OAJRC Environmental Science, 2024, 5(2), 39-46
https://www.hillpublisher.com/journals/oajrces/
ISSN Online: 2632-2331

Drivers of Soil Organic Carbon Accumulation in Afforestation Ecosystems of China

Yiwei Zhu*, Junling Lu

Central South University of Forestry and Technology, Changsha, Hunan, China.

How to cite this paper: Yiwei Zhu, Junling Lu. (2024). Drivers of Soil Organic Carbon Accumulation in Afforestation Ecosystems of China. *OAJRC Environmental Science*, 5(2), 39-46.
DOI: 10.26855/oajrces.2024.06.002

Received: July 21, 2024
Accepted: August 17, 2024
Published: September 13, 2024

Corresponding author: Yiwei Zhu, Central South University of Forestry and Technology, Changsha, Hunan, China.

Abstract

Afforestation is recognized as a crucial strategy for enhancing the carbon sink capacity of terrestrial ecosystems and mitigating the impact of global greenhouse gases. However, the primary factors influencing soil organic carbon (SOC) accumulation in Chinese afforestation ecosystems remain inadequately understood. We conducted a meta-analysis to identify the temporal patterns and key drivers of SOC accumulation using Structural Equation Modeling (SEM), providing new insights for the planning of timing and locations for afforestation in China. Our analysis revealed that SOC accumulation is positively correlated with stand age, driven by soil fertility, soil moisture, initial SOC stocks, and their interactions over the long term. The temporal pattern of SOC accumulation indicated that losses in SOC stocks can occur not only during the early years but also in the long term (> 20 years) within afforestation ecosystems. Soil fertility emerged as the most significant positive driver of SOC accumulation, followed by soil moisture and their interactions. Mean annual temperature (MAT) and initial SOC stocks were identified as significant negative drivers of SOC accumulation. Overall, these findings underscore the importance of selecting and managing afforestation ecosystems, serving as a scientific reference for maximizing the benefits of soil carbon sequestration and achieving carbon neutrality.

Keywords

Afforestation, Terrestrial ecosystem carbon sink, Carbon sequestration, Soil carbon dynamics, Carbon sink pathway

1. Introduction

Ecosystem services and biodiversity have been degraded by global warming [1, 2]. The ecosystem and socioeconomic system and might be suffering catastrophic without effective intervention [3]. In the global carbon cycle, the terrestrial ecosystem is absorbing CO2 and mitigating climate change [4]. Accounting for more than half of the soil C pool in the terrestrial ecosystem, SOC is an essential contributor to the variation of atmospheric CO_2 [5]. Afforestation accumulates SOC by increasing C derived from the new forest and decreasing C loss from decomposition and erosion [6]. Thus, afforestation is regarded as an important means that can help to increase carbon sinks and mitigate the effect of global greenhouse gases [4].

The timing and location of afforestation should be arranged by a scientific prediction in the ecosystem [4]. However, it is highly uncertain about the temporal pattern of SOC accumulation in the afforestation ecosystem. More importantly, we still do not understand the key factors that regulate the effectiveness of afforestation for SOC sequestration across a range of afforestation ecosystems. However, exploring the temporal pattern of SOC accumulation and the key factors driving SOC accumulation is a necessary informational backdrop allowing afforestation ecosystem management to more precisely relate C sequestration [2]. With the global carbon neutrality vision becoming clear and mitigation actions being accelerated, this exploration has become more prominent [7].

During the past decades of years, a number of studies have reviewed drivers in SOC accumulation, these studies revealed that the magnitude and direction of SOC accumulation is driven by multiple factors, including climate, tree species, and nutrient management [8-10]. However, these studies have generally concentrated on the effects of typical contributing factors, with little attention to the interactions among different factors, while the interactions may be crucial to exploring the key drivers of SOC accumulation.

With several afforestation activities such as the Natural Forest Protection Program, Grain for Green Project (GGP), and Three-Norths Project, the largest area of afforestation in the world has been established in China, which is a critical component of the global carbon cycle [11, 12]. Luckily, many areas in these large-scale projects implement both afforestation plots and corresponding control plots at the same site, allowing us to conduct paired comparisons between these two sites. Afforestation in these projects involves planting in former croplands, bare lands, grasslands, and deserts.

We aimed to synthesize the major drivers of SOC accumulation in the Chinese afforestation ecosystem by means of a meta-analysis. (1) to determine the temporal pattern of SOC stocks; and (2) to find out the vital drivers of SOC accumulation in Chinese afforestation ecosystems. In this study, we present our analysis and discuss the temporal pattern of SOC accumulation as well as the major drivers of SOC accumulation in Chinese afforestation ecosystems. It is not only an informational backdrop to guide Chinese afforestation ecosystem management practices but also a key to strengthening China's goal of achieving carbon neutrality.

2. Materials and methods

2.1 Data preparation

To include a study in the meta-analysis. Literature had to be fulfilled following 4 criteria: (1) the SOC concentrations (or SOC stocks) of non-afforest land (reference) and forested plots must have been assessed; (2) plantation age and dominant species of forested plots must have been reported; (3) the land use history has been showed and (4) the study identified the plantation age. In total, the final dataset comprised 72 studies published between 1985-2019, including 288 observations in 24 provinces or municipalities with corresponding control plots (a plot in which the SOC concentrations or SOC stocks from former land use prior to afforestation were known and could be compared with a nearby afforested plot within the same site).

The following information was compiled: source(s) of data, location (longitude and latitude), climatic information (mean annual temperature (MAT) and mean annual precipitation (MAP)), forest (arbor, divide tree type into conifer and broadleaf, and evergreen and deciduous), growth variability (coverage, tree height, DBH, planting density, canopy density, aboveground biomass, underground biomass, and total biomass), years since afforestation, soil bulk density, soil physical properties (SPP, including soil moisture (SM), silt, clay, and sand in soil), soil chemical properties (SCP, including TN, AN, TP, AP, TK, AK, PH, Ca, Mg), and amount of SOC concentrations or SOC stocks. The final dataset was divided into five groups according to stand ages: 1-5, 6-10, 11-20, 21-30, 31-40, and > 40 years. The raw data were either obtained from tables or extracted by digitizing graphs using the Web Plot Digitizer (version 4.2, Oakland, CA).

2.2 Data calculation

Units of soil carbon stocks like "g m^{-2}", "kg m^{-2}", "kg ha^{-1}" and "t ha^{-1}" were transformed to "Mg ha^{-1}". were transformed to "g kg^{-1}". While only SOM reported, its SOC value is calculated using the formula [13]:

$$SOC = SOM \times 0.58 \tag{1}$$

If there was no direct report of SOC stocks, we used the concentrations of SOC or the percentage of SOC concentration, bulk density, and sampling depth to calculate SOC stocks. The SOC stocks calculation equation is as follows [13]:

$$C_s = \frac{SOC \times BD \times D}{10} \tag{2}$$

where Cs is soil organic carbon stocks (Mg ha^{-1}), SOC is soil organic carbon concentration (g kg^{-1}), BD is soil bulk density (g cm^{-3}), and D is soil depth (cm).

2.3 Data analysis

A meta-analysis approach was used to determine the significance of soil C and N to altered cropland conversion. For each study, the response ratio (Ln (RR)) was calculated using the equation (1). However, the relationship between SOC stocks and afforestation plant biomass, as well as soil physicochemical properties, has to be explored, but many necessary data of plant indicators and soil physicochemical properties such as DBH, SM, PH, and TN is inefficient. Therefore, plant growth factors, SPP and SCP were converted into the combinations of average effect values. The specific steps are as follows:

The difference between the data after afforestation and the data before afforestation in a single experiment is taken as the natural logarithm [14]:

$$Ln(RR) = \ln\left(\frac{X_t}{X_c}\right) = \ln(X_t) - \ln(X_c) \quad (3)$$

where RR is the response ratio, X_t and X_c were means of SOC stocks from the afforested site and in the corresponding control site. If X_t and X_c are normally distributed and both are greater than zero, the RR was typically nearly normal distribution. The variance (v) of each log response ratio was approximated as:

$$v = \frac{s_t^2}{X_t^2 n_t} + \frac{s_c^2}{X_c^2 n_c} \quad (4)$$

Average the logarithmic data of plant affect value, soil physical properties affect value, and soil chemical properties affect value respectively. Then we get the average effect values of plant biomass, SPP, and SCP.

$$ES_{Average} = \frac{\sum ES_i}{i} \quad (5)$$

where i is the number of natural logarithms of different properties in a category.

Due to the big gap among the values of topographical variability, slope gradient, slope aspect, and elevation, we divide slope gradient, slope aspect, and elevation by 10, 100, and 1000 respectively, and then average to get a new value.

$$TR = \frac{\sum X_n}{10n} + \frac{\sum Y_n}{100n} + \frac{\sum Z_n}{1000n} \quad (6)$$

where X, Y, and Z represent slope gradient, slope aspect, and elevation, and n is the number of X, Y, and Z (the number of = slope gradient = the number of slope aspect = the number of elevation).

SPSS 26.0 statistical software was employed for the statistical analysis of all data, where the data of each variable were tested by normality and homogeneity. A linear regression analysis was adopted to examine the relationships between ln (RR) of SOC stocks, plant biomass, climatic variability (MAT, MAP), topographic variability (slope gradient, slope aspect, and elevation), SPP (silt, clay, sand, SM), SCP (PH, Ca, TN, AN, NH_4, NO_3, TP, AP, TK, AK, C: N) and initial SOC stocks. Duncan's test revealed significant differences under $P < 0.05$.

Structural Equation Modeling (SEM) was performed on the same variables as the multiple regressions by using the software program Amos (version 24.0; 2015 Amos Development Corporation). Structural equation models can be constructed using continuous categorical predictor variables and provide a graphical interpretation of complex ecological interactions. Sigma Plot 14.0 was used for plotting.

3. Results

3.1 General patterns in SOC accumulation

Positive effects on SOC stocks [ln(RR_{SOC}) > 0] were identified after afforestation, and significantly variated with age of afforestation ($P < 0.01$) (Fig. 1). SOC stocks initially decreased at the first 5 years, and then tended to increase, peaked at 11-20 years and then decreased slightly ($P > 0.05$) with increasing age of afforestation. However, there was a remarkable increase ($P > 0.05$) in SOC stocks for > 40 years afforestation (Fig. 2).

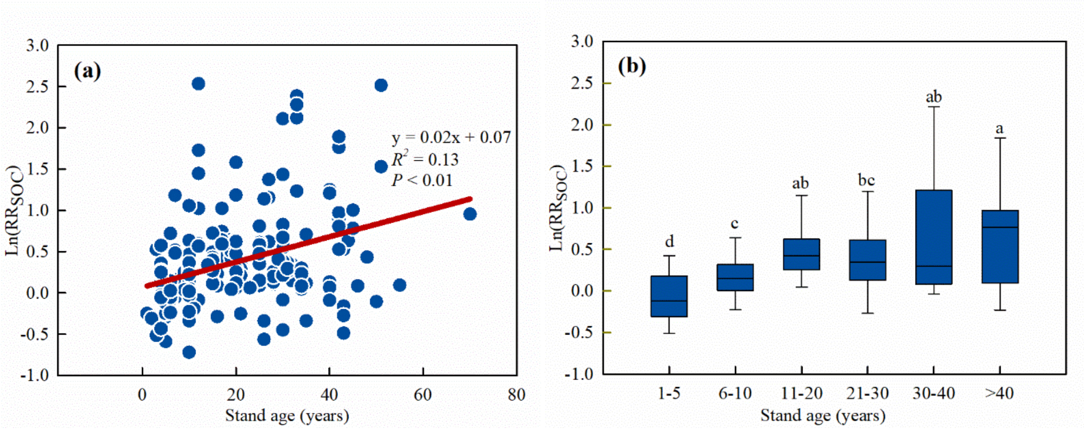

Figure 1. Variations in the effect size of soil organic carbon with stand age: (a) the linear regression equation (y = kx + y0) between the effect size of SOC stocks and stand age after afforestation; (b) the effect size of SOC stocks in response to the time after afforestation. The error bars represent standard errors, and different letters on the error bars indicate significant differences among different afforestation ages represent significant difference at P < 0.05 on values according to Duncan test (P < 0.05).

3.2 Changes in SOC accumulation with different tree species

Similar patterns of SOC accumulation were shown in the Chinese afforestation ecosystem using different tree species (Fig. 2). Conifer and evergreen forests started to significantly increase C stock after afforestation for 5 years, for broadleaf and deciduous forests after 10 years. By 20 years, SOC stocks in coniferous and evergreen forests had begun to decrease, while for deciduous forests this was after 30 years and in broadleaf forests, this was after 40 years. In addition, SOC stocks in conifer and deciduous forests more than in broadleaf and evergreen forests (Table 1), but the difference was not significant ($p > 0.05$). These results indicated tree species are not the key factors that mediated the difference in afforestation in terms of SOC accumulation.

Table 1. Changes in the effect size of SOC stocks in afforestation ecosystems of different tree species

Tree species	*N*	Ln (RR_{SOC})	*F*	*P*
Conifer	97	0.40 ± 0.61^{a}		
Broadleaf	79	0.27 ± 0.45^{a}	1.78	1.51
Evergreen	78	0.27 ± 0.58^{a}		
Deciduous	107	0.40 ± 0.51^{a}		

Notes. Values are mean ± standard error. Data followed by different superscript letters represent significant difference at $P < 0.05$ on values according to the Duncan test.

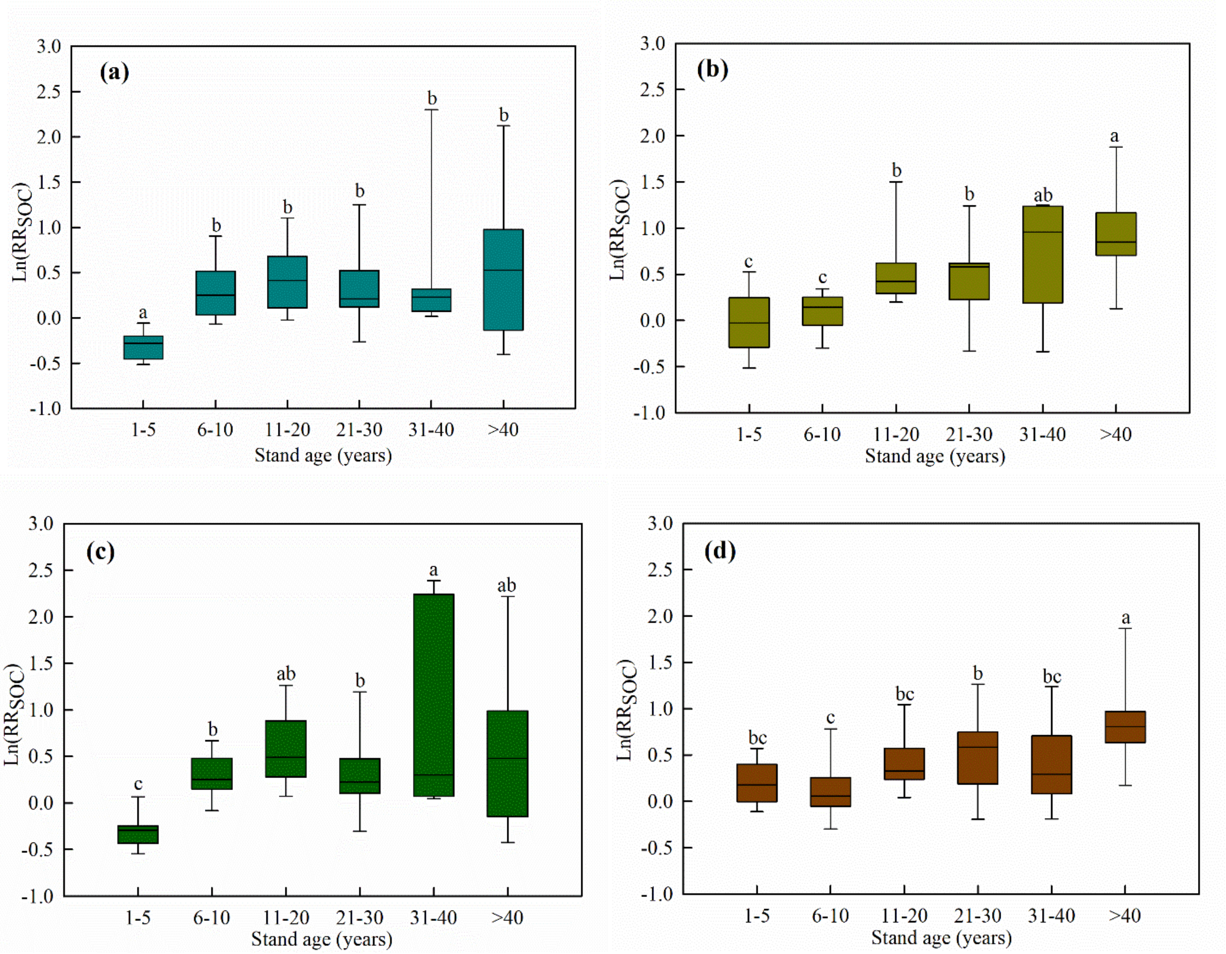

Figure 2. The difference between the two four types of forest in relation to change in the effect size of SOC stocks in response to time after afforestation: (a) conifer forest; (c) broadleaf forest; (c) evergreen forest; (d) deciduous forest. The error bars represent standard errors, and different letters on the error bars indicate significant differences among different afforestation ages represent significant difference at *P* < 0.05 on values according to Duncan's test.

3.3 Multiple factors of SOC accumulation

Stepwise regression showed that SOC accumulation had significant and positive correlations ($p < 0.05$) with plant growth variability, SM, and the majority of SCP, while the negative correlations ($p < 0.05$) with climate variability and initial SOC stocks. Furthermore, SEM illustrated that the most important factor explaining SOC accumulation was SCP (Standardized regression weight = 0.53), followed by MAT (-0.225), SPP (0.126), and initial SOC stocks (-0.079). Besides, the interactions between MAT and MAT had significant and positive effects on the SOC accumulation, followed by the interactions between SCP, SPP, and plant growth variability (Fig. 3). These results indicated that SCP, SPP, MAT, and initial SOC stocks generally mediated the difference on afforestation in terms of SOC accumulation.

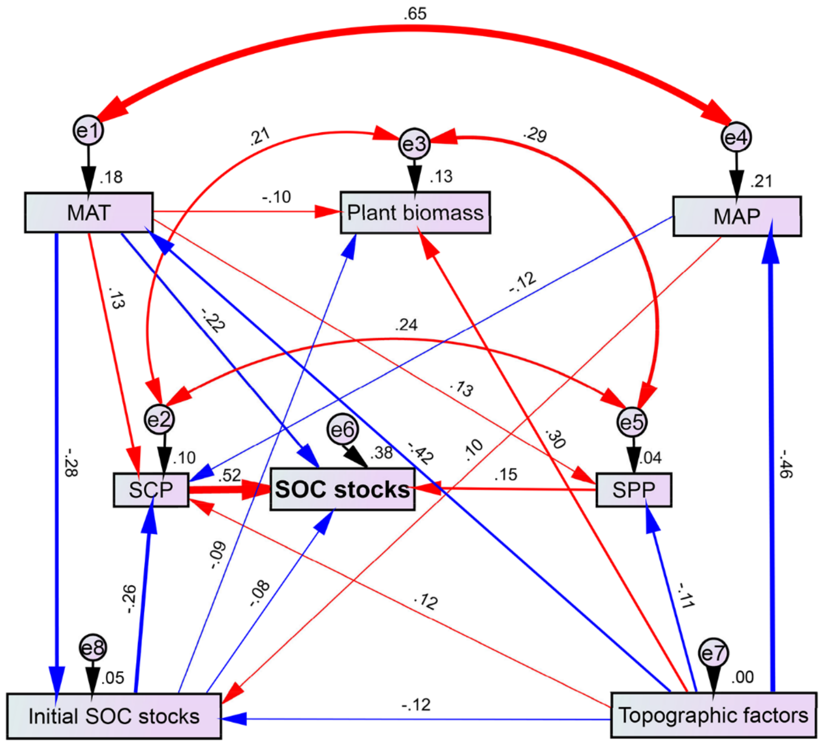

Figure 3. SEM among growth variability, MAT, MAP, SCP, SPP, SOC stocks, Topographic variability, and initial SOC stocks. Growth variability, SCP, and SPP all use the converted average effect size. The black arrows indicate positive effects and the red arrows indicate negative effects. The thickness of the arrow indicates the magnitude of standardized regression weight.

4. Discussion

4.1 Temporal pattern of SOC accumulation

Our synthesis revealed that SOC accumulation was significantly and positively correlated with stand age in the long term ($P < 0.01$) (Fig. 1), which can be explained that afforestation improved the number of C inputs with increasing time by a new microclimatic regime and enhanced organic matter protection [9]. A pattern of SOC accumulation an initial decrease in SOC stocks during the early stage, followed by a gradual return then to the accumulation of SOC has been reported by other authors [15-17], which were similar to the pattern in our synthesis (Fig. 1). Moreover, Den et al found that the initial decrease in SOC stocks occurs during the first 5 years, which is in agreement with our observation. This phenomenon can be by explained that lower productivity of new vegetation and soil disturbance make a loss in soil C [9, 15]. However, our synthesis found a disagreement with their observation that there was a slight loss during the 11-40 years after afforestation. This can be explained that stabilized input of C from litterfall increases requires approximately 30 years after afforestation with canopy closure [18]. Likewise, Barcena reported that there was a clear difference in SOC before and after 30 years in the Northern European afforestation ecosystem, shifting from negative to positive effects [19]. Taken together, these results increase our understanding of SOC accumulation of how to change during the long term, indicating losses in SOC stocks not only occur during the early years but also may occur in the long term (> 20 years) afforestation ecosystem.

4.2 Effect of tree species on SOC accumulation

Our synthesis revealed that tree species have affected SOC accumulation on magnitude and dynamics in the Chinese afforestation ecosystem (Table 1 and Fig. 2). This can be explained that soil C stocks differences are largely regulated by differences in aboveground litterfall inputs and decomposition, which is mainly controlled by litter quality tree species [20]. Deng reported that there were higher SOC stocks in deciduous forests than in evergreen forests after afforestation [6], which is similar to our findings (Table 1). Yet, Deng reported that the SOC content of broadleaf forests is higher than that of conifer forests [6], which differs from our findings (Table 1). This discrepancy may be attributed to the area with different climate conditions in studies. However, the difference in magnitude of SOC accumulation was not significant (Table 1), which can be explained that litterfall decomposition was regulated by soil temperature and moisture that was closely related to climate conditions. Our findings indicated that tree species were not the major driver of SOC accumulation in afforestation ecosystems.

4.3 Effect of soil fertility and moisture on SOC accumulation

Our synthesis revealed that the divergent effects of afforestation mainly depended on SCP and SPP SEM showed that SOC accumulation was positively correlated with SCP and SPP. This suggested that SOC accumulation is coupled with nutrient cycles in afforestation ecosystems [21, 22]. Sequestering C into soil organic matter needs sufficient nutrients, such as N, P, and K [23]. Shi demonstrated that SOC accumulation is also strongly and positively correlated with TN, TP, TS, and AN [24]. Likewise, as is shown in stepwise regression, there was a significant linear relationship ($P < 0.05$) between SOC accumulation and soil nutrient (Ca, TN, AN, TP, AK, and C: N) changes. Besides, we found a positive interaction between SOC accumulation, SM, and growth variability (Fig. 3), which can explain that SOM increases SWC by enhancing soil water-holding capacity [25]; moreover, SM is the main regulator and transporter in soil, controlling enzyme activities [26, 27], while forest regulates SM, nutrient availability and other edaphic characteristics. Taken together, these results indicate that afforestation ecosystems may have greater C sequestration potential with moist, nutrient-rich soil.

4.4 Effect of climate on SOC accumulation

Our synthesis revealed that SOC accumulation was significantly and negatively correlated with climate variability. Step regression showed that MAT and SM were the main factors affecting SOC accumulation after afforestation. These results can be explained that high temperatures stimulate decomposition and thus reduce SOC stocks [28]. Yet, Deng reported that the increase in temperature and moisture were the major factors determining the rate of accumulation [6]. This discrepancy may be attributed to strategy, site, and data processing in the studies. In addition, we found that there was a significant linear relationship between SOC accumulation and SM, which can be explained by the increment of topsoil moisture by rainfall, which in turn quickens litterfall decomposition [29]. In addition, the interaction between MAT and MAP had a significant side effect on SOC stocks, which can be explained that the leaching effect of SOC enhanced by rainfall reduced SOC stocks in topsoil [30]. Our findings indicate that the lower temperature sites with lower precipitation displayed a higher C sequestration in the afforestation ecosystem.

4.5 Effect of initial SOC stocks on SOC accumulation

Our synthesis revealed that the initial SOC stocks prior to afforestation also affect SOC accumulation. Shi reported that initial SOC stocks were significantly negatively correlated with SOC accumulation [31], which is similar to our findings shown in regression. This can be explained by different rates of decomposition in soil organic matter [15]. Our findings indicate that higher initial soil C stock sites having a negative effect on soil C accumulation in afforestation ecosystems.

5. Conclusion

SOC accumulation was positively correlated with the stand age, driven by soil fertility, soil moisture, and initial SOC stocks and their interactions in the long term. The temporal pattern for SOC accumulation showed that losses in SOC stocks not only occur during the early years but also may occur in the long-term (> 20 years) afforestation ecosystem. Soil fertility was the most significant and positive driver of SOC accumulation, followed by soil moisture and their interactions. MAT and initial SOC stocks were the significant and negative drivers of SOC accumulation. These results allow afforestation ecosystem management to more precisely relate C sequestration. Overall, our work suggests that managers would be better advised to invest more resources in the selection and management of afforestation ecosystems than in tree species or growth variability for soil C sequestration benefits. These findings can help guide the efficient management of the Chinese afforestation ecosystem, further maximizing the benefits of soil C sequestration to offset excess CO2 in the atmosphere, and strengthen the goal of achieving carbon neutrality.

References

[1] Bellard, C., Marino, C. & Courchamp, F. (2022). Ranking threats to biodiversity and why it doesn't matter. Nat Commun., 13, 2616.

[2] Li, G., Fang, C., Li, Y. et al. (2022). Global impacts of future urban expansion on terrestrial vertebrate diversity. Nat Commun., 13, 1628.

[3] Steffen, W., Rockstr¨om, J., Richardson, K., Lenton Timothy, M., Folke, C., Liverman, D., Summerhayes Colin, P., Barnosky Anthony, D., Cornell Sarah, E., Crucifix, M., Donges Jonathan, F., Fetzer, I., Lade Steven, J., Scheffer, M., Winkelmann, R., & Schellnhuber Hans, J. (2018). Trajectories of the earth system in the Anthropocene. Proc. Natl. Acad. Sci., 115 (33), 8252-8259.

[4] Piao, S., Yue, C., Ding, J., et al. (2022). Perspectives on the role of terrestrial ecosystems in the 'carbon neutrality' strategy. Sci. China Earth Sci., 65, 1178-1186.

[5] Song, X., Peng, C., Zhou, G., et al. (2014). Chinese Grain for Green Program led to highly increased soil organic carbon levels: A meta-analysis. Sci Rep., 4, 4460.

[6] Deng, L., Liu, G. B., & Shangguan, Z. P. (2014). Land-use conversion and changing soil carbon stocks in China's 'grain-for-green' program: a synthesis. Global Change Biology, 20(11), 3544-3556.

[7] China's National Development and Reform Commission. (2015). Enhanced actions on climate change: China's intended nationally determined contributions (http://www. china.org.cn/chinese/2015-07/01/content_35953590.htm).

[8] Paul KI, Polglase PJ, Nyakuengama JG, & Khanna PK. (2002). Change in soil carbon following afforestation. Forest Ecology and Management, 168, 241-257.

[9] Laganiere J, Angers DA, & Pare D. (2010). Carbon accumulation in agricultural soils after afforestation: a meta-analysis. Global Change Biology, 16, 439-453.

[10] Jaehyun Lee, Xue Zhou, Yeon Ok Seo, Sang Tae Lee, Jeongeun Yun, Yerang Yang, Jinhyun Kim, Hojeong Kang. (2023). Effects of vegetation shift from needleleaf to broadleaf species on forest soil CO2 emission, Science of The Total Environment, 856, 0048-9697.

[11] Fang, J., Y. Yang, W. Ma, A. Mohammat, H. Shen. (2010). Ecosystem carbon stocks and their changes in China's grasslands, Sci. China Life Sci., 53(7), 757-765.

[12] National Forestry and Grassland Administration. (2019). China forest resources report (2014-2018).

[13] Guo LB, Gifford RM. (2002). Soil carbon stocks and land use change: a meta-analysis. Global Change Biology, 8, 345-360.

[14] Hedges LV, Gurevitch J, Curtis PS. (1999). The meta-analysis of response ratios in experimental ecology. Ecology. 80: 1150-1156.

[15] Zhang K, Dang H, Tan S, Cheng X, Zhang Q. (2010). Change in soil organic carbon following the 'Grain-for-Green' programme in China. Land Degradation & Development, 21, 16-28.

[16] Karhu K, Wall A, Vanhala P, Liski J, Esala M, Regina K. (2011). Effects of afforestation and deforestation on boreal soil carbon stocks: comparison of measured C stocks with Yasso07 model results. Geoderma, 164, 33-45.

[17] Deng L, Wang KB, Chen ML, Shangguan ZP, Sweeney S. (2013). Soil organic carbon storage capacity positively related to forest succession on the Loess Plateau, China. Catena, 110, 1-7.

[18] Viechtbauer, W. (2007). Accounting for heterogeneity via random-effects models and moderator analyses in meta-analysis. Journal of Psychology, 215, 104-121.

[19] Bárcena, T.G., Kiær, L.P., Vesterdal, L. (2014). Soil carbon stock change following afforestation in Northern Europe: a meta-analysis. Global Change Biol., 20, 2393-2405.

[20] Hobbie S, Ogdahl M, Chorover J, Chadwick O, Oleksyn J, Zytkowiak R, Reich P. (2007). Tree species effects on soil organic matter dynamics: the role of soil cation composition. Ecosystems, 10, 999-1018.

[21] Goll DS, Brovkin V, Parida BR, Reick CH, Kattge J, Reich PB, van Bodegom PM, Niinemets U. (2012). Nutrient limitation reduces land carbon uptake in simulations with a model of combined carbon, nitrogen and phosphorus cycling. Biogeosciences, 9:3547-3569.

[22] Cleveland CC, Houlton BZ, Smith WK, Marklein AR, Reed SC, Parton W, Del Grosso SJ, Running SW. (2013). Patterns of new versus recycled primary production in the terrestrial biosphere. Proc Natl Acad Sci U S A, 110:12733-12737.

[23] Kirkby CA, Richardson AE, Wade LJ, Passioura JB, Batten GD, Blanchard C, Kirkegaard JA. (2014). Nutrient availability limits carbon sequestration in arable soils. Soil Biol Biochem., 68:402-409.

[24] Shi, S., Peng, C., Wang, M., et al. (2016). A global meta-analysis of changes in soil carbon, nitrogen, phosphorus and sulfur, and stoichiometric shifts after forestation. Plant Soil, 407, 323-340.

[25] Franzluebbers, A.J. (2022). Soil organic matter, texture, and drying temperature effects on water content. Soil Sci. Soc. Am. J., 86, 1086-1095.

[26] Steinweg, J.M., Dukes, J.S., Wallenstein, M.D. (2012). Modeling the effects of temperature and moisture on soil enzyme activity: linking laboratory assays to continuous field data. Soil Biol. Biochem., 55, 85-92.

[27] Vo, N.X.Q., Kang, H. (2013). Regulation of soil enzyme activities in constructed wetlands under a short-term drying period. Chem. Ecol. 29, 146-165.

[28] Lal R. (2005). Forest soils and carbon sequestration. Forest Ecology and Management, 220, 242-258.

[29] Olsson BA, Guedes BS, Dahlin AS, Hyvönen R. (2019). Predicted longterm effects of decomposition of leaf.

[30] Cleveland CC, Townsend AR. (2006). Nutrient additions to a tropical rain forest drive substantial soil carbon dioxide losses to the atmosphere. Proc Natl Acad Sci., 103:10316-10321.

[31] Shi SW, Zhang W, Zhang P, Yu YQ, Ding F. (2013). A synthesis of change in deep soil organic carbon stores with afforestation of agricultural soils. Forest Ecology and Management, 296, 53-63.