Advancing Real-Time Land Cover Classification for Biomass Density and Carbon Stocks Estimation in Google Earth Engine

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Abstract: Addressing climate change requires timely and accurate biomass and carbon stocks information. Traditional biomass estimation techniques rely on infrequent ground surveys and manual processing, limiting their scalability. This study proposes a novel framework that advances land cover classification to estimate biomass and carbon stocks using machine learning algorithms in Google Earth Engine. By integrating remote sensing data, machine learning algorithms, and allometric models, the framework automates above-ground biomass (ABG) and below-ground biomass (BGB) calculations, facilitating large-scale carbon stock assessments. The methodology leverages Landsat imagery, alongside derived Normalized Difference Vegetation Indices, to classify seven land cover types and estimate biomass. Equations are applied to derive AGB, with BGB calculated as a fraction of AGB. Carbon stock is estimated using a standard conversion factor of 0.47. Real-time processing capabilities of GEE ensure continuous monitoring and updates, enhancing accuracy and scalability. Findings demonstrate the potential for real-time biomass mapping and the identification of carbon-dense regions. The proposed approach is vital for sustainable land practices, carbon accounting, and forest conservation initiatives, to provide policymakers with accurate, real-time data, that supports climate mitigation efforts and contribute to realizing the Sustainable Development Goals 13 and 15.

1 INTRODUCTION

Forests and other vegetated landscapes are natural carbon sinks, playing a key role in mitigating climate change effects (Ma et al., 2022). Biomass, the total mass of living plant material, serves as a critical indicator of ecosystem health, carbon sequestration and energy potential (Makepa & Chihobo, 2024). Real-time biomass and carbon stock assessments are essential for meeting local commitments such as Nationally Determined Contributions (NDC) and international climate agreements, such as REDD+ (Reducing Emissions from Deforestation and Forest Degradation), which aim to incentivize sustainable forest management practices (Nakakaawa et al., 2011). Such real-time data empowers local authorities and conservation organizations to respond effectively to deforestation, and other environmental threats, contributing to the attainment of United Nations' Sustainable Development Goals 13 (climate action) and 15 (better life on land).

However, traditional methods of biomass and carbon stock estimation such as ground survey and manual image interpretation are time-consuming, expensive, and mostly constrained to small-scale applications (Paneque-Gálvez et al., 2014).

Recent developments in remote sensing technologies have enabled large-areal assessments of biomass and carbon stocks (Flores Lanza et al., 2024). Satellite imagery from programs such as Landsat, Sentinel, and MODIS provides the required localized data for monitoring land cover and vegetation

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dynamics. However, data processing limitations, inconsistent temporal updates, and complex modelling requirements hinder the scalability and real-time applicability of biomass and carbon monitoring systems. This is particularly pronounced in low-income countries, where technical and financial constraints limit the uptake of high-computational geospatial modelling (Kilama Luwa et al., 2020).

Google Earth Engine (GEE) provides a sustainable solution to these challenges. GEE is a cloud-based geospatial analysis platform that facilitates ingesting and processing satellite data in real-time (Gorelick et al., 2017). GEE's potential for continuous land cover monitoring is demonstrated by its ability to ingest large archives of remote sensing data, integrated with advanced classification algorithms, can be scaled to biomass and carbon stocks estimation at flexible scales.

This study proposes a framework for leveraging GEE to perform real-time land cover classification and forest biomass density estimation, with the goal of enhancing carbon stock assessments and informing climate mitigation policies. The proposed framework focuses on automating the classification of seven land cover classes, and the calculation of Above-Ground Biomass (AGB) and Below-Ground Biomass (BGB) for the forest land cover class. By applying allometric models and vegetation indices, the framework enables accurate mapping of forest biomass distribution across the landscape. Carbon stock is estimated by converting biomass values using established carbon fractions, providing insights into the role of forest land cover in carbon sequestration.

The study's contributions include (1) a framework for real-time biomass and carbon stocks estimation, (2) custom JavaScript code for real-time pre-processing of Landsat, Sentinel-2 A/B and Sentinel-1 SAR imagery in GEE, and (3) custom Python code for estimating forest biomass and carbon stocks for climate planning.

2 METHODOLOGIES

2.1 Study Area and Datasets

The developed land cover classification, biomass density, and carbon stock estimation framework was tested in Uganda, an East African country (Figure 1). Uganda experiences high rates of deforestation and forest degradation. However, the country holds significant potential for sustainable forest landscape restoration due to relatively low restoration costs and large socio-economic benefits compared to other countries (Brancalion et al., 2019). Several forest restoration hotspots have been identified (Figure 1).

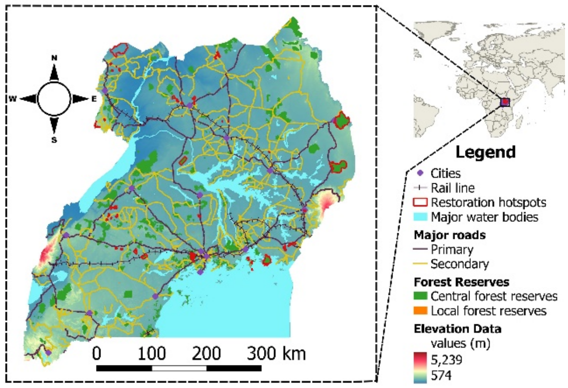

Figure 1: Map of the study area.

Uganda's diverse environmental and socio-economic conditions, driven by varying levels of forest degradation, restoration potential, and exposure to climate change impacts, presented an ideal setting to validate and refine our proposed framework.

A summary of the datasets used to achieve the study objectives is provided in Table 1. These datasets have been imported, pre-processed, and analyzed within the Google Earth Engine (GEE) environment to ensure efficient and scalable data handling.

Table 1: Data and data sources used in the study.

Data	Scale	Date	Purpose	Source
Landsat 7 ETM+, Landsat 8 OLI/TIRS	30 m	2000 - 2020	Land cover, Biomass, Carbon stocks	USGS ingested in GEE
Sentinel 2A/B	10 m	2019 - 2020	Land cover, Biomass, Carbon	ESA ingested in GEE
Sentinel 1C	10 m	2019 - 2020	Land cover classification	ESA ingested in GEE
Biomass data	30 m	2000, 2005	Validation / ground truthing	Uganda's Forest Authority

2.2 Development of Land Cover Classification Framework

Figure 2 illustrates the real-time land cover classification framework developed in GEE. The framework is applicable to satellite imagery with scalable temporal resolutions, such as the 16- and 10-day repeat cycles of Landsat 8/9 and Sentinel-2 A/B respectively. This allows for the selection and matching of imagery that aligns with specific temporal requirements, ensuring consistency and accuracy in land cover assessments.

2.2.1 Pre-Processing the Satellite Imagery

Pre-processing of satellite imagery followed the developed GEE JavaScript code (Abudu et al., 2024). to automatically select Blue, Green, Red and Near-infrared (RGBN) optical bands from available Landsat 7 ETM+, Landsat 8 OLI/TIRS, Landsat 9 archives and Sentinel 2A/B. The script calculates the Normalized Difference Vegetation Index (NDVI) using Equation 1 and applies GEE's quality mosaic algorithm (Gorelick et al., 2017) for each study period. This process ensures that the final mosaic imagery comprises pixels with the highest NDVI values. The ratioing approach, effectively reducing the impact of cloud cover and mixed-pixel effects, which are common in tropical regions. By prioritizing pixels associated with high biomass (high NDVI values), the approach enhances the accuracy of land cover classification.

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)} \quad (1)$$

Given that forest biophysical properties change gradually, we pre-processed optical imagery into annual composites. To align with Uganda's National Biomass Survey (NBS) periods (NFI, 2016), imagery for 2000, 2005, 2015, and 2020 were selected. The 2015 NBS period, being the most recent, served as the validation reference for biomass and carbon stock estimation, as detailed in Section 2.3.

To maintain spatial and geometric consistency during analysis, all datasets were reprojected to a spatial resolution of 30 meters (matching Landsat's resolution) and transformed to the WGS84-UTM Zone 36N projection, localized for the study area.

2.2.2 Land Cover Classification

We prioritized Landsat imagery for both land cover classification and estimation of biomass and carbon stocks due to rich temporal archives. Additionally, the focus on forest biomass estimation detailed in Section 2.3 meant that the 30-meter spatial resolution of Landsat imagery was sufficient for forest areal extents. Land cover classification was performed using a supervised Random Forest (RF) algorithm. Previous studies have explored different classification techniques, including Maximum Likelihood Classification (Abudu et al., 2019), Support Vector Machines (Opedes et al., 2022), and RF-based methods (Coker et al., 2021). RF demonstrated superior performance over other pixel-based methods in Uganda.

The choice of RF was influenced by its proven advantages, such as the ability to handle high-dimensional datasets and resilience to noise and outliers, owing to its ensemble approach of multiple decision trees (Coker et al., 2021). These attributes are particularly valuable for accurate characterization of Uganda's complex and heterogeneous landscapes.

The RF model was configured with 50 decision trees (n=50) and trained on 70% of the dataset, while

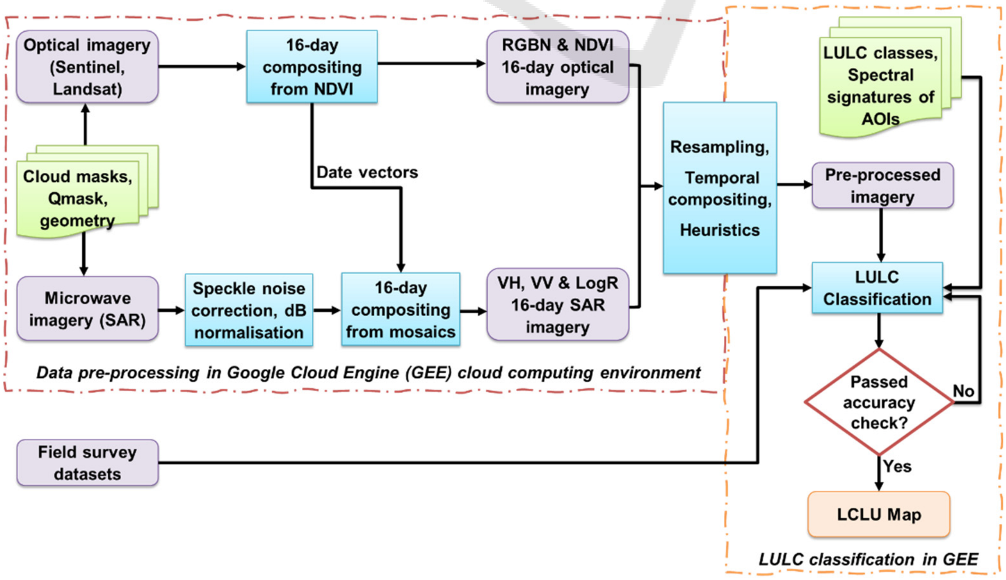

Figure 2: Land cover classification framework.

the remaining 30% reserved for validation. Classification targeted seven land cover classes, informed by local expertise, and previous study (Opedes et al., 2022). Table 2 summarizes the land cover classes. To work within GEE's memory limits, we utilized GEE Python API to develop custom code for land cover classification and estimation of biomass density and carbon stocks (Abudu et al., 2024).

Table 2: Land cover classification classes.

Class No.	Class name	Description
1	Forests	Natural and artificial tree covers, and woodlands.
2	Bushlands	Closed, open or very open shrubs
3	Grasslands	Graminoids and herbaceous areas for grazing, sports,etc
4	Agriculture	Small- and large-scale farmlands
5	Wetlands	Wet graminoids and herbaceous areas
6	Built up	Buildings, weathered roads, human settlements, and other artificial surfaces.
7	Open water	Standing and flowing water and water dams

2.2.3 Accuracy Assessment of the Land Cover Classification

The accuracy of the classification was assessed in two stages. The first stage involved testing the trained RF model on the reserved 30% of unseen data. In the second stage, accuracy was assessed on the final classified image. For this assessment, 300 random pixels were stratified by each land cover class, resulting in a total of 2,100 sampled pixels per year.

A confusion matrix; an accuracy assessment method previously utilized in this study area (Abudu et al., 2019; Kuule et al., 2022), was developed to summarize the counts of correct and incorrect predictions for each of the seven land cover classes (Table A1 in Appendix). Computed accuracy metrics included the Overall Accuracy (OA) which measures the proportion of correctly classified pixels across all classes, User Accuracy (UA) which is a classification precision indicator per class from user's perspective, Producer's Accuracy (PA) which is the model's recall classification and the Kappa Coefficient (K); a statistic measure with values toward one representing stronger agreement between predicted and true labels while accounting for chance agreement with values between zero and one.

Although, stratified sampling approach is a robust method, in practice biases still arise. In our case, while sampling 300 points per land cover class (N=300), we assumed equal distribution across all classes (n=7). However, within class distributions may vary, resulting into stratum variances (S_{PA}^{V} and S_{UA}^{V}). We applied Card's correction (Card, 1982), following the steps outlined in Olofsson et al., (2013), to check and correct any stratum variances, and correct the producer's (PA_n) and user's (UA_n) accuracies per class and overall accuracy (OA_c). The classified LULC sample size (N_n) varies per class. Equations 2, 3 and 4 were applied on results of the confusion matrix to correct PA, UA and OA.

$$S_{PA}^{V} = \sum_{n=1}^{n=7} \left(\frac{(1 - PA_n) * PA_n}{N} \right) \quad (2)$$

$$S_{UA}^{V} = \sum_{n=1}^{n=7} \left(\frac{(1 - UA_n) * UA_n}{N_n} \right) \quad (3)$$

$$OA_c = OA - \left(\frac{S_{PA}^{V} + S_{UA}^{V}}{2 * n} \right) \quad (4)$$

2.3 Biomass Density and Carbon Stock Estimation

We formulated a workflow for biomass density calculation in tons per hectare (t/ha). Biomass density is directly correlated with carbon stock, making it a critical parameter for estimating carbon reserves and evaluating the role of vegetation in sequestering atmospheric carbon and informing climate change mitigation strategies (UNFCCC, 2015).

Egeru et al., (2014) affirms that Normalized Difference Vegetation Index (NDVI) is an effective indicator of vegetation and biomass presence in north-eastern Uganda. NDVI values near +1 reflect dense vegetation, while values approaching zero indicating sparse or absent cover. The strong correlation between NDVI and biomass highlights its value for monitoring vegetation health and coverage.

We calculated NDVI from optical Landsat imagery using Equation 1. To establish the relationship between biomass and vegetation indices, we utilized classified forest land cover data, with field-measured biomass serving as the dependent variable and vegetation indices as independent variables. We applied linear regression models to determine the empirical constants (a and b) in Equation 5, using existing biomass data of 2000 and

2005, and calculated the above-ground biomass (AGB) from NDVI. Equation 6 was applied determine the below-ground biomass (BGB) as a fraction of the AGB according to the root-to-shoot ratio (r) for each land cover class. In Uganda, the default Intergovernmental Panel on Climate Change (IPCC) root-to-shoot ratio of 0.24 is commonly applied for such conversions (MWE-IPCC, 2014), which was adopted by study. Biomass density was calculated per hectare by reprojecting the Landsat's 30m pixel size to 100m and then calculating biomass per 100 x 100F m^2 pixel area.

Carbon stock in Uganda's forests is determined to be 47% of the total biomass stocks (NFA, 2009). Consequently, we focused on forest land cover for estimating biomass and carbon stocks. However, in cases where biomass conversion factors for other land covers exist, the model can be tested for other land cover types. Equations 7 and 8 were used to calculate the total forest biomass and carbon stocks respectively.

$$AGB = a\ x\ e^{b\ x\ NDVI} \quad (5)$$

$$BGB = r\ x\ AGB \quad (6)$$

$$Total\ Biomass = AGB + BGB \quad (7)$$

$$Carbon\ Stocks = 0.47\ x\ Total\ Biomass \quad (8)$$

3 RESULTS AND DISCUSSIONS

3.1 Characterization of Land Cover Changes in Uganda

Classification achieved an overall accuracy of 89% (Table A1 in Appendix). Over the past decade, agriculture had the largest expanded from 51% to 60% while open water remained stable at 11% of the total land area. In contrast, forests have experienced the worst instability, declining by over 3% (3.1 – 2.4 million hectares) respectively, as they are converted to agricultural land and grasslands.

Figure 3 highlights the scale of deforestation in Uganda, with the northern and eastern regions most affected. Deforestation also intensified in the western and central regions from 2015 onwards, where forest losses were previously minimal.

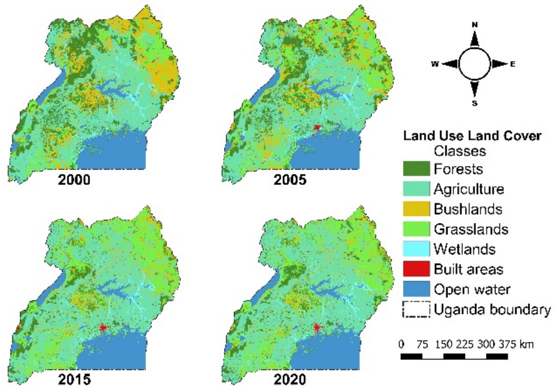

Figure 3: Uganda's Land use land cover (LULC) changes.

3.1.1 Temporal Transition of Land Cover Classes

Using Markov Chain transition matrix calculations (Abudu et al., 2019; Kuule et al., 2022), we analyzed the shifts between various land cover classes to understand the dynamics and extent of land cover changes over the study period. The results, illustrated in Figures 4 and 5, reveal significant patterns of change, with key transitions highlighting the widespread conversion of forest land into grasslands and agricultural areas. These transitions suggest increasing pressure from human activities such as agricultural expansion, settlement growth, and resource extraction, which are driving the reduction of natural vegetation cover. Notably, bushlands and forests are the most affected by land cover changes, experiencing significant losses with transition rates of approximately 80% and 75%, respectively, as they are increasingly converted to other land cover classes.

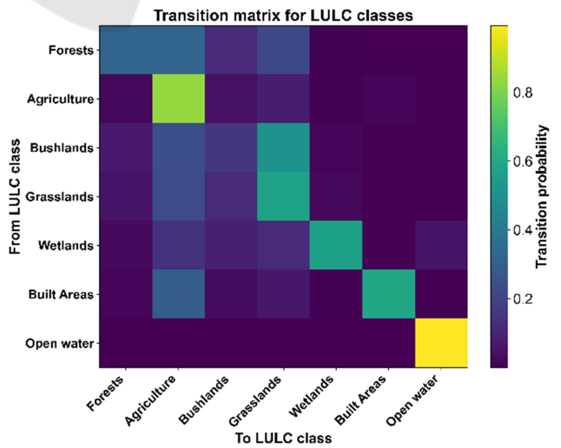

Figure 4: Markov transition matrix of land cover classes.

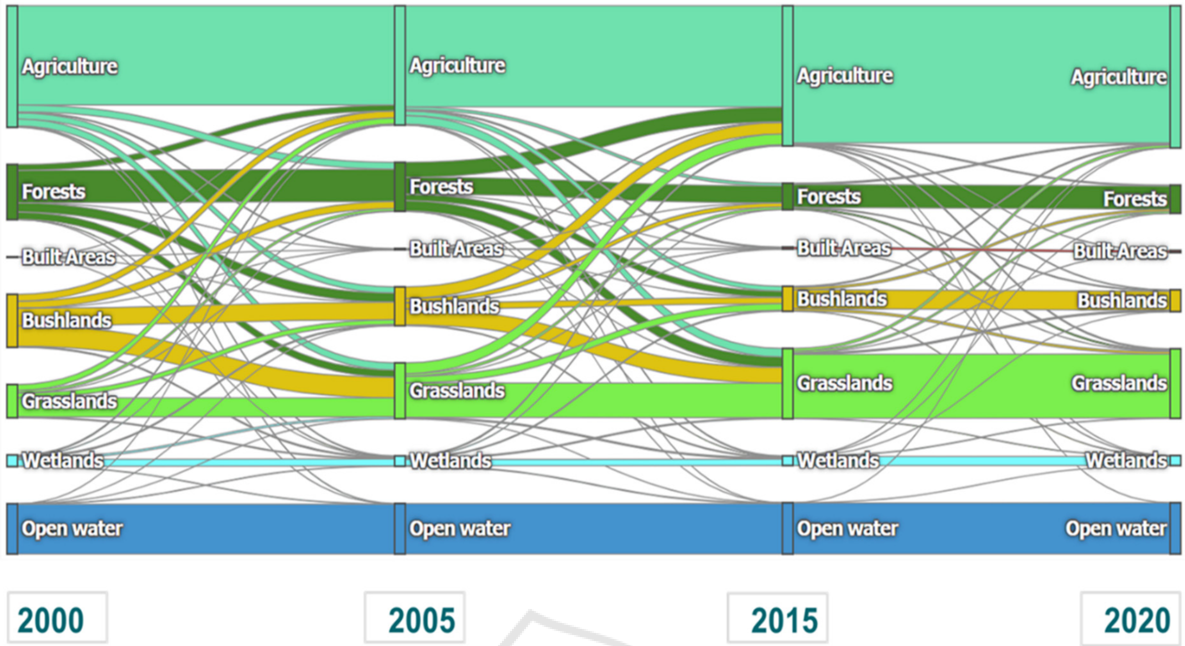

Figure 5: Land cover transitions from 2000 to 2020.

From Figure 5, forests primarily transition to agriculture, bushlands and grasslands. In Uganda, bushlands often represent secondary recovery stages of previously deforested areas. The transition patterns suggest that as forests are cleared, the land typically shifts to agricultural use or remains within the forest-bushland cycle. Agricultural expansion is the primary driver of deforestation in Uganda as initially cleared bushlands becomes grassland and is later cultivated for farming.

3.2 Biomass Density and Carbon Stock in Uganda

Biomass density is a strong indicator for carbon stocks potential and is also a key indicator of energy potential of an area because biomass is a primary resource for renewable energy. Since the energy potential is directly proportional to the biomass quantity and its calorific value (Barasa et al., 2022), areas with higher biomass densities represent more energy potential per unit area.

Figure 6 shows the baseline biomass density in the year 2000, and Figure 7 shows the results modelling biomass density from 2000 – 2040. We present a normalized data to show the trend of biomass density and carbon stocks, to inform future modelling, management, and policy decisions. In the trend analysis, biomass and carbon stocks are directly proportional following similar trends. To add context, we plotted the energy demand based on data from Ritchie et al., (2022) indicating a strong inverse relationship and suggesting Uganda's biomass loss is greatly influenced by the country's energy demand.

Uganda's biomass density is concentrated around the western and eastern hilly plains with highest biomass densities of 343 t/ha with most areas in the northern parts exhibiting the lowest densities. Other parts of the country exhibit low biomass density and consequently low carbon stocks (Figure 6).

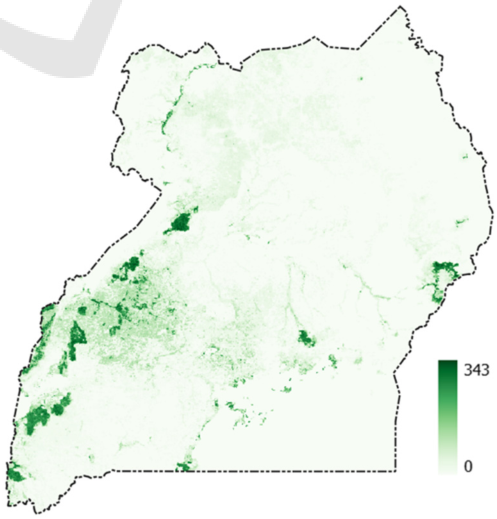

Figure 6: Biomass density in tons per hectare (t/ha) for 2000.

Figure 7 presents the projected trends in Uganda's biomass, carbon stocks, and energy landscape, reflecting the country's Vision 2040. The results show that Uganda's goal of reducing greenhouse gas emissions by 24.7% below the current 148.80 Mt CO_2e by 2030 (MWE, 2022) can only be feasible under targeted interventions. However, under a business-as-usual scenario, reducing carbon emissions and attaining sustainable biomass for energy consumption remains unattainable.

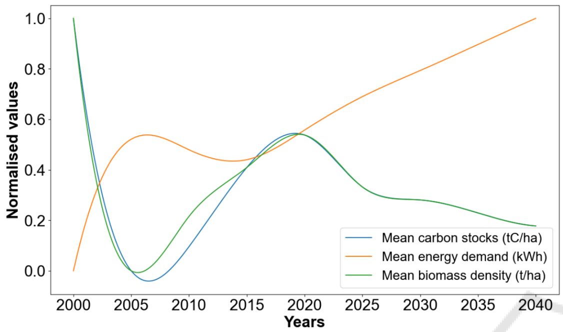

Figure 7: Projecting Uganda's carbon, energy, and biomass from 2000 - 2040.

4 CONCLUSIONS

Uganda's key forest and climate policy challenges are weak institutional capacity, limited coordination and insufficient financing (Renner, 2020). These challenges are exacerbated by a lack of up-to-date monitoring information and limited data-centric decision-making routines. Our results (data and analyses) are vital for policymakers to prioritize conservation efforts and design strategies that enhance carbon sequestration. Results such as trend analysis in Figure 7 indicate the need for urgent change from business-as-usual scenario to abate the dwindling biomass and carbon stocks in the future and meet the increasing energy demands. The results also underscore the significance of protecting diverse land cover classes as part of Uganda's strategy to meet climate goals, enhance biodiversity, and promote sustainable development.

This geospatial modelling approach offers a cost-effective and scalable method for carbon stocks assessment, particularly in low-resource settings. Future work will refine the model's accuracy, addressing uncertainties around biomass density and carbon stock estimation and improving confidence levels. This will be achieved through improved ground-truthing, model fit and confidence interval analyses and exploring its adaptability to related areas, such as energy demand forecasting.

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APPENDIX

Table 3: Confusion matrix for accuracy assessment of land cover classification.

	Reference data											
Classified land cover Map	Class Number	1	2	3	4	5	6	7	Total	User accuracy	Commission Error	Variance (Card's)
	1	**262**	10	14	20	5	1	0	312	0.8397	0.1603	0.0004
	2	16	**265**	10	6	5	3	2	307	0.8632	0.1368	0.0004
	3	6	8	**261**	23	8	2	4	312	0.8365	0.1635	0.0004
	4	9	5	4	**238**	6	4	2	268	0.8881	0.1119	0.0004
	5	2	4	5	4	**267**	4	4	290	0.9207	0.0793	0.0003
	6	3	6	2	4	5	**286**	0	306	0.9346	0.0654	0.0002
	7	2	2	4	5	4	0	**288**	305	0.9443	0.0557	0.0002
	Total	300	300	300	300	300	300	300	**1867**			
	Producer accuracy	0.8733	0.8833	0.8700	0.7933	0.8900	0.9533	0.9600	Overall accuracy (standard):			88.90476
	Omission Error	0.1267	0.1167	0.1300	0.2067	0.1100	0.0467	0.0400				
Variance strata (Card's)		0.0004	0.0003	0.0004	0.0005	0.0003	0.0001	0.0001	Overall accuracy (Card corrected):			88.90444
Row x Column totals		93600	92100	93600	80400	87000	91800	91500	Kappa coefficient (K):			0.87