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Patterns and drivers of tree carbon stocks in Kashmir Himalayan forests: implications for climate change mitigation

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Abstract

Background: Temperate forests are major carbon sinks because of their high storage potential and low decomposition processes. We quantified tree carbon (TC) storage from 143 plots distributed across three major forest types of Kashmir Himalaya, relative to differences in ecological factors. Combined regression and Random Forest (RF) analysis were used to examine the distribution of TC stock along ecological gradients and recognize the role of driving factors on TC stocks.

Results: Among the three forest types, sub-alpine (SA) forest was the primary TC sink, accounting for 228.73 t ha^{-1} of carbon, followed by mixed conifer (MC; 181.29 t C ha^{-1}) and blue pine (BP; 133.04 t C ha^{-1}) forests. The distribution of TC stocks among the three forest types differed significantly ($\chi^2 = 18.87$; $P = 0.000$). Relative carbon stock analysis demonstrated that *Abies pindrow* and *Pinus wallichiana* accounted 91% of TC stocks across the landscape. Basal area, mean diameter at breast height (DBH), elevation, disturbance and precipitation had significant effects on TC stocks in bivariate regression models. The RF model explained 86% of the variation; basal area interpreted 30.15%, followed by mean DBH (17.96%), disturbance complex (10.64%), precipitation (8.00%) and elevation (7.34%).

Conclusions: Kashmir Himalayan forests are significant carbon sinks as they store a substantial quantum of carbon in trees. Forest carbon, an essential climatic indicator, is determined by a complex interaction of other ecological variables, particularly stand structural features. The study provides insights into the role of these natural forests in climate change mitigation and in REDD+/national commitments to offset the carbon.

Keywords: Carbon stock, Climate change, Coniferous forest, Disturbance, Kashmir Himalaya, Stand structure

Background

The global carbon cycle relies greatly on biomass stored in forest ecosystems. More than 50% of the global gross primary output is accounted by forests (Beer et al. 2010; Pan et al. 2011), which alone represent nearly 48% of the planet's total terrestrial carbon (Watson et al. 2000; Liu et al. 2014). In natural forests, carbon can be accumulated as above-ground (AG) and below-ground (BG) in the form of vegetation, litter and soil organic carbon (Malhi et al. 2002). Soil and forest vegetation together hold around two-thirds of the terrestrial carbon (Lal 2005). The estimated 861 ± 66 gigatons (Gt) carbon in forest ecosystems of which 44% is found in soil, 42% is biomass, 8% is dead wood, and 5% is litter components (Pan et al. 2011), provides an important climate modulating service. Forest vegetation biomass is essential since it sequesters around 2.4 ± 0.4 Gt carbon per year (Pan et al. 2011), mitigating 21% of the yearly human emissions of 10.7 ± 1.2 Gt carbon (Le Quéré et al. 2018). Temperate forests encompass 767 million ha (16% of the cumulative forest area; Hansen et al. 2010) and retain 46.6 Pg carbon. For regions with data limitations, such as the Kashmir Himalayan forests, where collecting field-based data

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on carbon forestry is challenging, carbon estimation in forests is vital. With a predominance of coniferous tree species such as *Abies pindrow* and *Pinus wallichiana*, which have significant ecological relevance in the context of "Reducing emissions from deforestation and forest degradation" (REDD+), these forests serve as significant carbon sink. To comprehend the importance of the forest in mitigating activities to reach the National Determined Commitment (NDC), such as REDD+, accurate quantification of forest carbon is necessary (Kishwan et al. 2012).

Forest carbon, an essential climatic indicator, is, nevertheless, a complex and non-directional function of other ecosystem processes. Factors such as topography, climate, soil, stand features and disturbance are hypothesized to govern carbon reserves within the forest (Wei et al. 2013; Zhang et al. 2013). The interactions between these elements determine the efficiency of carbon fixation in forests. Such fundamental interactions, which have received little attention, have been stressed for precise carbon estimation, thus reducing uncertainties and leading to better decision-making on carbon mitigation programs. Understanding the connection between forest structure and ecological processes has gained much attention (Shugart et al. 2010). By efficiently allocating available resources via niche complementarity and facilitation mechanisms, structural diversity tends to increase productivity (Fotis et al. 2018; Ouyang et al. 2019). Fewer big trees, regardless of their stand density and richness, have been observed to constitute a significant percentage of the basal area and effectively predict AG biomass and carbon (Lung and Espira 2015; Slik et al. 2013). However, despite their significant contribution to carbon cycling, diverse size class trees may not produce the same amount of biomass as a few large-diameter trees (Lutz et al. 2018; Meakem et al. 2018). These findings point to a varied biomass distribution across trees of various sizes, but it is yet less understood if these distribution patterns of carbon hold or change depending on vegetation type. Although basal area and stand density are anticipated to be the main structural factors driving carbon stocks, a size-class-related approach might help to expand our knowledge. By improving canopy packing and light capture, stand density may enhance productivity (Forrester and Bauhus 2016). Contrastingly, tree abundance can also negatively affect productivity (Chen et al. 2016; Fortunel et al. 2018). Furthermore, in mountain forest ecosystems, topography has been an excellent spatial indicator of biomass production (de Castilho et al. 2006; Alves et al. 2010). Elevation influences vegetation growth and efficiency through temperature variations (Xu et al. 2017). To improve prediction models of how future climate can influence the global carbon cycle, it will be essential to reduce epistemic uncertainties in existing carbon stock measurements and determine crucial factors linked to vegetation growth and biomass (Anderson et al. 2011; Pan et al. 2013). Along these lines, a thorough investigation of biomass in forest ecosystems is critical to quantifying their commitment to carbon reserves.

On account of advanced observation systems and interpretation methods, understanding the nature, distribution patterns and carbon reserves of forest ecosystems are progressively advancing (Saatchi et al. 2011; Asner et al. 2012). Asia represents 31% of the forest area of the planet earth, whereas 21%, 17%, 17%, 9% and 5% correspond to South America, Africa, North and Central America, Europe and Oceania, respectively (FAO 2010). Coniferous forests, a distinguished temperate forest ecosystem with simple vegetation composition, varied stand age and heterogeneous tree size structure, account for approximately 14% of the global total forest carbon reserves (Pan et al. 2011). The maximal extent of carbon stocks in temperate ecosystems is typically located in vegetation biomass (Peichl and Arain 2006; Pugh et al. 2019). Despite the significant advances in understanding the temperate carbon cycle, the data on Indian temperate mountain forests, primarily the Kashmir Himalayas, remain limited. Temperate Kashmir Himalayan forest ecosystems are critical to carbon cycle management and are incredibly susceptible to the stimulatory effects of climate modifications, land-use transformations and fragmentation, besides habitat destruction (Wani et al. 2016; Rashid et al. 2017). In this study, we analyzed how forest structural attributes, disturbances, topography and climatic variables affect the tree carbon in forests of Kashmir Himalaya. In order to address the following research questions, we analyzed 143 vegetation plots in three forests, i.e., low-level blue pine (BP), mixed conifer (MC), and sub-alpine (SA) forests: (i) Do the three forest types vary in terms of tree carbon (TC) stocks? (ii) Does relative contribution of species to TC stocks differ? and (iii) What are the contributions and relative importance of interpreting drivers on TC stocks? Disentangling the determinants that influence tree carbon storage might lead to a better understanding of reducing climate change impacts by increasing forest carbon stocks.

Materials and methods

Site description

The study area lies in Kashmir Himalaya, a part of the Himalayan biodiversity hotspot, located in the geographical coordinates of 33° 30′ 31.2228″–34° 39′ 53.7768″ E and 74° 29′ 43.7064″–75° 3′ 43.6392″ N in the north of India (Fig. 1). Kashmir valley is characterized by a temperate climate exhibiting four distinct seasons with harsh winters and pleasant summers. The mean annual precipitation is 1005.5 ± 197.6 mm,

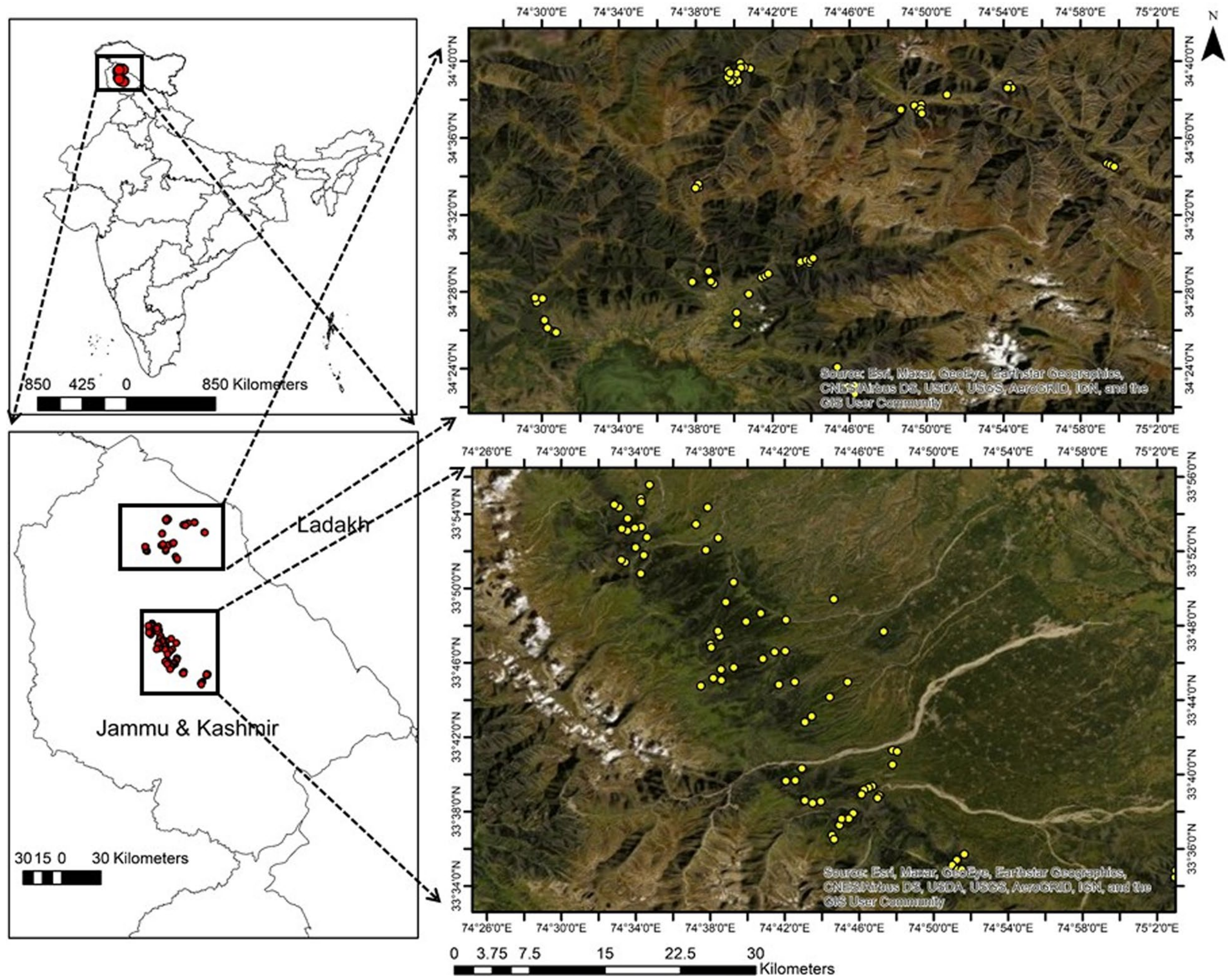

Fig. 1 Study area and geographical distribution of sampling plots in Kashmir Himalayan coniferous forests

and the mean minimum and maximum temperature range between 5.4 ± 0.4 and 17.6 ± 0.8 °C (Dad et al. 2021). Snowfall besides rain is frequent during winter season, and the period begins in October and extends till March. The landscape of the investigated area is mountainous, steep and rugged, with a mean elevation of 2553 m (1807–3300 m). The study area is transverse with a dense drainage structure comprising many rivers viz., Dodhganga, Romush, Veshaw, and Neelam, and small tributaries, streaming in various directions. Forest cover is mainly distributed from 2000 to 3300 m depending upon the physio-climatic conditions. Due to topography-induced alterations in climatic and edaphic characteristics, diverse vegetation types exist across the landscape. The major vegetation types are coniferous evergreen forests along with sub-alpine and alpine plant communities. The elevational distribution of three forest types includes low-level blue pine (BP), mixed conifer (MC) and sub-alpine (SA) forest types characterized by *Pinus wallichiana*, *Abies pindrow* and *Pinus wallichiana*, and *Abies pindrow*, respectively (Dar and Parthasarathy 2022, Dar et al. 2022). The understory vegetation is dominated by *Viburnum grandiflorum*, *Rosa webbiana*, *Fragaria nubicola*, *Poa alpina* and *Stipa sibirica*. The area is predominantly covered by entisols, alfisols and inceptisols with a loamy texture derived from Precambrian slates, phyllites and quartzites (Krishnan 1982). The study area has been jeopardized by natural and anthropogenic disturbances such as snow, windthrow, land-use conversions, tourism, grazing, plant material extraction of nutritional and medicinal significance, etc.

Experimental design and field survey

Field inventory across three forest types in Kashmir Himalaya was conducted between April–July 2019. The tree vegetation was sampled in 143 plots of 0.25 ha (50 m × 50 m) placed at random with an inter-plot distance of at least 500 m (Dar and Parthasarathy 2022). Efforts were made to replicate plots proportionally among the forest types, but this was unrealistic due to logistic constraints and accessibility. To minimize the confounding influence of the margins, all plots were laid within 100 m from the forest edges. Each plot was partitioned into 25 (10 m × 10 m) subquadrats, and all trees ≥ 10 cm in diameter at breast height (DBH; 1.37 m) were recognized to species-level, and their diameters were measured over-bark to characterize vegetation structure following standardized methods (Pearson et al. 2005). The diameter of the stem at breast height, i.e., DBH (1.37 m above ground level), was used to compute the basal area (BA) as $BA = 0.00007854 \times DBH^2$. The basal area of all trees is added and scaled to hectare level by dividing the area sampled ($m^2\ ha^{-1}$). Tree density, expressed as the number of trees per unit area, is defined as the individuals per hectare (ind ha^{-1}).

We estimated above-ground biomass (AGB) from DBH with *get_biomass()* function available in the "*allodb*" version (V) 0.0.1.9000 library for R (Gonzalez-Akre et al. 2021). In addition, the identification of species is essential for choosing suitable allometric equations. Species names were validated using *correctTaxo()* from the "*BIOMASS*" library to ensure consistency in spelling and nomenclature (Réjou-Méchain et al. 2017). The family names of the respective corrected species names were extracted using *tax_name()* in "*taxize*" library (Chamberlain et al. 2020) in R. Additionally, the site coordinates are required to consider climatic zones. Using the "*kgc*" R library, "*allodb*" determines the Köppen climatic zone of a particular place (Bryant et al. 2017). The resultant climate is then matched with the Köppen zone(s) of allometric equations and utilized in the weighting system. The below-ground biomass (BGB) is determined from the acquired above-ground counterpart by taking into account a root/shoot ratio of 26%, as recommended by Cairns et al. (1997). The total biomass is evaluated by considering the AGB and BGB together. Tree carbon (TC) stocks are then assessed via the result of all tree biomass determined from the biomass calculations and constant factor of 0.47 as recommended by Martin and Thomas (2011), implying 47% of biomass as carbon. The carbon content of individual trees within each plot is summarized and scaled to the hectare level (t ha^{-1}).

Predictors of forest TC stocks

Within each plot, the topographic (slope, aspect, elevation), climatic (mean annual temperature (hereafter temperature) and mean annual precipitation (hereafter precipitation)), and structural factors (mean DBH, basal area and density) are determined. Geographical position and elevation are recorded with a hand-held Global Positioning System (GPS; JUNO 3E). Slope and aspect are determined with Digital Elevation Model (DEM; 30 m resolution) in ArcGIS 10.3 (Luedeling et al. 2007). Climate data are extracted from WorldClim (V2.1; ~ 1 km^2 spatial resolution; Fick and Hijmans 2017) based on field geo-coordinates using *getData()* function in "*raster*" library (https://CRAN.R-project.org/package=raster) for R. The data are downscaled to 30-m resolution to maintain spatial uniformity with slope and aspect. To adjust for variations in scale, plot disturbances, non-timber forest product extraction, grazing, trails crossing the plot, lopping and counting the number of tree stumps are scaled and linearly integrated into a disturbance complex using Principal Component Analysis (PCA) axis-1 in "*FactoMineR*" V2.4 library (https://CRAN.R-project.org/package=FactoMineR). Test scores of the PCA-1 are described as the disturbance complex.

Data analyses

Kruskal–Wallis test and kernel density are used to examine the mean differences and distribution of carbon stocks among forest types in "*stats*" V4.1–2 library (https://CRAN.R-project.org/package=STAT). Multiple group comparisons are performed using the post hoc test. The Pearson's correlation coefficient (r) and variance inflation factor (VIF) in "*metan*" V1.16.0 (https://CRAN.R-project.org/package=metan) and "*car*" V3.0–12 (https://CRAN.R-project.org/package=car) libraries are estimated to analyze multi-collinearity and factors having non-collinear relationships ($r < 0.6$ and $VIF < 5$) are chosen for regression analysis. To satisfy the requirements of normality, the response and predictor variables are log-transformed (natural log scale) and standardized (mean = 0; standard deviation = 1), which enhances the interpretability of model estimates (Schielzeth 2010; Muscarella et al. 2020). Regression analysis is used to acknowledge the preselected non-collinear predictors (basal area, mean DBH, precipitation, aspect, slope, tree density, tree species richness and disturbance) of TC stocks in *"stats"* V4.1.2 and *"ggplot2"* V3.3.5 (https://CRAN.R-project.org/package=ggplot2) libraries.

Random Forest (RF), a supervised machine-learning algorithm/technique, is used to derive the relative importance of individual predictor variables in shaping TC stocks (Liaw and Wiener 2002). In the data matrix, 70% (100) of plots are selected to train (calibration) the bagged trees, while the remaining 30% (43) plots (out-of-bag (OOB)) are used independently to cross-validate (validation) the performance of the RF model (Cao et al. 2019). Two specifications need to be set to operate the RF technique: the number of decision trees to grow (*ntree*) or bootstrap samples drawn and the random sample of predictors selected as split candidates (*mtry*) at each node. The default setting of ntree = 500 is inadequate for producing consistent results. Therefore, the optimized number of trees (*ntree*) in the forest is set to 3000. However, we examined the predictive capability of the algorithms with various *mtry* values (from one to the total number (11) of predictor variables) in order to choose the most effective *mtry* in terms of minimal possible OOB mean square error (MSE) using a loop function in R. The tests validated that three sub-set of randomly selected independent variables made accessible for node splitting, i.e., *mtry* = 3, worked best. The "*randomForest*" V4.7–1 library (https://CRAN.R-project.org/package=randomForest) is used to generate the model. The relevance of each exogenous variable on the response variable is analyzed using "*rfpermute*" V2.5.1 library (https://CRAN.R-project.org/package=rfPermute). Moreover, model significance and cross-validated (CV) R^2 are tested with 5000 iterations of the dependent variable (TC stocks) in "*A3*" V1.0.0 library (https://CRAN.R-project.org/package=A3). Statistical analyses are concluded in R environment Rv4.2.1 (R Core Team 2021).

Results

Patterns of tree biomass and carbon stocks

The mean total biomass across the landscape is 386.05 ± 15.84 t ha^{-1} and in the three forests in decreasing order as 486.66 ± 35.80 t ha^{-1} (SA forest), 385.73 ± 20.22 t ha^{-1} (MC forest) and 283.07 ± 24.89 t ha^{-1} (BP forest). The mean above-ground carbon (AGC) is maximal in SA forest (181.53 ± 13.36 t C ha^{-1}) followed by MC forest (143.88 ± 7.54 t C ha^{-1}) and minimal corresponds to BP forest (105.59 ± 9.29 t C ha^{-1}). Similarly, the below-ground carbon (BGC) across the landscape is higher (37.44 ± 1.54 t C ha) than BP forest (27.45 ± 2.41 t C ha) and is equal (37.41 ± 1.96 t C ha^{-1}) and prominently (47.20 ± 3.74 t C ha^{-1}) lower than MC and SA forests, respectively. The total TC ranged from 133.04 ± 11.70 t C ha^{-1} (BP forest) to 228.73 ± 16.83 t C ha^{-1} (SA forest). Across the three forest types, TC stocks differ significantly (χ^2 = 18.87; P = 0.000). The post hoc test revealed that BP–MC (P = 0.000) and BP–SA (P = 0.000) forest combinations as principal contributors to this variation (Fig. 2).

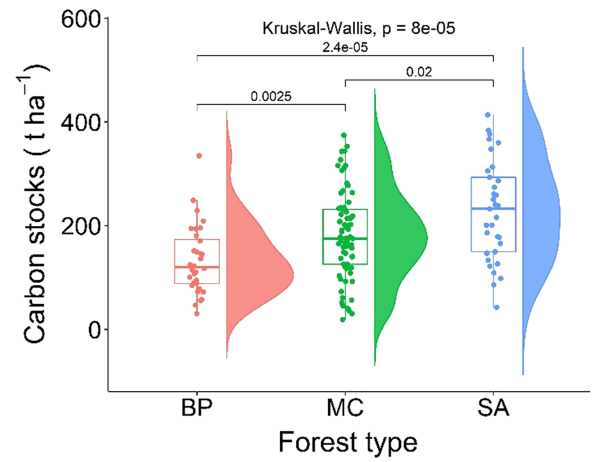

Fig. 2 Allocation of TC stocks by forest type (low-level blue pine, BP; mixed conifer, MC and sub-alpine, SA) in Kashmir Himalaya, India

Biomass and carbon stock contribution by species

With regard to tree species in BP forest *Pinus wallichiana* followed by *Abies pindrow* and *Cedrus deodara* are significant contributors sharing 65.74%, 17.60% and 13.80% to tree biomass/carbon stocks (Table 1). By family, Pinaceae, with four species, is dominant carbon sink, whereas the remaining two families contributed just 0.24%. In MC and SA forests, *Abies pindrow* contributed the major share with 50.91% and 76.57% to the TC stocks, respectively. In both MC and SA forests, Pinaceae (99.36%; 98.48%) and Sapindaceae (0.28%; 0.87%) constitute the important families from biomass and carbon perspective.

In all the three forest types, coniferous evergreen species held the maximum share (99.33%) of biomass and carbon stocks: *Abies pindrow* (52.91%), *Pinus wallichiana* (38.33%), *Picea smithiana* (5.76%), *Cedrus deodara* (2.16%), *Taxus wallichiana* (0.08%) and *Juniperus semiglobosa* (0.07%). The lowermost carbon among broad-leaved deciduous species corresponded to *Robinia pseudoacacia* (0.001 t C ha^{-1}), *Aesculus indica* (0.005 t C ha^{-1}) and *Populus ciliate* (0.03 t C ha^{-1}). Among the conifers, species with less than ˂10 t C ha^{-1} included *Juniperus semiglobosa* (0.13 t ha^{-1}), *Taxus wallichiana* (0.0.15 t ha^{-1}) and *Cedrus deodara* (3.92 t ha^{-1}), whereas *Abies pindrow*, *Pinus wallichiana* and *Picea smithiana* on an average contributed 96.00, 69.56 and 10.45 t C ha^{-1}.

Diameter class distribution

The distribution of carbon under various diameter classes varied significantly (F = 14.02; P = 0.000) among the three forest types. The percentage contribution of biomass/carbon stocks by diameter class represented a hump-shaped

Table 1 Species and family-based contribution to above-ground (AG), below-ground (BG), total and percentage (%) biomass and/or carbon in three forest types (low-level blue pine, BP; mixed conifer, MC and sub-alpine, SA) of Kashmir Himalaya, India

Species (family)	AGB/AGC (t ha^{-1})	BGB/BGC (t ha^{-1})	Total biomass/carbon (t ha^{-1})	% Biomass/carbon
BP forest				
Abies pindrow (Pinaceae)	39.54/18.59	10.28/4.83	49.83/23.42	17.60
Cedrus deodara (Pinaceae)	29.61/13.92	7.70/3.62	37.31/17.53	13.18
Juglans regia (Juglandaceae)	0.30/0.14	0.08/0.04	0.38/0.18	0.14
Picea smithiana (Pinaceae)	7.28/3.42	1.89/0.89	9.18/4.31	3.24
Pinus wallichiana (Pinaceae)	147.69/69.41	38.40/18.05	186.08/87.46	65.74
Populus ciliate (Salicaceae)	0.23/0.11	0.06/0.03	0.29/0.13	0.10
MC forest				
Abies pindrow	155.86/73.25	40.52/19.05	196.38/92.30	50.91
Acer caesium (Sapindaceae)	0.85/0.40	0.228/0.2285	1.07/0.50	0.28
Aesculus indica (Sapindaceae)	0.01/0.01	0.003/0.001	0.02/0.01	0.00
Corylus jacquemontii (Betulaceae)	0.22/0.10	0.063/0.0622	0.27/0.13	0.07
Juglans regia	0.01/0.002	0.001/0.0006	0.01/0.003	0.002
Juniperus semiglobosa (Cupressaceae)	0.42/0.20	0.113/0.1142	0.53/0.25	0.14
Picea smithiana	25.16/11.83	6.54/3.07	31.70/14.90	8.22
Pinus wallichiana	123.16/57.88	32.02/15.05	155.18/72.93	40.23
Robinia pseudoacacia (Fabaceae)	0.003/0.001	0.0009/0.00003	0.004/0.002	0.001
Taxus wallichiana (Taxaceae)	0.45/0.21	0.120/0.1245	0.56/0.27	0.15
SA forest				
Abies pindrow	295.76/139.01	76.90/36.14	372.66/175.15	76.57
Acer caesium	3.35/1.58	0.87/0.41	4.23/1.99	0.87
Betula utilis (Betulaceae)	2.50/1.18	0.65/0.31	3.15/1.48	0.65
Picea smithiana	9.97/4.69	2.59/1.22	12.56/5.90	2.58
Pinus wallichiana	74.65/35.09	19.41/9.12	94.06/44.21	19.33

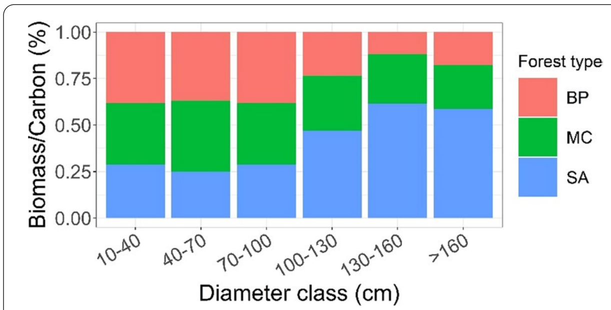

Fig. 3 Contribution to biomass/carbon by diameter class across three forest types: low-level blue pine forest, BP; mixed-conifer forest, MC and sub-alpine, SA forest in Kashmir Himalaya, India

pattern with a maximal percentage contribution from mid-diameter class (70–100 cm) in all three forest types (BP = 48.76%; MC = 42.43% and SA = 36.48%) and also across the landscape (41.74%). The lowest (10–40 cm) diameter class contributed ˂10% to the total biomass and carbon stocks across the three forest types (Fig. 3). In contrast, large trees (≥ 70 cm) stocked 66.86%, with a maximum proportion corresponding to MC forest (52.80%). Across the three forest types, BP forest constitutes the maximum biomass/carbon share in 10–40 cm (38.35%) and 70–100 cm (38.19%) diameter classes, whereas MC and SA forests represent the maximum proportion in 40–70 cm (38.01%), and above 100 cm (100–130 cm (46.90%), 130–160 cm (61.51%) and > 160 cm (58.63%)).

Drivers of TC stocks

Bivariate relationship between TC stocks and predictor variables

Certain structural attributes showed a high correlation with each other and with TC stocks. There is a positive correlation between mean DBH and basal area. These, in turn, presented high collinearity with TC stocks. Tree density exhibited a strong negative relationship with mean DBH, precipitation and temperature but not with basal area (Additional file 1: Fig. S1). Among the topographic variables, elevation depicted a significant correlation with basal area, disturbance, richness, and temperature besides TC stocks. However, aspect and

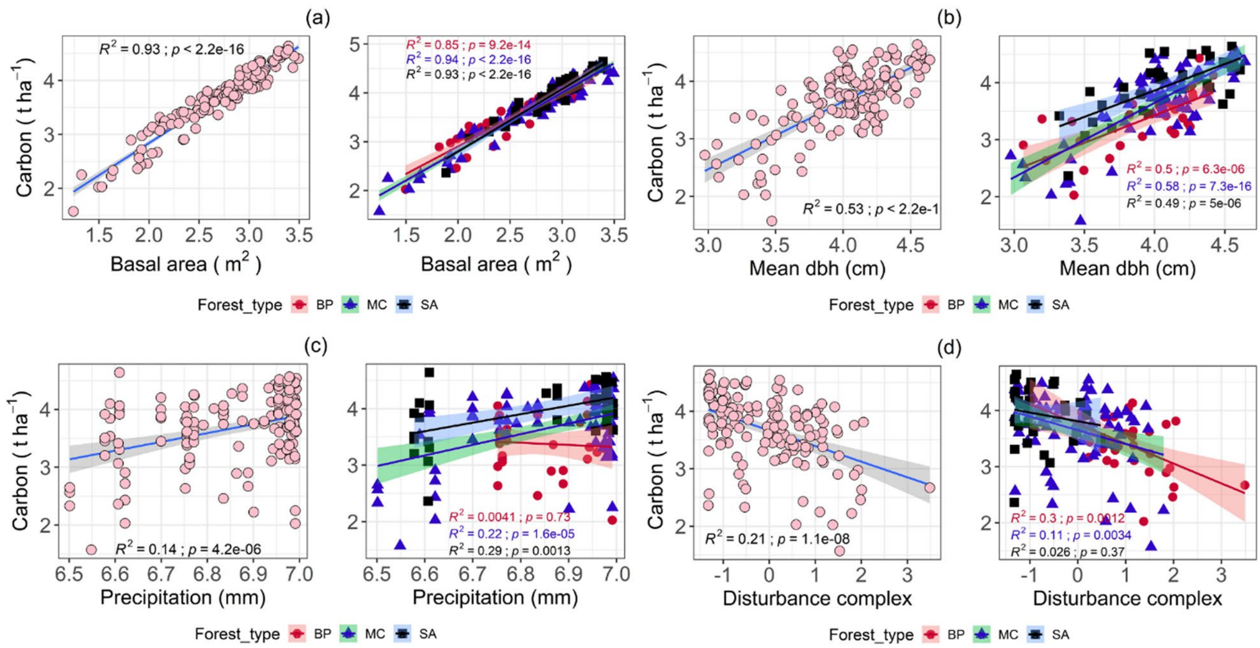

Fig. 4 Relationships of TC stocks with explanatory variables across three (low-level blue pine, BP; mixed conifer, MC and sub-alpine, SA) Kashmir Himalayan forests, India

slope did not show correlation with any variable. Moreover, a significant correlation is found between disturbance, and TC stocks, basal area, mean DBH, density, elevation and temperature. Tree species richness positively correlated with tree density and elevation, while it had a negative correlation with mean DBH and temperature (Additional file 1: Fig. S1).

Basal area and mean DBH proved to be the strong resilient predictor for TC stocks across the forests (Fig. 4a and b). TC stocks also increased linearly with precipitation (Fig. 4c). However, no relationship between TC stocks and aspect and slope was found (Additional file 1: Fig. S2). Similarly, temperature and tree species richness did not display any significant influence on TC stocks. TC stocks decreased along the disturbance complex gradient (Fig. 4d). Largest variation in the TC stocks is attributed to basal area ($R^2 = 0.93$) since the influence of other predictor variables remained smaller (Fig. 4).

Random forest (RF) algorithm

RF model explained 86.2% (CV R^2), variability of TC stocks across Kashmir Himalayan coniferous forests (Fig. 5). The analyses between TC stocks in sample plots and predictors (basal area, mean DBH, elevation, tree density, precipitation, temperature, tree species richness, forest type, aspect, slope and disturbance complex) proved that five variables (Fig. 5), out of a maximum of 11, are the minimum number of attributes that provided the optimum predictive validity ($P < 0.05$). Basal area, mean DBH, and disturbance complex had the strongest effects on TC stocks, with relative importance values of 30.15%, 17.96% and 10.64%, respectively, and collectively represent for over half (> 50%) of the relative influence in the RF model (Fig. 5). The importance of the predictor variables strongly decreases (60%) after the first variable, i.e., basal area. The followed variables with their respective Increment in Mean Square Error (% IncMSE) are: mean DBH (17.96%; $P = 0.000$) > disturbance (10.64%; $P = 0.002$) > precipitation (8.00%; $P = 0.012$) > elevation (7.34%; $P = 0.039$) (Additional file 1: Fig. S3). In contrast, the covariates temperature (6.12%; $P = 0.073$), density (3.48%; $P = 0.234$), forest type ($P = 2.94\%$; $P = 0.198$), slope (1.48%; $P = 0.269$), tree species richness (0.65%; $P = 0.348$) and aspect (-0.169; $P = 0.433$) are the least important (insignificant) variables to the modeled TC stocks.

Discussion

Patterns of tree carbon stocks

Carbon stocks and biomass are essential analytical aspects of forest ecosystems. Assessment of biomass demonstrates the extent of carbon a forest can hold and is an essential element for national development planning besides scientific analysis of carbon budget (Devagiri et al. 2013; Naveenkumar et al. 2017). The present work estimates the amount of biomass and carbon stored

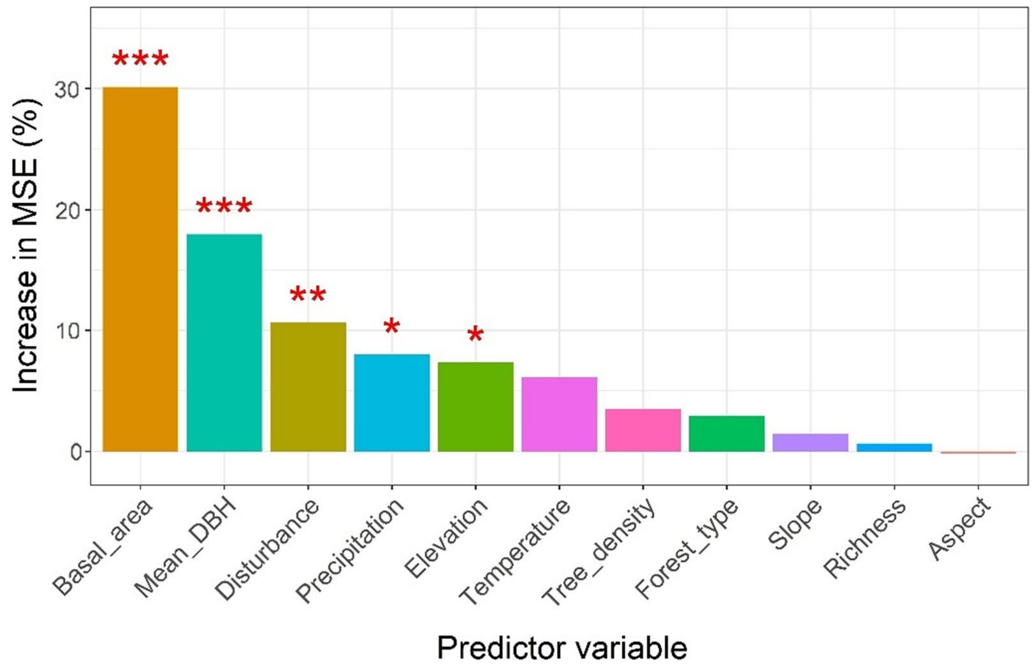

Fig. 5 Random forest mean importance (% increase of mean square error (MSE)) of predictor variables studied as drivers of TC stock in Kashmir Himalayan forests, India. Significance threshold of covariates are as follows: * < 0.05, ** < 0.01 and *** < 0.001

across three Kashmir Himalayan forests, India. The findings indicate a relatively high TC stocks ranging from 133.04 ± 11.70 t ha^{-1} (in BP forest) to 228.73 ± 16.83 t ha^{-1} (in SA forest). However, this is not as much as carbon-rich mountain ash forests of southern Australia (2844 t C ha^{-1}; Keith et al. 2009), Kauri coniferous forests of New Zealand (982 t C ha^{-1}; Silvester and Orchard 1999), and temperate coniferous forests of North-West United States (774 t C ha^{-1}; Smithwick et al. 2002). The estimates are higher than coniferous forests of India (51.39–68.81 t C ha^{-1} in Northern Kashmir Himalaya (Wani et al. 2019) and Western Kashmir Himalaya, India (Wani et al. 2015), mountain systems of Pakistan (85.04 ± 10.84–99.41 ± 15.59 t C ha^{-1} in Khyber Pakhtunkhwa region; Ali et al. 2020) and coniferous forests of Mexico (41.3 ± 1.1 t C ha^{-1}; Arasa-Gisbert et al. 2018). The heterogeneous drivers viz., vegetation structure, topography, climate and edaphic elements, stand age, forest type, adopted methodology, successional stage, previous tree felling, forest management history, and choice of regression equation used in biomass estimation may be attributed to this inconsistency (Peichl and Arain 2006; Jeyanny et al. 2014; Chave et al. 2014; Zhao et al. 2014; Wani et al. 2017). However, the projected carbon estimates in the current study accord with Western Himalayan forests, India (Haq et al. 2021); Garhwal Himalaya, India (Sharma et al. 2010, 2018); Outer Himalaya, Pakistan (Amir et al. 2018); Western Himalayas, India (Singh and Verma 2018); Wanglang Nature Reserve, China (Zhang et al. 2011) and dry coniferous forests of California, United States of America (North et al. 2009). The greater carbon reserves in SA forest might be ascribed to many bigger trees besides less disturbance in the setup plots contributing considerable tree carbon stocks. The large-size individuals which formed the major share of biomass and carbon stocks is possibly due to their elevated heights and disseminated canopies, which empower them to exploit growth area not accessible to small-diameter lower-height individuals and diverse canopy niches.

Tree diameter-class distribution is recognized as an essential feature of forest structural heterogeneity besides forest dynamics and functioning (Lutz et al. 2013). The existing pattern of greater carbon proportion from larger diameter classes (≥ 70 cm) thereof, regardless of their lower number of individuals, has already been documented at a regional scale as well as across the globe from diverse forest types (Slik et al. 2013; Lutz et al. 2018; McNicol et al. 2018, Ali et al. 2019). The observed differences in tree carbon portioning among diameter classes might be accounted to resource accessibility and growth habitat. Overall, the analyzed forest types were mature, large-diameter class, old-growth with carbon stocks on the upper limit of the range observed for Indian forests (Chhabra et al. 2002). Unlike earlier convictions (Odum 1969), old-growth trees continue to accumulate an appreciable quantity of carbon (Luyssaert et al. 2008) which infers that Kashmir Himalayan forests have a strong competence for climate change mitigation. Furthermore, the increased carbon storage across these forests underscores the significance of maintaining or expanding the conservation areas. Conservation implicates considering forests with high carbon stocks and their management to minimize pressure on forests by limiting biomass extraction. The Himalayan region, where green harvesting has been prohibited for the last three decades, might be a promising area for establishing the REDD+ idea of "Conservation of forest carbon stocks." Under REDD+, forest conservation as a mitigation strategy may also encourage biodiversity conservation (Gunilla et al. 2013). Moreover, the third REDD+ option, sustainable forest management (SFM), helps to build forest carbon reserves and assures the ongoing flow of other ecosystem services. The majority of the Kashmir Himalayan forests are natural and are maintained according to competent management plans, which satisfy the criteria of SFM of REDD+ (Wani et al. 2016).

Stand structural attributes override TC stocks

Tree carbon stocks are bound to be controlled by the attributes of the species present in a given area (Dănescu et al. 2016; Zhang et al. 2012). Our findings revealed that TC stocks in Kashmir Himalayan forests are shaped by structural, climatic, disturbance, and topographic variables, implying that many ecological processes work simultaneously. Moreover, numerous other processes such as competition (Coomes and Allen 2007), species composition and age of the stand (Wani et al. 2019) are known to determine the forest carbon stocks. Ecosystem production is larger in structurally diversified forests than in simpler ones (Ali 2019). Both regression and RF analyses demonstrated that the regression coefficients and importance of basal area and mean DBH are greater than other exogenous variables (climate, topography and disturbance complex), indicating that stand structure is the major factor in modulating TC stocks in Kashmir Himalayan forests (Figs. 4, 5). Due to complex stand structural features, greater light absorption and optimum utilization are believed to have resulted in these correlations (Zhang and Chen 2015; Dănescu et al. 2016). The results corroborate with other Himalayan forests (Banday et al. 2018; Khan et al. 2020; Kaushal and Baishya 2021; Gogoi et al. 2022) and elsewhere (Zhang and Chen 2015; Dănescu et al. 2016; Xu et al. 2018). Amir et al. (2018) and Sullivan et al. (2017), in congruence with our findings, reported that tree density negatively correlates with mean DBH suggesting that higher stem density may result in intraspecific and interspecific competition for resources limiting tree growth rate.

The significance of topographic elements in shaping stand structure, species composition, and functionality is well established (Sanaei et al. 2020; Ullah et al. 2021). Variations in topography, in particular, might lead to inequality in resource allocation (Boerner 2006), which could affect species richness, forest canopy, tree density, and basal area, affecting above-ground biomass and, consequently, carbon stock potential of the forest ecosystem (Jucker et al. 2018). In our study, where elevation extends from 1887 m to a high 3307 m, TC stocks which increased with elevation can be attributed to low disturbances and large-diameter trees at higher elevation. Furthermore, elevation can modify carbon stocks by adjusting moisture, temperature, plant community type, and water accessibility, which can significantly impact carbon output (Fisk et al. 1998; Sanaei et al. 2018). Similar results characterizing the positive association between elevation and carbon stocks are well-acknowledged from diverse forests of Loess Plateau, China (Liu and Nan 2018), Central Highlands, Vietnam (Van Do et al. 2017) and North Kashmir Himalaya, India (Wani et al. 2019). Nonetheless, contrasting outcomes were confirmed by Zhu et al. (2010) and Fehse et al. (2002). Determining the primary disturbances drivers that contributed to deforestation and degradation is critical, and concerted attempts to solve these challenges for effective implementation of REDD+ are required, particularly at disturbance-prone lower elevations. According to Sharma et al. (2011) and Moeslund et al. (2013), aspect and slope considerably affected carbon storage and biomass. In contrast, we found no significant link between slope and aspect and TC stocks, presumably because their impact on carbon stocks is negligible over a large scale (Xu et al. 2017).

Our study also revealed that precipitation displays a positive effect on the increase of TC stocks (Fig. 4c), which is in line with Usoltsev et al. (2022), implying an increase in net primary production (NPP) with precipitation gradient. Similarly, Fang et al. (2016) reported that precipitation is the most important climatic variable affecting TC stocks in Changbai Mountain and further concluded that precipitation is the principal element in forest production. By altering the decay rates of litter and organic matter content, climatic conditions can determine the accessibility of nutrients and photosynthesis. Nonetheless, Wang et al. (2018) revealed that temperature and precipitation had contrasting impacts on carbon stocks in eastern Chinese forests. TC reserves are affected by disturbances, yet, the link between the two is not straightforward (Thornley and Cannell 2000). Lower disturbances are often characterized by late-successional vegetation coupled with larger tree height (Chave et al. 2009). As a result, harvesting voluminous trees diminishes the potential of forests to store carbon (Lindsell and

Klop 2013). Himalayan temperate forests mainly experience disruptions driven by biomass harvest, notably for timber and firewood, intensive grazing and many others. These alterations prompt detrimental impacts on the structural attributes of plant communities (Vaidyanathan et al. 2010; Sapkota et al. 2018). Once the REDD + initiatives are implemented, these detrimental consequences may be rectified via REDD+ alternatives for deforestation and degradation. This demonstrates the region's significant potential for REDD+ initiatives, i.e., forest conservation, SFM, and enhancement of forest carbon stocks.

Conclusion and implications for climate change mitigation

In this study, the major focus is to determine the magnitude of carbon stocks and processes involved in temperate Kashmir Himalayan forests. Many distinct questions are addressed, and the information gathered enabled the following conclusions:

- Kashmir Himalayan forests are significant carbon reserves as they store substantial amounts of carbon in trees, particularly in SA forest, as TC density was positively associated with elevation.
- As per the findings, mature old-growth forests composed of *Abies pindrow* and *Pinus wallichiana* have a higher carbon storage capacity due to their prolonged turnover intervals and are thus suggested for the protection of tree species in undisturbed forests and carbon management in disturbed forest landscapes by afforestation.
- Carbon sequestration is a vital ecosystem service that results from interactions of ecological processes, including disturbance, climate, structural and topographic drivers.
- Structural attributes outperform the contribution of other drivers in interpreting the variation in TC stocks. Therefore, current research emphasizes the necessity of conserving large-diameter trees as well as managing and protecting old-growth forests, as corroborated by Lutz et al. (2018) globally. Safeguarding old-growth forests will ensure higher carbon storage while promoting conservation efforts at all trophic levels.
- Disturbance complex gradient, which negatively affected the TC stocks, may be attributed to illegal biomass harvesting of important timber species, notably *Pinus wallichiana* and *Cedrus deodara*.

Coniferous forests are the dominant forest type across Jammu and Kashmir Himalayan region; with FSI (2022), pure coniferous forests cover more than 70% of the total forest area of the entire Jammu and Kashmir. Therefore, knowledge of carbon storage in these coniferous forests will be of great importance for environmental management initiatives to mitigate future climate change effects.

Our conclusions on the extent of TC stocks in Kashmir Himalayan forests are pertinent to UNFCCC efforts to minimize deforestation and forest degradation emissions. Such forests with great carbon sink due to prolonged carbon retention render them good climate change mitigation tools. Since the analysis focuses on collected data with enough samples taken from a large distributional range of BP, MC, and SA forests along an elevation gradient, the conclusion is more realistic, hence an update of the tree carbon budget. These revised statistics can be used to analyze the role of forestry in reducing emissions in the region. The forest carbon assessment would also boost the efficiency of incentive-based conservation schemes for combating climate, particularly the REDD+ initiative. Both the positive and negative aspects of REDD+ have promising importance in Kashmir Himalaya. The area is intended to gain most from negative REDD+ choices since it has primarily experienced forest loss in the past. Knowledge of tree species with regard to carbon stores and degrees of vulnerability in forest stands helps develop successful REDD+ measures to protect tree biodiversity and linked socioeconomic implications for the local population. The rigorous quantification of carbon would stimulate more robust community engagement in forest-based mitigation efforts. Our knowledge on the forest types and factors that result in significant carbon accumulation may be designed to assist in highlighting conservation priorities. Protecting carbon-rich forests from anthropogenic disruptions minimize substantial CO_2 emissions, and current losses are reduced by carbon sequestration. To forecast the implications of climate change on forest carbon stocks and optimize the function of forests for carbon reduction, a greater knowledge of the link between carbon stock, environmental conditions, and forest structure is necessary. This involves enhancing carbon absorption, sustaining stand carbon reserves, and preventing carbon loss by strengthening their endurance.

Abbreviations

TC: Tree carbon; BP: Low-level blue pine; MC: Mixed conifer; SA: Subalpine; RF: Random forest; DBH: Diameter at breast height; UNFCC: United Nations Framework Convention on Climate Change; CO_2: Carbon dioxide; DEM: Digital Elevation Model; FAO: Food and Agricultural Organisation; BA: Basal area; AGB: Above-ground biomass; BGB: Below-ground biomass; GPS: Global Positioning System; PCA: Principal Component Analysis; VIF: Variance inflation factor; OOB: Out-of-bag; MSE: Mean Square Error; CV: Cross-validated; AGC: Above-ground carbon; BGC: Below-ground carbon; NPP: Net primary production; FSI: Forest Survey of India; REDD+: Reducing Emissions from Deforestation and forest Degradation; NDC: National Determined Commitment; SFM: Sustainable forest management; Gt: Gigatons.

Supplementary Information

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Additional file 1: Fig. S1. Correlation among predictor variables and with TC stocks across three (low-level blue pine, BP; mixed conifer, MC and sub-alpine, SA) Kashmir Himalayan forests, India. **Fig. S2.** Relationships of TC stocks with explanatory variables across three (low-level blue pine, BP; mixed conifer, MC and sub-alpine, SA) Kashmir Himalayan forests, India. **Fig. S3.** The significance scores (*P*) of importance (%MSE) for predictor variables studied as drivers of the TC stock in Kashmir Himalayan forests, India

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Author contributions
AAD and NP conceived the ideas and designed methodology; AAD did the fieldwork, analyzed the data and wrote the manuscript under the supervision of NP. Both authors read and approved the final manuscript.

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Availability of data and materials
Data and materials used in this study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors state that they have no competing interests or personal connections that might have compromised the research presented in this study.

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