Journal of Environmental Protection, 2024, 15, 401-414
https://www.scirp.org/journal/jep
ISSN Online: 2152-2219
ISSN Print: 2152-2197

Activity Data and Emission Factor for Forestry and Other Land Use Change Subsector to Enhance Carbon Market Policy and Action in Malawi

Edward Missanjo[1*], Henry Kadzuwa[2]

[1]Department of Environmental Sciences, University of Namibia, Ogongo Campus, Ogongo, Namibia
[2]Department of Physical Planning and Land Surveying, Malawi University of Business and Applied Sciences, Blantyre, Malawi
Email: *edward.em2@gmail.com

How to cite this paper: Missanjo, E. and Kadzuwa, H. (2024) Activity Data and Emission Factor for Forestry and Other Land Use Change Subsector to Enhance Carbon Market Policy and Action in Malawi. *Journal of Environmental Protection*, **15**, 401-414.
https://doi.org/10.4236/jep.2024.154023

Received: January 5, 2024
Accepted: April 16, 2024
Published: April 19, 2024

Abstract

Activity data and emission factors are critical for estimating greenhouse gas emissions and devising effective climate change mitigation strategies. This study developed the activity data and emission factor in the Forestry and Other Land Use Change (FOLU) subsector in Malawi. The results indicate that “forestland to cropland,” and “wetland to cropland,” were the major land use changes from the year 2000 to the year 2022. The forestland steadily declined at a rate of 13,591 ha (0.5%) per annum. Similarly, grassland declined at the rate of 1651 ha (0.5%) per annum. On the other hand, cropland, wetland, and settlements steadily increased at the rate of 8228 ha (0.14%); 5257 ha (0.17%); and 1941 ha (8.1%) per annum, respectively. Furthermore, the results indicate that the “grassland to forestland” changes were higher than the “forestland to grassland” changes, suggesting that forest regrowth was occurring. On the emission factor, the results interestingly indicate that there was a significant increase in carbon sequestration in the FOLU subsector from the year 2011 to 2022. Carbon sequestration increased annually by 13.66 ± 0.17 tCO_2 e/ha/yr (4.6%), with an uncertainty of 2.44%. Therefore, it can be concluded that there is potential for a Carbon market in Malawi.

Keywords

Activity Data, Emission Factor, Climate Change, Forestland, Carbon Market

1. Introduction

Malawi is a party to the United Nations Framework Convention on Climate

Change (UNFCCC) and to the Paris Agreement which are aimed at reducing Greenhouse Gas (GHG) emissions and managing the adverse impacts of climate change [1]. The Paris Agreement requested the establishment of the Capacity Building Initiative for Transparency (CBIT). Among others, CBIT will enhance the generation of more accurate and up-to-date data on emissions in all sectors [2] [3] [4] [5] [6]. Therefore, the development of specific activity data and Emission factors in different sectors is essential [7] [8] [9] [10].

The specific activity data form an integral part of measures that model the level of activity resulting in greenhouse gas (GHG) emission during a given period, *i.e.*, tonnes of carbon per year [11] [12] [13]. Complimentarily, the Emission factors in this regard denote the values quantifying the impact of the calculation to estimate the GHG emissions. Both the specific activity data and Emission factor render an enabling platform to consistently track and calculate emissions comprehensively [14]. Generation of the two parameters, therefore, leads to more targeted and effective emissions reduction and management strategies outlaid in Malawi's Nationally Determined Contributions, thus as advocated globally by the UNFCCC [1].

The objective of this study was to develop Malawi's activity data and emission factor for the Forestry and Land Use (FOLU) subsector. The findings from this study are essential as they will provide valuable insights into the carbon dynamics and emissions from the FOLU subsector in Malawi. The results will further enable policymakers and stakeholders to make informed decisions, enhance climate change mitigation efforts, and promote sustainable land-use practices. Moreover, the methodologies used in this research could serve as a template for other countries facing similar challenges in quantifying emissions from the FOLU subsector. Above all else, the results serve to bolster Malawi's pathway to meeting the global laid standards of the Reducing Emissions from Deforestation and Degradation (REDD+) Mechanism. This will help the country receive the long-awaited carbon payments issued under the Forest Carbon Partnership Facility scheme by the World Bank and other related schemes.

2. Materials and Methods

2.1. The Study Area

The study was conducted in Malawi (**Figure 1**). Malawi is located in Southern Africa. It is bordered by Zambia on the northwest and west, Tanzania on the northeast and north, and Mozambique on the southwest and east. Malawi experiences three seasons. These are cool-dry, warm-wet, and hot-dry seasons. The cool-dry season appears from May to August, and the average temperature ranges from 4˚C to 10˚C. On the other hand, the hot-dry season occurs from September to October with a mean temperature range of 25˚C to 37˚C. Finally, the warm-wet season is observed from November to April, and this is the season in which most of the annual rainfall befalls. The annual mean rainfall in this season ranges from 725 mm to 2500 mm [15].

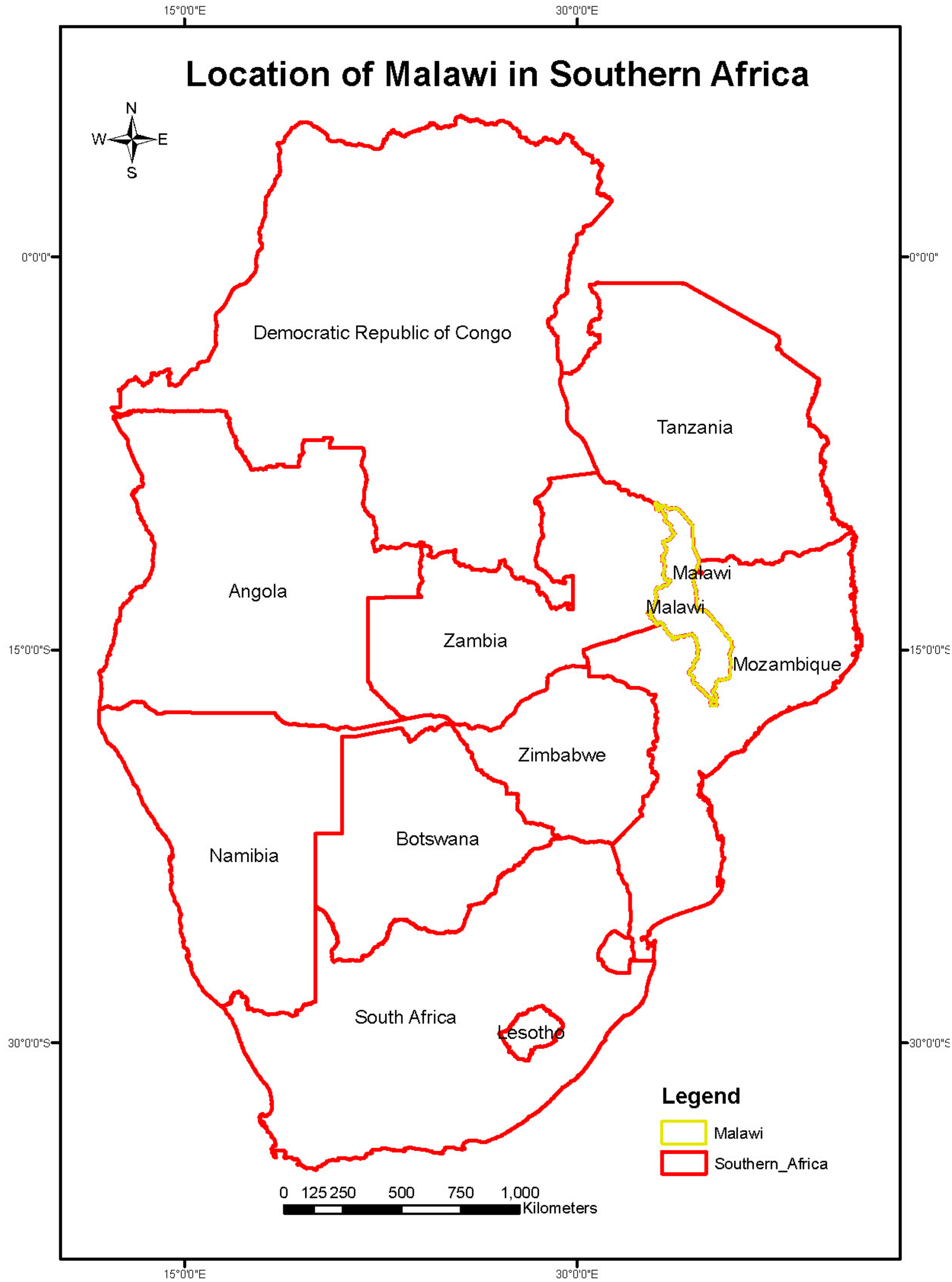

Figure 1. Location of Malawi (Source [15]).

2.2. Conceptual Framework Model

The conceptual framework model that was used in the development of Malawi's activity data and emission factor for the FOLU subsector is given in **Figure 2**. The framework model mainly adopted two parameters. Namely: Satellite Land Monitoring System (SLMS) and Forestry Inventory (FI). SLMS was used for the development of activity data. Activity data is described as the area of land undergoing the transition in question [9]. On the other hand, the FI was used for the development of the emission factor. The emission factor is the rate of emission per unit activity, output, or input [9] [16].

2.3. Data Collection and Analysis

2.3.1. Development of Activity Data

Activity data was developed using Geographic Information System (GIS) and remote sensing techniques. The area of land undergoing transition was determined using an integration of terrestrial/ground-based and remote sensing/Earth Observation, precisely satellite mapping techniques. The ground-based method involved ground surveys of individual tree measurements otherwise referred to as in-situ measurements of biomass pools [17]. Tier 2 category was used in the exercise. Tier 2, activity data is defined by the country for the most important land uses/activities. This level uses higher-resolution activity data to correspond to specific regions and land-use categories [2]. Malawi's land cover maps for the year 2022 were produced to supplement the land cover maps for the years 2000, and 2010 that were produced by AAS [18]. The remote sensing technique involved the employment of the optical Sentinel-2 MultiSpectral Instrumental (MSI) and Landsat 8 satellite image (**Figure 3**). The imagery was acquired from the Google Earth Engine (GEE) platform over Malawi in July 2023. The Malawi and districts perimeter boundary vector shapefiles layers were obtained from the Surveys Department of Malawi. These were reprojected to WGS84 (EPSG: 4326) UTM Zone 36 South for consistency and data interoperability. The vector layers were then imported and overlaid on the Sentinel-2 (S2) imagery to define the areas of interest (AOIs). This was followed by cloud masking the imagery using "maskS2clouds" function contained in the "ggplot2" library, a process that subtracts the contribution of the atmosphere from the

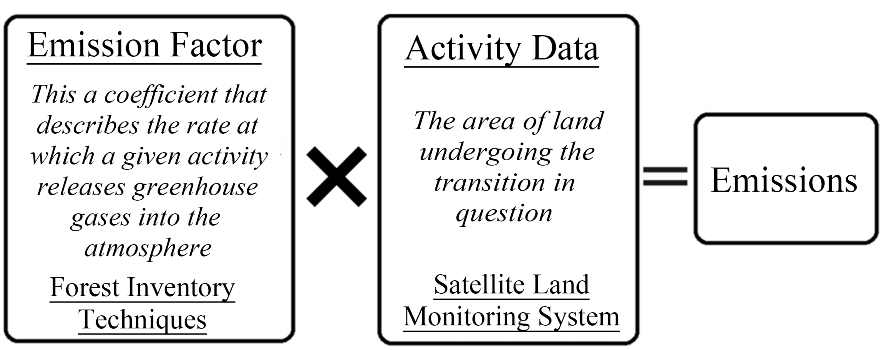

Figure 2. Conceptual framework model.

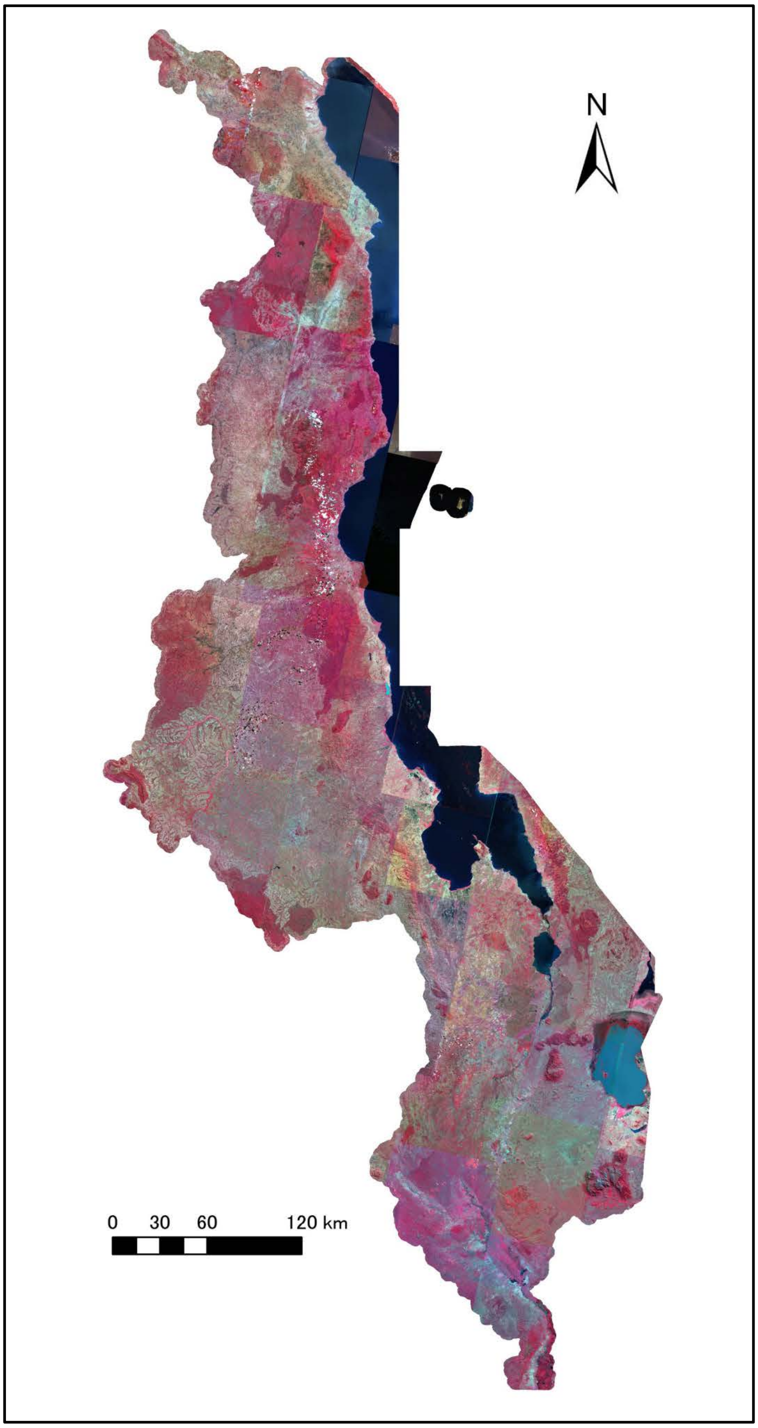

Figure 3. Satellite imagery mosaic for the year 2022.

signal at the satellite to obtain desirable radiance that is used for further analysis [17] [19].

The next step involved image filtering using cloud-pixel percentage (30%) and the closest dates to the acquisition period as the threshold. Furthermore, the spectral band 1 (B1) was excluded because this is a coastal aerosol channel that is better at estimating suspended sediment in water, an attribute that was not of interest to this research which focused on biomass. Hence, the 10 bands selected largely comprise the RE, NIR, and the Short-Wave Infrared (SWIR). The preference for the RE region is due to its capability of being more sensitive to vegetation [20] [21] which is vital for this study's biomass estimations in the Miombo Woodlands.

Additionally, the Kappa coefficient and Overall accuracy were estimated to determine the error of the maps. The Kappa coefficient was calculated using Equation 1, while the Overall accuracy was calculated by dividing the number of correct classifications by the total number of samples taken [22].

$$K = \frac{P_o - P_e}{1 - P_e} \tag{1}$$

where, K is the Kappa coefficient, P_o is the probability of agreement, and P_e is the probability of random agreement.

2.3.2. Development of Emission Factor

The emission factor was developed using Forest Inventory techniques. Essentially, the Carbon Stock Change approach was used (**Figure 4**). In the Carbon Stock Change approach, carbon stocks are measured at two-time intervals and the difference between those two intervals determines the carbon stock change. Equation 2 was used in the Carbon Stock Change approach [9].

$$\Delta C = \frac{C_{t2} - C_{t1}}{t_2 - t_1} \tag{2}$$

where: ΔC is annual carbon stock change in pool (tC/ha/yr); C_{t2} is carbon stock in pool at time t_2 (tC/ha); and C_{t1} is carbon stock in pool at time t_1 (tC/ha). In this study, Forest Inventory data collected by the JICA project in the year 2011 was used as time (t_1). On the other hand, Forest Inventory data collected by the Modern Cooking for Healthy Forests (MCHF) project in the year 2022 was used as time (t_2). Both data were obtained from the Department of Forestry Headquarters, National Forest Monitoring Unit. However, the time (t_2) data was supplemented by a forest inventory conducted in the Lilongwe Urban Forest in November 2022.

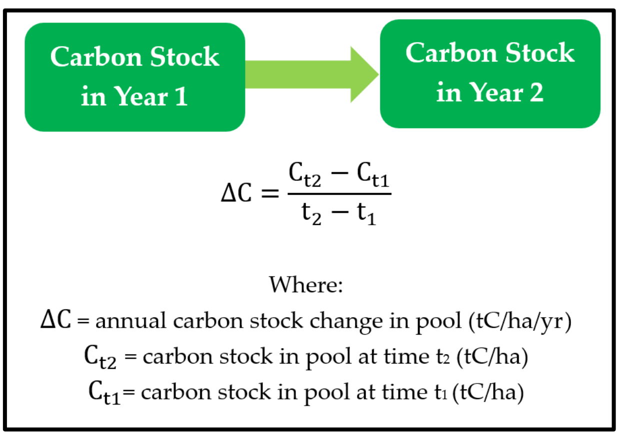

Figure 4. Carbon stock change approach.

2.3.3. Estimation of Biomass, Carbon Stock, and Uncertainty

Above-ground biomass (AGB) and below-ground biomass (BGB) were estimated using the site-specific allometric Equation 3 and Equation 4, respectively, developed by Kachamba *et al.* [23].

$$\mathrm{AGB} = 0.103685 \times (\mathrm{DBH})^{1.921719} \times ht^{0.844561} \tag{3}$$

$$\mathrm{BGB} = 0.284615 \times (\mathrm{DBH})^{1.992658} \tag{4}$$

where: AGB and BGB are above-ground biomass and below-ground biomass (kg dry matter per tree), respectively; DBH is a diameter at breast height (1.3 m above the ground level) (cm); and *ht* is the total tree height (m).

The total living biomass of a tree (TLB) was calculated as the sum of AGB and BGB, while carbon stock (C) was calculated using equation 5:

$$C = \mathrm{TLB} \times \mathrm{CF} \tag{5}$$

where: CF is the carbon factor and varies from 0.45 to 0.50 [24]. In this study, a value of 0.47 was used as recommended by other researchers [15].

Soil organic carbon (SOC) was calculated using equation 6 as recommended by Pan *et al.* [25].

$$\mathrm{SOC} = 0.571 \times (\mathrm{AGC} + \mathrm{BGC}) \tag{6}$$

where: SOC is soil organic carbon (tC/ha), AGC and BGC are above-ground carbon stock and below-ground carbon stock (tC/ha), respectively.

Carbon stock or biomass estimates are usually associated with uncertainties from sources such as sampling error, measurement error, and estimation error [26]. It is a good practice to quantify uncertainties to understand the accuracy of the Carbon stock estimations [27]. Therefore, the Monte Carlo procedure, well explained by other researchers [28] was used to estimate the uncertainty of the parameters studied at a 95% confidence interval.

3. Results and Discussion

3.1. Activity Data for FOLU Subsector in Malawi

A summary of the activity data for the FOLU subsector in Malawi from the year 2000 to the year 2022 is presented in **Table 1** and **Table 2** as well as in **Figure 5**. The results indicate that the forest area land steadily declined from 2,595,140 ha in 2000 to 2,282,540 ha in the year 2022. Therefore, for 23 years, Malawi has lost about 312,600 ha, thus a deforestation rate of 13,591 ha (0.5%) per annum. This deforestation continually stems from massive pressure from human activities related to agricultural expansion and unsustainable harvesting of fuelwood and timber [29]. Similarly, grassland declined from 335,860 ha in the year 2000 to 297,890 ha in the year 2022. Indicating a decline rate of 1651 ha (0.5%) per annum.

On the other hand, cropland, wetland, and settlements steadily increased at the rate of 8228 ha (0.14%); 5257 ha (0.17%); and 1941 ha (8.1%) per annum, respectively.

Further analysis (Table 2) shows that "Forestland to Cropland," "Cropland to Forestland," and "Wetland to cropland," were the major land use changes in Malawi between 2000 and 2010. It should also be noted that the wetland class includes dambo's, which have some tree species that are usually harvested [18]. On the other hand, the high rate of "forestland to cropland" changes compared to

Table 1. Malawi land use statistics from the year 2000 to 2022.

Year	2000		2010		2022	
Classes	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
Forest Land	25,951.4	21.9	24,177.0	20.4	22,825.4	19.3
Cropland	58,528.8	49.5	59,415.4	50.2	60,421.3	51.1
Grassland	3358.6	2.8	3180.4	2.7	2978.9	2.5
Wetland	30,097.1	25.4	30,902.1	26.1	31,306.1	26.5
Settlements	240.1	0.2	513.2	0.4	686.6	0.6
Other Land	144.4	0.1	132.3	0.1	102.1	0.1

Table 2. Major land use changes in km^2 for Malawi.

Land use cover change	2000 - 2010	2010 - 2022
Forest land to Cropland	3680.6	2208.4
Forest land to Grassland	255.9	153.6
Cropland to Forest land	1870.7	1122.4
Grassland to Forest land	220.6	312.4
Wetland to Forest land	392.4	235.4
Wetland to Cropland	1479.3	887.7
Forest land to Settlement	27.3	24.8

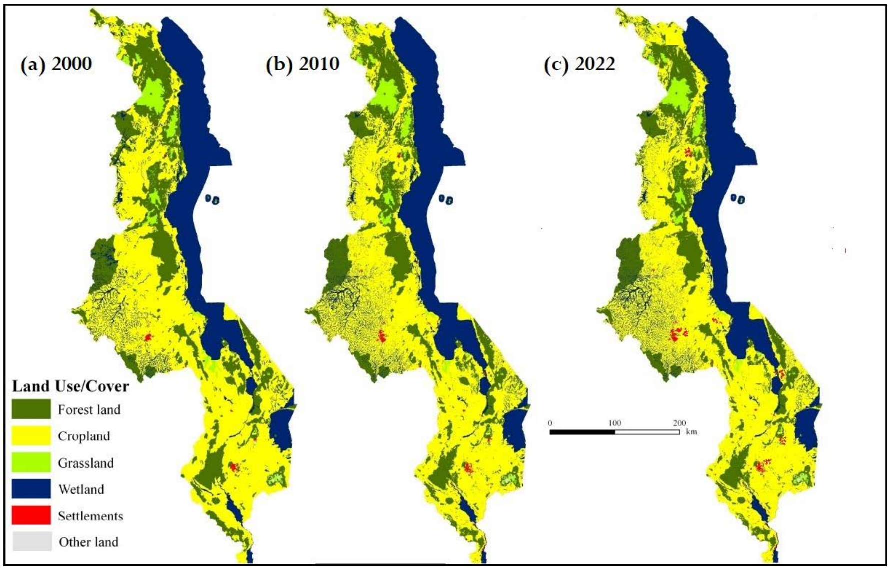

Figure 5. Malawi's Land use for the years 2000, 2010 and 2022.

the low rate of "cropland to forest land" changes for the "2000 - 2010" period indicates forest cover loss. Forest cover declined at an annual rate of 16,131 ha (0.6%) between 2000 and 2010.

Similarly, "Forestland to Cropland," "Cropland to Forestland," and "Wetland to cropland," were the major land use changes in Malawi between 2010 and 2022. However, forest cover declined at an annual rate of 10,397 ha (0.4%). Furthermore, it is important to note that the "grassland to forest land" changes were higher than the "forestland to grassland" changes for the period 2010 - 2022, suggesting that forest regrowth was occurring in the country [18].

The land use change analyses revealed a high rate of forest cover loss for the period 2000 - 2010 as compared to the period 2010 - 2022. The high rate of forest cover loss during the 2000 - 2010 period is attributed to several driving factors such as agricultural expansion, human settlement, unsustainable harvesting of forest products for energy and timber requirements, and uncontrolled fires [18]. It should be noted that the area under tobacco farming increased substantially from 194,000 ha to 253,000 ha between 2000 and 2007 [30], which increased the demand for agricultural land.

An extensive classification accuracy assessment was performed for the 2022 land use/cover map. The overall land use/cover classification accuracy was 94.7%, while the Kappa coefficient was 92.2% (**Table 3**). The kappa coefficient is frequently used to test interrater reliability. The significance of rater reliability lies in the fact that it represents the extent to which the data collected in the study are correct representations of the variables measured [22]. In this study, the high percentage of the Kappa coefficient and overall accuracy indicates that the level of agreement was perfect. Thus, the data used are immaculately reliable [31].

3.2. Emission Factor for FOLU Subsector in Malawi

A summary of the results on the Emission factor for the FOLU subsector in Malawi are presented in **Table 4**. The results interestingly indicate that there was a

Table 3. Accuracy Assessment for the Production of the 2022 Map.

Land Classification	Cropland	Grassland	Wetland	Settlements	Other land	Forestland	Total	User's Accuracy (%)
Cropland	410	3	9	0	0	6	**428**	**95.8**
Grassland	1	29	3	0	0	2	**35**	**82.9**
Wetland	2	0	201	1	0	0	**204**	**98.5**
Settlements	1	0	0	10	0	0	**11**	**90.9**
Other land	0	1	0	0	6	0	**7**	**85.7**
Forestland	17	2	1	0	1	243	**264**	**92.0**
Total	**431**	**35**	**214**	**11**	**7**	**251**	**949**	**X**
Producers Accuracy (%)	**95.1**	**82.9**	**93.9**	**90.9**	**85.7**	**96.8**	**X**	**X**

Overall Accuracy = 94.7%; Kappa Coefficient = 92.2%.

Table 4. Malawi's carbon stock for FOLU Subsector at different years.

Year	Mean Carbon Stock (tC/ha)	Standard Error	Uncertainty (%)
2011	80.62	8.51	2.60
2022	121.55	11.72	1.81
Annual Net Change in Carbon dioxide equivalent per area (Emission Factor) = 13.66 ± 0.17 tCO_2 e/ha/yr Uncertainty (%) = 2.44			

Note: The positive value of EF indicates carbon sequestration.

significant increase in carbon sequestration in the FOLU subsector from the year 2011 to the year 2022. Carbon sequestration increased annually by 13.66 ± 0.17 tCO_2e/ha/yr (4.6%), with an uncertainty of 2.44%. The increase may be attributed to the factor that the "grassland to forestland" changes were higher than the "forestland to grassland" changes, suggesting that forest regrowth was occurring [18]. Some of the key strategies that have contributed to the increase of carbon stock within the FOLU subsector in Malawi include; afforestation and natural/assisted regeneration; management and conservation of protected areas; National Forest Reference Level-2019; establishment of seed banks for raising drought tolerant trees species; breeding of fast-growing and drought-tolerant tree species; and screening of disease and pest-resistant species and promotion of biological control [15].

This is the first time the Emission factor in the FOLU subsector in Malawi has been developed. The findings are essential as they will provide valuable insights into the carbon dynamics and emissions from the FOLU subsector in Malawi. Emission factor estimation is always associated with uncertainties, and it is essential to minimise them [32] [33]. Sources of error in the estimation of Emission factors are associated with sampling and modelling [34] [35]. The sampling error was minimised by sampling in different forest types. This included; National Parks, Forest Reserves, Customary forests, and Urban forests. The use of different forest types in sampling leads to calculations that are normally distributed and have minimal effect on the final Emission factor determination [35]. Finally, the use of site-specific allometric modelling in the present study also helped to minimise the uncertainties. According to our previous research [36], the use of a site-specific allometric model contributes 97.95% of the total variation in the estimation of above-ground biomass.

The UNFCC guidelines require the use of five carbon pools when estimating emission factors. The carbon pools include: above ground biomass, below ground biomass, dead wood (DW), litter, and soil organic carbon (SOC) [9]. In this study, we used three carbon pools to estimate the emission factor. The carbon pools used are: above ground biomass, below ground biomass, and soil organic carbon. It should be noted that Malawi's populace is highly dependent on fuel wood and less wood is left lying for longer periods in the forestlands unlike in other highly significant areas like peatlands. Furthermore, litter is burned in the dry season to achieve ecosystem goals [37]. Therefore, the assumption is that the carbon stocks in dead wood and litter do not significantly change over time if the land remains within the same land-use category.

4. Conclusion

The study mainly investigated the activity data and emission factor in the Forestry and Other Land Use Change (FOLU) subsector in Malawi. After performing the investigation, the corresponding results shown that "forestland to cropland," and "wetland to cropland," were the major land use changes from the year 2000 to the year 2022. The forestland and grassland steadily declined. On the other hand, cropland, wetlands, and settlements steadily increased. Furthermore, the study revealed that the "grassland to forestland" changes were higher than the "forestland to grassland" changes, suggesting that forest regrowth was occurring. On the emission factor, the study interestingly revealed that there was a significant increase in carbon sequestration in the FOLU subsector from the year 2011 to 2022, with a low uncertainty. Therefore, there is potential for a Carbon market in Malawi.

Acknowledgements

The authors are thankful to the Department of Environment Affairs (EAD) staff (Clifford Mkanthama, Yamikani Idriss, and John Mathandalizwe) for administrative support, Mike Chirwa from Forestry Research Institute of Malawi (FRIM) for technical support, and Masautso Chikuwi for Urban forestry data collection. The research and the Article Processing Charge (APC) were funded by the Ministry of Natural Resources and Climate Change, Malawi through the Department of Environmental Affairs under the Climate Transparency Framework Project.

Data Availability Statement

The data that support the findings of this study can be obtained from the corresponding author upon request.

Conflict of Interests

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Government of Malawi (2021) Malawi's Updated Nationally Determined Contribution. Government Press, Lilongwe.

[2] Smith, P., Bustamante, M., Ahammad, H., Clark, H., Dong, H., Elsiddig, E.A., Haberl, H., Harper, R., House, J., Jafari, M., Masera, O., Mbow, C., Ravindranath, N.H., Rice, C.W., Robledo Abad, C., Romanovskaya, A., Sperling, F. and Tubiello, F. (2014) Agriculture, Forestry and Other Land Use (AFOLU). Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge.

[3] Zomer, R., Trabucco, J., Bossio, D.A. and Verchot, L.V. (2008) Climate Change Mitigation: A Spatial Analysis of Global Land Suitability for Clean Development Mechanism Afforestation and Reforestation. *Agriculture*, *Ecosystems & Environment*, **126**, 67-80. https://doi.org/10.1016/j.agee.2008.01.014

[4] Yu, P., Wang, Y., Du, A., Guan, W., Feger, K.H., Schwärzel, K., Bonell, M., Xiong, W. and Pan, S. (2013) The Effect of Site Conditions on Flow after Forestation in a Dryland Region of China. *Agricultural and Forest Meteorology*, **178**-**179**, 66-74. https://doi.org/10.1016/j.agrformet.2013.02.007

[5] Takimoto, A., Nair, P.K.R. and Nair, V.D. (2008) Carbon Stock and Sequestration Potential of Traditional and Improved Agroforestry Systems in the West African Sahel. *Agriculture*, *Ecosystems and Environment*, **125**, 159-166. https://doi.org/10.1016/j.agee.2007.12.010

[6] Semroc, B. L., Schroth, G., Harvey, C.A., Zepeda, Y. and Boltz, F. (2012) Climate Change Mitigation in Agroforestry Systems. Linking Smallholders to Forest Carbon Markets. In: *Climate Change Mitigation and Agriculture*, Routledge, London, 360-369.

[7] Hochul, K. and Seggos, B. (2022) Agriculture Forestry, and Other Land Use: Greenhouse Gas Emission. Department of Environmental Conservation, New York.

[8] Walters, B.F., Domke, G.M., Greenfield, E.J., Smith, J.E., Nowak, D.J. and Ogle, S.M. (2022) Greenhouse Gas Emissions and Removals from Forest Land, Woodlands, and Urban Trees in the United States, 1990-2020: Estimates and Quantitative Uncertainty for Individual States, Regional Ownership Groups, and National Forest System Regions. U.S. Department of Agriculture, Forest Service Research Data Archive, New York.

[9] IPCC (2019) 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Kanagawa, Japan, the National Greenhouse Gas Inventories Programme, the Intergovernmental Panel on Climate Change, Hayama.

[10] Domke, G.M., Walters, B.F., Nowak, D.J., Smith, J.E., Nichols, M.C., Ogle, S.M., Coulston, J.W. and Wirth, T.C. (2022) Greenhouse Gas Emissions and Removals from Forest Land, Woodlands, and Urban Trees in the United States, 1990-2020 (Resource Update FS-RU-382). U.S. Department of Agriculture, Forest Service, Northern Research Station, Madison. https://doi.org/10.2737/FS-RU-227

[11] Tubiello, F.N., Salvatore, M., Golec, R.D.C., Ferrara, A., Rossi, S., Biancalani, R., Federici, S., Jacobs, S. and Flammini, A. (2014) Agriculture, Forestry and Other Land Use Emissions by Sources and Removals by Sinks, 1990 to 2011 Analysis. FAO Statistics Division Working Paper Series ESS/14-02, Rome.

[12] Houghton, R.A., Van Der Werf, G.R., DeFries, R.S., Hansen, M.C., House, J.I., Le Quéré, C., Pongratz, J. and Ramankutty, N. (2012) Carbon Emissions from Land Use and Land-Cover Change. *Biogeosciences Discuss*, **9**, 835-878. https://doi.org/10.5194/bg-9-5125-2012

[13] Plevin, R.J., Gibbs, H.K., Duff, J., Yui, S. and Yeh, S. (2014) Agro-Ecological Zone Emission Factor (AEZ-EF) Model (V47). GTAP Technical Paper No. 34. https://doi.org/10.21642/GTAP.TP34

[14] Harris, N., Grimland, S. and Brown, S. (2008) GHG Emission Factors for Different Land-Use Transitions in Selected Countries of the World. Report Submitted to US EPA, Winrock International, Little Rock.

[15] Missanjo, E. and Kadzuwa, H. (2021) Greenhouse Gas Emissions and Mitigation Measures within the Forestry and Other Land Use Subsector in Malawi. *International Journal of Forestry Research*, **2021**, Article ID: 5561162.

https://doi.org/10.1155/2021/5561162

[16] Santilli, M., Moutinho, P., Schwartzman, S., Nepstad, D., Curran, L. and Nobre, C. (2005) Tropical Deforestation and the Kyoto Protocol. *Climatic Change*, **71**, 267-276. https://doi.org/10.1007/s10584-005-8074-6

[17] Kamusoko, C., Gamba, J. and Murakami, H. (2014) Mapping Woodland Cover in the Miombo Ecosystem: A Comparison of Machine Learning Classifiers. *Land*, **3**, 524-540. https://doi.org/10.3390/land3020524

[18] AAS (Air Asia Survey) (2012) Forest Resource Mapping Project under the Japanese Grant for the Forest Preservation Programme to Republic of Malawi: Final Report for the Implementation Phase. Department of Forestry, Lilongwe.

[19] Kamusoko, C. (2019) Explainable Machine Learning for Land Cover Classification: An Introductory Guide. *Geolabs*, **1**, 105-112.

[20] Wang, B., Jia, K., Liang, S., Xie, X., Wei, X., Zhao, X., *et al.* (2018) Assessment of Sentinel-2 MSI Spectral Band Reflectances for Estimating Fractional Vegetation Cover. *Remote Sensing*, **10**, Article No. 1927. https://doi.org/10.3390/rs10121927

[21] Wang, Y., Zhang, X. and Guo, Z. (2021) Estimation of Tree Height and Above-ground Biomass of Coniferous Forests in North China Using Stereo ZY-3, Multispectral Sentinel-2, and DEM Data. *Ecological Indicators*, **126**, Article ID: 107645. https://doi.org/10.1016/j.ecolind.2021.107645

[22] McHugh, M.L. (2012) Interrater Reliability: The Kappa Statistic. *Biochemia Medica*, **22**, 276-282. https://doi.org/10.11613/BM.2012.031

[23] Kachamba, D.J., Eid, T. and Gobakken, T. (2016) Above- and Belowground Biomass Models for Trees in Miombo Woodlands of Malawi. *Forests*, **7**, Article No. 38. https://doi.org/10.3390/f7020038

[24] Hirata, Y., Takao, G., Sato, T. and Toriyama, J. (2012) REDD-Plus Cookbook. REDD Research and Development Center, Forestry and Forest Products Research Institute, Tsukuba.

[25] Pan, Y., Birdsey, R.A., Fang, J., Houghton, R., Kauppi, P.E., Kurz, W.A., Hayes, D., *et al.* (2011) A Large and Persistent Carbon Sink in the World's Forests. *Science*, **333**, 988-993. https://doi.org/10.1126/science.1201609

[26] FAO (2005) Global Forest Resource Assessment: Progress towards Sustainable Forest Management. Food and Agriculture Organization Forestry Paper, No. 147, FAO, Rome.

[27] Food and Agricultural Organisation (FAO) (2015) Climate Change and Forestry Legislation in Support of REDD+. Paper No. 92.

[28] Sierra, C.A., Del Valle, J.I., Orrego, S.A., Moreno, F.H., Harmon, M.E., Zapata, M., Colorado, G.J., Herrera, M.A., Blara, W., Restrepo, D.E., Berrouet, L.M., Loaiza, L.M. and Benjumea, J.F. (2007) Total Carbon Stocks in a Tropical Forest Landscape of the Porce Region, Colombia. *Forest Ecology and Management*, **243**, 299-309. https://doi.org/10.1016/j.foreco.2007.03.026

[29] Ministry of Forestry and Natural Resources (2021) Malawi's First Biennial Update Report to the Conference of Parties (CoP) of the United Nations Framework Convention on Climate Change (UNFCCC). Lilongwe.

[30] National Statistical Office (NSO) and ICF Macro (2011) Malawi Demographic and Health Survey 2010. NSO and ICF Macro, Zomba, and Calverton.

[31] Kvan, P.H. and Lu, J.C. (2006) Statistical Reliability with Applications. In: Pham, H., Ed., *Springer Handbook of Engineering Statistics*, Springer-Verlag, London, 49-61. https://scholarship.richmond.edu/mathcs-faculty-publications/210

https://doi.org/10.1007/978-1-84628-288-1_2

[32] Eggleston, S., Buendia, L., Miwa, K., Ngara, T. and Tanabe, K. (2006) IPCC Guidelines National Greenhouse Gas Inventories Agriculture, Forest and Other Land Use. Vol. 4, IGES, Hayama.

[33] Djomo, A.N., Knohl, A. and Gravenhorst, G. (2011) Estimations of Total Ecosystem Carbon Pools Distribution and Carbon Biomass Current Annual Increment of a Moist Tropical Forest. *Forest Ecology and Management*, **261**, 1448-1459. https://doi.org/10.1016/j.foreco.2011.01.031

[34] Zhao, Y., Nielsen, C.P., Lei, Y., McElroy, M.B. and Hao, J. (2011) Quantifying the Uncertainties of a Bottom-Up Emission Inventory of Anthropogenic Atmospheric Pollutants in China. *Atmospheric Chemistry and Physics*, **11**, 2295-2308. https://doi.org/10.5194/acp-11-2295-2011

[35] Oda, T., Bun, R. and Kinakh, V. (2019) Errors and Uncertainties in a Gridded Carbon Dioxide Emissions Inventory. *Mitigation and Adaptation Strategies for Global Change*, **24**, 1007-1050. https://doi.org/10.1007/s11027-019-09877-2

[36] Kadzuwa, H. and Missanjo, E. (2022) Comparison of Varied Forest Inventory Methods and Operating Procedures for Estimating Above-Ground Biomass in Malawi's Miombo Woodlands. *Journal of Global Ecology and Environment*, **16**, 7-27. https://doi.org/10.56557/jogee/2022/v16i27675

[37] Nieman, W.A., Wilgen, B.W. and Leslie, A.J. (2021) A Reconstruction of the Recent Fire Regimes of Majete Wildlife Reserve, Malawi, Using Remote Sensing. *Fire Ecology*, **17**, Article No. 4. https://doi.org/10.1186/s42408-020-00090-0