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Spatial distribution of above ground carbon density in Harana Forest, Ethiopia

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Abstract

Background: The need for understanding spatial distribution of forest aboveground carbon density (ACD) has increased to improve management practices of forest ecosystems. This study examined spatial distribution of the ACD in the Harana Forest. A grid sampling technique was employed and three nested circular plots were established at each point where grids intersected. Forest-related data were collected from 1122 plots while the ACD of each plot was estimated using the established allometric equation. Environmental variables in raster format were downloaded from open sources and resampled into a spatial resolution of 30 m. Descriptive statistics were computed to summarize the ACD. A Random Forest classification model in the R-software package was used to select strong predictors, and to predict the spatial distribution of ACD.

Results: The mean ACD was estimated at 131.505 ton per ha in this study area. The spatial prediction showed that the high class of the ACD was confined to eastern and southwest parts of the Harana Forest. The Moran's statistics depicted similar observations showing the higher clustering of ACD in the eastern and southern parts of the study area. The higher ACD clustering was linked with the higher species richness, species diversity, tree density, tree height, clay content, and SOC. Conversely, the lower ACD clustering in the Harana Forest was associated with higher soil cation exchange capacity, silt content, and precipitation.

Conclusions: The spatial distribution of ACD in this study area was mainly influenced by attributes of the forest stand and edaphic factors in comparison to topographic and climatic factors. Our findings could provide basis for better management and conservation of aboveground carbon storage in the Harana Forest, which may contribute to Ethiopia's strategy of reducing carbon emission.

Keywords: Aboveground carbon density, Spatial modeling, Prediction, Random Forest, Cluster, Pattern

Introduction

The global forest resources have been estimated to store about 289 Gt of carbon which is approximately 80% of the global carbon stock (FAO 2010). Specifically, the tropical forests store around 460 billion tons of carbon in the biomass and soil (Alvarez-Davila et al. 2017). In this regard, the role of forests as a terrestrial sink of atmospheric carbon dioxide has globally received great

attention (FAO 2010). A forest resource has been identified one of the United Nations climate change mitigation strategies. This has been implemented through the initiative known as emission reduction from deforestation and forest degradation including sustainable forest management (REDD+) (Solomon et al. 2018). At this junction, estimation of forest aboveground carbon density (ACD) has emerged to provide a quantitative forest information to improve forest management (Sales et al. 2007; Fu et al. 2014; Rajashekar et al. 2018; Dang et al. 2019). However, estimations of the ACD in previous studies have not provided sufficient focus on identifying the spatial distribution of ACD.

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Techniques of spatial pattern analysis entail examining how biophysical factors can influence spatial distribution pattern of ACD (Ozcelik et al. 2008; Day et al. 2013; Sun et al. 2020). Spatial patterns of objects can be analyzed using Random Forest model and GIS techniques. Random Forest modeling techniques have been applied in many disciplines (Vincenzia 2011). The Random Forest is efficient in handling complex and nonlinear ecological interactions and provides a better accuracy (Cutler et al. 2007; Vincenzia 2011). The Moran's *I* statistics in ArcGIS helps to identify types of spatial clustering based on the theory of autocorrelation. The theory of autocorrelation states closer objects tends to show similarity but the similarity decreases as a distance increases between neighboring objects (Fu et al. 2014). The underlying causes of the spatial patterns could be further analyzed using Pearson correlation (Sánchez-Martín et al. 2020). The spatial distribution modeling of the ACD in this study is conceptualized to comprise producing the spatial prediction map, analysis of the spatial pattern of the ACD including exploring relationship between ACD and each predicting variable.

In Ethiopia, several studies have been conducted to estimate ACD of forests at different places (Asante et al. 2013; Yohannes et al. 2015; Getaneh et al. 2019). However, those studies have not provided sufficient information on how and what factors influence the spatial distribution of the ACD in forest ecosystems. The purpose of this study is to address three specific objectives: (i) to investigate spatial variation of ACD in the Harana Forest; (ii) to identify important predictor variables which influence the spatial distribution of ACD, and (iii) to examine a relationship between ACD and each biophysical predictor.

Materials and methods

The study area

Harana Forest is located between latitude 6° 14' 40" N and 6° 38' 30" N and longitude 39° 22' 10" E and 39° 27' 50" E (Fig. 1). Administratively, the Harana Forest is situated in northern parts of Delo Mena and Harana Buluk Districts in the Oromia National Regional State in south-east of Ethiopia. The northern and north-eastern parts of the Harana Forest lay inside the Bale Mountains National Park (BMNP).

The total study area covers 107,298.673 ha, with dimensions of 75 km from west to east and 115 km in the south–north direction. The rainfall follows a bimodal pattern, in which the first season starts in April and extends to June. The second rain season begins in the middle of September and lasts around the beginning of November. Annual temperature in the area ranges from 14 to 22 °C, while the mean annual temperature is 18 °C

(Ayele et al. 2019). Elevation ranges from 1270 to 3030 m a.s.l with an increasing pattern from south to north and decreasing from west to east. The annual rainfall ranges from 765 to 1110 mm year⁻¹. *Rendzic Leptosols* occupies 63% of the study area, *Chromic Luvisols* 35%, whereas other soil types accounted for only 2% (FAO 2009). The dominant tree species in the Harana Forest include *Podocarpus falcatus*, *Warburgia ugandensis*, *Celtis africana*, *Syzygium guineense*, *Olea capensis*, *Diospyros abyssinica* and *Filicium decipiens* (Ayele et al. 2019; Kewessa et al. 2019).

Sampling methods and data collection

The Harana Forest area is divided into different forest compartments for ease management practices of participatory forest management approach. A systematic random sampling technique was established by dividing each forest compartment into square grids of 1 km by 1 km distance from south–north and east–west using ArcGIS v10.4. During field data collection, sampling locations were identified at the place where grid lines intersect each other. The GPS coordinates at intersection points were marked using the handheld GPS receivers to identify each location at a time of field data collection. From the center of each location, three nested circular quadrats were laid with radii of 15, 5, and 2 m using a measuring tape, ropes, and ribbons.

A circular plot was chosen because the circular plot can be less vulnerable to errors due to incorrect omission or inclusion of trees around the plot boundary (UNFCCC 2015). In this study, within the circular plot of 15 m radius, the diameter was measured for all trees ≥ 5 cm at 1.3 m from the bottom of a tree using diameter tape. The height of trees was measured using a digital hypsometer. Saplings with a diameter of 1–5 cm counted within the circular plot of 5 m radius and seedlings below 1 cm root collar were counted within the circle of 2 m radius. The vernacular and botanical names of each tree species were recorded.

Biophysical variables

Identification of possible predictor variables was conducted based on an extensive review of relevant literature. The literature describes plant biomass and ACD could be mainly influenced by elevation, slope, aspect, soil texture, temperature, and precipitation (Merganić et al. 2012; Vayreda et al. 2012; Fibich et al. 2016; Sahragard et al. 2018; Hofhans et al. 2020). The ACD can be additionally influenced by biotic factors such as tree species richness and diversity including natural and human disturbances (Vayreda et al. 2012).

A total of 38 environmental variables in this study were collected from various data sources as shown in

Table 1. Temperature and precipitation variables (19 variables) were downloaded from the Bioclim data portal. Elevation data (SRTM Digital Elevation Model (DEM)) with 30 resolutions were downloaded from USGS data portal, whereas slope and aspect were derived from DEM using appropriate tools in ArcGIS

v10.4. Soil physical and chemical characteristics were downloaded from the open-access soil grid database of the International Soil Reference and Information Centre (ISRIC). The soil data in this study include physical and chemical properties at depths of 0, 5, 15, 30, 60, 100, and 200 cm. The raster layer of each

Table 1 List of biophysical variables used to predict the spatial distribution of ACD

Variables	Short name	Resolution	Data sources
Temperature (°C)	Temperature	10 arc-minute	Bioclim. www.org
Precipitation (mm)	Precipitation	10 arc-minute	Bioclim. www.org
Elevation (DEM) (m)	Elevation	30 m	http://earthexplorer.usgs.gov
Slope (%)	Slope	30 m	Derived from DEM
Aspect	Aspect	30 m	Derived from DEM
Clay content at 0 cm (%)	Clay0	250 m	https://soilgrids.org/SoilGrids
Clay content at 5 cm (%)	Clay5	250 m	https://soilgrids.org/SoilGrids
Clay content at 15 cm (%)	Clay15	250 m	https://soilgrids.org/SoilGrids
Silt content at 0 cm depth (%)	Silt0	250 m	https://soilgrids.org/SoilGrids
Silt content at 5 cm depth (%)	Silt5	250 m	https://soilgrids.org/SoilGrids
Soil organic content at 0 cm depth (%)	SOC0	250 m	https://soilgrids.org/SoilGrids
Soil organic content at 5 cm depth (%)	SOC5	250 m	https://soilgrids.org/SoilGrids
Soil cation exchange capacity at 0 cm depth (%)	CEC0	250 m	https://soilgrids.org/SoilGrids
Cation exchange capacity at 5 cm depth (%)	CEC5	250 m	https://soilgrids.org/SoilGrids
Cation exchange capacity at 15 cm depth (%)	CEC15	250 m	https://soilgrids.org/SoilGrids
Species richness	SR	Count	Forest inventory data
Shannon index	<i>H</i>	30 m	Forest inventory data
<i>Podocarpus falcatus</i>	<i>P. falcatus</i>	30 m	Forest inventory data
<i>Szgium guinesses</i>	<i>S. guinesses</i>	30 m	Forest inventory data
<i>Olea capensis</i>	<i>O. capensis</i>	30 m	Forest inventory data
<i>Filicium decipiens</i>	<i>F. decipiens</i>	30 m	Forest inventory data

environmental variable was resampled to 30 m resolution and extracted using the polygon of the study area. The dataset was projected to the common project coordinate system (UTM zone 37 N, WSG 84 datum, linear unit of meter).

Concerning human interference, it is reported that the Harana Forest is entirely and uniformly used by communities for livestock grazing, coffee management, and beekeeping (Ayele et al. 2019; Kewessa et al. 2019). These uniform human interferences assumed that could not show a significant difference in the overall pattern of ACD and were not included in the prediction model. However, the qualitative description was provided based on the observed human interferences at the plot level.

Species richness in this study refers to a count of woody species, whereas the species diversity index was estimated at plot level using Shannon diversity index (Eq. 1). This equation is widely employed by different authors (Ozcelik et al. 2008; Kent 2012; Fekadu et al. 2013). Regarding biotic factors, Shannon diversity index was used to estimate the biodiversity index of woody species using Eq. 1. A value of Shannon index ranges between 1.5 and 4.5. The increasing index shows the presence of high biodiversity (Gaines et al. 1999; Merganič et al. 2012).

$$\text{Diversity } H = - \sum_{i=1}^S P_i \ln P_i, \quad (1)$$

where S is the number of species, P_i is the proportion of individuals or the abundance of the i th species, and $\ln$, the log base e .

Data analysis techniques

Estimation of ACD

A count of each species for saplings and seedlings with radii of 2 m and 5 m were converted to a size of 15 m radius which was 0.07065 ha. This was required to make statistical computational analysis on the base of the common unit area as recommended in Zhang et al. (2019). ACD was estimated using an allometric equation (Eq. 2) that has been developed for the tropical moist forests (Chave et al. 2005). Previously, this equation was used by Asante et al. (2013) to estimate the ACD around this study area. The wood density in the equation was 0.60 which was an average of all forest species established for tropical forest (Chave et al. 2009).

The allometric equation used to estimate woody species biomass and the biomass was multiplied by 0.5 to calculate ACD with understanding that carbon content is assumed to be equivalent to half of the tree biomass

(Chave et al. 2009). The estimated ACD of each tree was finally converted from kg to ton and added at a level of each plot. ACD of each tree plant was multiplied by 3.67 to estimate the volume of carbon dioxide equivalent to understand the extent of carbon emission in case a deforestation might be happening:

$$Y = 0.65 * \exp(-1.499 + (2.148 * \ln(D)) + (0.207 * (\ln(D))^2) - (0.0281 * (\ln(D))^3)), \quad (2)$$

where Y represents aboveground biomass (kg) and D is DBH (cm).

Descriptive statistics were computed using Statistical package for the Social Sciences (SPSS) version 20.0. The mean value of ACD was used as a threshold to classify ACD into low and high classes. Each plot with ACD > the mean value of 31.27 ton was classified into the high-class, whereas the remaining were classified into the low class. This classification of ACD was done to prepare input data to predict the spatial distribution map of ACD.

Random Forest modeling and model validation

A prediction of spatial distribution of the ACD was conducted using the Random Forest package in R-software version 3.1.6. A preliminary prediction of ACD was performed using 38 rasterized variables to identify strength or importance of predictors, which was evaluated in terms of a mean decreased Gini value. A higher value indicates a strength or importance of each variable in the model (Scarnati et al. 2009). The preliminary prediction helped to identify 21 important predictors with high Gini values while 17 predictors showed lower importance values. A final spatial prediction of the ACD was conducted using 21 predictors with higher importance values. The prediction accuracy was evaluated based on out-of-bag (OOB) error. The OOB error uses to avoid overfitting of model output (Vincenzi 2011; Sahragard 2018 and Zhang et al. 2019).

The 'optimal' tuning parameters of the Random Forest model was determined by implementing the Random Search through applying Random threefold equal proportion of cross-validation which was repeated six times with a tune length of 15. The number of trees to grow per node was determined 500, and number of variables randomly split at each node was set at 10 which referred to as (mtry).

The OOB 28% was attained in this study which was the least error by changing model parameters. The Random Forest model in this study summarized values of the ACD which were correctly and incorrectly classified using a confusion matrix table. The values in the confusion

matrix were used to compute an overall accuracy of the Random Forest classification, as shown in Eq. 3:

$$\text{Overall accuracy \%} = \left[\frac{A + D}{A + B + C + D} \right] * 100 \quad (3)$$

where A =correctly classified low class of ACD; B =incorrectly classified low-class ACD; C =incorrectly classified high ACD, and D =correctly classified high classes of ACD.

Analysis of spatial cluster

Spatial clustering could be analyzed using Moran's I statistic which comprises local indicators of spatial association (LISA) and Global Moran's I (Fu et al. 2014). The Global Moran's I index helps to quantify spatial autocorrelation as whole but it fails to identify places where clustering could occur (Jacquez 2008; Fu et al. 2014). LISA describes an extent to which observations are similar or dissimilar to their neighbors (Bataineh 2006; Fu et al. 2014). The types of the spatial cluster can be described into four different distinct patterns: high cluster (HH), low cluster (LL), high-outlier (HL), and low outlier (LH). The high-clustering (HH) shows similarity of the ACD in neighboring locations, whereas LL represents a low clustering of ACD.

High-outlier indicates locations where high ACD is surrounded by low values of ACD. The low-outlier shows locations where a low ACD can be surrounded by high values of ACD (Camarero et al. 2005; Fu et al. 2014). The ACD of 1122 plots was converted to vector layer using ArcGIS v10.4 software. The vector layer was used to produce spatial cluster map of ACD using LISA statistics.

Pearson correlation and scatter plot analysis

Locations with high-high and low-low ACD were extracted using ArcGIS v10.4. The extracted values were imported to SPSS version 20.0 to conduct correlation analysis. The Pearson correlation was done between each extracted value and corresponding biophysical predictors of the same locations. This was done to investigate how those biophysical factors contributed to occurrences of high cluster areas.

A ggplot graphical analysis was conducted between the sum of ACD per plot against each predictor using the Random Forest model to identify type of relationship exists between the ACD and every biophysical predictor. This relationship was explored using the ggplot package in R-software. The relationship was shown graphically to display how a sum of ACD per plot relates with different environmental variables.

Table 2 Descriptive statistics of variables used to predict spatial distribution of the ACD

Predictors variables	Statistical values per plot			
	Mean	Std. error	Minimum	Maximum
Species richness	9.70	0.16	1.00	29.00
Shannon index (<i>H'</i>)	1.14	0.02	0.00	3.96
Elevation in m a.s.l	172.65	0.84	130	289.00
Slope in %	4.12	0.17	0.00	74.00
Temperature °C	20.36	0.09	17.00	31.00
Precipitation in mm	1000.00	2.62	765.00	1127.00
Clay0 in %	37.19	0.12	24.00	47.00
Clay5 in %	37.44	0.11	24.00	47.00
Clay15 in %	40.62	0.12	25.00	51.00
Silt0 in %	26.51	0.08	20.00	35.00
Silt5 in %	26.20	0.08	19.00	34.00
CEC0 in %	38.38	0.23	25.00	70.00
CEC5 in %	33.37	0.11	24.00	54.00
CEC15 in %	31.74	0.10	22.00	51.00
SOC0 in %	59.26	0.55	22.00	122.00
SOC5 in %	51.92	0.38	29.00	100.00

Table 3 The means and standard errors of woody species parameters per hectare

Statistical values		
Woody species parameters	Mean per ha	Std. error per ha
Biomass	263.004	8.83
ACD	131.505	4.415
CO ₂ equivalent	482.613	16.203

Results

Description of biophysical predictors

The mean values of species richness and Shannon diversity indices per plot were estimated at 9.7 and 1.14, respectively (Table 2). The mean proportion of clay content ranged from 37 to 40% while the mean soil organic content varied from 51.92% to 59.26%.

Descriptive statistics of ACD

A mean ACD in the Harana Forest was estimated at 131.505 ± 4.415 ton ha⁻¹. The forest was estimated to save an average emission of 482.613 ± 16.203 CO₂ equivalent ha⁻¹ (Table 3).

Proportion of ACD in dominant tree species

Table 4 shows 65% of a total ACD is occupied by 11 dominant forest tree species. Of those species, *Podocarpus*

Table 4 Summations of biomass and ACD of dominant tree species of all plots

Species name	Sum of parameters in ha		Contribution to a total ACD (%)
	Biomass ton	ACD ton	
<i>Podocarpus falcatus</i>	1646.61	823.31	11
<i>Syzygium guineense</i>	1593.87	796.93	11
<i>Croton macrostachyus</i>	969.47	484.74	7
<i>Vepris dainellii</i>	844.98	422.49	6
<i>Pouteria adolfriedericii</i>	831.78	415.89	6
<i>Filicium decipiens</i>	675.00	337.50	5
<i>Ocotea guineensis</i>	650.42	325.21	4
<i>Diospyros abyssinica</i>	622.72	311.36	4
<i>Celtis africana</i>	549.25	274.63	4
<i>Warburgia ugandensis</i>	536.08	268.04	4
<i>Millettia ferruginea</i>	398.69	199.35	3

falcatus and *Syzygium guineense* alone occupied 22%, with an equal proportion of 11%.

Spatial distribution pattern of ACD

A spatial prediction map of ACD with the classification technique was produced with an overall accuracy of 72%. The high class of ACD was confined in the eastern part of the study area (Fig. 2A). Correspondingly, the high-high clustering of ACD with the red color were observed in eastern and southwestern parts of the Harana Forest (Fig. 2B).

Importance of predictor variables in influencing ACD

The importance of each biophysical predictor in the Random Forest model was identified using Mean-Decreased-Gini values. The most top important variables to influence a spatial distribution of ACD were identified to include the species richness, Shannon index, *Filicium decipiens*, *Olea Capensis*, *SOC5*, *Podocarpus falcatus*, and *CEC15*. Conversely, elevation, precipitation, temperature, slope and aspect exhibited less importance with the ranks of 16th, 17th, 19th, 20th, and 21st, respectively (Table 5).

Association between ACD cluster area and biophysical variables

The species richness and species diversity in this study showed a strong positive correlation with the high-high cluster of ACD at $p < 0.01$ in Table 6. Tree height, DBH and tree density were positively correlated with the high-high clustering areas of ACD ($p < 0.01$). The clay and organic contents at various soil depths were positively correlated with the high-high clustering areas of ACD

($p < 0.01$). The silt content and CEC showed negative correlations with the high-high clustering areas of ACD ($p < 0.01$).

Ecological response of ACD to biophysical factors

The ggplot analysis in this study indicated increasing species richness and Shannon indices contributed to increasing ACD (Fig. 3A & B). The high concentration of ACD was detected between elevation ranges of 1400–2200 m a.s.l (Fig. 3C). East and west faced aspects in this study consisted 46% and 38% of a total ACD, respectively (Fig. 3G).

Discussion

Spatial distribution of ACD in Harana Forest

The mean ACD in this study area was estimated at 131.505 ton ha⁻¹. This mean value was lower than the mean value of 191.28 ton ha⁻¹, which was estimated for the moist forest of the Bale Mountains in the same study area (Asante et al. 2013). The variation in the mean ACD might be associated with a difference in sampling strategy. Asante et al. (2013) used 75 samples with a plot size of 1-ha which were randomly distributed over a total

forest area of 261,053 ha. In this study, a total of 1122 plots with a plot size of 0.07065 ha were systematically distributed across the total forest area of 107,298.673 ha. This shows our sampling intensity is 0.7%, which is more than a double of previous sampling intensity. This indicates difference in plot size and sampling intensity could lead to substantial differences in estimation of ACD. This highlights gray area where future studies need to focus on examining an efficiency of different plot sizes and sampling intensity to provide a reliable estimation of ACD.

Impacts of biotic factors on spatial distribution of ACD

Effect of plant species richness and species diversity

The species richness and species diversity in this study were identified the top predictors in shaping the spatial distribution patterns of the ACD (Table 5). Pearson correlation reiterated the positive correlation between the ACD and each of the species richness and Shannon diversity index (Table 6). Similar findings have been reported by different authors such as Vayreda et al. (2012) in case of the Spain forest; Labrière et al. (2016) in Panama forest; and Day et al. (2013) from the rain forest of the Central Africa. The positive relationships

Table 5 Strengths of a prediction power of model variables based on Gini values

Predicting variables	Designation	Gini values	Rank of strengths
Species richness	SR	46	1
Shannon index	<i>H</i>	43	2
<i>Filicium decipiens</i>	<i>F. decipiens</i>	33	3
<i>Olea capensis</i>	<i>O. capensis</i>	27	4
Soil organic content at 5 cm depth (%)	SOC5	26	5
<i>Podocarpus falcatus</i>	<i>P. falcatus</i>	26	6
Cation exchange capacity at 15 cm depth (%)	CEC15	24	7
Soil organic content at 0 cm depth (%)	SOC0	24	8
Soil cation exchange capacity at 0 cm depth (%)	CEC0	23	9
Silt content at 0 cm depth (%)	Silt0	23	10
Clay content at 5 cm (%)	Clay5	22	11
<i>Szygyium guinesses</i>	<i>S. guinesses</i>	22	12
Cation exchange capacity at 5 cm depth (%)	CEC5	22	13
Silt content at 5 cm depth (%)	Silt5	21	14
Clay content at 15 cm (%)	Clay15	21	15
Elevation	Elevation	20	16
Precipitation	Precipitation	20	17
Clay content at 0 cm (%)	Clay0	19	18
Temperature	Temperature	18	19
Slope in %	Slope in %	17	20
Aspect	Aspect	14	21

Table 6 Pearson correlation between locations of the ACD clustering and each biophysical variable

Biophysical variable	Pearson correlation	Biophysical variable	Pearson correlation
Species richness	0.625**	Silt15	−0.204**
Species diversity	0.530**	Silt30	−0.163*
DBH	0.750**	Silt60	−0.172*
Tree height	0.659**	Silt100	−0.212**
Coffee density	0.215**	Silt200	−0.207**
Tree density	0.500**	Sand200	0.180*
Elevation	−0.015	CEC0	−0.365**
Slope	0.044	CEC5	−0.442**
Temperature	0.119	CEC15	−0.466**
Precipitation	−0.180*	CEC30	−0.484**
Clay0	0.201*	CEC100	−0.432**
Clay5	0.220**	SOC0	0.164*
Clay15	0.234**	SOC5	0.490**
Silt0	−0.216**	SOC15	0.257**
Silt5	−0.204*	SOC100	0.187*

** Significant at $p < 0.01$, * significant at $p < 0.05$

between the ACD and species diversity in this study seems to support the niche complementarity hypothesis. This hypothesis states species diversity provides better opportunities for plants to utilize available

resources to accumulate more biomass (Vayreda et al. 2012; Labrière et al. 2016; Hofhansl et al. 2020).

Contrastingly, 65% of the total ACD in this study was occupied by 11 dominant tree species (Table 4). This seems to complement the mass ratio hypothesis which

Fig. 3 Relationships between ACD and each of elevation (A), slope (B), species richness (C), Shannon index (D), clay content (E), cation exchange capacity (F), aspect (G), and silt content (H)

explains a biomass accumulation associates with presence of dominant tree traits (Labrière et al. 2016; Fotis et al. 2018; Teixeira et al. 2020). Likewise, Hu et al. (2015) have reported a similar finding indicating that 89.7% of a total ACD was occupied by 10 dominant tree species in case of a subtropical forest of China. Evidence from this study area supports us to conclude that spatial distributions of ACD can be influenced by presence of dominant tree species as compared with the species richness and species diversity. In this sense, our finding appears to support the mass ratio hypothesis over the niche complementarity hypothesis.

Effect of forest structural diversity

Forest structure which comprises tree DBH, height, and stem density was identified to exert more influence on the spatial distribution of the ACD in this study area. The trees with DBH class of 10–50 cm accounted 68% of a total ACD while small trees < 10 cm DBH consisted of a large proportion of individual trees but showed a smaller contribution to a total ACD (Annex 1). Other studies have reported similar findings showing smaller trees consist of many individual trees but disproportionally contribute to the sum of an overall ACD (Vayreda et al. 2012; Hu et al. 2015; Padmakumar et al. 2018; Getaneh et al. 2019). This finding suggests trees with a big size store more ACD but it is still important to not overlook contribution of small trees in sequestration of carbon dioxide.

Average tree height in this study was positively correlated with the ACD while trees with the height classes of 20–40 m accounted 96% of a total ACD (Annex 2). This finding complements what Fotis et al. (2018) who have reported tall trees consist of a large proportion of ACD. Essentially, it seems that increase in tree height and DBH could exert more influence on spatial distribution patterns of ACD (Krankina et al. 2005; Getaneh et al. 2019).

A location with high-high clustering of ACD in this study showed strong positive correlations with tree density, DBH, and tree height, though the coffee density appeared to indicate a weak relationship with the high-high clustering areas of ACD. The negative relationship might be linked with farmers' activities of removing a forest regeneration to reduce effect of trees' competition with coffee plants. Previous studies have reported intensive coffee management practice has affected condition of a forest regeneration in the Harana Forest (Sembeta and Manfred 2006; Kewessa et al. 2019).

Impacts of abiotic factors on spatial distribution of ACD

Topographic factors

Elevation showed a weak correlation with the high clustering of ACD. This might be related with increasing of humidity and declining of the temperature at higher

elevation which directly influences plant distributions (Wang et al. 2007; Getaneh et al. 2019; Wodajo et al. 2020). Our observation is consistent with other findings which have been documented in literature (Wodajo et al. 2020 and Sun et al. 2020).

Pearson correlation indicated a weak association between the slope and the high clustering of the ACD while the ggplot graphic indicated the large proportion of ACD appeared to associate with the slope below 20% (Fig. 3D). Effect of slope on the ACD has been considerably varied in literature. For instance, a higher ACD has been reported at lower slope by Yohannes et al. (2015) in relation with a removal of soil nutrients from a steep slope which deposited at the lower slope which supports plants to store more biomass (Natake 2012; Mohammed et al. 2014; Wodajo et al. 2020). A contrasting finding has been reported to show less ACD at lower slope in Awi forest of Ethiopia in relation with illegal logging activity (Getaneh et al. 2019).

A large proportion of the ACD in this study area was associated with east and west faced aspects. The possible reason is that a longer duration of solar radiation prevails over the study area in east and west directions. Supply of solar radiation for longer period is essential for plants to facilitate effective photosynthetic process (Yohannes et al. 2015; Kobler et al. 2019). This finding seems to consistent with that of Yohannes et al. (2015) who have reported more plants association with the northeast and east-faced aspects.

Edaphic factors

The clay content from the top surface to the depth of 15 cm was found to associate with the high ACD. A suitable range of clay content appeared to range from 25% to 45% at all soil depths of 0–15 cm (Fig. 3E). The possible reason for this positive association might be linked to properties of clay which is rich of nutrients and water-holding capacity to enhance plant productivity (Natake 2012; Olorunfemi et al. 2018; Zhong 2018; Kome et al. 2019). The silt content beyond 30% in this study area appeared to less suitable for accumulation of ACD (Fig. 3H). This might be linked with poor water-holding capacity of silt which exerts unfavorable condition to plants due to moisture stress (Olorunfemi et al. 2018). The soil organic content (SOC) in this study has showed the positive correlation with the ACD. This may suggest strong contribution of the SOC in a formation of higher spatial clustering of ACD. Soil with high organic content is rich of nutrients with good water-holding capacity to support vigorous plant growth (Dölärsan et al. 2017; Olorunfemi et al. 2018). The ggplot in Fig. 3F indicates favorable CEC for plants seems to range from 25 to 45%. Conversely, the Pearson correlation showed the negative

association between CEC and ACD (Table 6). This observation seems to contradict with the opinion that CEC is a good indicator of soil fertility (Olorunfemi et al. 2018). However, a similar finding has reported to show the negative association between CEC and ACD (Poorter et al. 2015).

Climatic factors

Pearson correlation showed a positive relationship between the temperature and the ACD clustering locations. However, an extreme temperature affects plant productivity through influencing metabolic processes (Hatfield and Prueger 2015). Decreasing in temperature also leads to decline in growth of plant height and diameter, which reduces plant biomass and ACD (Alvarez-Davila et al. 2017). The annual precipitation in this study contributed to formation of a lower clustering of ACD (Table 5). Effects of precipitation on ACD might be considered indirectly as precipitation indirectly affects soil textures to influence plant distribution (Natake 2012). Moreover, higher precipitation may create excessive water to retain in capillaries of a clay soil, which may hinder availability of water and mobility of nutrients (Olorunfemi et al. 2018). Precipitation further reduces decomposition of organic matter by limiting activities of microorganisms, which play important roles in decomposing of organic matters (Taylor et al. 2017). This implies decreasing of organic matter content in the soil may lead to declining of the plant biomass and ACD.

Conclusion

Species richness, species diversity, DBH, tree height, soil properties in this study were found to show strong influences on spatial distribution of the ACD. This suggests the spatial distribution of ACD at scale of this study area can be more influenced by forest attributes and edaphic variables as compared to influences of topographic and climatic factors. Dominant tree species in this study occupied a large proportion of the ACD. In this sense, our findings support the mass ratio hypothesis which explains dominant traits accumulate more biomass. The intensive coffee management practice in the Harana Forest resulted in creating lower clustering of the ACD. The Pearson correlation showed positive correlations between locations of clustering area of ACD and each predictor variable. The ggplot illustration indicated similar positive relationship between the ACD and each variable, but relationships could be changed to negative relationship beyond certain limits. This shows that a positive relationship between two variables does not continue indefinitely due to various limiting factors. Our observation may suggest the ggplot analysis could provide better opportunity to identify how the ACD

interacts with various biophysical factors. This research has generated useful spatial explicit information which enhances understanding about dynamics of the ACD in the study area. The findings possibly support decision-makers to strengthening sustainable management of ACD in the Harana Forest which can contribute to the Ethiopia's green development strategy of reducing carbon emission from deforestation and forest degradation.

Annex 1: Sum of ACD in each diameter class of plots in the Harana Forest

Diameter class in cm	Sum of ACD in ton	%
0–10	5	1
10–20	741	0
20–30	2105	10
30–40	2110	29
40–50	1098	29
50–60	808	15
60–70	287	11
> 70	150	4
	7227	100

Annex 2: Sum of ACD in each height class of plots in the Harana Forest

Class	Height class in m	Sum of carbon density in ton	Proportion (%)
1	0–10	0	0
2	10–20	145	2
3	20–30	4023	56
4	30–40	2764	38
5	> 40	295	4
	Sum	7227	100

Abbreviations

ACD: Aboveground carbon density; DEM: Digital Elevation Model; FAO: Food and Agricultural Organization; GIS: Geographical Information Systems; ISRIC: International Soil Reference and Information Centre; REDD+: Reducing emission from deforestation and forest degradation plus sustainable management; SPSS: Statistical Package for the Social Sciences; UNFCCC: United Nations Framework Convention on Climate Change; UTM: Universal Transverse Mercator Coordinate.

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Authors' contributions

The first author was entirely engaged in field data collection, data entry, and data analysis. The second author immensely guided research design and analytical analysis. The third author mainly provided critical review and feedbacks during manuscript preparation. All authors read and approved the final manuscript.

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We the authors declare that we have no competing interests.

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