

A Spatio-temporal Assessment of Carbon Loss Associated With Campus Infrastructure Expansion

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Abstract

The expansion of university infrastructure can now be deemed a characteristic of Ghana's higher education development. As much as this mushrooming of infrastructure facilitates increased academic expansion, this happens at the cost of vegetation cover in campus settings, in particular, resulting in carbon emissions/losses and depletion of ecological systems. This study investigates the role of university expansion in influencing vegetation cover, which includes carbon levels, in the three major public institutions in Ghana: University of Ghana (UG), Kwame Nkrumah University of Science and Technology (KNUST), and University of Development Studies (UDS), for a period of 20 years (between 2003 and 2023). With the use of Landsat multi-temporal satellite imagery, ALOS PALSAR satellite radar data, vegetation indices, topographic variables, and measured above-ground biomass, a regression model from machine learning algorithms was employed in the study to map estimates of the specific changes in carbon levels spatially and temporally in the three institutions. The study reveals considerable carbon emissions attributed to the expansion of vegetative land into built-up land in UG and KNUST in particular, but with a gradual increase in vegetation cover in later years, yet with a net continuation of overall carbon emissions in all three institutions.

1. INTRODUCTION

Land use and land cover change induced by infrastructures has remained one of the leading sources of extinction of vegetation and release of carbon into the environment (Foley et al., 2005). The transformation of vegetation into infrastructure disrupts the ecological structure of an environment, reduces biodiversity, and directly releases carbon into the atmosphere. For developing countries, this problem is exacerbated due to a lack of control in land use and increased growth in population and conflicting land use in developing country (Lambin et al., 2001).

The expansion in the geographical/Mapping of Ghanaian public universities has been outstanding in the past 20 years, largely due to the expansion in the numbers enrolled, expansion in their fields of study, expansion in the partnerships between the government and the market, as well as changes in the national higher education systems. These expansions have happened in terms of the construction of lecture houses, residential estates for the students, road transportation systems, market centers, among other infrastructural developments that can easily contribute towards academics and competitiveness of these institutions. However, this happens at the expense of trees, grasslands, and secondary forests in the institutions. The reduction in woody vegetation also results in the resultant carbon emissions, in addition to the reduced possibility of carbon sequestration of these ecosystems in the long term (IPCC, 2022).

University campus systems are special land systems that exist in the boundary layers of the city and peripheral areas. Unlike in an urbanized environment, in university campus systems, the area retains a prominent level of vegetation and tree stands of an old age, and this makes them key contributors to the operational capacity of the city as an important carbon sink (Churkina et al., 2010). Generally, in terms of historical realities, the University of Ghana (UG) and Kwame Nkrumah University of Science and Technology (KNUST) were constructed on large pieces of land that were well vegetated, and tree avenues in conservation areas were considered to be conceptual in terms of the design of these institutions (Lartey & Marful, 2021). Moreover, University for Development Studies (UDS) was established across multiple campuses in naturally less vegetated savannah landscapes, with development shaped by community integration and existing land uses rather than

conservation-oriented design (Kwoyiga, 2024). However, the current level of development in these institutions reflects poorly on the environmental nature and the absence of carbon in semi-conserved territories.

Findings on carbon stock indicate that the destruction of vegetative cover because of the establishment of campuses has resulted in identifiable changes in above-ground biomass and total carbon content (Nowak et al., 2013). The areas that are transformed into built-up areas normally contain values that are close to zero and consist of strong spatial breakpoints that separate the developed areas from the vegetated areas. These changes especially occur at the center of the campuses and transport corridors where the intensity of infrastructure development is high (Lartey & Marful, 2021). Although there is a recovery of the vegetative cover at the campuses as a consequence of landscaping and tree-planting projects, the recovery normally happens at a slower pace compared to the development of infrastructure.

Remote sensing appears to be a fruitful technique to gauge the spatial and temporal variations of vegetation and carbon pools over landscape scales. Multi-temporal satellite data can further be utilized to detect slow and continuous transitions occurring in land use/cover, thereby correlating the change in biomass to a specific land use change activity (Elbeih & El-Zeiny, 2018). Integrating optical satellite data (such as Landsat) with Synthetic Aperture Radar (such as ALOS-PALSAR), the limitations associated with the sensitivity of the optical data to target vegetation structure and biomass can be overcome especially in areas dominated by human settlements (Frappart et al., 2011; Song et al., 2018). More advanced research work done using regression models within machine learning techniques has further advanced the estimation techniques with considerable improvements in the estimation accuracy of carbon stocks by adequately modeling non-linear interactions between spectral, radar, and topographic predictors (Goetz et al., 2009).

Though these are new developments in methodology, empirical studies that have explored long-term carbon fluxes in university campuses across sub-Saharan Africa are limited. Studies today that involve LULC mapping in Ghana receive little recognition concerning the land institutional systems and are generally confined and oriented in metropolitan regions or agricultural landscapes like agricultural reserves or forests (Ampim et al., 2021; Asibey et al., 2020). This is also a significant gap since university campuses occupy substantial land tracts and possess an institutional framework with the potential to set new LULC examples concerning habitat and aligned with the country's climatic objectives.

Thus, this research works to assess the change occurring in vegetation cover and carbon stocks over the last 20 years (2003–2023) in the three prominent universities' catchment areas in Ghana, which include the University of Ghana (UG), Kwame Nkrumah University of Science and Technology (KNUST), and University of Development Studies (UDS). Since this study provides a more spatio-temporal insight into the variation of carbon stock corresponding with the development of the campuses through the use of a fusion approach of optical and radar remote sensing images with a field-calibrated model for a better output, this research thus strives to:

1. Quantify the change in the amount of carbon stored in the three campus grounds.
2. Analyze the geographical relation between carbon losses and development in infrastructure; and
3. Discuss carbon-sensitive university land use planning and sustainable development in Ghana.

2. MATERIALS AND METHODS

2.1 Study Areas

The study was conducted on three major universities in Ghana, namely the University of Ghana (UG), Kwame Nkrumah University of Science and Technology (KNUST), and the University of Development Studies (UDS). These institutions were selected for the study owing to their disparate locations, developmental processes, and environmental trajectories. The amalgamation of the study locations provides the varied physical and human environments, enabling the scrutiny of the influence of the development on the vegetation and carbon content in the disparate environments.

The University of Ghana (UG) is located in Accra, in the coastal savannah climate zone. The campus is located in an urban area that is very rapidly expanding and is completely enveloped by a dense residential, business, and transport network. The land use/land cover of the campus in terms of vegetation types is dominated by widely spaced tree stands, cared-for lawns, secondary forests, and riparian vegetation along streams. The large area of land that has been transformed in the University of Ghana in the past 20 years is due to persistent urbanization pressure, and this makes the University of Ghana important to the case study of the concept of the loss of carbon in an intensely urban environment.

KNUST is located in Kumasi within the forest-savannah transition area, in which the land cover was previously dominated by semi-deciduous forests. The school campus was previously situated in a relatively thickly forested environment and is well known to have quite a considerable number of green buffers and trees. However, the trend in land cover is shifting, particularly around the central and peripheral campus area, due to the rise in infrastructural growth in the form of academic and residential buildings, as well as roads.

UDS is based in Ghana and is situated in the northern part of the country in the eco-zone of the Guinea savannah. Vegetation in this zone is characterized by grasslands with tree and bush arrangements in between. Compared with UG and KNUST, a relatively low level of development has been observed for UDS, and a substantial area of open and regrowing vegetation is left. With the inclusion of UDS, there is a chance for assessment of carbon mobilization in a scenario with reduced human pressure and a dominant savannah in a campus setting.

2.2 Data Sources

Satellite observation of a multi-temporal nature was conducted at three times: in the years 2003, 2013, and 2023 to capture long-term changes of vegetation and carbon stocks related to the development of campuses of universities. The time slots chosen capture significant stages of the infrastructure development of universities (Table 1).

They obtained optical satellite data utilizing the Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and Landsat 8 Operational Land Imager (OLI) sensors at a resolution of 30 meters and with a long-term of temporal coverage suitable for land cover and vegetation analyses (Roy et al., 2014). In this topic, data that was referred to as radar data was acquired from the Advanced Land Observing Satellite Phased Array L-band Synthetic Aperture Radar (ALOS-PALSAR). The data were acquired through HH and HV polarization modes that were particularly responsive to vegetation and wood biomass (Frappart et al., 2011; Song et al., 2018).

The procedure used in the derivation of the topographic variables elevation, slope, and aspect was carried out using the data from the NASA Shuttle Radar Topography Mission (SRTM) Digital Elevation Model data and the Copernicus GLO 30 data. The relationship between the variables derived in this study and the presence of

vegetation and the measure of biomass has been shown to affect soil moisture levels, drainage ability in soil, and the microclimate surroundings (Lozano-Parra et al., 2018).

Model calibrations and validations were carried out with above-ground biomass (AGB) data derived from field measurements of sample plots of vegetation around and inside campuses. The plot-level estimate of the biomass was calculated based on tree DBH and tree species-specific allometric formulas following general forestry practices (Chave et al., 2014).

Table 1
Summary of satellite datasets, spatial resolution, temporal coverage, and sources used in the study.

Dataset	Sensor / Product	Data Type	Spatial Resolution	Temporal Coverage (Study Years)	Key Variables Used	Data Source
Landsat 7	Enhanced Thematic Mapper Plus (ETM+)	Optical multispectral	30 m	2003, 2013	Surface reflectance bands, NDVI, EVI, SAVI, NDBI	USGS via Google Earth Engine
Landsat 8	Operational Land Imager (OLI)	Optical multispectral	30 m	2013, 2023	Surface reflectance bands, NDVI, EVI, SAVI, NDBI	USGS via Google Earth Engine
ALOS PALSAR	Phased Array L-band Synthetic Aperture Radar (HH, HV)	Radar (SAR)	25–30 m (resampled to 30 m)	2003, 2013, 2023	HH & HV backscatter, RFDI	JAXA via Google Earth Engine
NASA DEM	SRTM Digital Elevation Model	Topographic	30 m	Static	Elevation	NASA
Copernicus DEM	GLO-30 Digital Elevation Model	Topographic	30 m	Static	Slope, aspect	Copernicus Land Monitoring Service
Field Biomass Data	Plot-based AGB measurement	In-situ	Plot-level	Representative campaign	Above-ground biomass (AGB)	Field surveys / secondary datasets

2.3 Image Preprocessing

This entire process for satellite imagery preprocessing took place in the Google Earth Engine cloud platform in order to ensure that the efficiency and reproducibility of calculations were guaranteed (Gorelick et al., 2017). Radiometric correction and atmospheric correction for Landsat images used surface reflectance correction. Quality assessment bands and cloud probability threshold pixels were used in mapping clouds and cloud shadows.

In Landsat 7 ETM+ images, the scan-line corrector-off gaps were addressed by applying multi-date composition and spatial interpolation techniques to reduce the amount of data loss (Chen et al., 2011). Radiometric calibration of ALOS-PALSAR images to the gamma-naught value of the backscattering coefficient was carried out to correct topographic distortions and then topographically corrected using DEM data. Adaptive filtering algorithms were employed to filter speckle noise without compromising the spatial details (Ai et al., 2019). All these datasets are resampled to a common spatial resolution of 30m x 30m to enable synchronization of datasets both spatially and through time using a standard Coordinate Reference System as shown in Fig. 1.

2.4 Building Features

A set of vegetation indices, radar, and texture variables was developed to indicate vegetation health, land cover pattern, and land surface characteristics. The vegetation indices derived from optical satellite imagery employed in this study included the Normalised Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Soil-Adjusted Vegetation Index (SAVI), and the Normalised Difference Built-up Index (NDBI). The four indices are widely employed in assessing vegetation greenness, density, and growth of built-up vegetation (Zha et al., 2003).

The radar variables were HH and HV backscatter coefficient values and the Radar Forest Degradation Index (RFDI), which is sensitive to forest structure and degradation level (Frappart et al., 2011) (Table 2).

In addition, the GLCM texture values were determined (contrast, homogeneity, entropy, and variance) that are sensitive to spatial heterogeneity and structure complexity of the vegetation (Wietecha et al., 2019). Spectral and radar data were integrated with topographic data to improve the estimation of biomass, particularly in a region with a non-uniform topography (Fig. 1).

Table 2
List of predictor variables used in biomass and carbon stock modelling.

Category	Predictor Variable	Description	Source Dataset
Spectral Bands	Blue (B2)	Sensitive to atmospheric scattering and vegetation stress	Landsat 7 ETM+ / Landsat 8 OLI
	Green (B3)	Vegetation reflectance and canopy structure	Landsat 7 ETM+ / Landsat 8 OLI
	Red (B4)	Chlorophyll absorption, vegetation discrimination	Landsat 7 ETM+ / Landsat 8 OLI
	Near-Infrared (NIR)	Canopy biomass and vegetation vigour	Landsat 7 ETM+ / Landsat 8 OLI
	Shortwave Infrared 1 (SWIR-1)	Vegetation moisture content	Landsat 7 ETM+ / Landsat 8 OLI
	Shortwave Infrared 2 (SWIR-2)	Biomass structure and lignin content	Landsat 7 ETM+ / Landsat 8 OLI
Vegetation Indices	NDVI	Normalised Difference Vegetation Index	Landsat
	EVI	Enhanced Vegetation Index	Landsat
	SAVI	Soil-Adjusted Vegetation Index	Landsat
	NDBI	Normalised Difference Built-up Index	Landsat
Radar Metrics	HH Backscatter	Canopy structure and woody biomass	ALOS PALSAR
	HV Backscatter	Volume scattering from vegetation	ALOS PALSAR
	RFDI	Radar Forest Degradation Index	ALOS PALSAR
Texture Features (GLCM)	Mean	Average spatial variability of canopy structure	Landsat / SAR
	Variance	Structural heterogeneity	Landsat / SAR
	Entropy	Vegetation complexity	Landsat / SAR
	Homogeneity	Canopy uniformity	Landsat / SAR
Topographic Variables	Elevation	Controls vegetation distribution	NASA DEM
	Slope	Influences soil moisture and vegetation growth	Copernicus DEM
	Aspect	Affects solar radiation exposure	Copernicus DEM
Land-Use Indicator	Built-up Fraction	Proxy for development intensity	Derived from NDBI / LULC

2.5 Carbon Stock Modelling

Random Forest and Gradient Boosting Regression were the algorithms that estimated the value of above-ground biomass. RF and GBR were preferred for their ability to handle non-linearity, multicollinearity, and high-dimensional predictor spaces (Friedman, 2001). The Recursive Feature Elimination algorithm was used for variable selection, reducing the likelihood of overfitting (Peng et al., 2023).

The performance of the models was assessed using the independent validation dataset, based on the coefficient of determination (R^2) metric, as well as on the Root Mean Square Error (RMSE) metric. Spatially explicit maps of AGB were produced using the best-suited model for every campus, respectively, for every time period. The effectiveness of the RF model can be explained by its ability to work with non-linear relationships, high-dimensional feature spaces, and multi-collinearity among the predictor variables, which are also such features of heterogeneous semi-urban landscapes (Belgiu & Drăguț, 2016). Radar-derived variables (especially HV backscatter and RFDI) and vegetation indices (NDVI and EVI) were always among the most significant predictors, indicating the significance of the use of both optical and SAR data to estimate biomass (Frappart et al., 2011; Song et al., 2018)

Based on a carbon fraction of 0.5 of the estimated AGB, above-ground carbon (AGC) was calculated, which corresponds to the IPCC Good Practice Guidelines (Penman et al., 2003). A carbon contribution of the root biomass was assumed to be a quarter of AGC in order to calculate current below-ground carbon (BGC) (Cairns et al., 1997). BGC and AGC were then summed up in order to obtain the total carbon stock (Fig. 1).

2.6 Uncertainty and Validation

To perform uncertainty analysis, comparison of the predicted carbon stocks with the field measured values and sensitization of the models to predictor choice was done. Bootstrapped samples were used to cross-validate the model to determine its ability to withstand various training subsets. Through these procedures, the carbon estimates were solid and supportive to spatio-temporal comparison.

3. RESULTS

3.1 Model Performance and Biomass Estimation Accuracy

Random Forest (RF) regression model was found to perform better compared to the Gradient Boosting Regression (GBR) model in every location as well as period of time. The RF models attained coefficients of determination (R^2) between 0.55 and 0.76, which shows there is moderate to strong explanatory power of a combination of optical, radar, and topographic predictors in above-ground biomass (AGB) prediction. The values of Root Mean Square Error (RMSE) were also lower in the case of RF models, which is a measure of adequate prediction quality as well as minimized estimation bias (Table 3).

Table 3
Performance metrics (R^2 and RMSE) of Random Forest (RF) and Gradient Boosting Regression (GBR) models for above-ground biomass estimation

Year	Study Site	Model	R2	RMSE (kg/ha)
2003	UG	RF	0.625	30.956
	UG	GBR	0.568	33.218
	KNUST	RF	0.755	43.237
	KNUST	GBR	0.739	44.591
	UDS	RF	0.634	25.336
	UDS	GBR	0.584	27.023
2013	UG	RF	0.631	30.700
	UG	GBR	0.663	29.314
	KNUST	RF	0.721	46.174
	KNUST	GBR	0.756	43.155
	UDS	RF	0.580	27.068
	UDS	GBR	0.549	28.040
2023	UG	RF	0.575	32.922
	UG	GBR	0.551	33.834
	KNUST	RF	0.737	44.763
	KNUST	GBR	0.724	45.860
	UDS	RF	0.607	26.186
	UDS	GBR	0.561	27.681

3.2 A description of the spatio-temporal patterns of the carbon stocks.

The heterogeneity in carbon stocks on campuses and over time is high based on spatially explicit carbon stock maps. In 2003, the three universities had comparatively high densities of carbon in those areas where the tree cover and nonstop vegetation are predominant. Such areas were especially large at KNUST and in marginal areas of UG, and they were historically green in nature on the campuses. By 2013, massive carbon stock decrements were recorded in the areas that had been transformed to built-up land, such as academic blocks, residential hostels, access roads, and commercial facilities. Central campus areas and key transportation pathways were being used the most, and thus, losses of carbon would be concentrated in those areas. In some regions, mostly at UG and UDS, partial recovery of vegetation-derived carbon stocks was found by 2023. Nevertheless, the recovery was not evenly distributed across space, and there was not enough of it to compensate for past loss, thus leading to the net carbon deterioration of most developed areas (Fig. 2).

3.3 Carbon Stock Dynamics at the University of Ghana (UG).

The temporal variability in carbon stocks was the greatest at the University of Ghana compared to the other two campuses. The period between 2003 and 2013 recorded a significant decline in total carbon stocks at UG, and a faster pace at which infrastructure is built. The biggest cuts were achieved in the central campus areas where huge constructions of lecture complexes, administrative buildings, and residential ones took place.

Quantitative analysis shows that regions that were covered by vegetated land and transformed to built-up surfaces contributed most of the carbon loss in this ratio. Carbon (AGC) in the atmosphere above ground fell drastically, indicating massive cutting and deforestation of trees. Despite a visible vegetation regrowth and landscaping activity by 2023, overall carbon stocks were smaller than in 2003, which means that not all the carbon had not been restored (Table 4).

Table 4
Carbon stock dynamics at the University of Ghana (UG) between 2003 and 2023

Year	Mean Carbon Density (Mg C ha ⁻¹)	Total Carbon Stock (Mg C)	Change in Total Carbon (%)
2003	26.08 ± 0.02	562,282.8 ± 386.1	—
2013	16.80 ± 0.04	362,361.0 ± 968.1	-35.6
2023	24.61 ± 0.02	531,038.6 ± 362.5	+ 46.5 (from 2013)

3.4 Carbon Stock Trends at KNUST

KNUST displayed a distinct bell-shaped carbon stock trajectory over the study period. Between 2003 and 2013, total carbon stocks increased slightly, reflecting relatively stable vegetation cover and limited development during this phase. High carbon densities persisted across extensive portions of the campus, consistent with its location within the forest–savannah transition zone. However, between 2013 and 2023, a marked decline in carbon stocks was observed (Table 5).

Table 5
Carbon stock trends at KNUST between 2003 and 2023

Year	Mean Carbon Density (Mg C ha ⁻¹)	Total Carbon Stock (Mg C)	Net Change in Total Carbon (%)
2003	26.89 ± 0.01	775,032.2 ± 383.1	—
2013	30.95 ± 0.04	892,198.9 ± 1,294.3	+ 15.1
2023	27.74 ± 0.01	799,678.8 ± 397.7	-10.4

3.5 Carbon Dynamics at the University for Development Studies (UDS)

In contrast to UG and KNUST, UDS exhibited a gradual increase in carbon stocks over the study period. Carbon gains were particularly evident between 2013 and 2023, reflecting relatively low development pressure and ongoing vegetation regeneration within the campus landscape. Savannah vegetation, characterised by grasses interspersed with woody species, contributed to steady biomass accumulation over time (Table 6).

Table 6
Carbon stock dynamics at the University for Development Studies (UDS) between 2003 and 2023

Year	Mean Carbon Density (Mg C ha ⁻¹)	Total Carbon Stock (Mg C)	Change in Total Carbon (%)
2003	10.05 ± 0.01	18,999.7 ± 27.0	—
2013	11.20 ± 0.02	21,182.1 ± 28.7	+ 11.5
2023	12.74 ± 0.02	24,109.4 ± 33.1	+ 13.8

3. 6 Total Carbon Stock and Temporal Dynamics Estimation and Interpretation.

The total vegetation carbon stock across University of Ghana (UG), Kwame Nkrumah University of Science and Technology (KNUST), and University for Development Studies (UDS) exhibited distinct temporal trends between 2003 and 2023. KNUST recorded the highest values, rising from 775,032.2 Mg C in 2003 to 892,198.9 Mg C in 2013 before declining to 799,678.8 Mg C in 2023. UG showed a decline from 562,282.8 Mg C in 2003 to 362,361 Mg C in 2013, followed by a recovery to 531,038.6 Mg C in 2023. Conversely, UDS recorded the lowest values but displayed a steady increase from 18,999.7 Mg C in 2003 to 24,109.4 Mg C in 2023 (Fig. 3).

4. DISCUSSION

These results provide clear indications that the landscape development of university facilities has a serious implication for changing the vegetation cover and storage of carbon in the campus environment. In all three university campuses, lands that had been developed into built-up surfaces showed significant losses of above-ground biomass and total carbon stocks, confirming that land-cover conversion was one of the fundamental means through which institutional development occurs as a source of carbon emissions. These results corroborate various urban land-use studies in Africa and Asia that recognize infrastructure growth as the main cause of vegetation degradation and carbon loss (Puplampu & Boafo, 2021; Zhuang et al., 2023).

The scale and location distribution of the carbon losses in this study indicate that campus vegetation is sensitive to the issue of development pressures. The values of the built-up areas were always correlated with near-zero carbon, meaning that the vegetation was cleared as opposed to gradual degradation. These changes caused marked differences between urban and vegetated regions of the city, with zero to close-to-zero biomass and carbon indices, which is correlated with the results of the urban land-cover change literature (Elbeih & El-Zeiny, 2018; Seto et al., 2012). Same sudden carbon breaks have also been documented in peri-urban areas experiencing rapid institutional and residential development, whereby vegetation clearing comes first before construction work is carried out (Mitchard et al., 2009). The fact that low carbon values are maintained in the developed areas implies that post-construction landscaping and decorative planting has very little effect on biomass recovery compared with the cover of mature trees (Nowak et al., 2013).

Even differences in stock level fluctuations across the three universities on carbon over the years highlight that ecological setting, level of development, and historical planning are the factors aiding in changing carbon outcomes (While et al., 2010). The highest losses of carbon happened at the University of Ghana (UG), situated in a highly urbanized coastal savannah setting, between the years 2003 and 2013. This is the period when there

was an enhanced growth in infrastructure, with the increase in the number of students who enrolled and the expansion of institutions (Lartey & Marful, 2021). During this phase, several flagship development projects were undertaken, including the construction of major halls of residence such as Hilla Limann Hall, Alexander Adum Kwapong Hall, Jean Nelson Aka Hall (completed around 2010), and Elizabeth Frances B. Sey Hall (completed in 2012) (University of Ghana, 2023.). In addition, Phase I of the ultra-modern University of Ghana Medical Centre was initiated, alongside the construction of the University of Ghana Sports Stadium which commenced as early as 2004 (University of Ghana, 2024). These developments, among other academic, residential, and support infrastructure projects, resulted in the conversion of vegetated and open green spaces into built-up areas.

Even though the recovery of carbon was partly attained in 2023, the total carbon stocks were lower than when starting with the baseline, meaning vegetation is growing back and mitigation measures such as tree planting were not good enough to recover what was lost in the past (Churkina et al., 2010). The same type of partial recovery patterns has been observed in the urban green spaces where replanting processes are not as fast as land conversion. This modest recovery may be partly attributed to changes in policies such as the introduction of the Green Project Programme in 2017 under which approximately 10,000 tree seedlings were planted across the campus as part of efforts to enhance green cover and promote environmental sustainability (University of Ghana, 2017). While this initiative likely contributed to the observed increase in carbon stock, the results indicate that such interventions require longer timeframes, sustained maintenance, and broader spatial coverage to fully compensate for earlier vegetation losses and restore carbon stocks to baseline levels

The biased recovery that was found at UG still indicates that institutional green buffers, conservation areas, and controlled vegetation corridors can have a mitigation effect of decreasing long-term carbon loss. A literature of urban forestry has shown that green areas that are safeguarded by the area and riparian buffers have a higher proportion between carbon storage and their size (Nowak et al., 2013). The success of these measures, however, lies in long-term protection, species selection, and maintenance, and this has indicated that the provision of greening interventions should be strategic and not ad hoc.

KNUST portrayed a differing bell-shaped carbon curve, whereby there was an increase in the carbon stock until the year 2013 and, thereafter, an extreme decline between the years 2013 and 2023. The initial growth may indicate more vegetation cover of the forest-savannah transition zone in the past and the relative relief of the development intensity in the early years of study. This decline corresponded with intensified infrastructure development including expansion of academic facilities, student housing, and road networks. Carbon losses were particularly evident in formerly forested patches at the campus periphery which highlight the vulnerability of transition-zone vegetation to land conversion. The observed trend underscores the sensitivity of forest-savannah ecotones to anthropogenic disturbance and reinforces the importance of proactive land-use planning in maintaining campus carbon sinks (IPCC, 2022; Mitchard et al., 2009). The subsequent depletion is attributed to increased infrastructure development especially in the once vegetated peripheral areas. Indeed, it is documented that forest-savannah ecotones are very sensitive to land-use disturbance with the removal of vegetation normally entailing a structural change in the long term and low potential of biomass recovery. The case of KNUST, therefore, illustrates how the slow but accelerated development may cause rapid depletion in the carbon repositories that were built up over a long period.

In contrast to this was the slow growth in carbon stocks at UDS. This is consistent with savannah ecosystem characteristics, the positive trend highlights the capacity for carbon recovery in landscapes where development

intensity is limited (Elbeih & El-Zeiny, 2018). The trend just indicates low development pressure, and the Guinea savannah ecosystem is still within its vegetation regeneration (Adenle et al., 2020). Despite this, the absolute carbon densities were still lower than those at UG and KNUST; nevertheless, the positive trend suggests the potential of accumulating carbon in the savannah landscapes with minimal disturbance. Other recovery patterns such as the semi-natural savannah system which are passively regenerating report similar recoveries where woody biomass has slowly built without an active conversion of land (Silver et al., 2000).

The appropriateness of the ensemble machine-learning strategies in carbon stock estimation in heterogeneous campuses was also supported by the fact that a Random Forest model outperformed others consistently in this research (Song et al., 2018). It was highlighted that the different sets of optical vegetation indices, radar backscatter, and topographic variables resulted in the strong acquisition of horizontal and vertical vegetation structure, which is consistent with the prior research showing benefits from multi-sensor data fusion for biomass estimation (Belgiu & Drăguț, 2016; Silver et al., 2000). This methodological strength makes it more confident that the carbon trends observed will be useful, and such methods may be applied to monitor carbon in campuses on a regular basis.

From the wider sustainability perspective, the findings present a paradox for higher education institutions in rapidly developing regions. While universities in these regions continue to grow and become accommodating of societal needs, their growth may indirectly lead to a reversal in climate mitigation. In the absence of a conscious effort through carbon accounting in master planning of the campus, infrastructure expansion would result in the university being converted into a net source. International assessments conducted recently also point out that such land systems of an institution, including campuses, must be harmoniously integrated with urban climatic plans if the national goals of emission reduction are to be achieved (IPCC, 2021).

In a nutshell, this article shows that university campuses are not an environmentally neutral environment but dynamic landscapes, in which the choices of development have quantifiable carbon impacts. Therefore, proactive land-use planning, high-biomass protection, and long-term vegetation control should be instrumental in preserving the carbon stock in campuses and making universities more responsible as models of sustainable development.

5. CONCLUSION

The study demonstrates that infrastructure expansion across major public universities in Ghana has resulted in measurable vegetation loss and associated carbon emissions, with varying outcomes across campuses depending on development intensity and ecological context. Evidence from integrated multi-temporal optical and radar remote sensing, supported by field-calibrated biomass models, shows that while partial vegetation recovery occurs in some areas, it remains insufficient to offset long-term carbon losses, leading to a net decline in carbon stocks over the study period. The contrast between the declining carbon patterns at the University of Ghana and KNUST and the relatively stable trajectory at UDS highlights the critical influence of land-use decisions and environmental settings on campus carbon dynamics. Ultimately, the findings reinforce that university campuses function as active ecological systems where development choices have direct implications for carbon storage and environmental sustainability.

5.1 POLICY IMPLICATIONS

The findings emphasize the need for integrating carbon-sensitive land-use planning into university development frameworks. Campus master plans should incorporate carbon stock assessments as a decision-support tool to guide infrastructure expansion while safeguarding high-biomass areas. Policies should prioritize the preservation of mature tree stands, enforce minimum vegetation retention thresholds, and establish mandatory green buffers around new developments to reduce carbon loss. Embedding these measures within institutional planning processes will ensure that infrastructure growth is aligned with environmental sustainability goals, while also addressing broader urbanization challenges linked to unmanaged land-use change and carbon emissions.

5.2 RECOMMENDATIONS

It is recommended that remotely sensed regular monitoring of vegetation cover and carbon stocks be institutionalised in university planning and estate management units. The demonstrated effectiveness of multi-sensor satellite data and machine-learning models in the present study underlines their appropriateness for cost-efficient and repeatable campus-scale monitoring. These monitoring frameworks would serve to highlight vegetation loss early on, help comply with environmental requirements, and lead to adaptive management approaches.

Declarations

Competing Interests

The authors have no relevant financial or non-financial interests to declare.

Funding Declaration

The authors declare that no external funding was obtained for this study.

Author Contributions

Conceptualization: [PQ, BF-M, CG]; Data curation: [PQ, FA]; Formal analysis: [PQ, FA, EO]; Investigation: [PQ, FA, SA, EO]; Methodology: [PQ, FA, SA]; Project administration: [BF-M, CG]; Resources: [BF-M, CG]; Software: [PQ, FA]; Validation: [STA, MMM]; Visualization: [EO, SA]; Writing – original draft: [PQ, FA]; Writing – review & editing: [PQ, SA, BF-M, EO, BK, MMM, CG]; Supervision: [EOJ].

Data Availability

The primary data generated and used for this research are available upon reasonable request from the author (P. Quaye). Secondary sources of data supporting the findings of this study are included in this article for reference.

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Figures

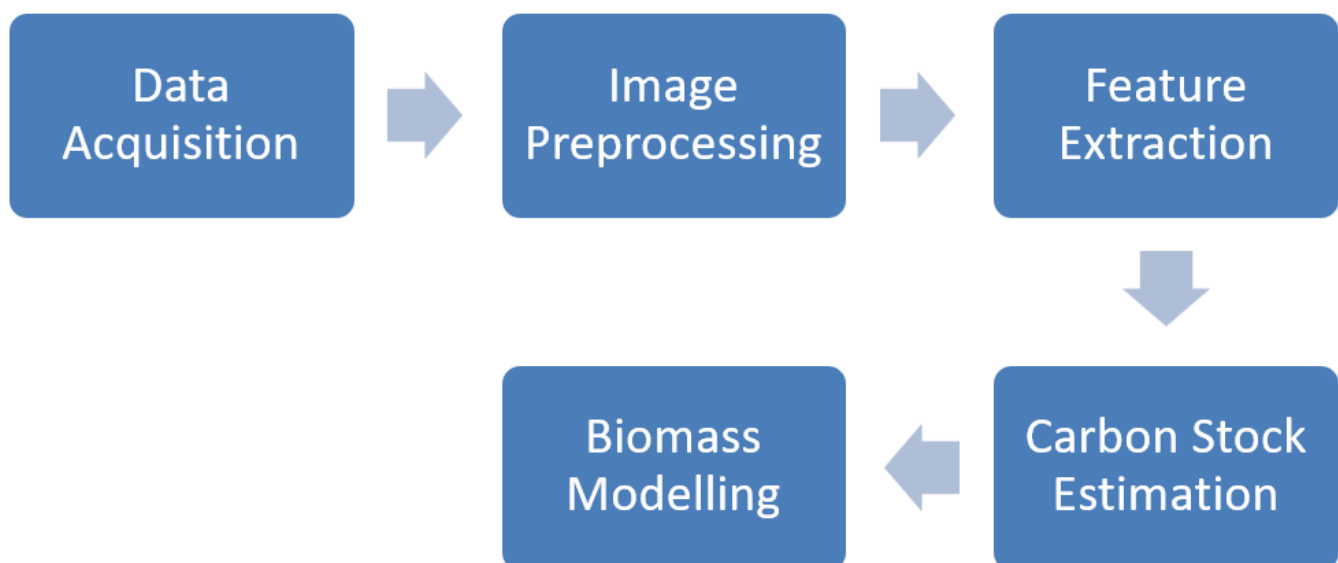


Figure 1

Methodological workflow illustrating data acquisition, preprocessing, feature extraction, modelling, and carbon stock estimation

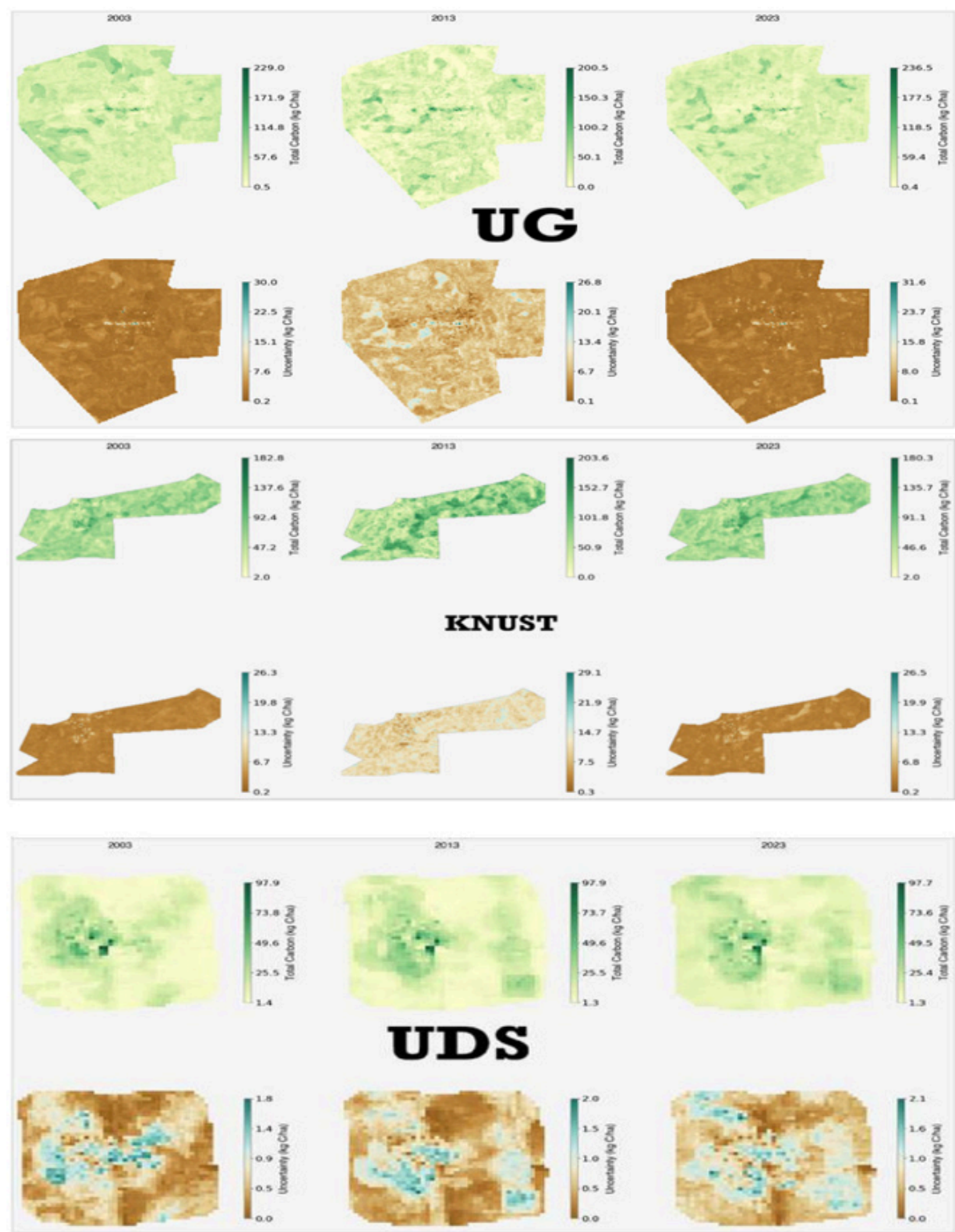


Figure 2

Spatial distribution of total carbon stocks (Mg C ha⁻¹) across UG, KNUST, and UDS for 2003, 2013 and 2023.

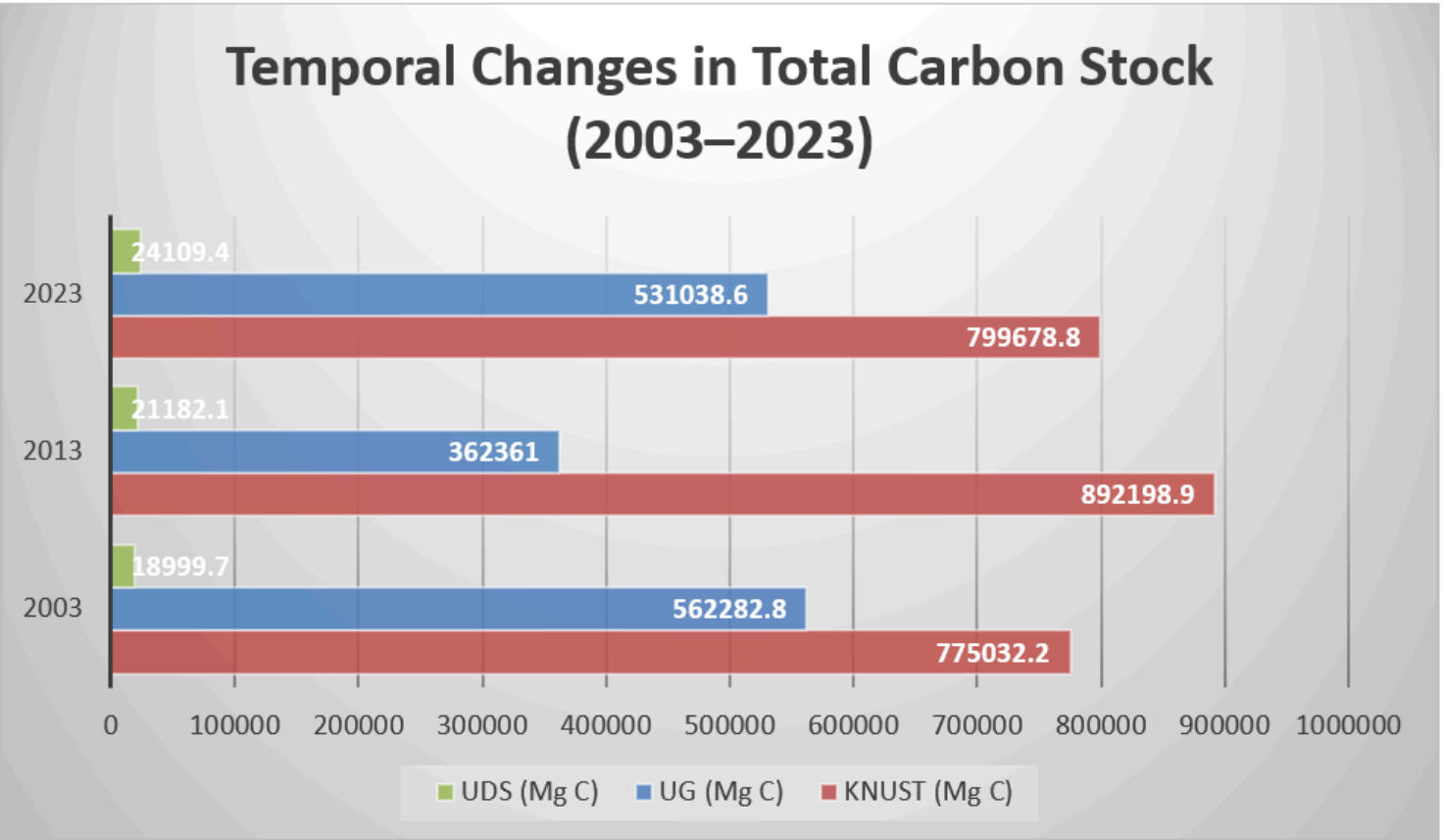


Figure 3

Data for Figure: Temporal Changes in Total Carbon Stock (2003–2023)