 and 2023 together with the random forest algorithm to perform LULC classification on the Google Earth Engine. Also, the study predicted how LULC will impact forest cover by 2050. The results revealed that forest hectares have generally changed approximately from 65% to 62% between 2005 and 2023, and this is projected to likely further decline to about 53% by 2050. This change in forest acreage has resulted decline in the health of the forest, that is the NDVI values changed from 0.992 to 0.866 between 2005 and 2023. The study concludes that the forest cover in southeast Georgia has changed to urban features over the years. Agriculture land is projected to gain most of the forest cover by 2050.

Keywords: sustainable forest management; LULC; NDVI; Landsat satellite; google earth engine

1. Introduction

A typical approach for depicting the relationship between human activity and the environment is landuse/cover (LULC) change [1, 2]. Over the decades, LULC has been rapidly exacerbating across the globe, most especially in developing countries [3, 4, 5] than in developed countries [6]. Anthropogenic activities are postulated to be the main driving force of LULC change [6, 7], and these major activities necessitating the changes are population growth, socio-economic conditions, urbanization, changes in lifestyle, agriculture expansion, increasing energy and wood demand, and economic growth [1, 3, 8]. The conversion of LULC classes, such as vegetation (forests), land, and water bodies negatively affects biodiversity, conservation, ecosystem services, carbon storage, hydrological processes, and sustainable environment management [2, 8, 9].

Globally, the forest is an indispensable natural resource to many countries and has been used by millions of people over the decades [10], for instance, communities tend to focus on forests since they are endowed with myriad resources, such as minerals, timber, and food [11, 12]. This instance calls for sustainable forest management. The question of how communities can sustainably utilize forest resources to meet their needs without adversely affecting the forest cover has been a major concern of environmental advocates, land-use planners, natural resource managers, and other stakeholders [1, 11, 12, 13, 14, 15]. Sustainable forest management is the systematic approach employed to ensure both judicious utilization of forests and continuous growth of forests without harming other dependent organisms [12]. Furthermore, sustainable forest management includes environmental benefits, such as ecosystem sustainability, carbon storage and sequestration, improved water and air

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quality, habitat for endangered species and wildlife, and protects forest health in addition to the social and economic benefits [10, 12, 16].

Remote sensing data has been broadly utilized in monitoring and assessing environmental changes, such as LULC at the global, regional, and local scales [8, 17]. Moreover, under the direction of the LULC change project of the International Geosphere-Biosphere Programme (IGBP) and International Human Dimensions Programme on Global Environmental Change (IHDP), several researchers have improved measurements of land-cover change, the understanding of the causes of landuse change, and predictive models of LULC change over the last few decades [4, 18. 19]. Again, many studies have explored time-series mapping of LULC change globally using multispectral satellite images in fields, such as forestry, agriculture, and natural resources.

Mikeladze et al. [20] used Sentinel-2 multispectral imagery to detect forest cover change in Georgia (the Caucasus). Forest cover estimates were fitted to Sentinel-2A spectral band data that had been altered using various topographic correction techniques using generalized additive models (GAMs). When Sentinel-2 spectral data were topographically adjusted using the Minnaert Correction (R2 = 0.882), the best forest cover metric that could be accounted for was canopy closure, which was computed from upward-looking fisheye pictures obtained beneath the forest canopy. Band 3 (green), Band 8 (NIR), and Band 12 (SWIR) were the spectral bands that best explained canopy closure.

In addition, Housman et al. [21] evaluated forest health insect and disease survey data and satellite-based remote sensing forest change detection methods and assessed them over Southern New England and the Rio Grande National Forest in the US. They compared the performances of the three products employed, namely Insect and Disease Survey (IDS), Modis Real-Time Forest Disturbance (RTFD), and Operational Remote Sensing (ORS) in the analysis. The ORS uses Modis and Landsat data to identify disturbances in the forest. They found that their models performed better in the Southern New England study area, with overall accuracies ranging from 71.63% to 92.55% than in the Rio Grande National Forest area 63.48% to 79.13%. They argued that while many ORS products were as accurate as or more accurate than IDS and RTFD products overall, the differences were not statistically significant at the 95% confidence range. This shows that the data provided by the existing ORS implementation is adequate to supplement IDS data.

Wang et al. [22] explored the use of remote sensing data in analyzing forest health. The results of their review showed that, when cost, bands, temporal and spatial resolutions were taken into account, the majority of the studies concluded that Moderate Resolution Imaging Spectroradiometer satellite data (MODIS) are more suitable than other current satellite data for most remote sensing applications for forest health. However, Landsat images have a better spatial resolution, which aids in detecting smaller changes in the earth’s surface, as well as it is cost-free and can provide historical information than MODIS [23, 24].

Furthermore, Vogelmann et al. [25] employed time-series Landsat data to map forest degradation in Lam Dong Province, Vietnam between 1973 and 2014. Based on their results, the province of Lam Dong has seen numerous land-use changes, including slow shifts from forest to non-forest areas. The interfaces between forest and agricultural areas that are quite small and occur closer to the province’s borders are where the most notable recent changes can be seen. A noteworthy finding was that during the Landsat era (1972–present), there has been minimal change in the region’s most heavily protected national reserves.

Kanjin and Alam [9] quantified LULC changes and estimated the Normalized Difference Vegetation Index (NDVI) in Sundarbans (Bangladesh and India) for six different years, such as 1973, 1980, 1990, 2000, 2013, and 2023. The LULC was done using Landsat data, while Modis data was used to calculate the NDVI. According to their findings, over the twenty years in Sundarbans, there have been significant changes in dense and sparse forest. For instance, dense forest has been rapidly converted to sparse indicating that the mangrove vegetation is getting lost due to climate and anthropogenic activities.

Yang and Lo [26] estimated LULC changes using time-series satellite images in the Atlanta, Georgia metropolitan area, US over the past 25 years. They used different methods to map the LULC in the study area, such as radiometric normalization, unsupervised classification, a GIS-based

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reclassification, and post-classification. The post-classification product was compared with the GIS overlay to detect the LULC changes. The findings reveal the loss of forest and urban sprawl as the main issues associated with Atlanta's rapid urbanization. Also, Moisen et al. [27] indicated that North Central Georgia has experienced a great deal of forest land and tree cover reduction over the past 30 years. Using remotely sensed observations to supplement standard forest inventory data, their study identified the temporal patterns and thematic shifts associated with this loss.

Despite much research done on LULC changes in the world and most especially in Georgia, US, there is limited knowledge on the extent to which LULC has impacted forest cover and health in Southeast Georgia. Therefore, this study seeks to estimate the impact of LULC on forest cover and forest health in the study area. The study is deemed necessary since the findings will have policy implications on forest management in the study area and also contribute to the body of knowledge on forest cover change estimation. The research specifically addressed four specific questions such as: (1) How much forest cover has been lost from 2005 to 2023? (2) Which LULC class has significantly gained the most area from forest cover over the period? (3) What will be the impact of LULC change on forest cover by 2050? (4) How has LULC change affected forest health between 2005 and 2023?

2. Materials and Methods

2.1. Study Area

The study area is Southeast Georgia in the United States of America (Figure 1). The US has a vast amount of vegetation, with 154 national forests and 20 national grasslands, totaling 193 million acres, under the management of the US Forest Service (USFS) [28]. Georgia, the southern state, is thought to have the most forestland in the US suitable for commercial usage out of all the states [29]. The benefits of Georgia's forestland to society are numerous and include social, economic, and environmental aspects. In addition to providing timber and forest products, Georgia's forestlands also store carbon, control erosion and soil formation, pollinate, filter water, provide habitat for wildlife, offer recreational opportunities, and serve an aesthetic, cultural, and passive purpose [29, 30]. Southeast Georgia is one of the regions in Georgia that is within a diverse industry base, where manufacturing and agriculture are two of the main economic drivers. This region has 18 counties, with over 431,000 people and it hosts the Okefenokee Swamp [31].

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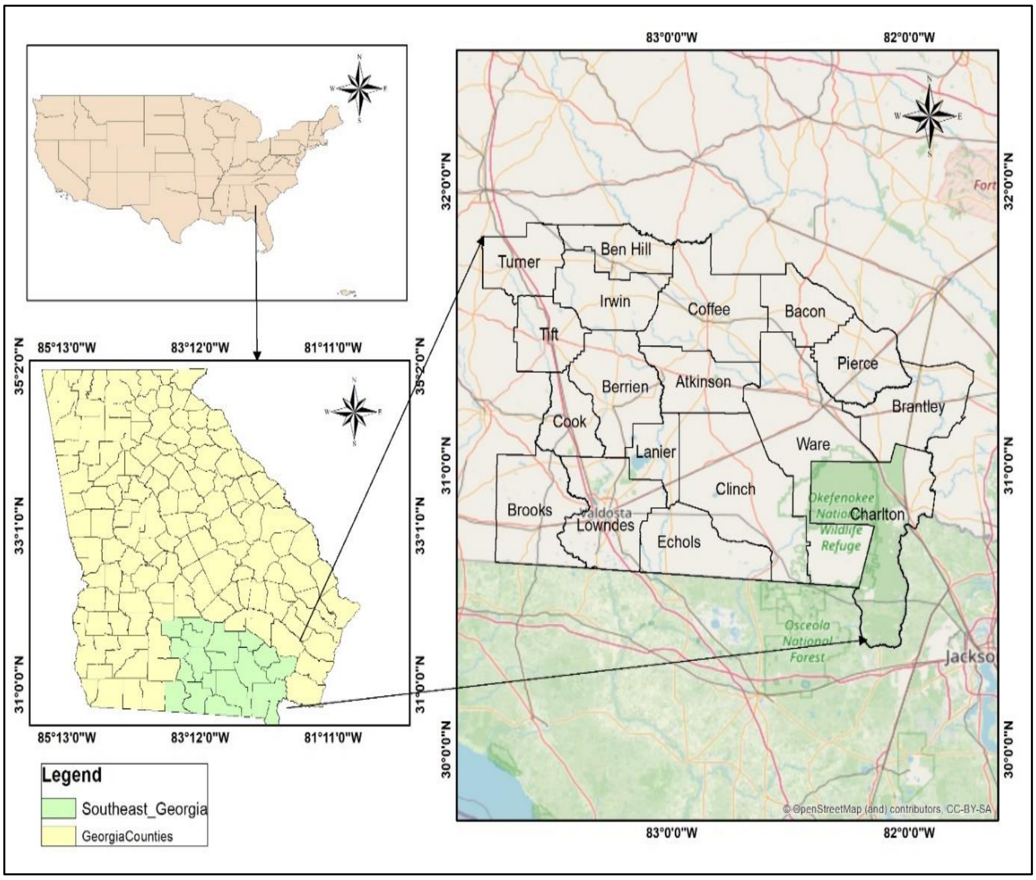

Figure 1. Map of Southeast Georgia, US.

2.2. Data Acquisition and Processing

This study used Landsat 7 and 8 multispectral images, which were obtained in 2005 and 2023. These satellite images were extracted and preprocessed in the Google Earth Engine platform (Figure 2). The pixels of the preprocessed images were then classified into four classes (Table 1) using random forest algorithm. With this, a total of 746 ground truth points was randomly gathered for the LULC classes from Google Earth (high spatial resolution imagery), consisting of 251 samples in 2005 and 495 samples in 2023. The random forest algorithm was used because it is a powerful machine learning classifier that performs well and achieves better accuracy than classical algorithms, such as spectral angle mapper [32]. The random forest algorithm was trained using 60 percent of the ground truth samples for each year. In addition to the random forest model training, the spectral bands incorporated were Blue, Green, Red, Near-Infrared, Shortwave Infrared 1, Shortwave Infrared 2, and NDVI, as well as 1000 decision trees were used.

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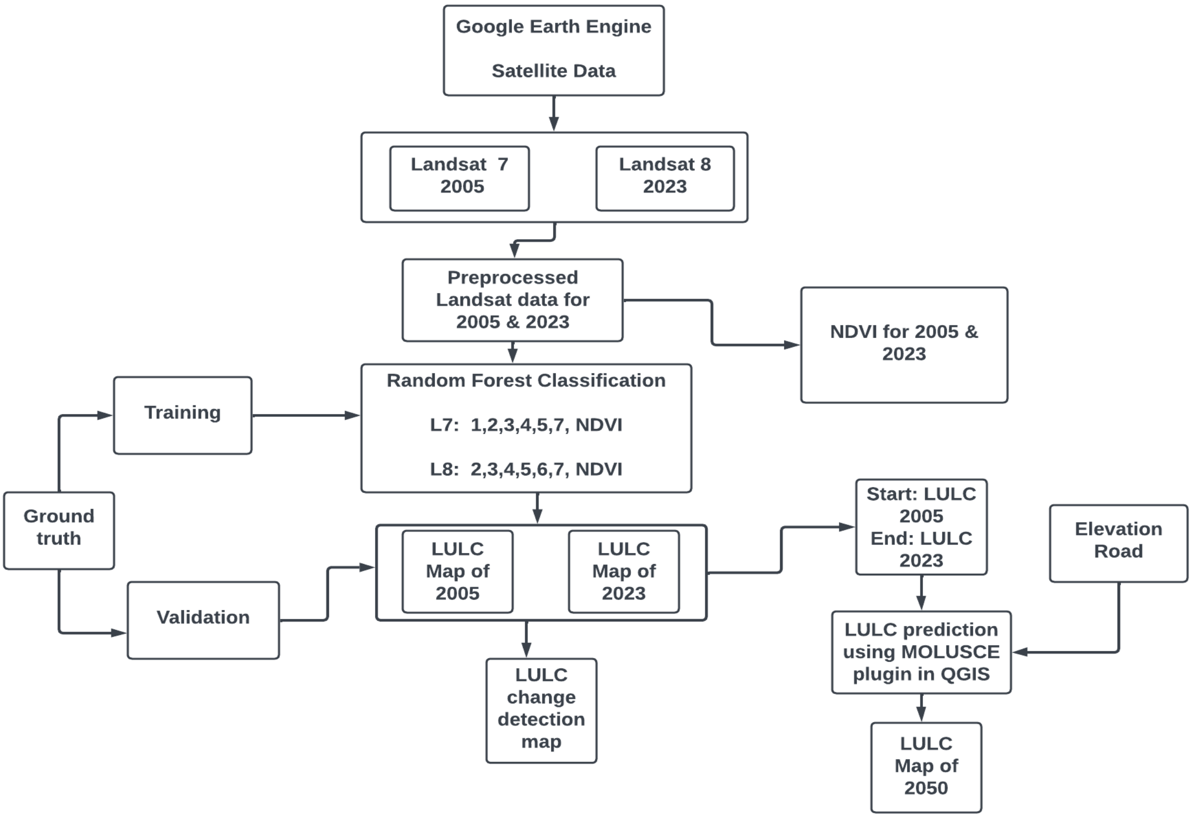

Figure 2. Flowchart of the methodology for this study.

Table 1. LULC class description.

LULC Class	Description
Urban:	Human-induced features: included settlement, roads, areas under construction, bare land, pathways, etc.
Forest:	All forms of vegetation, particularly, trees, plantations, etc.
Water bodies:	Rivers, ponds, streams, etc.
Agricultural land:	Included all lands reserved for farming, such as harvested lands, land under cultivation, etc.

2.2. Prediction of LULC for 2050

Prediction for 2050 was derived using Modules for Land Use Change Evaluation (MOLUSCE) integrated into QGIS version 2.18 [33]. This software tool employs Cellular Automata and Artificial Neural Network (CA-ANN) methodologies alongside simulations [33, 34], which is to anticipate changes in Southeast Georgia classes based on landuse/cover maps from 2005 and 2023. The analytical process primarily involves evaluating correlation (EC), quantifying area alterations, transition potential computation (TPC) modeling, and validation conducted across four (4) iterations. Baseline data for the predictions include a Digital Elevation Model (DEM), and a road raster georeferenced image of Southeast Georgia. Principal predictor variables for future projections encompass elements of the built environment, socio-economic indicators, and natural environmental parameters (Figure 2).

2.3. Accuracy Assessment of LULC Classification

In assessing the accuracy of the classified images for 2005, 2015, and 2023, 40 percent of the ground truth samples for each year were used. The 2050 classified map accuracy was evaluated by using 2000 stratified samples of the LULC change map of 2005 and 2023. The LULC classification

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accuracy, which is made up of a "confusion matrix" or "error matrix," was assessed using the producer's accuracy (PA), user's accuracy (UA), overall accuracy (OA), and kappa coefficient (K) [8]. The overall accuracy is determined by calculating the user's accuracy and the producer's accuracy (Hu et al., 2023). The range of values for Kappa is 0 to 1, with 0 denoting no agreement and 1 denoting total agreement between the two sets of data. When Kappa is less than 0.4, it is deemed poor, between 0.4 and 0.7, it is deemed good, and over 0.75, it is deemed excellent [17,35].

2.4. Post-Classification Change Detection

A post-classification was carried out for each Landsat image that was classified [5, 8]. Subsequently, a comparative analysis was conducted comparing the three sets of classified LULC maps from 2003 to 2023 and 2023 to 2050.

2.5. Trends of LULC Change Analysis

The LULC change analysis trend offers insights into the temporal extent, trend, and amount of conversions [17]. The pattern of changes in LULC in the study area was analyzed and detected using comparisons of land cover classifications from 2005 to 2023 and 2023 to 2050. The percentage and rate of changes were calculated based on the size of the changes between the two periods. This is expressed as:

$$\text{Rate of change}\left(\frac{\text{km}^2}{\text{Year}}\right) = \frac{\text{A2}-\text{A1}}{Z} \quad (1)$$

where Z is the period interval in years between A2 and A1, A2 is the area of LULC (km2) in period 2, and A1 is the area of LULC (km2) in period 1. This computation was in Google Earth Engine.

2.6. Normalized Difference Vegetation Index (NDVI) Estimation

Normalized difference vegetation Index (NDVI) is the estimation of vegetation health based on how a plant absorbs and reflects light at specific frequencies. Using NDVI is a great method to ascertain the level of vegetative cover and the conditions necessary for vegetative growth [17]. Also, it evaluates vegetation dynamics, tracks change over time and identifies regions of interest for environmental management, land use planning, and conservation [5, 36]. This is calculated by the difference between the Near Infrared (NIR) band and the Red band, and it is mathematically expressed in the equation [37].

$$\text{NDVI} = \frac{\text{NIR}-\text{RED}}{NIR+RED} \quad (2)$$

the value of NDVI ranges from -1 to 1, where values closer to 1 show high vegetation cover or presence/abundance whilst low values represent little or no vegetation cover [5, 37]. This index was calculated in Google Earth Engine (Figure 2).

3. Results

3.1. Analysis of LULC Classification

The supervised classification performed showed the LULC Classification map (Figure 3), the accuracy of the LULC classification (Table 2), and the LULC area changes (Figure 4) from 2005 to 2050. The overall accuracy for LULC classification for 2005 and 2023 were 83% and 85%, respectively.

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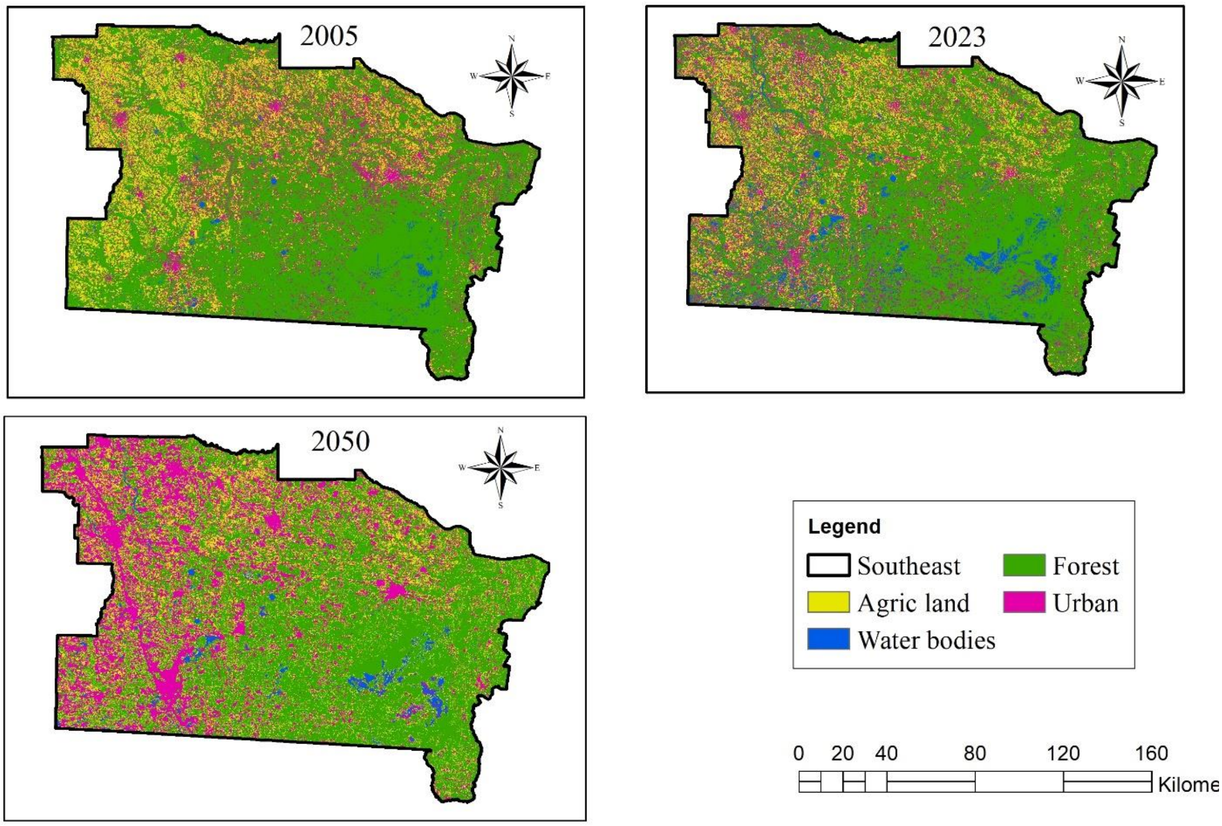

Figure 3. LULC classification for 2005, 2015, 2023, and 2050.

According to Figure 4, forests decreased from 2005 to 2023, and it is expected to decrease by 2050. The agricultural land also decreased between 2005 and 2023, and it is projected to increase by 2050.

Table 2. LULC classification accuracy assessment.

	2005		2023	
LULC Classes	**Producer Accuracy**	**User Accuracy**	**Producer Accuracy**	**User Accuracy**
Urban	0.70	0.69	0.74	0.71
Forest	0.88	0.97	0.94	0.92
Water bodies	0.89	0.88	0.91	0.94
Agricultural land	0.87	0.76	0.79	0.81
Overall Accuracy	0.83		0.85	
Kappa	0.75		0.80	

In addition, the urban class increased between 2005 and 2023, and it is forecasted to increase by 2050. On the other hand, the water body class increased from 2005 to 2023, and it is expected to decrease by 2050.

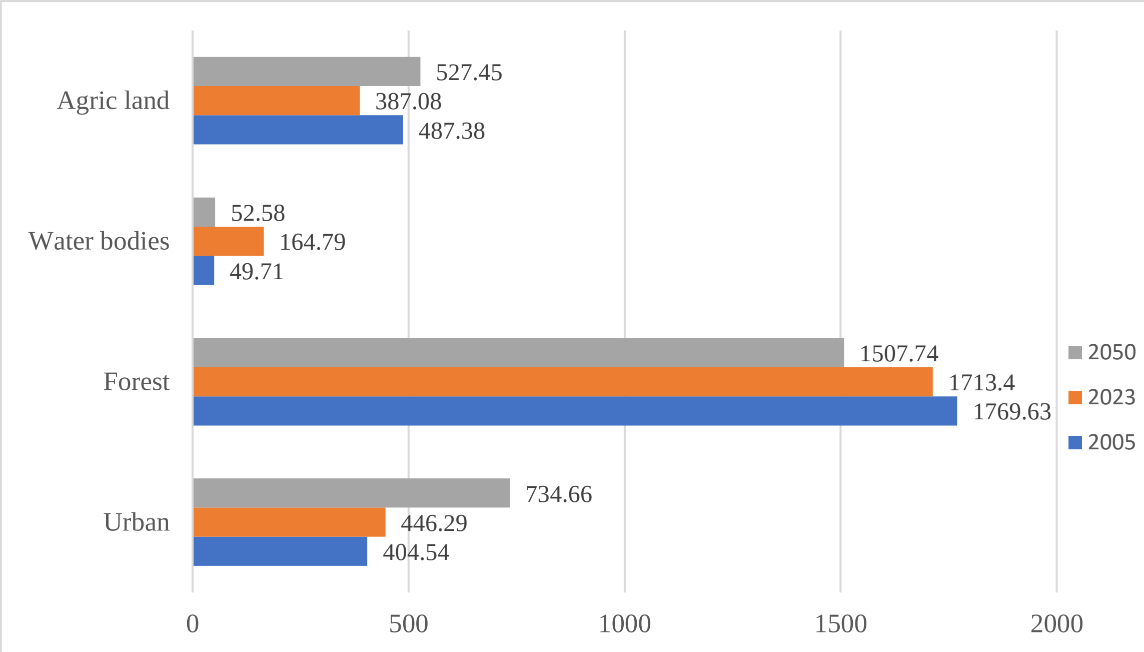

Figure 4. Changes in the LULC acreage from 2005 to 2050 in hectares.

3.1.1. Rate of LULC Classes Changes

The LULC classes have undergone various changes across the study period (Table 3). For instance, the forest cover lost was approximately 2.1% between 2005 and 2023, and in 2050, it is estimated to further reduce by 9.78%. The agricultural land lost 3.7% of its acreage during the same period, and this is expected to increase by 2050 by approximately 4.4%.

Table 3. Percentage acreage changes from 2005 to 2050.

LULC classes	Percentage changes in acreages				
	2005	**2023**	**2050**	**2023 – 2005**	**2050 -2023**
Urban	14.92	16.46	26.03	1.54	9.57
Forest	65.27	63.20	53.42	-2.07	-9.78
Water bodies	1.83	6.08	1.86	4.25	-4.22
Agricultural land	17.98	14.28	18.69	-3.7	4.41

Regarding Table 4, the rate of change for forest cover decreased by 3.09 hectares (-0.12%) between 2005 and 2023. Similarly, agricultural lands declined by approximately 5.6 hectares (-0.21%) during the same period.

LULC classes	2005	2023	Change in 2005 and 2023		Rate of change	
	Hectares	**Hectares**	**Hectares**	**%**	**Hectares**	**%**
Urban	404.54	446.29	41.75	1.54	2.32	0.09
Forest	1769.63	1713.4	-55.6	-2.07	-3.09	-0.12
Water bodies	49.71	164.79	115.08	4.25	6.39	0.24
Agricultural land	487.38	387.08	-100.3	-3.7	-5.57	-0.21

The rate of LULC acreage changes between 2023 and 2050 (Table 5) revealed that forest cover might lose about 7.6 hectares which is -0.36% over that period. In addition, during the same period, the agricultural lands will likely gain about 5.2 hectares (0.16%).

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Table 5. Rate of LULC changes between 2023 and 2050.

LULC classes	2023	2050	Change in 2023 and 2050		Rate of change	
	Hectares	Hectares	Hectares	%	Hectares	%
Urban	446.29	734.66	288.37	9.57	10.68	0.35
Forest	1713.4	1507.74	-205.66	-9.78	-7.62	-0.36
Water bodies	164.79	52.58	-112.21	-4.22%	-4.16	-0.16
Agricultural land	387.08	527.45	140.37	4.41%	5.20	0.16

3.1.2. LULC Classes Change Maps and Detection Statistics

The results from the change detection statistics between 2005 and 2023 are shown in Table 6 and Figure 5 displays the change detection map. Table 6 indicated that forest cover maintained approximately 1417 hectares of its cover over the period, however, it lost about 187 hectares, 111 hectares, and 53 hectares of its size to urban, water bodies, and agricultural lands, respectively. For agricultural lands, it retained approximately 278 hectares of its land size, but classes, such as urban, forest, and water bodies gained 130.58 hectares, 77.12 hectares, and 1.35 hectares, respectively from agricultural land size during the same span-time.

Table 6. LULC change detection statistics between 2005 and 2023.

Change (2023-2005)	Area in Hectares
Urban - Urban	126.11
Urban - Forest	206.55
Urban - Water bodies	15.71
Urban - Agricultural land	55.90
Forest - Urban	187.33
Forest - Forest	1417.24
Forest – Water bodies	111.40
Forest – Agricultural land	52.66
Water bodies - Urban	1.96
Water bodies - Forest	11.41
Water bodies – Water bodies	35.92
Water bodies – Agricultural land	0.17
Agricultural land - Urban	130.58
Agricultural land - Forest	77.12
Agricultural land – Water bodies	1.35
Agricultural land - Agricultural land	278.19

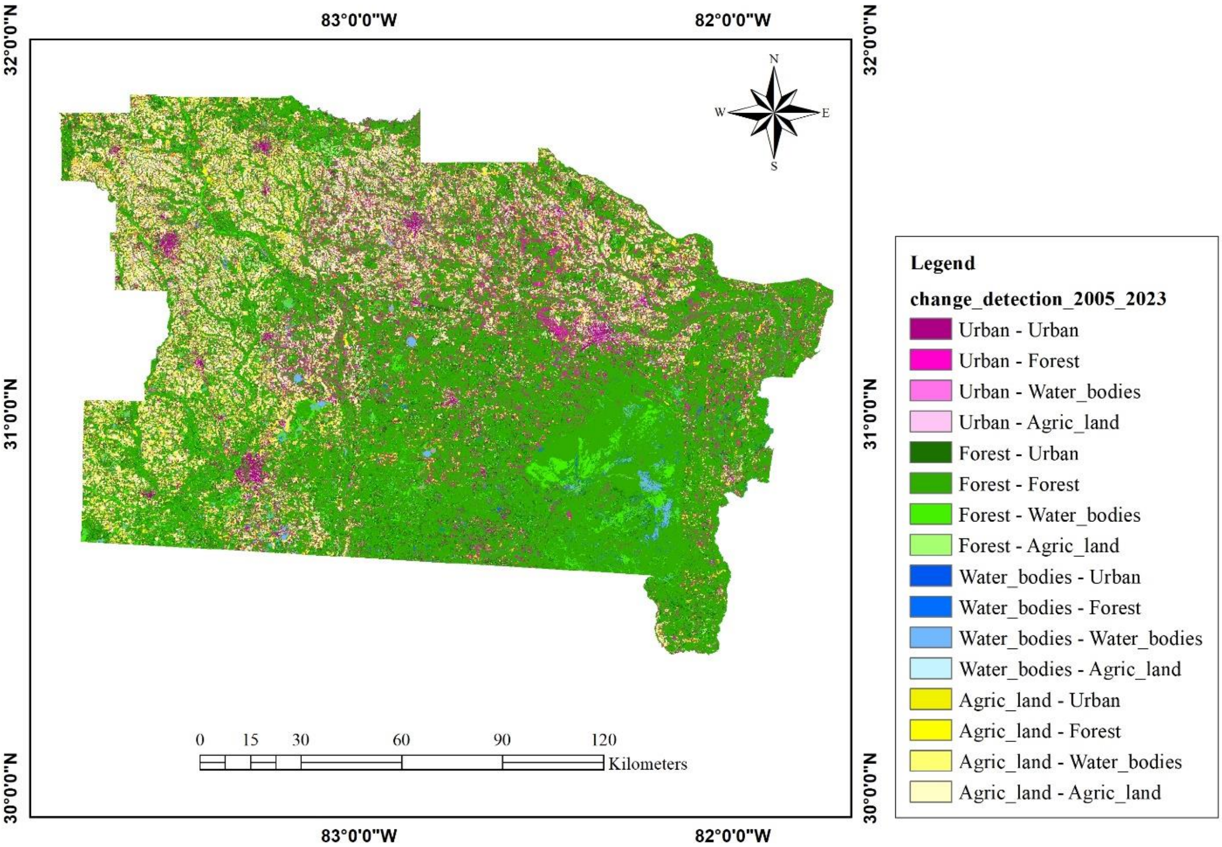

Figure 5. LULC change detection map between 2005 and 2023.

3.2. NDVI Estimation for 2005, 2015, and 2023

Figures 6 and 7 display the NDVI changes over the period for the study area. For 2005, the NDVI ranged between -0.979 to 0.992 with a mean value of 0.007, whereas for 2023, the NDVI range was -0.997 to 0.866 and the mean value was -0.66.

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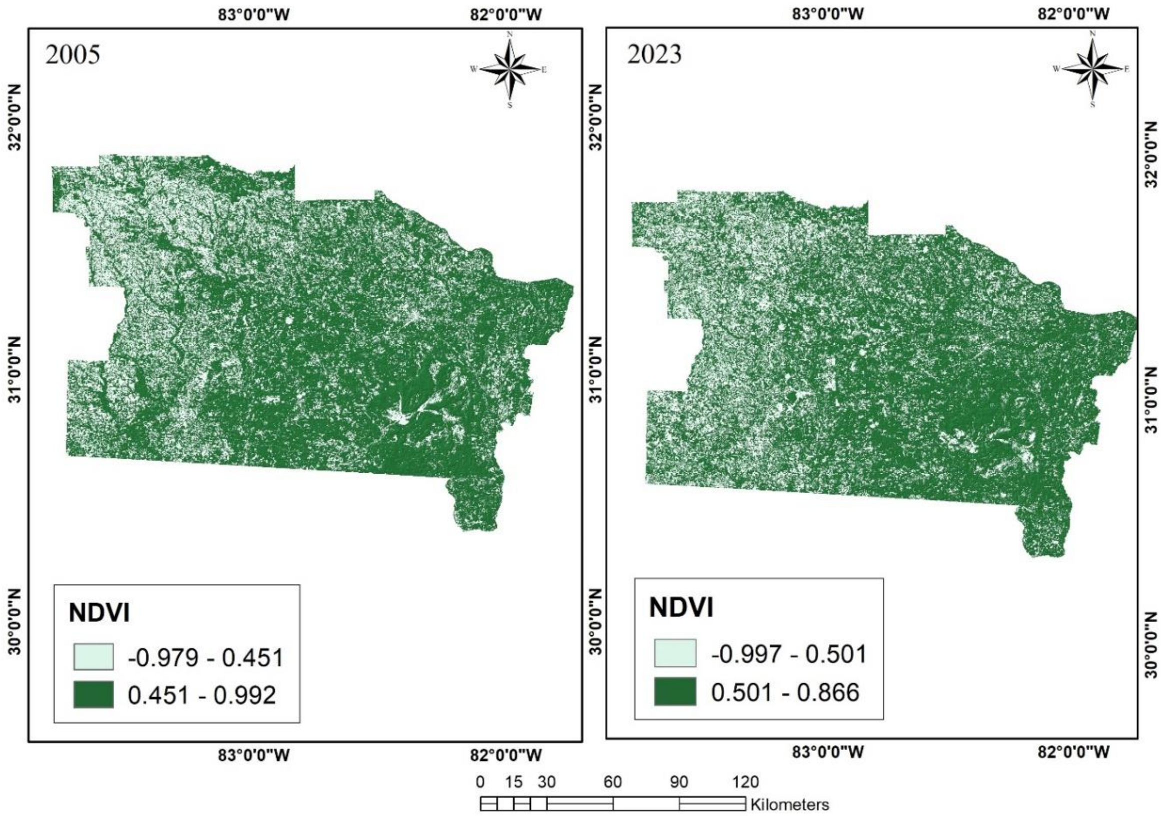

Figure 6. A map of NDVI changes from 2005 to 2023.

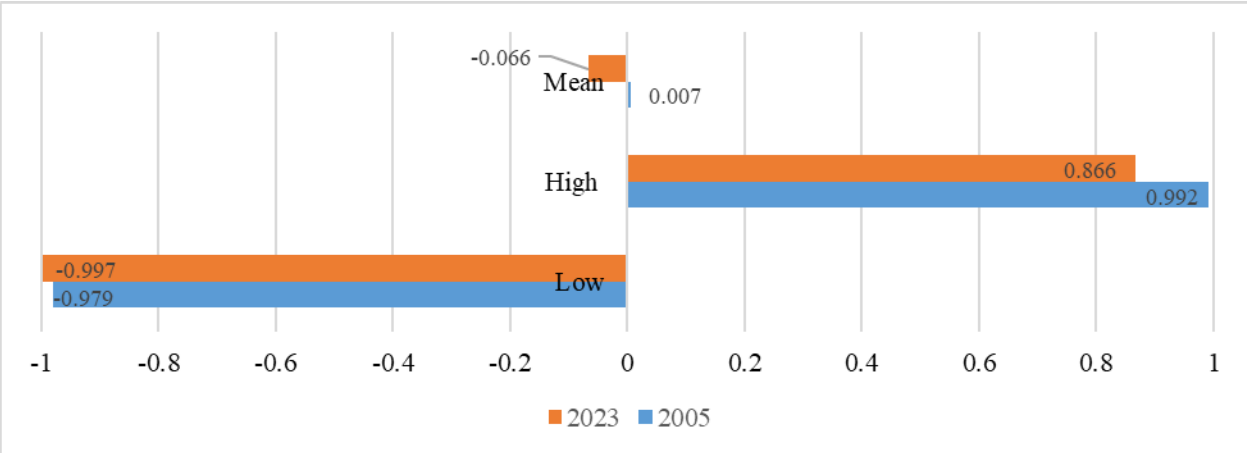

Figure 7. Temporal variation of NDVI values.

4. Discussion

Multispectral satellite imagery, particularly Landsat aids in monitoring environmental changes, such as LULC at a 30-meter resolution [24]. The use of Landsat images for 2005, 2015, and 2023 assisted in estimating LULC changes in Southeast Georgia, US. This study showed that the combination of Landsat imagery and random forest classification algorithm proved to yield a good classification accuracy (83% for 2005 and 85% for 2023), and this supports existing literature [38, 39, 40].

The LULC classes in the study area have experienced drastic changes across the period. For instance, the forest cover decreased from 65.27% to 63.20% between 2005 and 2023, and this is predicted to decrease to 53.42% by 2050 (Table 3). The change detection statistics (Table 6) presented

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that the forest cover was mostly lost to the urban class. Also, the 2050 LULC projection showed that agriculture might increase by approximately 18.7%. Because Southeast Georgia is mainly driven by manufacturing and agriculture (Georgia Department of Economic Development, 2024), this could explain the reason for the agricultural expansion by 2050. The studies of Moisen et al. [27] and Yang and Lo [26] also had a relatable finding, which suggested that forest cover in Atlanta and North Central Georgia has declined over the years. Again, Vogelmann et al. [25] findings supported that of this current study, which found that the forests are steadily changing to non-forest areas in Lam Dong Province, Vietnam. Furthermore, Hu et al. [17] unveiled that forest lands in the Southern Punjab Province, Pakistan were converted to urban areas and cropland, which aligned with the results of this study. Moreover, Table 6 shows that forest cover lost about 111 hectares to water bodies. This could partially be the construction of more irrigation facilities to aid agricultural activities and efforts geared towards the restoration of wetlands, like swamps.

According to Figure 8, the NDVI values gradually changed from 0.992 to 0.866 between 2005 and 2023, suggesting that the health of the vegetation cover, such as forest is dwindling in the study area. For instance, Negative NDVI values (-1 to 0) are associated with areas of bare rock, sand, water, urban areas or snow; low values (0 to 0.2) indicate sparse or stressed vegetation, like sparse grassland/shrubland, and areas with low vegetation cover; moderate values (0.3 to 0.5) represent moderate to dense vegetation, namely forest, croplands, and savanna; and high values indicate dense and vigorous vegetation, including dense forests and highly productive agricultural fields [5, 17]. This finding corroborates with that of Sarfo et al. [5], who found that the vegetation health in southeastern Ghana had significantly reduced. The reduction of forest health implies carbon sequestration, wildlife-dependent, other ecosystem services, and revenue generation [2, 8]. This temporal variation in the NDVI values could partly be due to the annual harvesting of forest products and seasonal variation, such as timbers in the study area.

5. Conclusions

Forest cover provides enormous significance, such as carbon sequestration and ecosystem services to the environment and humans. However, forest cover and health reduction in Southeast Georgia are a threat to the benefits derived from the forest. The use of Landsat images with a random forest classifier made it possible to map and quantify LULC's influence on forest land and health from 2005 to 2023. The predicted LULC also gives an early warning of how most likely future LULC would be in the study area. The study concludes that forest cover in Southeast Georgia has significantly decreased between 2005 and 2023, with further projections indicating continued decline by 2050. Agriculture, driven by local economic factors, is expected to increase. The analysis of NDVI values supports the finding of declining vegetation health, correlating with reduced forest health and potential ecological impacts. This information is very crucial for landuse planning and management, as well as for sustainable forest management in the study area. This study had a few setbacks concerning some satellite data unavailability. Regardless of these challenges, the study's findings were not influenced.

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Conflicts of Interest: The authors declare no conflicts of interest.

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