Forest Ecology and Management 505 (2022) 119951

Contents lists available at ScienceDirect

Forest Ecology and Management

journal homepage: www.elsevier.com/locate/foreco

Acidification of soil due to forestation at the global scale

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ARTICLE INFO

Keywords:
Global pattern
Random forest
Mean annual temperature
Mean annual precipitation
Initial pH
Forestation

ABSTRACT

Forestation is a key strategy to mitigate climate change caused by anthropogenic carbon dioxide emissions. However, the impacts of forestation on soil pH remain unclear, despite critical roles of soil pH in regulating key soil biogeochemical processes. Here, we collected a global dataset of soil pH change after forestation, which included 1082 observations from 171 published papers. Results showed that soil pH declined significantly by 0.23 after forestation over the globe. Soil pH consistently declined after forestation, no matter the forest was established naturally or by planting, on croplands or grasslands. The decline of pH after forestation was generally larger in neutral soils (pH 6–7) than in acidic soils (pH < 6) and alkaline soils (pH > 7), and larger in boreal and temperate forests than in tropical forests. Soil pH decreased significantly in humid areas but not in arid regions. Random forest analysis showed that climate was the most important regulatory factor to influence soil pH change after forestation. Mean annual temperature and precipitation probably affected soil pH both directly and indirectly via altering soil physiochemical properties. Given vital roles of soil pH in regulating carbon and nutrient dynamics, our findings have important implications for the long-term impacts of forestation on carbon and nutrient dynamics.

1. Introduction

Forestation is employed globally for several forest services such as timber production and the conservation of water and soil (Berthrong et al., 2014; Jackson et al., 2005). Forestation on bare lands can also improve water and nutrient cycles and enhance soil properties such as microbial activities, thereby boosting the quality and functionality of the ecosystem (Wu et al., 2019; Schwärzel et al., 2020). Moreover, forestation can increase the efficiency of terrestrial ecosystems to remove carbon dioxide from the atmosphere (Parfitt and Ross, 2011; Dou et al., 2016). Forestation has been selected by the Paris Agreement as a key approach toward the mitigation of climate change (Wu, 2016).

Forested areas have increased rapidly, at approximately 300,000 km^2 per year from 2000 to 2017, a trend that is projected to continue (Chen et al., 2019). The effects of forestation on ecosystem functions such as nutrient cycling, are strongly linked to changes in soil pH values. Consequently, it is universally agreed that potential impacts of forestation on soil pH need to be better understood (Ji et al., 2014; Guo et al., 2021; Dorak et al., 2017).

Numerous studies have explored the regional and global patterns of soil pH changes after forestation (Rasiah et al., 2015; Fung et al., 2017; Ozalp and Cavdar, 2016; Yazici and Turan, 2016). However, the results have been inconsistent. For example, an early global analysis concluded that after forestation soil pH dropped by 0.3 on average (Berthrong et al., 2009). Studies in tropical regions also found that the pH value of soil (topsoil in particular) decreased following forestation in the absence of calcification, which may have been related to net nutrient export and leaching loss (Veldkamp et al., 2020). However, a recent study in Northern China found that forestation neutralized the soil pH (decreased it in alkaline soil and increased it in acidic soil), and that the initial (pre-forestation) pH had a significant effect on the downstream soil pH (Hong et al., 2018). Several other studies claimed that forestation had a negligible effect on the soil pH (e.g., Da et al., 2011). Thus, it is necessary to comprehensively synthesize available data in literature to reveal generalizable patterns of soil pH response to forestation at the global scale.

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https://doi.org/10.1016/j.foreco.2021.119951
Received 8 September 2021; Received in revised form 6 December 2021; Accepted 8 December 2021
Available online 17 December 2021
0378-1127/

Given considerable variations in soil pH change after forestation found in previous studies (e.g., Hong et al., 2018; Veldkamp et al., 2020), it is critical to understand why forestation impact on soil pH varies across sites. There is no consensus on the major drivers of soil pH changes after forestation. For example, the Global Soil Data Task Group (2000) suggests that climate is the single most critical factor to influence soil pH at the global scale, presumably because of great variations in precipitation and temperature at the global scale (Hijmans et al., 2005). Precipitation and temperature may affect soil pH change after forestation through their effects on the growth and metabolism of tree species (Laganiãre et al., 2010). Meanwhile, precipitation and temperature may affect soil pH change after forestation via their impacts on soil organic carbon concentration, a high value of which may result in a low soil pH due to more organic acids production and a stronger sorption of H^+ (Deng et al., 2014). The original pH of soil may also significantly determine the direction and degree of soil pH changes following forestation (Hong et al., 2018). Time since the ages of forestation can also affect soil pH either positively or negatively (Zhang et al., 2018). Furthermore, site properties such as geography and soil clay content have been also reported to regulate the changes of soil pH following forestation (Sidari et al., 2008; Fabian et al., 2014; Guo et al., 2021).

In this study, we aimed to improve our understanding of the global variations and driving factors of soil pH changes after forestation. We explored the modulations of site properties such as mean annual temperature (MAT) and precipitation (MAP) on the change in soil pH after forestation, and quantified the relative importance of these moderators using machine learning methods. We hypothesized that the global variations in soil pH are primarily determined by climatic factors, namely climatic zones (e.g., tropical, temperate, and boreal zones), aridity index (e.g., humid, dry sub-humid, semi-arid, and hyper-arid arid regions), MAT, and MAP. Results in this study would provide scientific bases for the management and restoration of forested lands.

2. Methods and materials

2.1. Data selection

We searched for published articles that involved reforestation and soil pH using Web of Science and the China National Knowledge Infrastructure with titles, abstracts, or keywords referring to 'land use change', 'land cover change', 'reforestation', 'afforestation', or 'forestation', and 'soil pH', or 'soil acidification' from 1984 to 2020. We selected relevant studies based on the title and abstract, and then scanned their full texts and supporting materials to extract data on soil pH change following forestation. We removed duplicated observations of soil pH change after forestation reported in different papers.

To avoid bias in literature selection, the studies to be included were identified based on the following four criteria. (i) Only field studies were selected, with soil pH determined in water, $CaCl_2$, or KCl solution. (ii) Studies should be performed using a paired plot design, with paired plots adjacent to each other. (iii) Only pH measurement of mineral soil with specific depth were selected, with forest floor litter measurements excluded. (iv) Forestation belong to one of the following four types: conversion of cropland or grassland to secondary forest or plantation forest. The conversion to secondary forest means that the forest is regenerated naturally; the conversion to plantation forest means that the forest is planted manually.

2.2. Data extraction and overview

After screening the eligible published papers, we extracted soil data including the initial pH (ipH) (i.e., soil pH prior to forestation), soil pH value after forestation, initial soil organic C concentration (SOC), soil depth, years since forestation, and soil clay content. We used GetData Graph Digitizer (version 2.0) to extract the numerical values from digitized graphs when the data were not presented as text or in table form. Moreover, we extracted site properties such as site coordinates (i.e., latitude and longitude), MAT, MAP, slope, and aspect from the published papers.

Any missing MAT or MAP were filled with values derived from the WorldClim2 Dataset (add reference) using the geographic site locations. Any missing values of soil properties were filled with values derived from the SoilGrids database (Hengl et al., 2017) or the Regridded Harmonized World Soil Database v1.22 (FAO, 2012). Any missing values of site slope and aspect were filled with values derived from the shuttle radar topographic mission DEM data with 30 m resolution from NASA using the SAGA-GIS software v2.1.4 (Conrad et al., 2015).

Our database covered all continents (except for Antarctica) and included 1082 observations of soil pH change following forestation from 171 published studies. Site locations and climate spanned a large scope. For example, latitude was from 46.1°S to 65.1°N, longitude varied from 155.2°W to 176.5°E, MAT ranged from −6.6℃ to 27.2℃, whereas MAP ranged from 8 mm yr^{-1} to 3950 mm yr^{-1} (Fig. 1). Forestation types included the conversions of cropland to plantation forest (N = 564), grassland to plantation forest (N = 320), cropland to secondary forest (N = 106), and cropland to grassland (N = 92).

2.3. Data analysis

We used absolute soil pH change (SPC) to indicate the responses of soil pH to forestation, which was calculated as follows:

$$\mathrm{SPC} = \mathrm{pHafterforestation} - \mathrm{InitialpH} \tag{1}$$

where Initial pH represents soil pH before forestation. The variance of each study of SPC was calculated as follows:

$$v_i = \frac{S_a^2}{n_a \overline{X}_a^2} + \frac{S_i^2}{n_i \overline{X}_i^2} \tag{2}$$

where S_a and S_i are the standard deviations for soil pH after forestation (treatment groups) and initial pH (control groups), X_a and X_i are the mean soil pH after forestation and mean initial soil pH, and n_a and n_i are the sample sizes for the treatment and control groups, respectively, of the study (i).

The weighted mean response SPC_+ of each group was as follows:

$$SPC_+ = \frac{\Sigma_{i=1}^{m} w_i^* \times SPC}{\Sigma_{i=1}^{m} w_i^*} \tag{3}$$

where m is the number of experiments in each treatment group, andw_i^* is the weighting factor of the ith experiment in each treatment group. The$w_i^*$was calculated as follows:

$$\mathrm{w_i^*} = \frac{1}{\mathrm{v_i^*}} \tag{4}$$

where $\mathrm{v_i^*}$ is the variance of study (i) in each group. The $\mathrm{v_i^*}$ was calculated as follows:

$$\mathrm{v_i^*} = \mathrm{v_i} + \mathrm{T}^2 \tag{5}$$

where T^2 is the between-studies variance and calculated process, which can be seen in Borenstein et al., (2010).

The standard error of the SPC_+ was calculated as:

$$S_{SPC_+} = \sqrt{\frac{1}{\sum_{i=1}^{m} w_i^*}} \tag{6}$$

The 95% confidence interval (CI) for the SPC_+ was calculated as follows:

$$95\%CI = SPC_+ \pm 1.96 S_{SPC+} \tag{7}$$

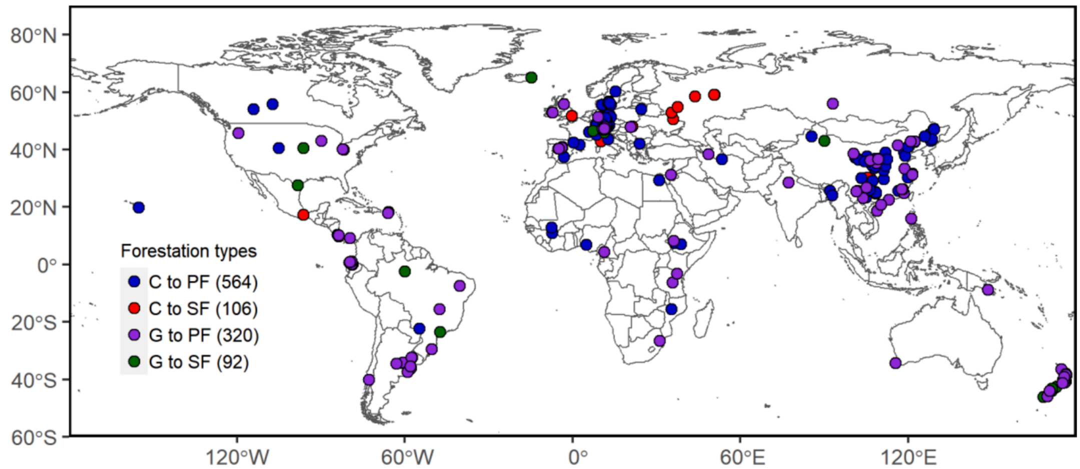

Fig. 1. Global distribution of sites where the soil pH was assessed after forestation. Capital letters "C", "G", "PF", and "SF" indicate cropland, grassland, plantation forest, and secondary forest, respectively.

For literature sources where the standard error (SE) rather than SD was reported, we recalculated the SD by:

$$SD = SE\times \tag{8}$$

If neither SD nor SE was reported, we approximated the missing SD by multiplying the reported mean by the average coefficient of variance of our complete dataset. If sample size was not reported, we assigned sample sizes as the median sample size of our complete dataset.

We used the random forest method to quantify the relative importance of moderators in explaining variation in soil pH change following forestation. Random forest is an example of a machine learning method that consists of an ensemble of randomized classification and regression trees (Breiman, 2001). For all random forest computations, we used the "randomForest" package (Liaw and Wiener, 2002) for the R statistical language (R Development Core Team, 2020). We sorted the %IncMSE value obtained by *"importance"* function and the importance of different factors is obtained according to the sequence. The *"importance"* function and *"randomForest"* function were used to produce Fig. 3. In addition, we used boosted regression tree analysis (max.trees = 30000) to verify the results. The *"gbm.step"* function in gbm package was used to produce Supplementary Fig. 3. The moderators we used in the analysis included climate factors (i.e., MAT and MAP), forestation regime (i.e., forestation type, and the year after forestation), soil physiochemical properties (i.e., SOC, clay, and ipH), and site geographical properties (i.e., aspect and slope).

Compared with other statistical modeling approaches, random forest has several advantages (Breiman, 2001; Liaw and Wiener, 2002). The variables can be both continuous and categorical. The random forest algorithm is quite robust against noise in its predictors, which does not require the pre-selection of variables (Diaz-Uriate and de Andres, 2006). Random forest provides reliable error estimates by using the Out-Of-Bag (OOB) data (the proportion which is not used in the bootstrap subset - on average about one third of the data is excluded, while some others will be repeated in the sample). Thus, eliminating the need for an independent validating dataset.

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*) are the three user-defined parameters of random forest. We initially tested the combination of *ntree*, *nodesize*, and *mtry* with a training set. The default of *ntree* was 500, however, more stable results for estimating variable importance were achieved with a higher *ntree* number (Díaz-Uriarte and Alvarez de Andrés, 2006). Therefore, we used *ntree* = 1000. For *nodesize* we used the default for regression random forest, which has five instances in each terminal node. The default value of *mtry* is one third of the total number of predictors. However, since the random forest prediction performance can be sensitive to *mtry* (Breiman and Cutler, 2004), we employed an iterative approach to determine the best *mtry* in terms of the smallest OOB mean square error (Eqn. (9)). Within each interval we applied the random forest algorithm with *ntree* = 2000, *nodesize* = 5, and *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.

The model performance was ideally addressed by using a large independent test dataset that was not used in the training procedure. k-fold cross-validation is often used when data is limited, cross-validation is a parameter within the R package randomForest function, we set the parameter to k.fold = 5. Random forest uses an extension of cross-validation, where each OOB sample is predicted by its corresponding bootstrap training tree. The forest mean square error (MSE) can be estimated by aggregating the OOB predictions of all trees in the forest (Liaw and Wiener, 2002):

$$MSE^{OOB} = \frac{\sum_{i=1}^{n}\left\{Y_i - \widehat{Y}_i^{OOB}\right\}^2}{n} \tag{9}$$

Svetnik et al., (2003) showed that the OOB estimate of prediction accuracy yields results comparable to k-fold cross-validation. However, the OOB estimates of error rate are computationally less expensive than standard k-fold cross-validation.

After the key moderators of soil pH after following forestation were identified, we plotted the bivariate relationships between SPC and its key moderators. We used Equation (5) to calculate v* as the random effect, SPC as the dependent variable, MAP, ipH, MAT as the independent variable, and used *"rma"* function from the metafor package (Viechtbauer, 2010) made the bivariate relationship fitting graph. We used *"AICc"* function to get the corrected Akaike's Information Criterion (AICc) value, when the corrected Akaike's Information Criterion (AICc) value of a quadratic regression was two units less than that of a linear regression, the quadratic regression was selected as the final model, otherwise the linear regression was chosen. In all of these analyses, we defined it was significant when p value < 0.01.

3. Results

3.1. Global patterns of soil pH changes after forestation

Soil pH declined significantly following forestation, with a mean soil pH change of −0.23 (95% confidence intervals: −0.26 to −0.23, N = 1082) (Fig. 2). Soil pH declined consistently after forestation across

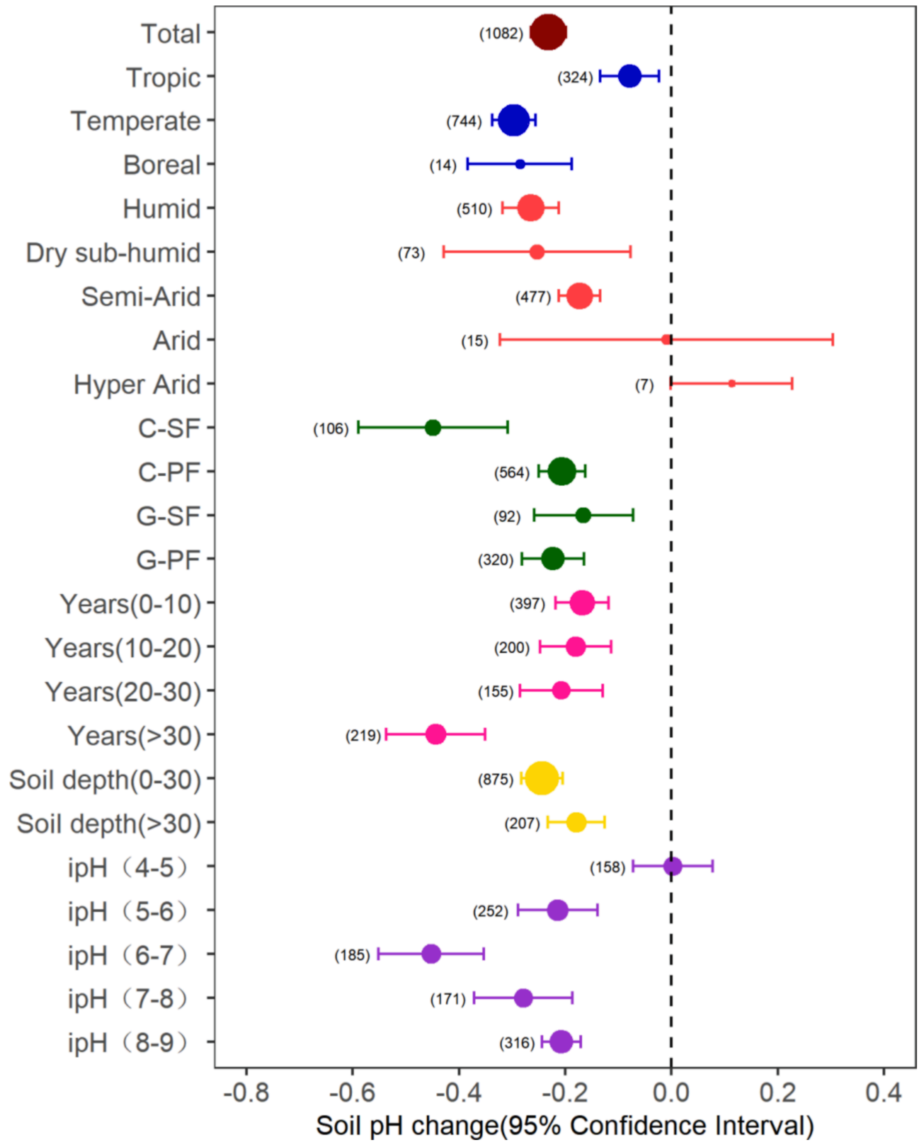

Fig. 2. Soil pH change after forestation grouped by climate zone, aridity, forestation types, years after forestation, soil depth, and initial soil pH (ipH). The points are averages, and the bars are 95% confidence intervals. Point sizes are proportional to the number of studies, which are given in brackets. Capital letters "C", "G", "PF", and "SF" indicate cropland, grassland, plantation forest, and secondary forest, respectively.

climate zones, with a significant less magnitude in the tropics (-0.08) than in the temperate (-0.30) and boreal (-0.29) regions (Fig. 2). Soil pH declined significantly after forestation in humid (-0.26), dry sub-humid (-0.25), and semi-arid (-0.17) regions but not in arid or hyper-arid regions (Fig. 2). Moreover, soil pH declined consistently across types of forestation, with a significant larger decline after the conversion of croplands to secondary forests than other types of forestation (Fig. 2).

After forestation, pH declined the most in neutral soils (i.e., pH 6–7: −0.45), followed in acidic (i.e., pH 5–6: −0.21) and alkaline (i.e., pH 7–8: −0.28; pH 8–9: −0.21) soils, with no significant change in very acidic soils (i.e., pH 4–5) (Fig. 2). Moreover, the reduction of soil pH after forestation increased significantly with time after forestation, and tend to be larger in surface soils (i.e., 0–30 cm depth: −0.24) than in deep soils (i.e., > 30 cm depth: −0.18) (Fig. 2).

3.2. *Factors driving soil pH changes following forestation*

Random forest model with ten moderators explained a total of 74% of the variation in soil pH change following forestation (Fig. 3). Among the ten moderators, MAP, ipH, years after forestation, and MAT were the most important ones. Similar results have been obtained using another machine learning method – boosted regression tree analysis (Fig. S2). Correlation analysis confirmed that soil pH change after forestation was significantly related to MAP, ipH, years after forestation, and MAT (Fig. S3). Regression analyses further showed that change in soil pH after forestation had a convex relationship with MAP (Fig. 4a, Table S2, $p < 0.01$) but a concave relationship with ipH (Fig. 4b, Table S2, $p < 0.01$). Negative effect of forestation on soil pH diminished gradually with increasing MAT (Fig. 4c, Table S2, $p < 0.01$).

Moreover, climate (MAT and/or MAP) significantly affected soil pH, organic C concentration, and clay content before forestation (Figs. S4-S6), which modulated the change in soil pH following forestation (Figs. 3 and S3). These results indicate that climate may modulate soil pH change after forestation both directly and indirectly via its impacts on soil physiochemical properties.

4. Discussion

This study examined the general patterns and controlling factors of soil pH changes following forestation at the global scale. Soil pH

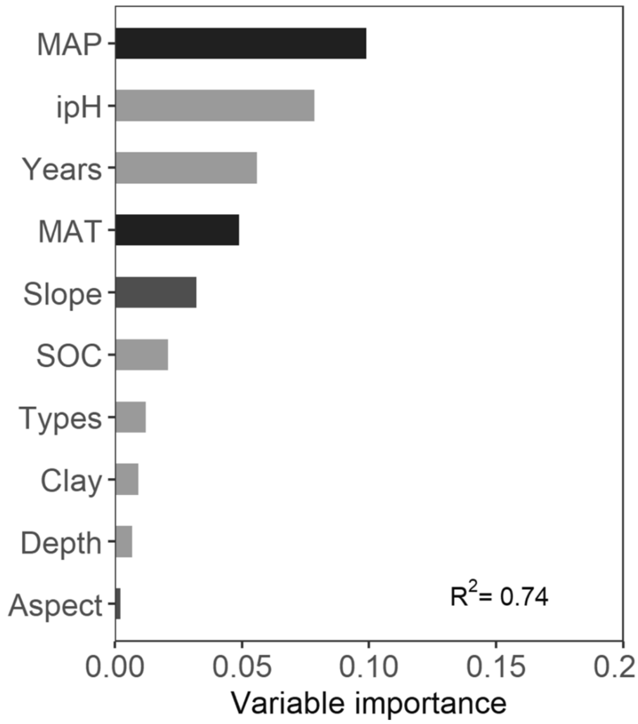

Fig. 3. Relative importance of moderators for predicting soil pH changes following forestation quantified using a random forest analysis. R^2 value indicates the total proportion of variation explained by the random forest model. Moderators include mean annual precipitation (MAP), soil pH before forestation (ipH), years after forestation (Years), site slope (Slope), soil organic C concentration (SOC), forestation types (Types), soil clay content (Clay), and site aspect (Aspect).

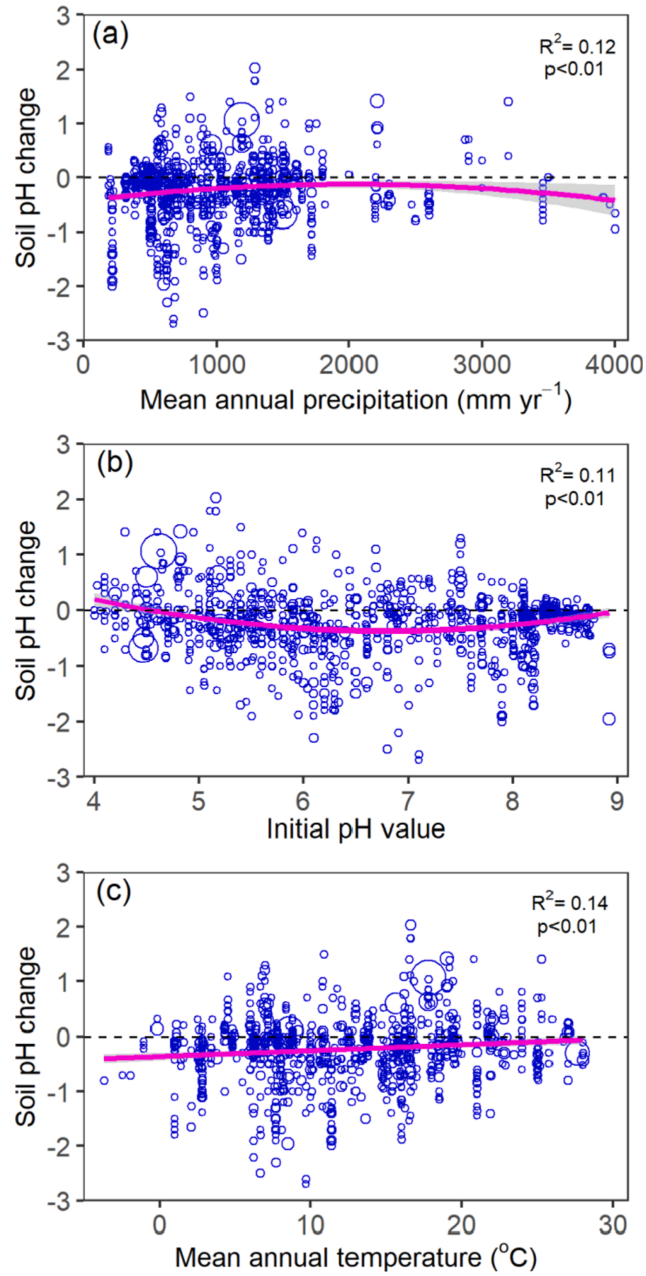

Fig. 4. Observed changes in soil pH following forestation in relation to MAT, MAP, and ipH. If one relationship is statistically significant ($p < 0.01$), a regression line (for numeric predictor only), 95% confidence interval (shaded area, for numeric predictor only) and R^2 are shown. Point sizes are proportional to the weights used for statistical analyses.

decreased significantly after forestation, with a great variation in the change among climate zones and aridity levels. MAP, ipH, years since forestation, and MAT were the most important predictors of the variation in soil pH change after forestation. The change in soil pH after afforestation decreased linearly with increasing MAT, was smaller at intermediate MAPs (1500–2500 mm yr^{-1}) than at lower (<1500 mm yr^{-1}) and higher (>2500 mm yr^{-1}) MAPs, and larger at intermediate ipH (5–8) than at lower (<5) and higher (>8) ipH (Fig. 4). These findings are critical toward elucidating changes in ecosystem processes (e.g., C and nutrient cycles) and functions (e.g., C sequestration) following forestation.

4.1. Climate mediated changes in soil pH after forestation

As hypothesized, climate was the most important predictor of the variation in soil pH change after forestation. More decline in soil pH following forestation in boreal and temperate zones than in tropical zones (Fig. 2) may be attributed to more accumulation of soil organic C and more depletion of base cations, which both can lower soil pH, after forestation in boreal and temperate climate zones (Berthrong et al., 2009; Laganiãre et al., 2010). These hypotheses were supported by the linear positive relationship between soil pH change after forestation and MAT observed in this study (Fig. 4c).

Soil pH decreased significantly in humid regions but did not change significantly in arid or hyper-arid regions. This result may be related to difference in tree growth rate in these regions. Humid regions favor tree growth that deplete base cations (e.g., Ca^{2+}, Mg^{2+}, and K^{+}) (Chen et al., 2004) and thus may have lower soil pH values after forestation than drier regions. Indeed, a previous global data synthesis showed that the response ratios of soil pH or hydrogen ion concentrations to forestation were negatively correlated with the response ratios of calcium ions and base saturation (Berthrong et al., 2009).

Climate may modulate soil pH change after forestation via its impacts on ecosystem properties such as soil base cation and organic C concentrations and tree growth (Deng et al., 2014; Hong et al., 2018; Veldkamp et al., 2020). For example, high MAT and MAP can promote the release of base cations by soil weathering and thus may alleviate the negative impacts of forestation on soil pH. This hypothesis probably explains why soil pH change after forestation increased with MAT and as well as with MAP when MAP was <2000 mm yr^{-1} (Fig. 4a and c). When MAP was higher than 2000 mm yr^{-1}, increase MAP may have caused an exponential increase in the leaching and runoff of base cations from soils and therefore may lowered soil pH after forestation (Fig. 4a). More reduction of soil pH after forestation at low MAT than at higher MAT

(Fig. 4c) may be additionally explained by the typically more accumulation of organic matter in soil in cold than warm environments after forestation. Moreover, high MAT and MAP can promote weathering, resulting in a high content of soil clay (Stewart and Lal, 2018), which has a stronger pH buffering capacity than soil sand (Fabian et al., 2014).

4.2. Other factors influence soil pH after forestation

Soil pH before forestation has been identified as a key predictor of the change in soil pH following forestation in previous studies (e.g., Hong et al., 2018). However, in contrast to the previous study that reported a trend of neutralizing soil pH after forestation in northern China (Hong et al., 2018), our global meta-analysis showed that soil pH decreased the most in neutral soil (Fig. 2). This inconsistency may be due to difference in spatial scales between Hong et al. (2018) and our study. Hong et al. (2018) studied forestation impacts on soil pH at a regional scale, where initial soil pH and forest species could be important factors of soil pH after forestation while variation in climate conditions was small. In our study, climate covered a larger range and therefore could become a more important factor of soil pH change after forestation at the global scale. Moreover, climate could modulate soil pH change after forestation through its effect on initial soil pH, i.e., soil pH before forestation (Figs. S3 and S4).

The reduction of soil pH following forestation increased with years since forestation and was up to 0.5 after half a century of forestation. The change in soil pH was negatively correlated with soil depth as acidity typically proceeds from the topsoil and slowly works its way down the soil profile, where the acidic input derives from precipitation and the decomposition of plant litter falling on the soil surface (Xu et al., 2005). Due to the activities of soil macrofauna, mesofauna, and soil microbes, soil resident macroaggregates are primarily formed in the top layer of the soil. In forests, higher soil aggregation capacities drive a lower soil pH, thus, we found that the topsoil pH decreased the most after forestation (Guo et al., 2021). The effects of forest litter and the reduced use of alkaline fertilizers may also lead to higher acidity in the forest surface soil (Du et al., 2010).

4.3. Implications and uncertainties for soil pH changes on a global scale

By compiling a comprehensive dataset of soil pH changes following forestation across the prominent terrestrial ecosystem types, our study provides a benchmark for an accurate global evaluation. Meta-analysis was an effective way to examine the global pattern of soil pH changes after forestation. Our results suggested that Earth system models should consider soil acidification due to forestation in terms of not only latitudinal zones but also aridity indices. The positive impacts of MAT on soil pH changes suggested that soil acidity caused by forestation might be buffered through future global warming.

There were some uncertainties in this synthesis. First, some studies removed forest residuals such as leaves, branches, and bark from their sites, which may influence the soil pH change following forestation through accelerated export and loss of cations (Day and Monk, 1977; FAO, 2002). Although we did verify that exchangeable cation concentrations were intimately linked to soil pH, we did not test the specific impacts of forestation on soil exchangeable cation concentrations. Future studies may examine forestation impacts on soil exchangeable cation concentrations to provide a more mechanistical understanding of forestation impacts on soil pH (Allen et al., 2016; Carlson et al., 2018). Second, while atmospheric nitrogen deposition is an important driver of soil pH (Lu et al., 2011), its interaction with forestation on soil pH was not addressed in the present study. Finally, the development of root networks following forestation, which can alter soil enzyme activities and microbial compositions, may be evaluated to understand whether root development following forestation caused changes in soil pH following forestation (Berthrong et al., 2009).

5. Conclusion

Our study revealed global patterns and predictors of soil pH change following forestation. We found that forestation significantly decreased soil pH by 0.23. Moreover, we identified climate was the most important predictor of soil pH change after forestation. Climate may modulate soil pH change after forestation both directly and indirectly through altering soil physicochemical properties. Our results highlight the critical role of climate in modulating soil pH after forestation and have important implications for carbon and nutrient dynamics after forestation in the context of global climate change.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Financial support was provided by the National Key R&D Program of China (2018YFD1000600; 2021YFC3100400) and Anhui Provincial science and technology special project (202123a06020007).

References

Allen, K., Corre, M.D., Kurniawan, S., Utami, S.R., Veldkamp, E., 2016. Spatial variability surpasses land-use change effects on soil biochemical properties of converted lowland landscapes in Sumatra, Indonesia. Geoderma 284, 42–50.
Berthrong, S.T., Jobbágy, E.G., Jackson, R.B., 2009. A global meta-analysis of soil exchangeable cations, pH, carbon, and nitrogen with afforestation. Ecol. Appl. 19 (8), 2228–2241.
Borenstein, M., Hedges, L.V., Higgins, J.P.T., Rothstein, H.R., 2010. A basic introduction to fixed-effect and random-effects models for meta-analysis. Res. Synth. Methods 1 (2), 97–111.
Carlson, K.M., Robert, H., Holly, K.G., Praveen, N., David, N.B., Douglas, C.M., Nathalie, F.W., Gary, D.P., Claire, K., 2018. Effect of oil palm sustainability certification on deforestation and fire in Indonesia. PNAS 115, 121–126.
Chen, C., Park, T., Wang, X., Piao, S., Xu, B., Chaturvedi, R.K., Fuchs, R., Brovkin, V., Ciais, P., Fensholt, R., Tømmervik, H., Bala, G., Zhu, Z., Nemani, R.R., Myneni, R.B., 2019. China and India lead in greening of the world through land-use management. Nat. Sustainability 2 (2), 122–129.
Chen, C.R., Condron, L.M., Davis, M.R., Sherlock, R.R., 2004. Effects of plant species on microbial biomass phosphorus and phosphatase activity in a range of grassland soils. Biol. Fert. Soils 40 (5), 313–322.
Conrad, O., Bechtel, B., Bock, M., Dietrich, H., Fischer, E., Gerlitz, L., 2015. System for Automated Geoscientific Analyses (SAGA) v. 2.1.4. Geosci Model Dev. 8(7), 1991-2007.
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. Glob. Change Biol. 20 (11), 3544–3556.
Du, Z., Zhou, J., Wang, H., Chen, X., Wang, Q., 2010. Soil pH changes from fertilizer site as affected by application of monocalcium phosphate and potassium chloride. Commun. Soil Sci. Plan. 41 (15), 1779–1788.
Díaz-Uriarte, R., Alvarez de Andrés, S., 2006. Gene selection and classification of microarray data using random forest. BMC Bioinformatics 7 (1). https://doi.org/10.1186/1471-2105-7-3.
Dorak, S.J., Green, M.L., Wander, M.M., Ruiz, M.O., Buhnerkempe, M.G., Tian, T., Novakofski, J.E., Mateus-Pinilla, N.E., 2017. Clay content and pH: soil characteristic associations with the persistent presence of chronic wasting disease in northern Illinois. Sci. Rep. 7 (1) https://doi.org/10.1038/s41598-017-18321-x.
Dou, X., Zhou, W., Zhang, Q., Cheng, X., 2016. Greenhouse gas (CO_2, CH_4, N_2O) emissions from soils following afforestation in central China. Atmos. Environ. 126, 98–106.
Day, F.P., Monk, C.D., 1977. Seasonal nutrient dynamics in the vegetation on a southern Appalachian watershed. Am. J. Bot. 64 (9), 1126–1139.
Fabian, C., Reimann, C., Fabian, K., Birke, M., Baritz, R., Haslinger, E., Gemas, P.T., 2014. GEMAS: Spatial distribution of the pH of European agricultural and grazing land soil. Appl. Geochem. 48, 207–216.
FAO, IIASA, ISRIC, ISSCAS & JRC. Harmonized World Soil Database (version 1.22). (FAO and IIASA: Rome, Italy, and Laxenburg, Austria, 2012).
Global Soil Data Task Group, 2000. Global Gridded Surfaces of Selected Soil Characteristics (IGBP-DIS).
Guo, Y., Abdalla, M., Espenberg, M., Hastings, A., Hallett, P., Smith, P., 2021. A systematic analysis and review of the impacts of afforestation on soil quality indicators as modified by climate zone, forest type and age. Sci Total Environ, 757, 143824.

Hengl, T., de Jesus, J.M., Heuvelink, G.B.M., Gonzalez, M.R., Kilibarda, M., Blagotic, A., 2017. SoilGrids250m: Global gridded soil information based on machine learning. Plos One, 12(2).

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G., Jarvis, A., 2005. Very high resolution interpolated climate surfaces for global land areas. Int. J. Climatol.: A J. Roy. Meteorol. Soc. 25 (15), 1965–1978.

Hong, S., Piao, S., Chen, A., Liu, Y., Liu, L., Peng, S., Sardans, J., Sun, Y., Peñuelas, J., Zeng, H., 2018. Afforestation neutralizes soil pH. Nat. Commun. 9 (1) https://doi.org/10.1038/s41467-018-02970-1.

Jackson, R.B., Jobbagy, E.G., Avissar, R., Roy, S.B., Barrett, D.J., Cook, C.W., Jackson, R.B., Farley, K.A., Maitre, D.C., Mccarl, B.A., 2005. Trading water for carbon with biological sequestration. Science 310, 1944–1947.

Ji, C.-J., Yang, Y.-H., Han, W.-X., He, Y.-F., Smith, J., Smith, P., 2014. Climatic and edaphic controls on soil ph in alpine grasslands on the Tibetan plateau, China: a quantitative analysis. Pedosphere 24 (1), 39–44.

Kai, S., Zhang, L., Montanarella, L., Wang, Y., Sun, G.J., 2019. How afforestation affects the water cycle in drylands: A process-based comparative analysis. 26.

Laganiere, J., Angers, D.A., Pare, D., 2010. Carbon accumulation in agricultural soils after afforestation: a meta-analysis. Global Change Biology, 16, 439-453.

Liaw, A., Wiener, M., 2002. Classification and regression by random forests. R News, 18–22.

Lu, M. Yang, Y., Luo Y., Fang, C., Zhou, X., Chen, J., Yang, X., Li, B. 2011. Responses of ecosystem nitrogen cycle to nitrogen addition: a meta-analysis. New Phytol., 189: 1040-1050.

Ozalp, M., Cavdar, G., 2016. Responses of some soil properties to 14th-year forestation efforts in the semi-arid grasslands of ankara, turkey. Fresenius Environ. Bull. 25, 4589–4597.

Parfitt, R.L., Ross, D.J., 2011. Long-term effects of afforestation with Pinus radiata on soil carbon, nitrogen, and pH: a case study. Soil Res. 49.

Rasiah, V., Florentine, S., Dahlhaus, P., 2015. Environmental benefits inferred from impact of reforestation of deforested creek bank on soil conditioning: a case study in Victoria, Australia. Agrofor. Syst. 89, 345–355.

R Development Core Team, 2006. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Sidari, M., Ronzello, G., Vecchio, G., Muscolo, A., 2008. Influence of slope aspects on soil chemical and biochemical properties in a Pinus laricio forest ecosystem of Aspromonte (Southern Italy). Eur. J. Soil Biol. 44, 364–372.

Stewart, B.A., Lal, R., 2018. Managing water to enhance global cereal yields. J. Soil Water Conserv. 73, 49A–52A.

Wu, L., 2016. Paris Agreement: a roadmap to tackle climate and environment challenges. Natl. Sci. Rev. 3, 153.

Wu, S.H., Huang, B.H., Gao, J., Wang, S., Liao, P.C., 2019. The effects of afforestation on soil bacterial communities in temperate grassland are modulated by soil chemical properties. 7, e6147.

Yazici, N., Turan, A., 2016. Effect of forestry afforestation on some soil properties: a case study from turkey. Fresenius Environ. Bull. 25, 2509–2513.