Spatial Patterns and Drivers of Soil Chemical Properties in a Typical Hickory Plantation

Mengjiao Sun
Anhui Agricultural University

Enqing Hou
zhong guo ke xue yuan hua nan zhi wu yuan: South China Botanical Garden

Jiasen Wu
Zhejiang Agriculture and Forestry University: Zhejiang A and F University

Jianqin Huang
Zhejiang Agriculture and Forestry University: Zhejiang A and F University

Xingzhao Huang (xingzhaoh@163.com)
Anhui Agricultural University

Research

Keywords: Soil nutrients, Spatial pattern, Soil-forming factors, Random forest, Hickory plantation

Posted Date: September 3rd, 2021

DOI: https://doi.org/10.21203/rs.3.rs-845777/v1

License: © This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License
Abstract

**Background:** Soil nutrients play critical roles in regulating and improving the sustainable development of economic forests. Consequently, an elucidation of the spatial patterns and drivers of soil nutrients in these forests is fundamental to their management. For this study, we collected 314 composite soils at a 0-30 cm depth from a typical hickory plantation in Lin’an, Zhejiang Province, China. We determined the concentrations of macronutrients (i.e., soil organic carbon, hydrolyzed nitrogen, available phosphorus, and available potassium) and micronutrients (i.e., iron, manganese, zinc, and copper) of the soils. We employed random forest analysis to quantify the relative importance of soil-forming factors to predict the soil nutrient concentrations, which could then be extrapolated to the entire hickory region.

**Results:** Random forest models explained 61%–88% of the variations in soil nutrient concentrations. The mean annual temperature and mean annual precipitation were the most important predictor of soil macronutrient and micronutrient concentrations. Moreover, parent material was another key predictor of soil available phosphorus and micronutrient concentrations. Mapping results demonstrated the importance of climate in controlling the spatial distribution of soil nutrient concentrations at finer scales, as well as the effect of parent material, topography, stand structure, and management measures of hickory plantations.

**Conclusions:** Our study highlights the biotic factors, abiotic factors, and management factors control over soil macronutrient and micronutrient concentrations, which have significant implications for the sustainability of soil nutrients in forest plantations.

**Background**

Economic forests provide food and timber for human society, and therefore should be managed responsibly, efficiently, and sustainably (Patil 2017). The quantity and quality of economic forests are determined by soil nutrients as well as other factors (e.g., climate) (Littke et al. 2014). Consequently, it is imperative to understand the drivers and spatial patterns of soil nutrients for the efficient and precise management of soil nutrients in these forests (Grimm et al. 2008). For example, soil nutrient mapping may be employed to identify areas where nutrients are deficient and fertilization may be required, and where nutrients are too enriched via environmental overloads, which may have negative impacts (Guan et al. 2017).

There is no consensus on the major driver of soil nutrients for economic forests. The spatial patterns of soil nutrients have been a research focus in the soil and environmental sciences (Liu et al. 2014). However, due to the high cost of sample collection and analysis, large-scale sampling to obtain the details of the distribution of soil nutrients at regional scales is difficult (Yang et al. 2016). Considerable efforts have been expended in recent years to estimate the spatial variability of soil nutrients and elucidate the causative factors involved across different regions (Wanshnong et al. 2013; Elbsaiony et al. 2014). Owing to the complexity of terrestrial ecosystems, the spatial patterns of soil nutrients vary in...
different regions (Roger et al. 2014; Xin et al. 2016). The spatial distribution of soil nutrients is mediated by the five state factors of soil formation, namely climate, topography, parent material, organisms, and pedogenic time (Jenny 1941). In addition, stand structure (e.g., stand age and stand density) and management measures (e.g., fertilization and weeding) of economic forests are also closely related to the spatial pattern of soil nutrients (Ronenberg et al. 2011; Lucas-Borja et al. 2016). These factors vary across different temporal scales and regions, which together affect the spatial variability of soil nutrients (Wang et al. 2009). Consequently, the precise estimation of soil nutrient concentrations across regional scales remains a significant challenge (Wang et al. 2018).

Geostatistical methods have been developed to predict the spatial variability of soil nutrients, with the objective of utilizing quantified soil properties at a given time and place to predict soil variables at unknown locations (Saito et al. 2005). The promotion of precision forestry and advances in the integration of geostatistical and geographic information systems (GIS) have further evolved the prediction of regional soil nutrients (Lacoste et al. 2014). However, further study is still required to identify the relative importance of different factors and the main controlling factors that affect the spatial variability of soil nutrients. The ensemble approaches of machine learning methods can also be used for the prediction of soil nutrients. Random forest can generate abundant data, which includes information of variable importance and critical variables that control changes in soil nutrients (Liaw et al. 2002). Random forest has proven to be an effective method for predicting the spatial distribution characteristics and changes in soil organic carbon. This information can be employed to model the soil organic carbon data for each depth interval, to facilitate the comparison of vertical and lateral distribution patterns (Grimm et al. 2008; Heung et al. 2014; Zhu et al. 2018).

Hickory (*Carya cathayensis* Sarg) is an elite subtropical nut and oil tree that is native to China, whose nuts are popular due to their high nutritional value, good taste and unique flavor (Wu et al. 2019). Zhejiang Province accounts for more than 70% of the total production of hickory in China, with a total planting area of 86,700 hm$^2$. In the main producing area of Lin 'an, hickory accounts for more than 70% of the total income of farmers; thus, it is one of the main economic trees that allows farmers to significantly enrich their quality of life. The hickory plantation is restricted by the topographic conditions, with different management methods, and there are also some unmanaged phenomena. To meet the increasing demands for hickory while maximizing its economic benefits, it is of particular importance to select areas that are highly suitable for its growth (Shen et al. 2016).

There is universally agreed that the potential impact on the spatial patterns of soil nutrients needs to be included in biotic factors (e.g., stand density and stand age), abiotic factors (e.g., climate and topography), and management factors (e.g., fertilization and weeding). Here, we aim to improve our understanding of the variation and the driving factors of the spatial patterns of soil nutrients. Moreover, we hypothesize that the spatial variation of soil nutrients is mainly determined by the climatic factors. Consequently, it is necessary to fully investigate the spatial patterns of soil nutrients in the main producing areas of hickory so as to master the relationships between impact factors and soil nutrients.

\[\text{Loading [MathJax]/jax/output/CommonHTML/jax.js}\]
distribution of soil nutrients. 2) predict and map the spatial distribution of soil nutrients in hickory plantations.

Materials And Methods

Study area

This study was conducted in Lin'an City (118° ~ 120° E, 29° ~ 31° N), Zhejiang Province, China, which is the central hickory producing area that includes Changhua, Daoshi, Qingliangfeng, and other towns (Chen et al. 2010). This area, is home to a typical subtropical climate with an average annual temperature that ranges from 10°C-16°C. The annual precipitation is 1350–1500 mm, with 1774 h of daylight per year and 235 frost free days (Huang et al. 2010). Chinese hickory plantations are primarily distributed at altitudes of from 140 m to 1050 m. The main types of parent materials are acidic volcanic rocks, mixed sedimentary rocks, and pyroclastics. A pure hickory forest was planted in 1982, with a density of from 300–375 plants hm$^{-2}$.

Soil sampling and analysis

For this study, soil samples were collected from 314 sites using the grid method within 1×1 km areas (Fig. 1). Each site was arranged with 10×10 m plots, layout 5 points on the “S”-shaped lines of each plot. Surface soil samples (0 ~ 30 cm) were collected from 5 points and mixed evenly. Approximately 1kg of samples were divided by a quartering method and then transferred to the laboratory for air drying. Meanwhile, data including longitude, latitude, slope, aspect, parent material, stand density and soil type were recorded for each sample site. Moreover, a complete hickory plantation-owner consultation was also carried out to collect the sample sites information such as stand age, fertilization and weeding management measures. Two climate variables (mean annual temperature and precipitation) derived from the WorldClim2 Database at a 1 km spatial resolution (http://worldclim.org/) were used in this study. A distribution map of the sample points in the study area was generated by ArcGIS 10.3.

The soil properties of the different sampling sites were measured based on the standard methods in China, and the soil bulk density was determined using a ring knife method (Wang et al. 2010). A hydrometer technique was used to establish the mechanical composition of the soil (Blake 2008), whereas the pH was analyzed using a soil/water ratio of 1:2.5 in an aqueous suspension (Samuels 1976). The soil organic matter (SOM) was determined via wet oxidation using concentrated H$_2$SO$_4$ and K$_2$Cr$_2$O$_7$, and titrating with (NH$_4$)$_2$(SO$_4$)$_2$·6H$_2$O (Nelson 1996). Based on the assumption that soil organic matter contains 58% carbon, the soil organic carbon concentration was calculated as the soil organic matter concentration × 0.58 (Jackson 1974). Hydrolyzable nitrogen (HN) was hydrolyzed using 0.1 mol L$^{-1}$ of NaOH (Wu et al. 2014), whereas soil available phosphorus (AP) was extracted by HCl-NH$_4$F and determined by a molybdenum-antimony colorimetric method (Wu et al. 2014). Soil available potassium (AK) was extracted using ammonium acetate and determined by a flame photometric method.
Microelements, namely, iron (Fe), manganese (Mn), zinc (Zn), and copper (Cu) were extracted with dilute acid and determined by an atomic absorption spectrophotometer (Wu et al. 2014).

**Correlation analysis**

Pearson correlation coefficients were calculated to determine the strength of the associations between soil organic carbon, hydrolyzed nitrogen, available potassium, phosphorus, iron, manganese, zinc, and copper. The advantage of the correlation coefficient is that the relationships between variables can be numerically measured and it is directional (Cohen et al. 2009), where 1 represents a positive correlation and −1 represents a negative correlation. The strengths of the relationships between variables may be quantified, and the closer the number is to 0, the weaker the correlation. Correlation analyses were performed in the R software (version 4.0.4), using the direct function cor() calculation and the corrplot package.

**Random forest analysis**

Data from 314 sampling sites surveyed during our study were analyzed (the frequency distribution of soil nutrient concentrations are depicted in the Additional file (Additional file 1 Fig. S1, Fig. S2). For each soil nutrient data set, we randomly split the data into training and test sets using a 2:1 split. Random forest depends only on three user-defined parameters: the number of trees (ntree) in the forest, the minimum number of data points in each terminal node (nodesize), and the number of features attempted at each node (mtry). Initially, we tested the combination of ntree, nodesize, and mtry with a training set. More stable results for estimating variable importance were achieved with a higher ntree number (Díaz-Uriarte et al. 2006); thus, we used ntree = 2000, 3000, 5000.

For nodesize we used 3, 5, 7 for regression, which are 3, 5, 7 instances in each terminal node. The default value of mtry in the regression problem is one third of the total number of predictors (p). The predictors we selected included two climate variables: mean annual temperature and mean annual precipitation; two topographical factors: slope and aspect; two stand structure variables: stand age, stand density; two management practices variables: fertilization times, weeding frequency; and parent material. Nevertheless, as the performance of random forest prediction can be sensitive to mtry (Bento et al. 2002; Heung et al. 2014), we applied the mtry values of 1/3p, 2/3p, p. The random forest analysis was then repeated with different parameter combinations for each variable set, and the goodness of fit (% var explained) of each combination was compared. We selected the parameter combination with the highest goodness of fit. Finally, the data of the training set were predicted by the established model.

**Assessment of predictions**

The 1/3 test set, namely the out of bag (OOB) sample, primarily uses the common statistical parameters, coefficient of determination (denoted as $R^2_{oob}$), root mean square error ($RMSE_{oob}$), and mean absolute error ($MAE_{oob}$) to evaluate the random forest model established by the training set. This was calculated by the following formula,
\[ R^2_{oob} = 1 - \frac{\sum_{i=1}^{m} (x_i - y_i)^2}{\sum_{i=1}^{m} (x_i - \bar{x})^2} \]

\[ RMSE_{oob} = \frac{1}{m} \sum_{i=1}^{m} (x_i - y_i)^2 \]

\[ MAE_{oob} = \frac{1}{m} \sum_{i=1}^{m} |x_i - y_i| \]

where \( x_i \) is the \( i \)th original value, and \( y_i \) is the \( i \)th estimated value. The \( R^2 \) value can assess the model performance, where the larger the \( R^2 \) the better the predictive effect. RMSE can evaluate the degree of data change. MAE can better reflect the actual situation of a predicted value error. The smaller the RMSE and MAE values, the higher the accuracy of data described by the predictive model. All random forest computations and prediction of soil nutrients were performed in the R 4.0.4, using the random forest package. Spatial distribution maps were produced with ArcGIS10.3 software (Minami 2002).

**Results**

**Correlation analysis of soil physicochemical properties in hickory plantation**

Correlation analysis is an effective method to reveal the relationship between soil nutrients. The result (Fig. 2) showed that there was a significantly positive correlation between soil organic carbon, available potassium, available phosphorus, hydrolyzed nitrogen and zinc, manganese, iron, which further proved that these nutrients may be affected by similar factors. The correlation coefficient between soil organic carbon and hydrolyzed nitrogen was as high as 0.87. Copper had correlations with the other nutrients with small correlation coefficients, which indicated that copper may have had different driving factors compared with other nutrients in the soil.

**Performance and variable importance of random forest models for predicting soil nutrients in a hickory plantation**

To optimize the performance of random forest predictions in terms of the fitting interpretation (% var explained), we used the training set to test the combination of ntree, mtry, and nodesize. The parameter ntree was set to 2000, 3000, 5000, mtry values were 3, 5, 9, and nodesize values were 3, 5, 7. We selected the parameter combination with the highest goodness of fit, that is, ntree = 5000, mtry = 3, nodesize = 3 (Additional file 1 Table. S1). In general, the performance of the models was limited. On average, the prediction accuracy was lowest for zinc compared to micronutrient components, namely iron, manganese, copper, and macronutrients ranging from between 0.75 and 0.90 in \( R^2_{oob} \) (Table 1). These results suggested that in the topsoil the spatial distribution patterns of soil nutrients were highly variable.
due to small scale variations in input, redistribution, as well as in the intrinsic random variability of soil nutrients.

Table 1

| Soil properties | $R^2_{oob}$ | RMSE$_{oob}$ | MAE$_{oob}$ |
|-----------------|------------|--------------|-------------|
| SOC             | 0.82       | 1.52         | 1.28        |
| HN              | 0.77       | 13.14        | 11.39       |
| AP              | 0.88       | 1.3          | 1.14        |
| AK              | 0.81       | 12.31        | 10.88       |
| Fe              | 0.79       | 2.48         | 2.17        |
| Mn              | 0.68       | 6.00         | 5.22        |
| Zn              | 0.61       | 0.29         | 0.24        |
| Cu              | 0.87       | 0.11         | 0.12        |

Variable importance revealed different dominating influencing features between soil nutrients random forest models (Figs. 3–4). Mean annual temperature and annual precipitation had a strong impact on the prediction of soil organic carbon (Fig. 3a). The level of organic carbon in topsoil is contingent on the inputs of biomass into the soil, which are influenced by climate. Similar to soil organic carbon, for the prediction of hydrolyzed nitrogen and available potassium, climate was also more crucial than other variables (Fig. 3b, Fig. 3d). Mean annual temperature and parent material both showed high relative importance in the random forest prediction models of available phosphorus (Fig. 3c).

Climate and parent material were also the most critical factors controlling variability of soil iron and copper (Fig. 4a, Fig. 4d). Mean annual precipitation was the dominant variable affecting the spatial distribution of manganese (Fig. 4b), mean annual temperature was the most important factor driving the spatial distribution of zinc (Fig. 4c). Parent material was the second-most important variable that influenced the manganese and zinc concentration. The role of the parent material was apparent in the spatial distribution of micronutrients. The variables were ranked in the order of climate, parent material, topography, stand structure and management measures. Climate was the most critical predictor for soil nutrients, as it determined their spatial distribution.

Spatial pattern of soil nutrients in a hickory plantation
The spatial distribution of soil nutrient concentrations in the hickory plantations mapped by the RF model revealed that all of the soil nutrients had obvious spatial patterns (Figs. 5–6). The concentrations of soil organic carbon and hydrolyzed nitrogen in the soil had similar spatial distribution patterns, with high concentrations primarily located in the west, and obviously low concentrations in the other areas. The concentrations of soil available potassium and available phosphorus in the study area were generally low. The high-value regions of soil available potassium were unevenly distributed exhibited, with the maximum value being 175.10 mg/kg, the minimum value being 118.77 mg/kg. Only a few areas in the northwest of the hickory plantations had the highest soil available phosphorus concentration, which reached up to 15.72 mg/kg.

The soil concentrations of manganese and copper had similar spatial distribution patterns, with high concentrations being located mainly in the northwest and east of the hickory plantation, and obviously low concentration areas in the west and southwest. The iron concentrations in the study area were relatively low. The concentrations of zinc were high, up to 2.44mg/kg, while low-value regions were unevenly distributed.

**Discussion**

In our study, Random Forest modeling was employed to improve the prediction results, and the optimal settings were selected for each parameter. Through the analysis of each evaluation index, $R^2$ was as high as 0.88, and the prediction performance of each nutrient model was enhanced. Variable importance revealed different dominating influencing factors between soil nutrients. Climate variables, namely mean annual temperature and mean annual precipitation were the key factors that drove the spatial changes and concentrations of soil organic carbon, hydrolyzed nitrogen, available potassium. Climate and parent material were the main controlling factor in spatial distribution of soil available phosphorus and micronutrients.

**Climate controls the spatial distribution of soil nutrients**

As hypothesized, climate was the most important predictor of variation in soil nutrients. Correlation analysis revealed that there was a significant positive correlation between soil nutrients. The variable importance of soil nutrients was basically the same, which further verified that these nutrients may be influenced by similar factors (Fig. 2). Climate drive the spatial distribution of soil nutrients to a greater degree than do the topography, stand structure and management measures factors. The concentration of soil nutrients is generally negatively associated with temperature and positively associated with the annual mean precipitation (Yang et al. 2010; Hobley et al. 2015). Precipitation and temperature determine the level of plant productivity, quantity and quality of inputs into the soil organic matter pool, microbial community composition, and decomposition activities (Zhu et al. 2018; Neff et al. 2002; Torn et al. 2009). Decreased temperatures reduce the rates of organic matter decomposition more than litter production; thus, inducing the accumulation of organic matter (Choudhury et al. 2016; Tsozué et al. 2019).
Hickory requires appropriate temperatures for growth and sufficient water to sustain the physiological processes involved. Soil nutrients in well-developed mountain soils are typically in dynamic equilibrium; however, they are particularly sensitive to climate change (Bowman et al. 2014). When temperatures and water parameters are beyond the range required for optimal growth, soil nutrients can be constrained (Eamus 2003; Huang et al. 2019). We observed that soil nutrients were limited by seasonal temperatures and precipitation. Our models suggested that climate factors outweighed the influences of any other factors, at least in the region and across the environmental gradients that our study encompassed. Parent materials may act indirectly on the distribution of soil organic carbon, hydrolyzed nitrogen and available potassium through their effects on the mechanical compositions of soil (Liu et al. 2016; Doetterl et al. 2015).

**Parent material drives the spatial distribution of soil nutrients**

Variable importance as assigned by random forest clearly indicated that parent material and climate were equally important in controlling the spatial distribution of available phosphorus and micronutrients in hickory plantations. The most fundamental source of soil nutrients were those released by soil mineral weathering, where parent materials determined the weathering speed, physical characteristics, and chemical properties of the soil (Bai et al. 2020). The mineral composition of the parent materials determined the type and quantity of nutrients released in the weathering products. There are three classes of soil in the hickory plantations, which derived from acid volcanic rocks, mixed sedimentary rocks, and pyroclastics. The soil nutrients of the soil formed by the three parent materials have great diversity. High concentrations of iron, manganese, zinc and copper were derived from acidic volcanic rocks in the northwest of the hickory plantation. Since our results did not suggest a strong anthropogenic impact on micronutrient concentrations in the soils investigated, our data may be utilized in the assessment of soil quality (Leitgeb et al. 2019).

The proven trend, based on the combination of global data on soils and geology, is that highly weathered soils are more likely derived from acidic or intermediate parent materials, than from calcareous or mafic parent materials (Augusto et al. 2017). Weathered soils derived from acid volcanic rocks were higher in micronutrients than other types of soils. Volcanic rocks are rich in zinc and copper, which can promote the good growth of trees and lay the foundation for obtaining high-quality fruits. Consequently, forest soils from which such parent materials are derived should be given priority when planting hickory. The concentration of soil sand elucidated the spatial distribution of micronutrients better than the soil clay content did, as the sand content is a surrogate of the quartz content, and because the concentration of quartz in rocks is closely related to soil iron and copper (Rahardjo et al. 2004; Bui et al. 2013). Since the sand concentrations of soil and parent materials were independent of climate (Suchet et al. 2003; Huston et al. 2009), this explained why parent materials were important in predicting the spatial distribution of soil iron and copper.

**Effects of other factors on soil physicochemical properties**

Loading [MathJax]/jax/output/CommonHTML/jax.js
In our study, slope also showed a certain relative importance in the spatial prediction of soil available phosphorus. Slope affects runoff, soil moisture concentrations, and the soil erosion rate, which in turn influences soil nutrients (Johnson et al. 2000; Wang et al. 2009). As the slope angle increases, the precipitation received per unit area, as well as its infiltration decreases due to the greater slope area and higher water flow velocity. Meanwhile, the soil moisture concentration is reduced due to the higher runoff and evaporation area (Florinsky 2016). Consequently, we could not exclude the slope effects even though they were not the most important factor to drive other soil nutrient concentration variabilities in our study.

Aspect had low potential in forecasting soil nutrients. One possible explanation for this phenomenon is that (to some extent) climate has an overriding influence on large scale patterns in ecosystems, including soil carbon cycling, via its control of plant community composition and productivity (Sinoga et al. 2012). The effects of aspect on soil organic carbon are related to temperature and moisture, and primarily manifested by the sunny aspect being dry, under which the soil organic carbon is decomposed more rapidly, with concentrations lower than that under shady conditions (Zhang et al. 2018).

Stand age influenced the spatial distribution of soil nutrients more than stand density did. Stand age can play a significant role in determining forest floor processes and chemistry. Soil nutrients concentration were mainly affected in three ways: soil nitrogen mineralization, litter decomposition and microbial activity (Welke et al. 2005). The litter input and microbial respiration varied significantly under different stand structures. Stand structure can drive soil processes in different ways by altering light, soil temperature and moisture conditions (Hasenauer et al. 2015). However, our study was located in hickory plantation with no obvious difference in stand structure, so the stand age and stand density had little impact on the spatial distribution of soil nutrients.

Our result showed that fertilization and weeding management were not pivotal factors affecting the spatial distribution of soil nutrients, which was inconsistent with management measures being important artificial means to improve soil nutrient levels (Ronnenberg et al. 2011; Lucas-Borja et al. 2016). The main reason was that the factor used in our analysis was the frequency of fertilization and weeding, not the amount of fertilizer. Because hickory plantation was mostly in mountainous areas, there are many semi-artificial research sites. We investigated 229 sites without fertilization and 102 sites without weeding. In addition, even though some study sites were managed, local farmers had not adopted uniform standards. A variety of fertilizers were used in the production of hickory, including compound fertilizers, nitrogen, phosphorus and potassium fertilizers, and weeding methods contain herbicides or weeding machine. Therefore, we could only record the frequency of fertilization and weeding. Management measures were vital factors driving the spatial variability of soil nutrients. In random forest modeling and prediction, factors need to be selected reasonably to manifest their effects.

Our study analyzed soil nutrients at a surface depth of 30 cm. The spatial patterns and drivers of deeper subsoils remain unknown and might be important for the production of hickory plantations. However, our results provide a reference for the maintenance and management of soil nutrients in other economic forests. To improve the quantity and quality of economic forest, factors such as climate and parent
sufficient and uniform rainfall. Soil formed by the weathering of parent rocks that are most suitable for the growth of economic forests should be prioritized.

**Conclusions**

Through the systematic sampling of soils in a typical hickory region, we quantified the relative importance of soil-forming factors to explain regional variations in its physicochemical properties. Macronutrients and micronutrients in hickory plantations all had obvious spatial patterns. The mean annual temperature and mean annual precipitation were found to be the most significant factors for elucidating the spatial variations in soil nutrients. Climate and parent material were the critical factor involved in controlling the spatial variations of soil available phosphorus and soil micronutrients. Slope was also important for explaining the spatial variations in soil available phosphorus and iron. Aspect, stand structure and management measures were less important in the prediction of spatial variations for both soil macronutrients and micronutrients but should not be ignored. An improved understanding of the spatial variations and drivers of soil nutrients in plantations will aid in the development of effective strategies for soil nutrient sustainability.

**Declarations**

**Ethics approval and consent to participate**

Not applicable.

**Consent for publication**

Not applicable.

**Availability of data and materials**

The data that support the findings of this study are available from the corresponding author upon reasonable request.

**Competing interests**

The authors declare that they have no competing interests.

**Funding**

Financial support was supported by the National Key R&D Program of China (2018YFD1000600) and Anhui Provincial science and technology special project (202103a05020044).

**Authors’ contributions**
XH, EH, JW and JH conceived the idea. MS analyzed the data. MS and XH drafted the manuscript. All authors commented preliminary versions of the manuscript and contributed to improve the final version. All authors read and approved the final manuscript.

Acknowledgements

Not applicable.

References

1. Augusto L, Achat DL, Jonard M, Vidal D, Ringleval B (2017) Soil parent material-A major driver of plant nutrient limitations in terrestrial ecosystems. Global Change Biology 23(9):3808–3824. https://doi.org/10.1111/gcb.13691
2. Bai YX, Zhou YC (2020) The main factors controlling spatial variability of soil organic carbon in a small karst watershed, Guizhou Province, China. Geoderma 357:113938. https://doi.org/10.1016/j.geoderma.2019.113938
3. Bento A, Gaulton A, Hersey A, Bellis LJ, Chambers J, Davies M, Kruger FA, Light Y, Mak L, Mcglinchey S (2002) Classification and Regression by randomForest. R News 23(23)
4. Blake GR (2008) Particle density. Methods of Soil Analysis 1:504–505
5. Bowman DMJS, Williamson GJ, Keenan RJ, Prior LD (2014) A warmer world will reduce tree growth in evergreen broadleaf forests: evidence from Australian temperate and subtropical eucalypt forests. Global Ecol Biogeogr 23(8):925–934. https://doi.org/10.1111/geb.12171
6. Bui EN, Henderson BL (2013) C:N:P stoichiometry in Australian soils with respect to vegetation and environmental factors. Plant Soil 373(1–2):553–568. https://doi.org/10.1007/s11104-013-1823-9
7. Chen SQ, Huang JQ, Huang XZ, Lou Z, Lv JQ, Xia GH, Wu JS (2010) Nutrient elements in soil and Carya cathayensis leaves from four parent rock materials. Journal of Zhejiang Forestry College. https://doi.org/10.3724/SP.J.1142.2010.40486
8. Choudhury BU, Fiyaz AR, Mohapatra KP, Ngachan S (2016) Impact of Land Uses, Agrophysical Variables and Altitudinal Gradient on Soil Organic Carbon Concentration of North-Eastern Himalayan Region of India. Land Degradation Development:1163–1174. https://doi.org/10.1002/ldr.2338
9. Cohen I, Huang Y, Chen J, Benesty J (2009) Pearson Correlation Coefficient. Springer Berlin Heidelberg(5):1–4
10. Díaz-Uriarte R, Alvarez de Andrés S (2006) Gene selection and classification of microarray data using random forest. BMC Bioinformatics 7(1):3. https://doi.org/10.1186/1471-2105-7-3
11. Doetterl S, Stevens A, Six J, Merckx R, Van Oost K, Casanova Pinto M, Casanova-Katny A, Muñoz C, Boudin M, Zagal Venegas E, Boeckx P (2015) Soil carbon storage controlled by interactions between geochemistry and climate. Nature Geoscience. https://doi.org/10.1038/ngeo2516
12. Eamus D (2003) How does ecosystem water balance affect net primary productivity of woody species? Biogeosciences 6(4):1045–1063. https://doi.org/10.1071/FP02084
13. Elbasiouny H, Abowaly M, Abu_Alkeir A, Gad A (2014) Spatial variation of soil carbon and nitrogen pools by using ordinary Kriging method in an area of north Nile Delta. Egypt CATENA 113:70–78. https://doi.org/10.1016/j.catena.2013.09.008

14. Florinsky IV (2016) Digital Terrain Analysis in Soil Science and Geology: Second Edition.377–385

15. Grimm R, Behrens T, Mrker M, Elsenbeer H (2008) Soil organic carbon concentrations and stocks on Barro Colorado Island — Digital soil mapping using Random Forests analysis. Geoderma 146(1–2):102–113. https://doi.org/10.1016/j.geoderma.2008.05.008

16. Guan F, Xia M, Tang X, Fan S (2017) Spatial variability of soil nitrogen, phosphorus and potassium contents in Moso bamboo forests in Yong’an City, China. CATENA 150:161–172. https://doi.org/10.1016/j.catena.2016.11.017

17. Hasenauer H, Poetzelsberger E (2015) Forest-water dynamics within a mountainous catchment in Austria. Nat Hazards 77(2):625–644. https://doi.org/10.1007/s11069-015-1609-x

18. Heung B, Bulmer CE, Schmidt MG (2014) Predictive soil parent material mapping at a regional-scale: A Random Forest approach. Geoderma 214–215:141–154. https://doi.org/10.1016/j.geoderma.2013.09.016

19. Hobley E, Wilson B, Wilkie A, Gray J, Koen T (2015) Drivers of soil organic carbon storage and vertical distribution in Eastern Australia. Plant Soil 390(1–2):111–127. https://doi.org/10.1111/j.1365-2486.2009.02123.x

20. Huang MT, Piao SL, Ciais P, Peñuelas J, Wang XH, Keenan TF, Peng SS, Berry JA, Wang K, Mao JF (2019) Air temperature optima of vegetation productivity across global biomes. Nature Ecology Evolution. https://doi.org/10.1038/s41559-019-0838-x

21. Huang XZ, Huang JQ, Hong CD, Lu JQ, Wu JS (2010) Comparison on Soil Physical and Chemical Properties at Different Vertical Zones of Carya cathayensis Stands. Journal of Zhejiang Forestry Science and Technology

22. Huston MA, Wolverton S (2009) The global distribution of net primary production: resolving the paradox. Ecol Monogr 79(3). https://doi.org/10.1890/08-0588.1

23. Jackson ML (1974) Soil Chemical Analysis — An Advanced Course

24. Jenny H (1941) Factors of Soil Formation: A System of Quantitative Pedology. McGraw-Hill, New York

25. Johnson CE, Ruiz-Mendez JJ, Lawrence GB (2000) Forest Soil Chemistry and Terrain Attributes in a Catskills Watershed. Soil Sci Soc Am J 64(5):1804–1814. https://doi.org/10.2136/sssaj2000.6451804x

26. Lacoste M, Minasny B, Mcbratney AB, Michot D, Walter C (2014) High resolution 3D mapping of soil organic carbon in a heterogeneous agricultural landscape. Geoderma. https://doi.org/10.1016/j.geoderma.2013.07.002

27. Leitgeb E, Ghosh S, Dobbs M, Englisch M, Michel K (2019) Distribution of nutrients and trace elements in forest soils of Singapore. Chemosphere.
28. Liaw A, Wiener M (2002) Classification and Regression with Random Forest. R News 23(23)

29. Littke K, Harrison R, Zabowski D, Briggs D, Maguire D (2014) Effects of Geoclimatic Factors on Soil Water, Nitrogen, and Foliar Properties of Douglas-Fir Plantations in the Pacific Northwest. FOREST SCI 60(6):1118–1130

30. Liu DW, Wang ZM, Zhang B, Song KS, Li XY, Li JP, Li F, Duan HT, Liu DW, Wang ZM, Zhang B, Song KS, Li XY, Li JP, Li F, Duan HT (2016) Spatial heterogeneity distribution of soil total nitrogen and total phosphorus in the Yaoxiang watershed in a hilly area of northern China based on geographic information system and geostatistics. Ecology Evolution 113:73–81. https://doi.org/10.1002/ece3.2410

31. Liu Z, Zhou W, Shen J, He P, Lei Q, Liang G (2014) A simple assessment on spatial variability of rice yield and selected soil chemical properties of paddy fields in South China. Geoderma 235–236:39–47. https://doi.org/10.1016/j.geoderma.2014.06.027

32. Lucas-Borja ME, Hedo J, Cerda A, Candel-Perez D, Vinegla B (2016) Unravelling the importance of forest age stand and forest structure driving microbiological soil properties, enzymatic activities and soil nutrients content in Mediterranean Spanish black pine (Pinus nigra Ar. ssp. salzmannii) Forest. Sci Total Environ 562(15):145–154. https://doi.org/10.1016/j.scitotenv.2016.03.160

33. Minami M (2002) Using ArcMap. ESRI

34. Neff JC, Hooper DU (2002) Vegetation and climate controls on potential CO2, DOC and DON production in northern latitude soils. Glob Change Biol 8(9):872–884. https://doi.org/10.1046/j.1365-2486.2002.00517.x

35. Nelson DW (1996) Total carbon, organic carbon, and organic matter. Methods of Soil Analysis 9:961–1010

36. Patil P (2017) Forest Accounting and Ecological Sustainability. Global Journal of Management and Business Research 17(1)

37. Rahardjo H, Aung KK, Leong EC, Rezaur RB (2004) Characteristics of residual soils in Singapore as formed by weathering. Eng Geol. https://doi.org/10.1016/j.enggeo.2004.01.002

38. Roger A, Libohova Z, Rossier N, Joost S, Maltas A, Frossard E, Sinaj S (2014) Spatial variability of soil phosphorus in the Fribourg canton, Switzerland. Geoderma 217–218:26–36. https://doi.org/10.1016/j.geoderma.2013.11.001

39. Ronnenberg K, Wesche K (2011) Effects of fertilization and irrigation on productivity, plant nutrient contents and soil nutrients in southern Mongolia. Plant soil 340(1–2):239–251. https://doi.org/10.1007/s11104-010-0409-z

40. Saito H, McKenna SA, Zimmerman DA, Coburn TC (2005) Geostatistical interpolation of object counts collected from multiple strip transects: Ordinary kriging versus finite domain kriging. Stochastic Environmental Research Risk Assessment 19(1):71–85. https://doi.org/10.1007/s00477-004-0207-3

41. Samuels G (1976) Técnicas de Análisis de Suelos. Soil Sci 122(3).
42. Shen YF, Qian JF, Zheng XP, Yuan ZQ, Huang JQ, Wen GS, Wu JS (2016) Spatial-temporal variation of soil fertility in Chinese walnut (Carya cathayensis) plantation. Scientia silvae sinicae 52(7):1–12. https://doi.org/10.11707/j.1001-7488.20160701

43. Sinoga JDR, Pariente S, Diaz AR, Murillo JFM (2012) Variability of relationships between soil organic carbon and some soil properties in Mediterranean rangelands under different climatic conditions (South of Spain). CATENA 94:17–25. https://doi.org/10.1016/j.catena.2011.06.004

44. Suchet PA, Probst JL, Ludwig W (2003) Worldwide distribution of continental rock lithology: Implications for the atmospheric/soil CO2 uptake by continental weathering and alkalinity river transport to the oceans. Global Biogeochem Cycles 17(2). https://doi.org/10.1029/2002GB001891

45. Torn MS, Swanston CW, Castanha C, Trumbore SE (2009) Storage and Turnover of Organic Matter in Soil. https://doi.org/10.1002/9780470494950.ch6

46. Tsozué D, Nghonda JP, Tematio P, Basga SD (2019) Changes in soil properties and soil organic carbon stocks along an elevation gradient at Mount Bambouto, Central Africa. CATENA 175:251–262. https://doi.org/10.1016/j.catena.2018.12.028

47. Wang HJ, Shi XZ, Yu DS, Weindorf DC, Huang B, Sun WX, Ritsema CJ, Milne E (2009) Factors determining soil nutrient distribution in a small-scaled watershed in the purple soil region of Sichuan Province, China. Soil Tillage Research 105(2):300–306. https://doi.org/10.1016/j.still.2008.08.010

48. Wang S, Jin X, Adhikari K, Li W, Yu M, Bian Z, Wang Q (2018) Mapping total soil nitrogen from a site in northeastern China. CATENA 166:134–146. https://doi.org/10.1016/j.catena.2018.03.023

49. Wang YG, Yan L, Ye X, Chu Y, Wang X (2010) Profile storage of organic/inorganic carbon in soil: From forest to desert. Sci Total Environ 408(8):1925–1931. https://doi.org/10.1016/j.scitotenv.2010.01.015

50. Wanshnong R, Thakuria D, Sangma C, Ram V, Bora P (2013) Influence of hill slope on biological pools of carbon, nitrogen, and phosphorus in acidic alfisols of citrus orchard. CATENA 111:1–8. https://doi.org/10.1016/j.catena.2013.07.009

51. Welke SE, Hope GD (2005) Influences of stand composition and age on forest floor processes and chemistry in pure and mixed stands of Douglas-fir and paper birch in interior British Columbia. Forest Ecology Management 219(1):29–42. https://doi.org/10.1016/j.foreco.2005.08.040

52. Wu JS, Lin HP, Meng CF, Jiang PK, Fu WJ (2014) Effects of intercropping grasses on soil organic carbon and microbial community functional diversity under Chinese hickory (Carya cathayensis Sarg.) stands. Soil Research 52(6):575. https://doi.org/10.1071/SR14021

53. Wu WF, Lin HP, Fu WJ, Penttinen P, Li YF, Jin J, Zhao KL, Wu JS (2019) Soil Organic Carbon Content and Microbial Functional Diversity Were Lower in Monospecific Chinese Hickory Stands than in Natural Chinese Hickory–Broad-Leaved Mixed Forests. Forests 10(4):357–357. https://doi.org/10.3390/f10040357

54. Xin ZB, Qin YB, Yu XX (2016) Spatial variability in soil organic carbon and its influencing factors in a hilly watershed of the Loess Plateau, China. CATENA 137:660–669.
55. Yang R, Zhang G, Liu F, Yang F, Lu Y, Yang F, Li D, Yang M, Zhao Y (2016) Comparison of boosted regression tree and random forest models for mapping topsoil organic carbon concentration in an alpine ecosystem. 60:870–878

56. Yang YH, Fang JY, Wenhong MA, Smith P, Wang W (2010) Soil carbon stock and its changes in northern China's grasslands from 1980s to 2000s. Glob Change Biol 16(11):3036–3047. https://doi.org/10.1111/j.1365-2486.2009.02123.x

57. Zhang Z, Zhou Y, Wang S, Huang X (2018) The soil organic carbon stock and its influencing factors in a mountainous karst basin in P. R. China. Carbonates Evaporites 34:1031–1043. https://doi.org/10.1007/s13146-018-0432-3

58. Zhu J, Wu W, Liu HB (2018) Environmental variables controlling soil organic carbon in top- and sub-soils in karst region of southwestern China. Ecological indicators 90:624–632. https://doi.org/10.1016/j.ecolind.2018.03.073

Figures

Figure 1

Location of the study area and soil samples.
Figure 2

Correlation analysis of soil physicochemical properties in hickory plantations. SOC indicates soil organic carbon. HN indicates soil hydrolyzed nitrogen. AP indicates soil available phosphorus. AK indicates soil available potassium. Fe, Mn, Zn, and Cu indicate soil iron, manganese, zinc, and copper. *Correlation is significant at the 0.05 level **Correlation is significant at the 0.01 level ***Correlation is significant at the 0.001 level.
Figure 3

Variable importance of predictors in forecasting soil physicochemical properties. MAT indicates mean annual temperature, MAP indicates mean annual precipitation. (a) SOC indicates soil organic carbon concentration. (b) HN indicates soil hydrolyzed nitrogen concentration. (c) AP indicates soil available phosphorus concentration. (d) AK indicates soil available potassium concentration.
Figure 4

Variable importance of predictors in forecasting soil physicochemical properties. MAT indicates mean annual temperature, MAP indicates mean annual precipitation. (a) Fe indicates soil iron concentration. (b) Mn indicates soil manganese concentration. (c) Zn indicates soil zinc concentration. (d) Cu indicates soil copper concentration.
Figure 5

Mapping spatial distribution maps of macronutrients in soils. SOC indicates soil organic carbon, HN indicates soil hydrolyzed nitrogen, AP indicates soil available phosphorus, AK indicates soil available potassium.
Figure 6

Spatial distribution maps of micronutrients in soils. Fe, Mn, Zn, and Cu indicate soil iron, manganese, zinc, and copper.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Additionalfile1.docx