Evaluating Dynamics of Carbon Pools Resulting from Redistribution Among Biomass Components Following Wildfires in Aberdare Afromontane Forests, Kenya

John N. Kigomo[1,2]*, Gilbert Obwoyere[2] & Bernard Kirui[2]

[1]*Kenya Forestry Research Institute, Kenya*

[2]*Egerton University, Kenya*

**Corresponding author- jkigomo@kefri.org*

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Abstract

East African Afromontane Forests are among the carbon-rich ecosystems, but their stability is mainly compromised due to seasonal wildfires. The objectives of the study were (1) to determine the impacts of wildfires on various carbon pools and (2) to evaluate carbon stock redistributions among biomass components after wildfires within Aberdare Afromontane Forest ranges, The study was conducted in nine sites that experienced wildfires in 2022 within two months after the fire occurrence. A total of 35 concentric plots of 15m radius distributed in high severity (12), low (9) and unburnt areas (14) were used. Our findings indicated that the mean carbon stock for all biomass components assessed changed from 96.4 tons C ha-1 to 46.6 tons C ha-1 due to wildfires. Most carbon stock losses were derived from litter and herbs biomass components with a combustion of 97% and 86% respectively. Further, course wood debris and dead standing trees increased with increasing wildfire severity while standing live trees and soil organic carbon decreased with increasing fire severity. Carbon redistribution from live-standing trees to dead lying and standing trees after wildfires were mainly from young small trees. This study indicates that future forest stock will have an impact on the carbon budget if urgent measures are not put in place to control and manage wildfires. The findings of this study suggest the inclusion of wildfire assessment attributes within the national forest inventory framework to assist in accounting for losses due to disturbances. Our findings can support improvement in reporting Kenya's carbon emission factors from land use. The study recommends periodical monitoring to evaluate long-term post-fire carbon dynamics.

Keywords: Wildfire, Carbon Emissions, Burnt Area, Forest Biomass, Sentinel-2

Introduction

Biomass burning has been recognized as the second largest source of trace gases in the global atmosphere and strongly influences climate change (Chowdhury & Hassan, 2015). Biomass burning releases large amounts of carbon and other trace gases such as carbon monoxide, methane, hydrocarbons, nitric oxide and nitrous oxide and particulates leading to increased concentrations in the atmosphere and enhanced radiative forcing that induces climate change (Saranya *et al*., 2016). Biomass fires significantly affect the Green House Gases (GHGs) atmospheric balance with a contribution of 7600 ± 359 Tg CO_2 eq year^{-1}, this is an equivalent of 5% of total emissions from agriculture, forestry, and other land use (AFOLU) between 2001 to 2016 (Prosperi *et al*., 2020). During the same duration, Sub-Saharan Africa contributed 569 ± 34 Tg CO_2eq year^{-1} to the overall emissions. This indicates the significance of addressing wildfires due to its contribution of GHGs especially from the developing countries.

Kenya is a signatory of United Nations Framework Convention on Climate Change (UNFCCC), which requires accurate and reliable reporting of carbon emissions and sinks in various land uses. The parties to the UNFCCC must report periodically their emissions from wildfires on managed land and human-induced fires. However, in the latest submission to UNFCCC, emissions from wildfires were not included because of a lack of comprehensive data on the extent and damage (GoK, 2020). Studies of Barlow *et al*. (2012) indicates negotiators for Reducing Emissions from Deforestation and Degradation (REDD+) have largely ignored the inclusion of wildfires in their negotiations. Therefore, improving wildfire burnt area mapping and understanding the carbon dynamics in Kenya would not only improve emissions estimates and enhance international reporting under UNFCCC but will also help with developing fire management policy, understanding fire management and assisting rehabilitation and restoration interventions in forest and landscape ecosystems.

Kenya is also in the process of developing a System for Land-based Emission Estimation in Kenya (SLEEK) to improve on GHGs reporting. In the current implementation of SLEEK, data on forest disturbance is an important input variable in the carbon accounting processes. Whereas data on forest management practices such as pruning, thinning and harvested area is available in Kenya, the estimates on forest fire disturbances are mostly obtained from expert estimation. There are currently inadequate ground-truthed burnt area maps for major critical protected areas in Kenya. This greatly reduces the ability of the SLEEK to support estimating emissions from various land use types and carbon pools in fire-prone areas and managing its effects. The proposed study will support wildfire management in Kenya, which will eventually have an impact on vegetation sustainability and long-term carbon storage leading to mitigation of climate change.

According to Watson (2009), the Intergovernmental Panel on Climate Change (IPCC) recognizes five carbon pools within a natural ecosystem that can accumulate or release carbon namely; aboveground biomass (AGB), belowground biomass (BGB), dead organic matter (DOM) in wood, DOM in litter and soil organic matter (SOM). According to Keith *et al*. (2014), the AGB can further be classified into Standing Live Trees (SLT), Standing Dead Trees (SDT) and Shrubs and Herbs (S&T). The DOM can be categorized into Coarse Wood Debris (CWD) mainly composed of dead and downed woody debris and litter, which is composed of fallen leaves, twigs, flowers and fruits. There are two methods recognized by the IPCC for carbon stock accounting and emissions (GoK, 2020). This includes the inventory approach and the activity-based approach (Watson, 2009). The inventory approach uses a two-forest carbon stock accounting assessment at different periods to derive the difference as either loss or gain. On the other hand, the activity-based approach estimates carbon stock change by multiplying the area of land-use change by the impact of the change. The use of the activity approach requires an understanding of the rates of carbon gain and loss, commonly expressed as average biomass increments, for growth, and emissions factors for biomass losses, due to harvesting of wood products and disturbances such as wildfires (Keith *et al*., 2014).

Carbon stock changes due to wildfires occur at different temporal scales causing emissions. The periods can range from hours to days or weeks due to combustion and are highly variable each year due to wildfire occurrence. However, recovery through vegetation regrowth and losses through decomposition of dead biomass occur over decades to centuries (Saranya *et al*., 2016). For the wildfire disturbance to be included in the national carbon accounting, the carbon stock loss due to combustion, redistribution of carbon stocks between living and dead biomass components; subsequent rates of decomposition; and carbon uptake by regenerating vegetation need to be considered (Stenzel *et al.*, 2019). Several studies have tried to determine these variables (Sibanda *et al.*, 2011; Keith *et al.*, 2014; Fairman *et al*., 2022). However, since wildfires typically extend over large areas, within which fire severity varies spatially and considering carbon stocks vary across the landscape in response to differences in forest type, age, disturbance history and environmental factors then the existing methods are still in their infancy. Furthermore, biomass components are combusted with differing efficiencies. The redistribution of carbon stock and emission among live carbon pools, dead pools and soil organic carbon will be investigated in this study.

East African Afromontane forests are among the carbon-rich ecosystems with a high water catchment potential and a rich biodiversity (Ministry of Environment and Forestry, 2019). Historically, the vegetation within Afromontane forests consists of extensive areas of woodlands and planted forest plantations at lower elevations which later change to the mosaic of forest, bamboo, and grasslands within its middle elevations and later in the higher elevations consisting of heathland which is also known as moorlands (Kipkoech *et al*., 2019). However, due to their location in humid and sub-humid areas where the human population is high, they are mainly threatened by wildfires, encroachment, grazing and other human activities (Kinyanjui *et al*., 2015; Kigomo *et al*., 2015)

Despite Kenya having recurrent wildfire episodes targeting highly productive ecosystems (GoK, 2020), Greenhouse Gas (GHGs) emissions from wildfires have not been included in the country reporting to the United Nations Framework Convention on Climate Change (UNFCCC) under Land Use, Land Use Change and Forestry (LULUCF). Reporting emissions from wildfires will require comprehensive, accurate and reliable methods, which is the main thrust of this study. The objectives of this study were (1) to determine the impacts of wildfires on various carbon pools in Aberdare Afromontane Forest ranges and (2) to evaluate carbon stock redistributions among biomass components after wildfires within Aberdare Afromontane Forest ranges, Kenya

Materials and Methods

Study Area

The study was carried out in Aberdare ranges, the third highest mountain in Kenya and located in the central highlands (Figure 1). The mountain comprises of ranges covered mainly by forests, grassland and moorland. Administratively it’s managed as a forest reserves (149,822 ha) by Kenya Forest Service (KFS) and a National Park (76,700 ha) by Kenya Wildlife Service (KWS). It’s located to the east of the Great Rift Valley and lies along the equator between 36º30’ E, 0º 05’ S and 36º 55’E, 0º 45’S. The altitude ranges from 2000 m to its highest peak of 4000 m above sea level. The general climate of Aberdare ecosystem is largely determined by altitude with long rainfall periods mainly experienced from March to May, while short rainfall periods are received from October to November. Annual rainfall varies with altitude and exposure to the dominant winds from the Indian Ocean, ranging from 700 mm on the drier north-western slopes to 3000 mm on the wetter south-eastern slopes (Kipkoech *et al*., 2019). The mean temperature decreases with increasing altitude with a mean varying between 10.3° to 25.8 °C daily. However the lowest temperatures is mainly experienced between July and August (Kenya Forest Service, 2010). Long rains usually come from March to May and short rains from October to November (KWS, 2010; Lambrechts *et al.*, 2003). The vegetation of Aberdare ranges comprises of typical Afromontane forest characterized by broad vegetation zonation along altitudinal and climatic gradients (KWS, 2010; Kipkoech *et al*., 2019). Four broad vegetation zones have been described, including montane humid forest at lower altitudes, sub-montane forest at mid elevations, sub-alpine vegetation at the moorlands and dry xeromorphic evergreen forest at the northern parts of the forest (Lambrechts *et al*., 2003).

Wildfires play an important role in the Aberdare ecosystem functions and the livelihoods of the adjacent local community. Records of fire occurrence from way back in 1912 to date indicates 96 % of fires occurs in January, February and March while 4% occurs around September (Kigomo *et al*., 2015; KWS, 2010). The frequency and spatial extent of these fires pose serious threats to the structure and composition of the forest which can lead to changes in potential carbon stock and sequestration.

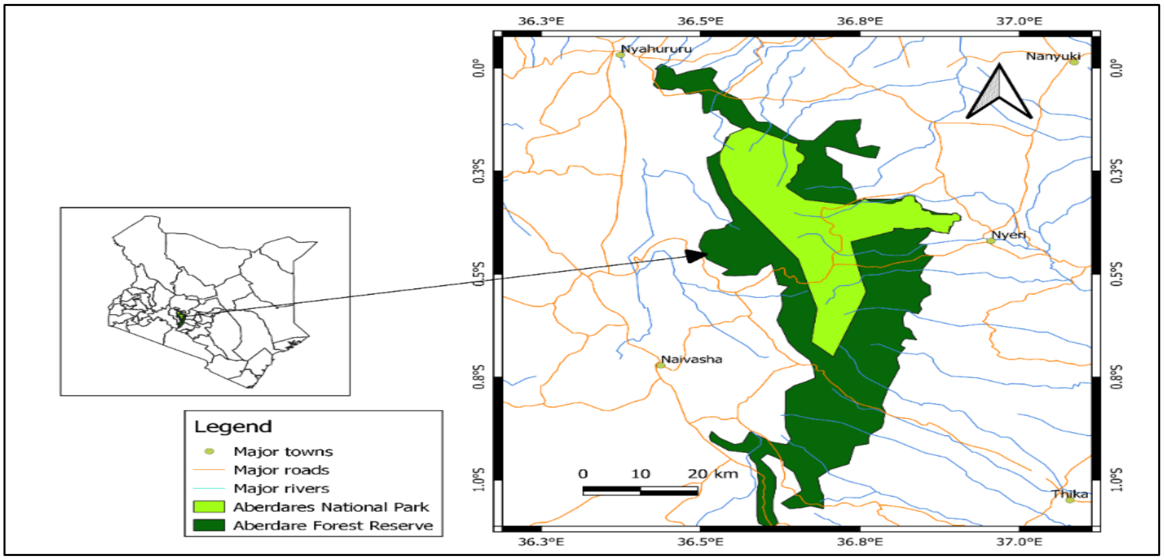


Figure 1: The location of study area in Kenya showing the extent of national park and forest reserve (Source-Author).

Delineation of Burnt Area and Severity Classes

A multispectral Sentinel-2A satellite images with a cloud cover of below 5 % for January to March 2022 were freely searched from European Space Agency (ESA) Copernicus Open Access Hub (https://scihub.copernicus.eu/dhus/#/home) and processed using Google Earth Engine (GEE) environment. The choice of the period was guided by wildfire occurrence season within the study area ((Kigomo *et al*., 2015). Sentinel-2 sensor acquires images at 13 spectral channels at varying spatial resolutions of 10, 20, and 60 m and it is readily available for frequent vegetation assessment and monitoring. A detailed description of sentinel satellite data can be found in Weiss & Baret (2016).

Pre-processing within GEE environment involved importing a shapefile for the study area to retrieve appropriate Sentinel-2 scenes before and after the wildfires according to studies of Xulu *et al*. (2021). This was followed by filtering, compositing and clipping. The preprocessed images were downloaded and exported to QGIS for processing of the burned area.

Within the QGIS platform, the processed Sentinel-2 images were loaded to derive NBR and dNBR according to studies of Liu *et al*. (2021). To minimize computing time, only band 8A and band 12 were loaded which corresponds to Near Infrared (NIR) and Shortwave Infrared (SWIR) since they are the only bands that were used in processing NBR using Equation 1. This was repeated for all the images to produce burned area maps within the entire coverage of the Sentinel 2 scenes.

Equation 1

$$NBR = \frac{NIR - SWIR}{NIR + SWIR}$$

The dNBR is calculated from one pre- and one post-fire image

Equation 2

$$dNBR = NBR_{pre-fire} - NBR_{post-fire}$$

To calculate dNBR, the NBR of the post-fire images was subtracted from the NBR of the pre-fire images as shown in Equation 2 (Llorens *et al*., 2021). The wildfire severities were delineated according to thresholds described by Mallinis *et al*. (2018). Finally, nine sites within Aberdare ranges were selected for detailed data collection to cover the altitudinal ranges and forest types along wildfire severities

Field Measurements

The concentric plots of radius 15m were randomly established within unburnt and burnt areas along fire severity classes for data collection. For the assessment of vegetation variables, 35 plots distributed in high severity (12), low (9) and unburnt areas (14) were used. Tree variables data was collected within a radius of 15 m, 5 m and 2 m for trees with a diameter at breast height of (DBH) >20 cm, >5 cm and >2cm, respectively using the national forest inventory biophysical data collection protocol (KFS, 2016). Specifically, the data was used to derive information on carbon stock of Standing Live Trees (SLT) and Standing Dead Trees (SDT). The respective concentric plots were used to identify tree species, count the number of trees, measure tree height, diameter at breast height, and assess percentage damages if there are any noticeable indicators (dead trees, crown, branches, and stem). In the small circular plots of 2m radius, saplings were assessed. However, more data was collected on the stumps, Coarse Wood Debris (CWD), Fine Wood Debris (FWD), forest floor herbs/shrubs, litter and Soil Organic Carbon (SOC).

A composite soil sample was prepared by sampling soil at the four cardinal points of the circular plot at least 1 m away from the boundary of the plot to avoid disturbed areas within the plot. Soil samples will be taken from the first 20 cm of the topsoil with a 7.5 cm diameter soil core (Nezhadgholam-Zardroodi *et al*., 2022). Soil samples were put in Ziploc bags and then transferred to the laboratory for analysis. The top and bottom diameter and height of the standing stumps will be measured within the main plot of a 15 m radius and data recorded. The CWD was defined as dead laying wood with a diameter greater than or equal to 7 cm according to Filicetti *et al*. (2021) and it was assessed in the main plot of a 15 m radius. The small and large-end diameters, lengths, and decomposition stages of CWD in each plot were assessed. The FWD (woody debris of diameter less the 7 cm) and finally the herbs and litter were collected separately in three representatives randomly located subplots using one m^2 ring and put in respective large plastic bags. In each plot, the three samples were combined to form a composite sample of litter, herbs and FWD. The weight of litter, herbs and FWD was taken in the field using a digital weighing scale. The results were recorded after subtracting the weight of the empty bag. A sub-sample of about 500 g was collected for further analysis in the laboratory.

Laboratory Work

The sub-samples of FWD, herbs and litter were weighed and oven-dried at 105 ◦C for at least 48 h to assess the biomass. The soil samples were weighed and then oven-dried at 105 °C for 24 h. After drying, the soil was sieved with a 2 mm sieve to remove the coarser particles and debris and each component was weighed. The bulk density was determined as the oven-dried weight of the soil divided by the volume of the core. The air-dried samples were then analyzed for organic carbon using standard laboratory methods as described by Okalebo *et al.* (2002). About 0.5 g of soil sample was weighed and put in a block digester tube then 5 ml of potassium dichromate solution and 7.5 ml of conc. sulphuric acid added and heated at 145-155ºC for 30 minutes. After cooling, the digested material was transferred to a 100 ml conical flask and 0.3 ml of indicator solution was added. The digest was titrated with a ferrous ammonium sulphate solution. The end was realized when the colour changed from greenish to brown. Then the titre reading was recorded to estimate the organic carbon.

Determination of Carbon Content in Various Biomass Components

To estimate the above-ground biomass of SLF and SDT, the global allometric equation of Chave *et al.* (2014) was used since it has been used to derive above-ground biomass with high accuracy in many studies within the tropics (Pellikka *et al*., 2018 ; Walker *et al*., 2016 ; Leley *et al*., 2022). The total AGB for all the trees in each plot was summed up and converted to per ha basis (Pellikka *et al*., 2018). The tree basic density for each tree encountered during the assessment was mined from the world database as described by Chave *et al*. (2014). The volume of standing stumps and CWD was calculated using Equation 3. Then the volume was converted to biomass by multiplying with a wood density of similar tree species within the montane forests of Kenya (Equations 4 and 5) (KFS, 2016). For all the biomass components, carbon stock was calculated by multiplying the amount of biomass with a carbon content of 0.47 (KFS, 2016). However, the Total Organic Carbon (TOC) in the soils, was calculated from the product of the average bulk density, the soil organic carbon content derived from the laboratory analysis, and the soil depth using equation 6 (Pearson *et al*., 2005)

Equation 3

$$V_{CWD} = (\pi * (d_1/2)^2 + \pi * (d_2/2)^2)/2 * l$$

Where V= volume; $d_{1=}$ large end diameter; d_2=small end diameter; l= length

Biomass of CWD was calculated using below equations (adopted form; KFS, 2016)

Equation 4

$$B_{CWD=} WD * V \qquad \text{Solid wood}$$

Equation 5

$$B_{CWD}= 0.5* WD * V \qquad \text{Burned wood}$$

Where WD is wood density was generalized as 0.6 (KFS, 2016)

Equation 6

$$SC = BD \times D \times C \times 100$$

Whereby SC = soil carbon content (ton ha-1), BD = bulk density (gm^3), D = depth of soil sample collection (30 cm) and C = % carbon content estimated in the laboratory.

Before conducting statistical analysis, all data were standardized to per hectare values then conducted normality test using the Kolmogorov–Smirnov test (Li et al., 2015). We tested for significant differences in carbon values between burnt and unburnt areas using a paired t-test (X. Hu *et al*., 2015). However, for testing significant differences along fire severities one way ANOVA was used (Ribeiro-kumara *et al*., 2020). Descriptive statistics was also used to evaluate various variables of biomass components. All statistical analysis was done with the Minitab Software (Michael, 2022)

Results

Impacts of Wildfires on Carbon Stock

A comparison of biomass combusted by wildfires varied considerably among the carbon pools (Table 1). Except for stump and standing dead trees, all carbon pools were significantly different (t-test, $p<0.05$). The amount of carbon measured in CWD was highly significant with a considerable increase within the burnt areas. However, although there was an increase in the amount of stump carbon stock within the burnt areas it was not significant (t-test, $p >0.05$). Within the standing live trees, the amount of carbon (79.4±21.1-ton C ha^{-1}) decreased by more than half (28±7.7 ton Cha^{-1}) in unburnt and burnt areas, respectively Irrespective of the changes within burnt and unburnt areas, over 90% of carbon is held in standing live trees and soils (Table 1). Further, Figure 2 shows the dynamics of soil carbon stocks within various sites. The comparison of burnt and unburnt sites indicated Kamuri, Kahuho and Muridjo within Ndaragwa forest station experienced more than a 50% reduction of the SOC with Mikaro having minimal changes (Figure 2).

Table 1: Carbon stock within burnt and unburnt areas within Aberdare Forest ranges

Biomass component	**Burnt area**		**Unburnt area**		***p***
	Mean tons C ha^{-1}	SE	Mean tons C ha^{-1}	SE	
Standing living trees	28.00	7.70	79.40	21.12	0.004*
Standing Dead Trees	1.13	0.80	0.88	0.66	0.881
Coarse Wood Debris	8.90	6.20	0.25	0.26	0.000*
Stump	0.65	0.45	0.57	0.57	0.100
Litter	0.02	0.01	0.83	0.16	0.001*
Fine Wood Debris	0.06	0.06	1.37	0.11	0.01*
Herbs/shrubs	0.02	0.01	0.14	0.02	0.000*
Soil organic carbon	7.71	0.58	13.97	1.24	0.002*

* $p<0.05$

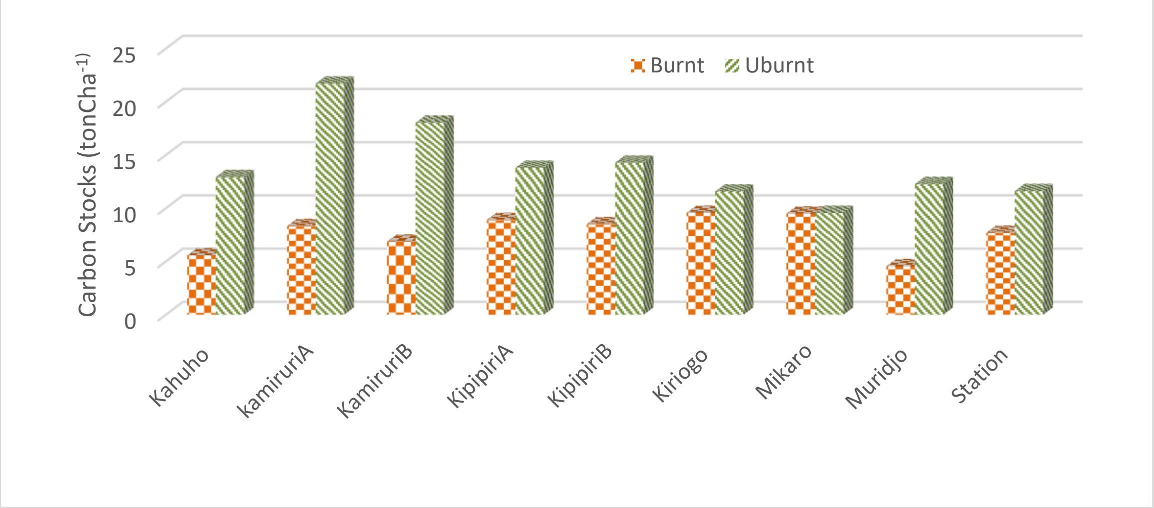
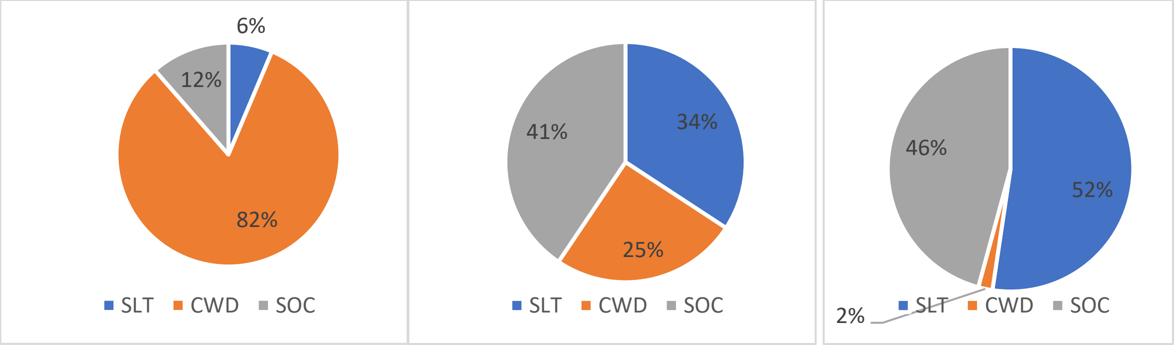


Figure 2: Distribution of soil carbon stocks within study sites of Aberdare ranges.

Distribution of Major Carbon Pools along Wildfire Severity

Among the carbon pools evaluated in this study (Table 1), only SLT, CWD and SOC had significant amounts of carbon which was considered for further analysis on redistribution along wildfire severity. Our findings indicated that CWD increased with increasing wildfire severity while SLT and SOC decreased with increasing severity (Figure 3). This indicates an enormous shift of carbon from SLT to CWD. Within the low-severity fires, the Soils had higher carbon stock compared to other pools under study. Further, all the carbon pools had over 25% of the stock within the low-severity fires (Figure 3)



High Severity Low Severity Unburnt

Figure 3: Redistribution of carbon after wildfires among standing live biomass, soil organic matter and coarse wood debris.

Distribution of Carbon Stock in Standing Live Trees (SLT) Within Various Sizes along Wildfire Severity Classes

Our findings indicated that the large diameter trees (over 30cm DBH) contained more proportion of carbon stock in high severity areas. The high contribution of carbon was further shown by a high mean DBH of 14.6±1.1 cm within high-severity areas which plays a critical role in the overall carbon estimation (Table 2). In contrast, most of the carbon was quantified in the young small-sized trees within the unburnt forests

(Figure 4). Within the low severity areas, trees of diameter ranges of 10-30 cm, 30-40cm and above 50 cm contained similar proportions of carbon stock.

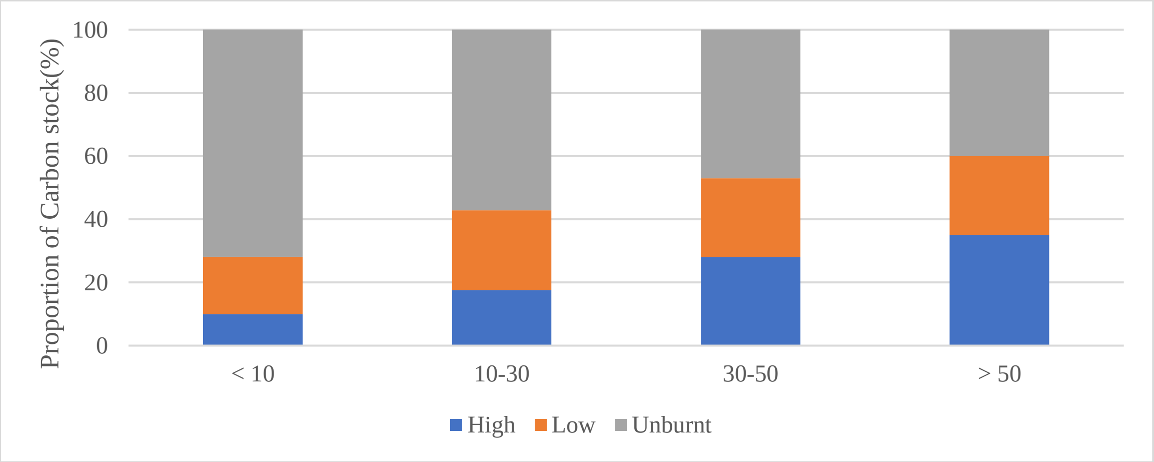


Figure 4: Distribution of carbon stock in various live tree sizes along severity classes

Table 2: Characteristics of standing live trees along wildfire severity classes

Severity	N	Density (trees ha^{-1})	Mean DBH (cm)	Mean Height (m)
High	12	272	14.6 ± 1.1	7.4 ± 0.3
Low	9	314	13.6 ± 0.7	7.8 ± 0.4
Unburnt	14	762	11.2 ± 0.5	8.9 ± 0.2

*$p<0.05$ n.s. *

N-number of plots: DBH- Diameter at Breast Height measured at 1.3 m from the ground.

Discussions

With a diverse contrast of carbon stock within burnt and unburnt areas among most carbon pools (Table 1), it is evident wildfires play a critical role in carbon dynamics within Afromontane Forest ecosystems. The total carbon stock changed from 96.4 tons C ha^{-1} to 46.6 tons C ha^{-1} due to wildfires and most of the biomass component changes were significant ($p<0.05$). This high conversion can be attributed to high number of old trees and young small trees which felled after high fire severity coupled with strong winds characterised in Aberdare ranges especially before the onset of long rains in the months of March and early April (KWS, 2010). The amount of above ground carbon estimated from burnt areas (82.4 tons ha^{-1}) concurs with the national estimate which ranges from 8.6 tons ha^{-1} in open forest, 27.4 tons ha^{-1} in moderate forest and 115 tons ha^{-1} in dense montane forests (Ministry of Environment and Forestry, 2019). Most of the wildfires occur in transition zones between dense and moderately disturbed areas mainly near open grazing glades where the tree density is relatively moderate. This is further exemplified by the studies of Kinyanjui *et al.* (2014) within the Mau montane complex forest which indicated a significant reduction of carbon stock within the dense forest from 132 ton ha^{-1} to an average of 18 tons ha^{-1} measured in disturbed areas due to drivers of degradation including logging and wildfires. To enhance the carbon stock within degraded areas a study by Edwards *et al*. (2010) recommends restoration through forest-based carbon mitigation REDD+

strategies such as using indigenous trees which will also enhance biodiversity status within montane forests. The negotiation of carbon offset schemes can be greatly improved if the impact of wildfires is considered especially in REDD+ projects due to the role wildfires play in disrupting long-term carbon storage within reforestation and natural regeneration programmes (Barlow *et al*., 2012). Our findings will support the improvement of the SLEEK program which has been having challenges due to a lack of locally based data as highlighted by the national assessment report (Kenya Forest Service, 2021) on forest disturbance which is a key driver for carbon dynamics.

Although our results indicated a decline in soil organic carbon within burnt areas (Table 1) and even along fire severity (Figure 3), there are contrasting findings in various studies. With some showing an increase of SOC (Varela *et al*., 2015; Cheng *et al*., 2023) while others indicated a decrease to concur with our findings (Moya et al., 2019). Within the alpine moorlands of Kenya and *Pinus pinuster* plantation in Spain studies by Downing *et al*. (2017) and Fernández-García *et al*. (2019), respectively have showed no change in SOC after wildfires. In concurrence with our study, the reduction of SOC can be attributed to the complete combustion of soil organic matter and increased rates of carbon mineralization resulting in high PH as the carbon is turned into ash, especially within the high-severity areas (Carrión-Paladines *et al*., 2023). The studies reporting increased SOC can be due to pyrogenic carbon arising from incomplete combustion of organic matter and also the decomposition of partially burnt biomass. Studies by Hu *et al*. (2020) indicated that after wildfires the resultant black carbon is highly resistant to microbial activities and consequently the amount of carbon will be high after wildfires. Irrespective of the soil property changes due to wildfires, the amount of carbon held in the soils will have a profound impact on the vegetation which will grow and survive and consequently the carbon stock within the wildfire-prone forest ecosystems.

The degree of redistribution of carbon pools to various biomass components after wildfires is highly influenced by fire severities, disturbance history, the type, age and growing habit of vegetation (van Bellen *et al*., 2010; Van Leeuwen *et al*., 2014). Our findings have shown that although the highest carbon stocks were recorded in SLT, this was redistributed to dead stock in either SDT or CWD pools while others shifted to decomposing stocks under high-severity fires. This can be attributed to the fuel load consumption of small-sized trees, and fallen branches which were recorded as CWD. Further, the presence of stumps could indicate that some trees have fallen after severe fires or were cut probably to assist in fire suppression or creating fire breaks within thick forests. Stumps have been noted to propagate wildfires especially where there is minimal undergrowth and can sustain fires for many days due to difficulties in suppression since they contain massive biomass just below the ground (Yang *et al*., 2021; North & Hurteau, 2011) In Kenya, most of the forest station-based management plans are normally prepared for the plantation forests and do the government agents focus on the natural forests hence wildfires within natural forest spreads fast as compared to plantation forest where silvicultural operations mainly adhere. However, over the last 5 years, the government imposed a moratorium on logging of forest products (Kagombe *et al*., 2021) and this affected the plantation forest operations such as thinning and pruning regimes. Consequently, this has increased the fuel load and enhanced the wildfire risk. The size and density of SLT (Figure 4) have a major role in ignition and propagation of fire hence unmanaged plantations have been a threat to highly susceptible natural forests. This poses a threat to the carbon stock held by various biomass components as demonstrated by this study (Table 1) and also by studies of Pawar *et al*. (2014) in the dry tropics of India. The findings of this study suggest the inclusion of wildfire assessment attributes within the national forest inventory framework to assist in accounting for losses due to disturbances.

Conclusions and Recommendations

We used ground-based concentric plots robust carbon assessment methods and statistical analysis to estimate the impacts of wildfires on carbon stock and the redistribution of biomass components after wildfires. We used a case study of Aberdare ranges to represent East African afromontane ranges which are biodiversity hotspots but highly threatened by wildfires. Nine sites within the project area which experienced wildfire in the year 2022 were mapped and used for this study. The carbon pools measured in this study included Standing Live Trees (SLT), Standing Dead Trees (SDT), Stumps, Coarse Wood Debris (CWD), Fine Wood Debris (FWD), Forest floor herbs/shrubs, Litter and Soil Organic Carbon (SOC). Our results indicated that all carbon pools are affected by wildfires but with different magnitudes. Most of the affected carbon pools is the forest floor materials due to their vulnerability to wildfires. Although the SLT carbon pool is also affected, most of it is redistributed to other biomass components mostly SDT and CWD. Carbon redistribution after wildfires is an important input parameter for forest carbon cycling models and during estimation of forest carbon budgets within forests having anthropogenic disturbances. However, this is a complex interaction process among various carbon pools which requires detailed modelling to quantify how much and for how long is transferred within different environmental conditions. However, our findings have advanced the current knowledge but cannot be enough considering the extent and dynamics of vegetation types. Hence, this is still an active area of research which may require to be explored in future. To improve the reliability of global carbon emissions from wildfires, ground truthing using the methods discussed in this paper is highly recommended.

Data Availability

The data that supports the findings of this study can be made available through the management of Kenya Forestry Research Institute who can be contacted at director@kefri.org or directly through the corresponding author

Conflicts of Interest

All authors declare that they have no conflicts of interest. The Government of Kenya who funded this research has no involvement in study design, data collection, analysis, preparation of manuscript and even the decision to publish the findings.

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References

Barlow, J., Parry, L., Gardner, T. A., Ferreira, J., Aragão, L. E. O. C., Carmenta, R., Berenguer, E., Vieira, I. C. G., Souza, C., & Cochrane, M. A. (2012). The critical importance of considering fire in REDD+ programs. *Biological Conservation*, *154*, 1–8. https://doi.org/10.1016/J.BIOCON.2012.03.034

Carrión-Paladines, V., Fries, A., Hinojosa, M. B., Oña, A., Álvarez, L. J., Benítez, Á., Rodríguez, F. L., & García-Ruiz, R. (2023). Effects of Low-Severity Fire on Soil Physico-Chemical Properties in an Andean Páramo in Southern Ecuador. *Fire*, *6*(12), 1–20. https://doi.org/10.3390/fire6120447

Chave, J., Réjou-Méchain, M., Búrquez, A., Chidumayo, E., Colgan, M. S., Delitti, W. B. C., Duque, A., Eid, T., Fearnside, P. M., Goodman, R. C., Henry, M., Martínez-Yrízar, A., Mugasha, W. A., Muller-Landau, H. C., Mencuccini, M., Nelson, B. W., Ngomanda, A., Nogueira, E. M., Ortiz-Malavassi, E., … Vieilledent, G. (2014). Improved allometric models to estimate the aboveground biomass of tropical trees. *Global Change Biology*, *20*(10), 3177–3190. https://doi.org/10.1111/gcb.12629

Cheng, Y., Luo, P., Yang, H., Li, H., Luo, C., Jia, H., & Huang, Y. (2023). Fire effects on soil carbon cycling pools in forest ecosystems: A global meta-analysis. *Science of the Total Environment*, *895*, 165001. https://doi.org/10.1016/j.scitotenv.2023.165001

Chowdhury, E. H., & Hassan, Q. K. (2015). Development of a new daily-scale forest fire danger forecasting system using remote sensing data. *Remote Sensing*, *7*(3), 2431–2448. https://doi.org/10.3390/rs70302431

Downing, T. A., Imo, M., Kimanzi, J., & Otinga, A. N. (2017). Effects of wildland fire on the tropical alpine moorlands of Mount Kenya. *Catena*, *149*, 300–308. https://doi.org/10.1016/j.catena.2016.10.003

Edwards, D. P., Fisher, B., & Boyd, E. (2010). Protecting degraded rainforests : enhancement of forest carbon stocks under REDD +. *Conservation Letters 3* (5), 313–316. https://doi.org/10.1111/j.1755-263X.2010.00143.x

Fairman, T. A., Nitschke, C. R., & Bennett, L. T. (2022). Carbon stocks and stability are diminished by short-interval wildfires in fire-tolerant eucalypt forests. *Forest Ecology and Management*, *505*, 119919. https://doi.org/10.1016/J.FORECO.2021.119919

Fernández-García, V., Marcos, E., Fernández-Guisuraga, J. M., Taboada, A., Suárez-Seoane, S., & Calvo, L. (2019). Impact of burn severity on soil properties in a Pinus pinaster ecosystem immediately after fire. *International Journal of Wildland Fire*, *28*(5), 354–364. https://doi.org/10.1071/WF18103

Filicetti, A. T., Lapointe, R. A., & Nielsen, S. E. (2021). Effects of fire severity and woody debris on tree regeneration for exploratory well pads in jack pine (Pinus banksiana) forests. *Forests*, *12*(10). https://doi.org/10.3390/f12101330

GoK. (2020). *Draft National Forest Policy*, Government of Kenya

Hu, M., Song, J., Li, S., Li, Z., Hao, Y., Di, M., & Wan, S. (2020). Understanding the effects of fire and nitrogen addition on soil respiration of a field study by combining observations with a meta-analysis.

Agricultural and Forest Meteorology, *292–293*, 108106. https://doi.org/10.1016/J.AGRFORMET.2020.108106

Hu, X., Zhu, J., Wang, C., Zheng, T., Wu, Q., Yao, H., & Fang, J. (2015). Impacts of fire severity and post-fire reforestation on carbon pools in boreal larch forests in Northeast China. *Journal of Plant Ecology*, *9*(1), 1–9. https://doi.org/10.1093/jpe/rtv036

Kagombe, J., Kiprop, J., Langat, D., Cheboiwo, J., Wekesa, L., Ongugo, P., Mbuvi, M. T., & Leley, N. (2021). *Socio-economic Impact of Forest Harvesting Moratorium in Kenya*. Kenya Forestry Research Institute.

Keith, H., Lindenmayer, D. B., MacKey, B. G., Blair, D., Carter, L., McBurney, L., Okada, S., & Konishi-Nagano, T. (2014). Accounting for biomass carbon stock change due to wildfire in temperate forest landscapes in Australia. *PLoS ONE*, *9*(9). https://doi.org/10.1371/journal.pone.0107126

Kenya Forest Service. (2010). *Aberdare forest reserve managment plan*. Kenya Forest Service http://www.kenyaforestservice.org/documents/Aberdare.pdf

Kenya Forest Service. (2021). *National forest resources assessment report 2021*, Kenya Forest Service

KFS. (2016). *Improving Capacity in Forest Resources Assessment in Kenya (IC-FRA):Field Manual for Biophysical Forest Resources Assessment in Kenya*. Kenya Forest Service

Kigomo, J. N., Kimani, S. M., & Mucheke, W. (2015). *Mapping forest fires under changing land use and climate variability in Aberdare ecosystem.* Kenya Forestry Research Institute

Kinyanjui, M. J., Kigomo, N. J., Wambui, K. M., Kariuki, N. J., Charles, N., Macharia, N. J., Odidi, O. W., Fredrick, A., Omamo, O. A., & Katumbi, N. M. (2015). Comparing Tree Heights among Montane Forest Blocks of Kenya Using LiDAR Data from GLAS. *Open Journal of Forestry*, *05*(01), 80–89. https://doi.org/10.4236/ojf.2015.51009

Kinyanjui, M. J., Latva-käyrä, P., & Bhuwneshwar, P. S. (2014). An Inventory of the Above Ground Biomass in the Mau Forest Ecosystem , Kenya. *Open Journal of Ecology*, *4*(10), 619-627. https://doi.org/10.4236/oje.2014.410052

Kipkoech, S., Melly, D. K., Mwema, B. W., Mwachala, G., Musili, P. M., Hu, G., & Wang, Q. (2019). Conservation priorities and distribution patterns of vascular plant species along environmental gradients in Aberdare ranges forest. *PhytoKeys*, *131*, 91–113. https://doi.org/10.3897/phytokeys.131.38124

KWS. (2010). *Aberdare ecosystem Management Plan , 2010-2020*. Kenya Wildlife Service

Lambrechts, C., Woodley, B., Church, C., & Gachanja, M. (2003). *Aerial Survey of the Destruction of the Aberdare Range Forests*. UNEP http://www.unep.org/dewa/Portals/67/pdf/Aber_final_report.pdf

Leley, N. C., Langat, D. K., Kisiwa, A. K., Maina, G. M., & Muga, M. O. (2022). Total Carbon Stock and Potential Carbon Sequestration Economic Value of Mukogodo Forest-Landscape Ecosystem in Drylands of Northern Kenya. *Open Journal of Forestry*, *12*(01), 19–40. https://doi.org/10.4236/ojf.2022.121002

Li, S., Su, J., Liu, W., Lang, X., Huang, X., Jia, C., Zhang, Z., & Tong, Q. (2015). Changes in biomass carbon and soil organic carbon stocks following the conversion from a secondary coniferous forest to a pine plantation. *PLoS ONE*, *10*(9), 1–14. https://doi.org/10.1371/journal.pone.0135946

Liu, J., Maeda, E. E., Wang, D., & Heiskanen, J. (2021). Sensitivity of spectral indices on burned area detection using landsat time series in savannas of southern Burkina Faso. *Remote Sensing*, *13*(13), 1–12. https://doi.org/10.3390/rs13132492

Llorens, R., Sobrino, J. A., Fernández, C., Fernández-Alonso, J. M., & Vega, J. A. (2021). A methodology to estimate forest fires burned areas and burn severity degrees using Sentinel-2 data. Application to the October 2017 fires in the Iberian Peninsula. *International Journal of Applied Earth Observation and Geoinformation*, *95*,102243. https://doi.org/10.1016/j.jag.2020.102243

Mallinis, G., Mitsopoulos, I., & Chrysafi, I. (2018). Evaluating and comparing sentinel 2A and landsat-8 operational land imager (OLI) spectral indices for estimating fire severity in a mediterranean pine ecosystem of Greece. *GIScience and Remote Sensing*, *55*(1), 1–18. https://doi.org/10.1080/15481603.2017.1354803

Michael, E. (2022). *MINITAB Manual,* University of Toronto

Ministry of Environment and Forestry. (2019). *Republic of Kenya The National Forest Reference Level for REDD + Implementation*. Republic of Kenya.

Moya, D., González-De Vega, S., Lozano, E., García-Orenes, F., Mataix-Solera, J., Lucas-Borja, M. E., & de las Heras, J. (2019). The burn severity and plant recovery relationship affect the biological and chemical soil properties of Pinus halepensis Mill. stands in the short and mid-terms after wildfire. *Journal of Environmental Management*, *235*, 250–256. https://doi.org/10.1016/J.JENVMAN.2019.01.029

Nezhadgholam-Zardroodi, M., Pourbabaei, H., Ghodskhah-Daryaei, M., Salehi, A., Enayati-Charvadeh, S., & Eslamdoust, J. (2022). Vegetation dynamics and soil properties followinglow-intensity wildfire in loblolly pine (Pinus taeda L.) planted forest in Northern Iran. *Journal of Forest Science*, *68*(4), 145–155. https://doi.org/10.17221/16/2022-JFS

North, M. P., & Hurteau, M. D. (2011). High-severity wildfire effects on carbon stocks and emissions in fuels treated and untreated forest. *Forest Ecology and Management*, *261*(6), 1115–1120. https://doi.org/10.1016/j.foreco.2010.12.039

Okalebo, J.R., Gathua, K.W., Woomer, P. L. (2002). *Laboratory Methods of Soil and Plant Analysis: A Working Manual. 2nd edition.* TSBF-CIAT and SACRED Africa.

Pawar, G. V., Singh, L., Jhariya, M. K., & Sahu, K. P. (2014). Effect of anthropogenic disturbances on biomass and carbon storage potential of a dry tropical forest in India. *Journal of Applied and Natural Science*, *6*(2), 383–392. https://doi.org/10.31018/jans.v6i2.432

Pearson, T.R.H., Walker, S., Brown, S. (2005). Sourcebook for land use, land-use change and forestry projects. Report from BioCF and Winrock International. http://www.winrock.org/ecosystems/tools.asp?BU=9086 World Bank, Washington DC.

Pellikka, P. K. E., Heikinheimo, V., Hietanen, J., Schäfer, E., Siljander, M., & Heiskanen, J. (2018). Impact of land cover change on aboveground carbon stocks in Afromontane landscape in Kenya. *Applied Geography*, *94*(March), 178–189. https://doi.org/10.1016/j.apgeog.2018.03.017

Prosperi, P., Bloise, M., Tubiello, F. N., Conchedda, G., Rossi, S., Boschetti, L., Salvatore, M., & Bernoux, M. (2020). New estimates of greenhouse gas emissions from biomass burning and peat fires using MODIS Collection 6 burned areas. *Climatic Change*, *161*(3), 415–432. https://doi.org/10.1007/s10584-020-02654-0

Ribeiro-kumara, C., Pumpanen, J., Heinonsalo, J., Metslaid, M., & Orumaa, A. (2020). Science of the Total Environment Long-term effects of forest fi res on soil greenhouse gas emissions and extracellular enzyme activities in a hemiboreal forest. *Science of the Total Environment*, *718*, 135291. https://doi.org/10.1016/j.scitotenv.2019.135291

Saranya, K. R. L., Reddy, C. S., & Rao, P. V. V. P. (2016). Estimating carbon emissions from forest fires over a decade in Similipal Biosphere Reserve, India. *Remote Sensing Applications: Society and Environment*, *4*(June), 61–67. https://doi.org/10.1016/j.rsase.2016.06.001

Sibanda, C., Hussin, Y. A., Weir, M., & Gilani, H. (2011). Modelling forest fire behaviour and mapping carbon emission in the Ludikhola watershed, Gorkha district, Nepal. *32nd Asian Conference on Remote Sensing 2011*, *ACRS 2011*, *2*, 881–886.

Stenzel, J. E., Bartowitz, K. J., Hartman, M. D., Lutz, J. A., Kolden, C. A., Smith, A. M. S., Law, B. E., Swanson, M. E., Larson, A. J., Parton, W. J., & Hudiburg, T. W. (2019). Fixing a snag in carbon emissions estimates from wildfires. *Global Change Biology*, *25*(11), 3985–3994. https://doi.org/10.1111/gcb.14716

van Bellen, S., Garneau, M., & Bergeron, Y. (2010). Impact of climate change on forest fire severity and consequences for carbon stocks in boreal forest stands of Quebec, Canada: A synthesis. *Fire Ecology*, *6*(3), 16–44. https://doi.org/10.4996/fireecology.0603016

Van Leeuwen, T. T., Van Der Werf, G. R., Hoffmann, A. A., Detmers, R. G., Rücker, G., French, N. H. F., Archibald, S., Carvalho, J. A., Cook, G. D., De Groot, W. J., Hély, C., Kasischke, E. S., Kloster, S., McCarty, J. L., Pettinari, M. L., Savadogo, P., Alvarado, E. C., Boschetti, L., Manuri, S., … Trollope, W. S. W. (2014). Biomass burning fuel consumption rates: A field measurement database. *Biogeosciences*, *11*(24), 7305–7329. https://doi.org/10.5194/bg-11-7305-2014

Varela, M. E., Benito, E., & Keizer, J. J. (2015). Influence of wildfire severity on soil physical degradation in two pine forest stands of NW Spain. *CATENA*, *133*, 342–348. https://doi.org/10.1016/J.CATENA.2015.06.004

Walker, S. M., Murray, L., & Tepe, T. (2016). *Allometric equation evaluation guidance document*; Winrock International: North Little Rock, AR, USA.

Watson, C. (2009). *Forest carbon accounting: overview and principles*. Capacity Development in Eastern and Southern Africa, UNDP, UNEP. http://www.cabdirect.org/abstracts/20103082947.html

Weiss, M., & Baret, F. (2016). S2ToolBox Level 2 products: LAI, FAPAR, FCOVER - Version 1.1. *Sentinel2 ToolBox Level2 Products*, 53. http://step.esa.int/docs/extra/ATBD_S2ToolBox_L2B_V1.1.pdf

Xulu, S., Mbatha, N., & Peerbhay, K. (2021). Burned area mapping over the southern cape forestry region, South Africa using sentinel data within gee cloud platform. *ISPRS International Journal of Geo-Information*, *10*(8). https://doi.org/10.3390/ijgi10080511

Yang, G., Han, D., Di, X., Sun, L., & Weng, Y. (2021). Quantifying fire severity: a brief review and recommendations for improvement. *Ecosystem Health and Sustainability*, *7*(1). https://doi.org/10.1080/20964129.2021.1973346