# Patterns of nitrogen and phosphorus pools in terrestrial ecosystems in China

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## Abstract

Recent increases in atmospheric carbon dioxide ($CO_2$) and temperature relieve ~~the limitation of these two~~their limitations on terrestrial ecosystem productivity, while nutrient availability constrains the increasing plant photosynthesis more intensively. Nitrogen (N) and phosphorus (P) are critical for plant physiological activities and consequently regulates ecosystem productivity. Here, for the first time, we mapped N and P densities and concentrations of leaves, woody stems, roots, litter and soil in forest, shrubland and grassland ecosystems across China, based on an intensive investigation in ~~4175~~4,865 sites, covering species composition, biomass, and nutrient concentrations of different tissues of living plants, litter and soil. Forest, shrubland and grassland ecosystems in China stored ~~7665.62 × $10^6$ Mg~~6803.6 Tg N, with ~~7434.53 × $10^6$ Mg (96.99~~6635.2 Tg N (97.5%) fixed in soil (to a depth of one metre), and ~~32.39 × $10^6$ Mg~~27.7 Tg N (0.~~42%), 59.~~4%), 57~~ × $10^6$ Mg~~.8 Tg N (0.~~78%), 124.21 × $10^6$ Mg~~8%), 71.2 Tg N (1~~.62~~%) and ~~14.92 × $10^6$ Mg~~11.7 Tg N (0.~~19~~2%) in leaves, stems, roots and litter, respectively. The forest, shrubland and grassland ecosystems in China stored ~~3852.66 × $10^6$ Mg~~2806.0 Tg P, with ~~3821.64 × $10^6$ Mg~~2786.1 Tg P (99.~~19~~3%) fixed in soil (to a depth of one metre), and ~~3.36 × $10^6$ Mg (0.09%), 14.06 × $10^6$ Mg~~2.7 Tg P (0.~~36%), 11.47 × $10^6$ Mg~~1%), 9.4 Tg P (0.~~30~~3%), 6.7 Tg P (0.2%) and ~~2.14 × $10^6$ Mg (0.06~~1.0 Tg P (< 0.1%) in leaves, stems, roots and litter, respectively. Our estimation showed that N pools were low in northern China except Changbai Mountains, Mount Tianshan and Mount Alta, while relatively higher values existed in eastern Qinghai-Tibetan Plateau and Yunnan. P densities in ~~plant organs~~vegetation were higher towards the south and ~~east~~northeast part of China, while soil P density was higher towards the north and west part of China. The estimated N and P density and concentrtaion datasets, “Patterns of nitrogen and phosphorus pools in terrestrial

ecosystems in China” (the pre-publication sharing link: https://datadryad.org/stash/share/78EBjhBqNoam2jOSoO1AXvbZtgIpCTi9eT-eGE7wyOk), are available from the Dryad Digital Repository (Zhang et al., 2020). These patterns of N and P densities could potentially improve existing earth system models and large-scale researches on ecosystem nutrients.

**Key words:** climate; nitrogen pools; phosphorus pools; nutrient limitation; spatial distribution

## 1 Introduction

Nitrogen (N) and phosphorus (P) play fundamental roles in plant physiological activities and functioning, such as photosynthesis, resource utilization and reproductive behaviours (Fernández-Martínez et al., 2019; Lovelock et al., 2004; Raaimakers et al., 1995), ultimately regulating plant growth and carbon (C) sequestration efficiency (Terrer et al., 2019~~).~~; Sun et al., 2017). Under the background of global warming, the limiting factors for the plant growth, such as carbon dioxide ($CO_2$) and temperature, are becoming less restrictive for terrestrial ecosystem productivity (Norby et al., 2009; Fatichi et al., 2019), while nutrient availability tends to constrain the increasing plant photosynthesis more intensively (Cleveland et al., 2013; Du et al., 2020). As the key nutrients for plant growth, N and P independently or ~~together~~jointly limit biomass production (Elser et al., 2007; Finzi et al., 2007~~).~~; Hou et al., 2020). N influence $CO_2$ assimilation in various ways (Vitousek and Howarth, 1991; Campany et al., 2017). For example, N is a critical element in chlorophyll (Field, 1983), and plant metabolic rates are also regulated by N content (Elser et al., 2010). P is crucial in RNA and DNA construction, and its content is associated with water uptake and transport (Carvajal et al., 1996; Cheeseman and Lovelock, 2004) as well as energy transfer and exchange (Achat et al., 2009). P shortage could lower photosynthetic C-assimilation rates (Lovelock et al., 2006).

In spite of the key importance of N and P for plants, knowledge on the patterns of their storage in terrestrial ecosystems are limited. With additional $CO_2$ entering atmosphere, more N could be ~~allotted~~allocated to plant growth and soil organic matter (SOM) accumulation, which may lead to less available mineral N for plant uptake (Luo et al., 2004). Direct and indirect evidences show that N limits productivity in temperate and boreal areas (Bonan, 1990; Miller, 1981; Vitousek, 1982). P originates from bedrock weathering and litter decomposition in terrestrial ecosystems, and it experiences long-term biogeochemical processes before available to plants (Föllmi, 1996), which consequently makes P a more predominant limiting factor to ecosystem productivity (Reed et al., 2015). Additionally, P decomposition rates are constrained by limited soil labile P storage, especially in tropical forests where soil P limitation is extreme (Fisher et al., 2012).

Ecosystem models based on Amazon forest free air $CO_2$ enrichment (FACE) experiments consistently showed that biomass C positively responded to simulated elevated $CO_2$, but the models incorporating N and P availability showed lower plant growth than those not (Wieder et al., 2015). Moreover, a recent study suggested that the inclusion of N and P availability into the earth system models (ESMs) remarkably improved the estimation accuracy of C cycles over previous models (Fleischer et al., 2019). Hence, understanding and predicting the patterns and mechanisms of global C dynamics require well characterizing of N and P conditions.

N and P pools in ecosystems consist of several components that cast different influences on ecosystem C storages and fluxes. For example, N and P in plants directly affect C sequestration (Thomas et al., 2010), but their activities differ among organs (Elser et al., 2003; Parks et al., 2000); the soil pools are the source of plant nutrition; and the litter pools act as a transit link that returns nutrients from plants to soil (McGrath et al., 2000). Thus, an accurate estimation of ecosystem N and P pools involves calculating specific nutrient densities in all these components.

Terrestrial ecosystems in China play a considerable part in the continental and global C cycles. Satellite data verified that China contributed to a 1/4 of global net increase in leaf area from 2000 to 2017 (Chen et al., 2019). The total C pool in terrestrial ecosystems in China is 79.2 Pg C, and this number is still growing because of the nationwide ecological restoration constructions, which accounted for 56% of the total C sequestration in the restoration area in China from 2001 to 2010 (Lu et al., 2018). N and/or P limitations are ubiquitous in natural ecosystems in China (Augusto et al., 2017; Du et al., 2020~~).~~; Elser et al., 2007; LeBauer and Treseder, 2008; Hou et al., 2020). Understanding the distribution and allocation of N and P in ecosystems is of great significance for a precise projection of C cycle in China. Although there are a few studies on the spatial patterns of soil nutrient storages in China (Shangguan et al., 2013; Xu et al., 2020; Yang et al., 2007; Zhang et al., 2005), a thorough study on the distribution of N and P pools of the whole ecosystems is still lacking, as vegetation (living or dead biomass) composes the most active part of the nutrient stocks.

To fill this knowledge gap, here we identified N and P density patterns in China based on an intensive field investigation, covering all components of the entire ecosystem, including different plant organs, litter and soil. The present study aims to provide ~~a~~ high-resolution ~~map~~maps of nutrient densities in different ecosystem components and to answer the following questions.

1) How much N and P are stored in different components, i.e., leaf, stem, root, litter and soil, of terrestrial ecosystems in China?

2) How do different components of N and P pools spatially distribute in China?

## 2 Material and methods

### *2.1 Field sampling and nutrient density calculation*

Forest, shrublands and grasslands constitute major vegetation type groups in China. Focusing primarily on these three groups, a nationwide, methodologically consistent field investigation was conducted in June and September, 2011-2015.

In total, ~~4175~~4865 sites, including ~~2385~~3061 forest, ~~1069~~1081 shrubland and ~~721~~723 grassland sites, were investigated~~.~~ (Fig. S1a). At each site, one 20 × 50 m² plot was set for forests, three replicated 5 × 5 m² plots were set for shrublands, and ten 1 × 1 m² plots were established for grasslands. Species composition and abundance were investigated in plots. Height (for trees, shrubs and herbs), diameter at breast height (DBH, at height 130 cm) (for trees), basal diameter (for shrubs) and crown width (for shrubs and herbs) were measured for all plant individuals in the plots (Tang et al., 2018a).

Leaves, stems (woody stems) and roots (without distinguishing coarse and fine roots) were sampled for the five top dominant tree and shrub species, and above- and belowground parts were sampled for dominant herb species. Soil was sampled to the depth of 1 m or to bedrock at the depths of 0–10, 10–20, 20–30, 30–50, and 50–100 cm with at least five replications per site to measure nutrient concentrations and bulk density after removing roots and gravels. Litter was sampled in at least three 1 × 1 $m^2$ quadrats per site (for detailed survey protocol, see Tang et al., 2018a).

All samples were transported to laboratory, dried and measured. N concentrations of all samples were measured by a C/N analyzer (PE-2400 II; Perkin-Elmer, Boston, USA), while P concentrations were measured using the molybdate/ascorbic acid method after $H_2SO_4$-$H_2O_2$ digestion~~.~~ (Jones Jr, 2001). For the three organs, the community-level N or P density was the cumulative sum of the products of the corresponding biomass density (i.e. biomass per area, Mg $ha^{-1}$) and community-level concentrations for each co-occurring species. For detailed calculation of species biomass and community-level concentrations in each site, please referred to Tang et al (2018b).

$$N(P) = \sum_{\cancel{\sum B_i \times \theta_i} i=0}^{n} B_i \times \theta_i \qquad (1)$$

~~$N (P)$~~ $N (P)$ represents the community-level N or P density (Mg $ha^{-1}$); $n$ is the total number of plant species in one site; $B_i$ is the biomass density of a specific organ of the $i^{th}$ plant species in ~~one~~that site, where the plant organ biomass was estimated by allometric equations or harvesting; $\theta_i$ represents the N or P concentration (g kg$^{-1}$) of the same organ of the $i^{th}$ plant species in that site. Allometric equation methods were adapted to trees and some shrubs (tree-like shrubs and xeric shrubs) for biomass estimation, while the biomass of grass-like shrubs and herbs were obtained by direct harvesting. Litter N or P density was litter biomass density (by harvesting) multiplied by litter N or P concentration of each sampling site. The soil N or P density was calculated to a depth of one metre. Soil N or P concentration and bulk density were measured at different depths (0–10, 10–20, 20–30, 30–50, and 50–100 cm) to determine the community-level soil N or P density using Equation (2):

$$\cancel{SOND(SOPD) = \sum(1-\delta_i)\times\rho_i\times C_i\times T_i/10}\ SND(SPD) = \sum_{i=0}^{n}(1-\delta_i)\times\rho_i\times C_i\times T_i/10 \qquad (2)$$

where ~~$SOND(SOPD)$~~$SND\ (SPD)$ is the total N or P density of the soil within top 1 m (Mg ha$^{-1}$); $n$ is the total number of soil layers (ranging from one to five) in ~~the $i^{th}$ layer (0-10, 10-20, 20-30, 30-50 and 50-100 cm),~~one site; $\delta_i$ is the volume percentage of gravel with a diameter > 2mm, $\rho_i$ is the bulk density (g cm$^{-3}$), $C_i$ is the soil N or P concentration (g kg$^{-1}$), and $T_i$ is the depth (cm) of the $i^{th}$ layer. For detailed calculations of species biomass and community-level concentrations at each site, please refer to previous studies (Tang et al., 2018a, ~~2018b~~b).

*2.2 Climatic and vegetation data*

The daily meteorological observation data from 2,400 meteorological stations across China were averaged over the 2011-2015 period to generate a spatial interpolation dataset of mean annual temperature (MAT) and precipitation (MAP), using a smooth spline function

(McVicar et al., 2007) , with a spatial resolution of 1 km. MAT and MAP of each site were extracted from this dataset.

Elevation was extracted from GTOPO30 with a spatial resolution of 30 arc-seconds (http://edc.usgs.gov/products/elevation/gtopo30/gtopo30.html). The mean enhanced vegetation index (EVI) from June to September during the 2011–2015 period was calculated based on MOD13A3 data with a resolution of 1 km (https://modis.gsfc.nasa.gov/).

The ranges of these variables of our field sites (EVI: 0.03~0.7; elevation: -137 m~5797 m; MAP: 19.8 mm~2316.3 mm; MAT: -5.2 °C~ 26.0 °C) could generally cover the ranges of corresponding variables in the focused vegetation types across China (99% ranges of EVI: 0.03~0.6; of elevation: 24 m~5628 m; of MAP: 50.6 mm~2956.5 mm; of MAT: -6.6 °C~ 22.8 °C).

Based on the level II vegetation classification of ChinaCover (Land Cover Atlas of the People's Republic of China Editorial Board, 2017), we classified the vegetation type groups into the following 13 ~~Vegetation~~vegetation types: five forest types, i.e., evergreen broadleaf forests, deciduous broadleaf forests, evergreen needle-leaf forests, deciduous needle-leaf forests, broadleaf and needle-leaf mixed forests; four shrubland types, i.e., evergreen broadleaf shrublands, deciduous broadleaf shrublands, evergreen needle-leaf shrublands, and sparse shrublands; and four grassland types, i.e., meadows, steppes, tussocks, and sparse grasslands.

*2.3 Prediction the nationwide nutrient pools and distribution patterns*

We used ~~back-propagation artificial neural network for nutrient density spatial interpolating. The input layer contained~~random forest to predict the nutrient densities and concentrations across China. The predictors included MAT, MAP, longitude, latitude, elevation, EVI and vegetation types (as dummy variables). We established one ~~artificial neural network~~ random forest model for N or P in each component (three plant organs, litter and ~~P in~~ five ~~components,~~soil layers), respectively. ~~The observation data~~In each model, six variables were randomly ~~grouped into two subsets, 90% data for training~~sampled at each split, and ~~the other 10% for~~500 trees were grown. Larger values of these parameters did not increase validation~~. When building the artificial network, we used one and two layers, one to 20 hidden neurons per layer, respectively, to find out a model configuration with the best predicting ability. The training and testing process~~ $R^2$ obviously. Model prediction were repeated ~~100 times for each configuration. The best predicting model was selected according to the minimal mean root mean square error (RMSE). Then the chosen model was used to predict the nationwide nutrient distribution in corresponding component~~ for 100 times to obtain the average ~~conditions.~~

results. When modelling the nutrient densities in woody stems, we excluded the four grassland types. ~~The vegetation N or P density was the sum of all plant organs, and the ecosystem N or P density was the sum of all components.~~

All densities were log-transformed based on $e$, and explanatory variables were transformed using the following equation to ensure they were in the same range before modelling.

$$x_i' = \frac{x_i - min(x)}{max(x) - min(x)} \quad (3)$$

where $x_i$ means the $i^{th}$ value of the environmental variables $x$, and max($x$) and min($x$) represent the maximum and minimum values of $x$, respectively. We estimated the relative importance of predictors using the increase in node purity for the splitting variable, which was measured by the reduction in residual sum of squares. The same procedures were repeated for the prediction of N and P concentrations in different components across China. The spatial pattern of N:P ratio was calculated from the predicted N and P density datasets of the corresponding component.

The vegetation N or P density was the sum of all plant organs, the soil N or P density was the sum of all soil layers, and the ecosystem N or P density was the sum of all components. The soil depth data across China were obtained from Shangguan et al (2017).The N and P pools in 13 ~~Vegetation~~vegetation types were estimated, respectively. The N and P pools were calculated from the predicted nationwide densities. The predicted N and P densities were in 1 km spatial resolution, so the nutrient stock is the density multiply the grid area (1 km$^2$) for each grid. The nutrient pools of a given vegetation type equals the sum of stocks of the grids belonging to that type.

*2.4 ~~Data~~ Model validation and uncertainty ~~and validation~~*

To evaluate the model performance, we calculated the linear relationship between the observed validation data (10% of the dataset by random sampling) and predicted data that was estimated based on training data (90% of the dataset by random sampling) for 100 times with the ~~selected~~ models for every component. ~~The~~We then calculated means of validation $R^2$, slopes and intercepts of ~~these~~the 100 relationships ~~were estimated using standard major axis regression.~~. We also ~~mapped~~calculated the standard deviations (SDs) of the 100-time predictions of each component in each map grid to show the uncertainty of ~~our results in different regions~~the models.

All statistical analyses were performed using R 3.6.1 (R Core Team, 2019), ~~artificial networks~~random forests were built using ~~*neuralnet*~~*randomForest* package (~~Günther~~Liaw and

~~Fritsch, 2010), and standard major axis regression was conducted using *smatr* package (Warton et al., 2012~~Wiener, 2002).

## 3 Data accessibility

The datasets of N and P densities and concentration of different ecosystem components, " Patterns of nitrogen and phosphorus pools in terrestrial ecosystems in China", are available from the Dryad Digital Repository (the pre-publication sharing link: https://datadryad.org/stash/share/78EBjhBqNoam2jOSoO1AXvbZtgIpCTi9eT-eGE7wyOk) (Zhang et al., 2020).

## 4 Results

### *4.1 ~~Site average allocation~~Allocation of ~~nutrient~~nutrients among ecosystem components*

The ~~site averaged~~ mean N and P densities varied among ~~forests, shrublands~~forest, shrubland and ~~grasslands~~grassland sites and among different tissues (Fig. 1 & 2) according to the measured ~~plot~~ data. ~~In~~On average, leaves and woody stems in the forests stored more N than those in the shrublands ~~(11 ± 10~~0.1 ± 0.1 (mean ± SD) ~~× 10$^{-2}$~~ Mg N ha$^{-1}$ vs. ~~3~~4.2 ± 10 × 10$^{-2}$ Mg N ha$^{-1}$for leaves, and ~~260 ± 340 × 10$^{-}$~~0.3 ± 0.6 Mg N ha$^{-1}$ vs. 5.~~8 ± 11~~1 ± 20 × 10$^{-}$~~$^{3}$~~$^{2}$ Mg N ha$^{-1}$ for woody stems). Similarly, P densities were higher in the forests leaves and woody stems than those in the shrublands (~~12 ± 13~~1.3 ± 1.5 × 10$^{-}$~~$^{3}$~~$^{2}$ Mg P ha$^{-1}$ vs. ~~2.9~~ 3.1± 6.~~1~~5 × 10$^{-3}$ Mg P ha$^{-1}$ for leaves and ~~52 ± 110~~5.6 ± 11× 10$^{-}$~~$^{3}$~~$^{2}$ Mg P ha$^{-1}$ vs. ~~4.~~4~~ ± 11~~.7 ± 19 × 10$^{-3}$ Mg P ha$^{-1}$ for woody stems). ~~than those in shrublands (3.2 ± 10 × 10$^{-2}$ Mg N ha$^{-1}$ and 2.9 ± 6.1 × 10$^{-3}$ Mg P ha$^{-1}$ for leaves; 5.8 ± 11 × 10$^{-3}$ Mg N ha$^{-1}$ and 4.4 ± 11 × 10$^{-3}$ Mg P ha$^{-1}$ for woody stems) and grasslands (2.7 ± 2.4 × 10$^{-2}$ Mg N ha$^{-1}$ and 2.7 ± 2.9 × 10$^{-3}$ Mg P ha$^{-1}$ for leaves).~~ However, the root N and P densities in forests (0.1 ± 0.2 Mg N ha$^{-1}$ and 2.1~~.~~ ± 3~~ ± 1.6 × 10$^{-1}$ Mg N ha$^{-1}$ and~~ ~~1.8 ± 2.8~~.9 × 10$^{-2}$ Mg P ha$^{-1}$) and grasslands (~~1.9 ± 1.7 × 10$^{-1}$~~0.2 ± 0.2 Mg N ha$^{-1}$ and 1.5 ± 1.6 × 10$^{-2}$ Mg P ha$^{-1}$) were remarkably higher than in shrublands (6.~~5 ± 11 × 10$^{-2}$ Mg N ha$^{-1}$ and~~ 6.~~1~~ ~~± 9.9~~ ± 11 × 10$^{-2}$ Mg N ha$^{-1}$ and 5.6 ± 8.8 × 10$^{-3}$ Mg P ha$^{-1}$).

The ~~site-averaged~~mean litter N densities ~~in forests, shrublands and grasslands~~for forest, shrubland and grassland sites were 6.~~3 ± 8.~~1 ± 7.6 × 10$^{-2}$ Mg N ha$^{-1}$, 3.~~2~~8 ± 4.~~1~~6 × 10$^{-2}$ Mg N ha$^{-1}$ and 5.5 ± 9.3 × 10$^{-3}$ Mg N ha$^{-1}$, respectively. The ~~site-averaged~~mean litter P densities in ~~forests, shrublands~~forest, shrubland and ~~grasslands~~grassland sites were 5.3 ± 9.~~9~~3× 10$^{-3}$ Mg P ha$^{-1}$, 2.5 ± 2~~ ± 2.9~~.3× 10$^{-3}$ Mg P ha$^{-1}$ and 4.~~14~~1 ± 7.1 × 10$^{-4}$ Mg P ha$^{-1}$, respectively.

The ~~site-averaged~~mean soil N densities ~~in forests, shrublands and grasslands~~for forest, shrubland and grassland sites were ~~11.2 ± 9.2~~12.1 ± 10.8 Mg N ha$^{-1}$, ~~9.4~~8.8 ± 7.~~8~~4 Mg N ha$^{-1}$ and 9.9 ± 8.9 Mg N ha$^{-1}$, respectively. The ~~site-averaged~~mean soil P densities were 4.9 ± 6~~ ± 4.2~~.5 Mg P ha$^{-1}$ in forest~~, 4.0 ±~~ sites, 3.~~0 Mg P ha$^{-1}$ in shrublands and 4.1 ± 2~~9 ± 3.7 Mg P ha$^{-1}$ in ~~grasslands~~shrubland sites and 4.4 ± 2.8 Mg P ha$^{-1}$ in grassland sites.

~~Both belowground~~Belowground vegetation N and P densities were higher than aboveground in grasslands and sparse shrublands~~ and grasslands~~. By contrast, this condition was reversed in forests and other 3 shrubland types (Fig. 3). Among various forest types, deciduous broadleaf forests and deciduous needle-leaf forests held the highest aboveground N and P densities, respectively. Evergreen needle-leaf forests held the lowest vegetation N density and evergreen broadleaf forests owned the lowest P density. For grassland types, ~~the density allocation varied markedly. Meadows and steppes~~meadows held higher N and P densities in belowground biomass than ~~tussocks and sparse grasslands~~the other 3 grassland types, whereas these four grasslands types had relatively approximate nutrient densities in aboveground biomass. Shrublands possessed the lowest vegetation N and P densities among three vegetation groups. Sparse shrublands owned the lowest vegetation nutrient densities and soil N density but the highest soil P density among four shrubland types.

*4.2 Mapping of N and P densities in China's terrestrial ecosystems*

All models of the N and P densities of different components performed well~~ (~~, with the validation $R^2$ ranging from 0.55 to 0.78 for plant organs and litter (Fig. 4), ~~especially those for the woody stems ($R^2$ = 0.81 and 0.69 for N~~ and ~~P densities, respectively)~~from 0.47 to 0,62 for soil layers (Fig. 5). As to the concentration models, the validation $R^2$ varied from 0.45 to 0.63 for plant organs and litter (~~$R^2$=0.66~~Fig. S2), and ~~0.62 for N and P densities, respectively).~~from 0.53 to 0.70 for soil layers (Fig. S3). Prediction results of 100-time repetitions were quite stable, as shown by SDs of ~~N and P densities were relatively higher in western and northeastern China, with values > 5 (Fig. 5k–t). For example, the~~ the predictions ~~of litter N (Fig. 5q) and P (Fig. 5r) showed larger SDs in western Xinjiang and Tibet.~~close to zero in all components. (Fig S4 & S5).

~~The leaf~~Leaf N density was high in southern and eastern China, but low in northern and western China. It was especially high in the Changbai Mountains, the southern Tibet and the southeast coastal areas (Fig. ~~5), with a density~~6a, see Fig S1b for the topographic map of ~~>0.1 Mg N ha$^{-1}$. In comparison,~~China), while it was low in the northern Xinjiang and northern Inner Mongolia~~ (< 0.01 Mg N ha$^{-1}$).~~. The woody stem and litter N densities showed the similar patterns to ~~those~~that of the leaves~~,~~ (Fig. 6c & g), whereas ~~that in roots~~root N density was high in the Mount Tianshan, Mount Alta, Qinghai-Tibetan Plateau, northeastern mountainous area and the eastern Inner Mongolia ~~steppe~~ (Fig. ~~5~~6e). The vegetation N density was relatively

~~high~~higher in eastern China, eastern Qinghai-Tibetan Plateau, Mount Tianshan and Mount Alta~~, ranging from 0.5 to 2.5 Mg N ha$^{-1}$.~~ (Fig. 7a). The soil and ecosystem N densities were low in northern China except the Changbai Mountains, Mount Tianshan and Mount Alta, but high in the eastern Qinghai-Tibetan Plateau and the Yunnan Province (Fig. ~~6~~7c & e).

The P densities in leaves, woody stems, roots, litter and ~~litter~~the whole vegetation showed similar patterns to the N densities in the corresponding components, respectively~~.~~ (Fig. 6b, d, f & h; Fig 7b). However, soil and ecosystem P densities were high in western and northern China but low in eastern and southern China~~, but low at high altitudes in the Qinghai-Tibetan Plateau (Fig. 5 & 6~~ (Fig. 7d & f).

The N and P concentrations in plant organs and litter were generally higher in northern and western mountain regions, but larger values of the former often occurs in northwestern part of China, while those of the latter often occurs in northeastern part of China (Fig. S6a–h). The spatial patterns of soil nutrient concentrations at different depths were consistent with those of soil nutrient densities (Fig. S6i–r).

N:P ratio of plant organs and litter showed similar distribution patterns, higher values occurring in southeastern and northwestern China and Qinghai-Tibetan Plateau (Fig. S7a–d). Soil N:P ratio was higher in northeastern and southern China but lower in northwestern China (Fig. S7e).

*4.3 N and P pools in China's terrestrial ecosystems*

In total, the terrestrial ecosystems in China stored ~~7665.62 × 10$^{6}$ Mg~~6803.6 Tg N, with ~~2632.80 × 10$^{6}$ Mg~~2634.9 Tg N, ~~830.24 × 10$^{6}$ Mg~~873.0 Tg N and ~~4202.58 × 10$^{6}$ Mg~~3295.8 Tg N stored in the forests, shrublands and grasslands, respectively (Table 1). Vegetation, litter and soil stored ~~216.17 × $10^6$ Mg~~156.7 Tg N (2.~~82%), 14.92 × $10^6$ Mg~~3%), 11.7 Tg N (0.~~19~~2%) and ~~7434.53 × $10^6$ Mg~~6635.2 Tg N (~~96.99~~97.5%), respectively~~.~~ (Table 1).

China's terrestrial ecosystems stored ~~3852.66 × $10^6$ Mg~~2806.0 Tg P, with ~~1037.34 × $10^6$ Mg~~981.1 Tg P, ~~361.62 × $10^6$ Mg~~381.8 Tg P and ~~2453.70 × $10^6$ Mg~~1443.0 Tg P stored in the forest, shrublands and grasslands, respectively. Vegetation, litter and soil accounted for ~~28.88 × $10^6$ Mg~~18.8 Tg P (0.~~75%), 2.14 × $10^6$ Mg~~7%), 1.0 Tg P ~~(~~(< 0.~~06~~1%) and ~~3821.64 × $10^6$ Mg~~2786.1 Tg P (99.~~19~~3%), respectively~~.~~ (Table 1).

Meanwhile, N and P stocks among plant organs showed different allocation patterns (Table 2). Compared with the other two vegetation type groups, forests allocated the majority of N and P to the stem pool (~~59.29× $10^6$ Mg~~55.5 Tg N and ~~13.81× $10^6$ Mg~~9.2 Tg P), followed by the root pool (~~28.55× $10^6$ Mg~~23.4 Tg N and ~~5.53× $10^6$ Mg~~3.3 Tg P) and leaf pool (~~23.84× $10^6$ Mg~~21.0 Tg N and 2.~~49× $10^6$ Mg~~1 Tg P). However, the root pools in shrublands and grasslands held the most of N and P (~~4.44× $10^6$ Mg~~3.8 Tg N and 0.~~38× $10^6$ Mg~~3 Tg P for shrublands, and ~~91.22× $10^6$ Mg~~71.2 Tg N and ~~5.55× $10^6$ Mg~~6.7 Tg P for grasslands) (Table 2).

Among ~~4~~four grassland types, steppe had the largest N stock (~~1599.47× $10^6$ Mg~~1370.1 Tg N), and sparse grasslands had the largest P stock (~~1578.83× $10^6$ Mg~~507.2 Tg P) taking the ecosystem as a whole. Deciduous broadleaf shrublands owned the largest N and P stocks considering the whole ecosystem (~~605.09× $10^6$ Mg~~577.6 Tg N and ~~211.15× $10^6$ Mg~~234.2 Tg P) as well as in vegetation (5.~~30× $10^6$ Mg~~5 Tg N and 0.~~58× $10^6$ Mg~~5 Tg P), compared with the other 3 shrubland types. The largest ecosystem N and P stocks across all ~~13 vegetation~~five forest types appeared in evergreen needle-leaf forests (~~43.43× $10^6$ Mg~~984.0 Tg N) and deciduous broadleaf forest (353.8~~.37× $10^6$ Mg~~ Tg P) (Table 2).

## 5 Discussion

### *5.1 Performance ~~and uncertainty~~ of density models*

The accuracy of the density models varied among different components. ~~Soil interpolation models~~ Models for soil showed ~~poorest~~relatively poorer accuracy ~~($R^2$=0.38~~than models for ~~N~~plant organs and ~~0.27 for P) among these models,~~litter (Fig. 4 & 5), partly because that soil N and P were ~~more stable than those in the plants and litters (Matamala et al., 2008) and that soil nutrient exchange and storage were~~ largely ~~controlled~~influenced by ~~geochemical and geophysical processes (~~geological conditions, soil age and parent material (Buol and Eswaran, 1999; Doetterl et al., 2015; Gray and Murphy, 2002), which ~~are~~were not ~~considered~~included in our ~~models.~~analysis because of the limited data availability. This can be evidenced by the decreasing validation $R^2$ of the models for soil N and P concentrations as well as N densities with soil depths (Fig. 5 and S3). The models preformed best for the stem N and P, because woody stems occupied the most biomass in the forest and shrublands (stem biomass/vegetation biomass were 0.68 and 0.48 for forest and shrublands, respectively). Climate variables could affect vegetation growth and biomass accumulation, and the variation in stem biomass could be the most direct reflection (~~Jozsa and Powell, 1987;~~ Kirilenko and Sedjo, 2007; Jozsa and Powell, 1987; Poudel et al., 2011).

~~The predicted SDs were relatively higher in high-latitudes and high-altitudes, such as the northeastern mountainous area and the Qinghai-Tibet Plateau, probably because of the lower sampling density. Meanwhile, the temperature in these regions was about the lower limit of the temperature range in our dataset, which could consequently lead to the weaker validity of the prediction results in such cold regions.~~

~~5.2~~It is also noteworthy that the validation $R^2$ of the density models were higher than those of the concentration models for plant organs and litter (Fig. 4 & S2), which was opposite for soil layers (Fig. 5 and S3). They might reflect that biomass were more constrained by the selected factors in this study than nutrient concentrations in vegetation, while bulk density was less affected than nutrient concentrations in soil.

### *5.2 Nutrient pools in terrestrial ecosystems in China*

Previous researches have estimated N and P stocks in soil across China. For example, Shangguan et al (2013) estimated that the storage of soil total N and P in the upper 1m of soil in China were 6.6 and 4.5 Pg. Yang et al (2007) estimated China's average density of soil N at a depth of one meter which was 0.84kg $m^{-2}$ and the soil N stock was 7.4 Pg. Zhang et al (2005) investigated soil total P pool at a depth of 50 cm in China and concluded that the soil stock was 3.5 Pg with the total P density of soil $8.3 \times 10^2$ g/$m^3$. Our estimation of the soil N pool in China (6.6Pg) agreed with Shangguan et al (2013), but the estimated soil P pool (2.8Pg) was lower than the results of aforementioned studies. The mean soil N:P ratio in our study (2.5 of the predicted dataset and 2.1 of the training dataset) was lower than the result of Tian et al (2010), 5.2, while the spatial patterns in both studies are similar. Other than the researches focusing on soil, Xu et al (2020) estimated China's N storage by calculating the mean N densities of vegetation and soil from different ecoregions, and the reported that there were 10.43 Pg N in China's ecosystems, 10.14 Pg N in top 1 m soil and 0.29 Pg N in vegetation, both higher than our results (6.6 Pg N in soil and 0.16 Pg N in vegetation).

### *5.3 Potential driving factors of the N and P densities in various components*

The distribution and allocation of N and P pools in ecosystems were largely determined by vegetation types and climate. The difference in the spatial patterns of nutrient pools could reflect the spatial variation in local vegetation. For example, it is obvious that the regions covered by forests tend to have higher ~~the~~ aboveground nutrient densities than those covered by other types, while the regions covered by sparse shrublands tend to have the lowest nutrient densities (Fig. 3). Despite its decisive influences on vegetation types, climate also impacts greatly on the nutrient utilization strategies of vegetation (Kirilenko and Sedjo, 2007; Poudel et al., 2011). For example, in southeastern China with higher precipitation and temperature, forests tend to allot more nutrient to organs related to growth, for example, leaves that perform photosynthesis and stems that related to resource transport and light competition (Zhang et al., 2018). These influences were reflected in our models (Fig. S8-S11). In the models of densities for plant organs and litter, vegetation types and climate variables showed higher relative importance. Heat and water are usually limited in the plateau and desert regions in western China, where shrublands and grasslands are dominant vegetation type groups. More nutrients are allocated to root systems by dominant plants in such stressful habitats to acquire resources from soil (Eziz et al., 2017; Kramer-Walter and Laughlin, 2017). ~~Soil nutrient densities were relatively larger~~Spatial variables, longitude and latitude, also held high importance, especially in the models for soil nutrients. On the one hand, it may result from their tight links with climate conditions. On the other hand, it may imply the influence of spatial correlation on nutrient pools. The effects of elevation and spatial variables were obvious from the prediction maps. There were relatively larger values of soil nutrient densities in the plateau and mountainous area in western China, possibly because of the lower rates of decomposition, mineralization, and nutrient ~~uptake~~input as well as less leaching loss in high-altitude regions (Bonito et al., 2003;

Vincent et al., 2014). However, the distribution patterns of soil nutrient densities in eastern China were generally consistent with the Soil Substrate Age hypothesis that the younger and less-leached soil in temperate regions tend to be more N limited but less P limited than the elder and more-leached soil in tropical and subtropical regions (Reich and Oleksyn, 2004; Vitousek et al., ~~2010~~2010; Walker and Syers, 1976). Additionally, such patterns reflect that the factors not investigated in this study, such as soil age and parent material, could contribute to the patterns of nutrient pools, which should be considered in future researches as potential drivers (Augusto et al., 2017; Porder and Chadwick, 2009).

### *5.~~3~~4 Potential applications of the data*

Atmospheric $CO_2$ enrichment trend was undoubtable, but how this procedure will develop is still unclear (Fatichi et al., 2019). A number of previous studies proved that global carbon cycle models would produce remarkable bias if overlooking the coupled nutrient cycle (Fleischer et al., 2019; Hungate et al., 2003; Thornton et al., 2007). However, high-resolution and accurate ecosystem nutrient datasets were unattainable and hard to be modeled without enormous field investigation basis. This study relied on nationwide field survey data, providing comprehensive N and P density datasets of different ecosystem components. Based on the present dataset, enhancement could be made in various ecosystem research aspects.

First and foremost, the dataset could facilitate the improvement in the prediction of large-scale terrestrial C budget, thereby to better understand patterns and mechanisms of C cycle as well as the future trend of climate change (Le Quéré et al., 2018). Numerous projections of future C sequestration overestimated the amount of C fixed by vegetation due to the neglect of nutrient limitation (Cooper et al., 2002; Cramer et al., 2001). Global C cycling models coupled with nutrient cycle ~~could~~may make more accurate predictions of carbon dynamics. Moreover, our dataset illustrated N and P densities of major ecosystem components and vegetation types at a high spatial resolution for the first time, which could help identify C and nutrient allocation patterns from the tissue level to the community level, especially for vegetation organs which still lack large-scale nutrient datasets.

In addition, large-scale N and P pool spatial patterns could provide the data references for the vegetation researches using remote sensing (Jetz et al., 2016). Vegetation nutrient densities was important traits but hard to be extracted and detected remotely. With the development of hyperspectral remote sensing technology and theory of spectral diversity, foliar nutrient traits can be successfully predicted (Skidmore et al., 2010; Wang et al., 2019). However, previous studies still focused on finer-scale patterns and were constrained by the lack of large-scale field datasets for uncertainties assessment (Singh et al., 2015). Our nationwide nutrient dataset offers an opportunity to enlarge the generality of remote-sensing models and algorithms at large scales.

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**Author Contributions**

Z.T. designed the research. Y.W.Z, Y.G., Y.F., and X.Z. analysed the data. W.X., Y.B., G.Z., Z.X. and Z.T. organized the field investigation. Y.W.Z, Y.G., Z.T. wrote the manuscript and all authors contributed substantially to revisions.

## Competing interests

The authors declare no competing interests.

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**Table.1.** N and P stocks of vegetation, litter, soil and total ecosystem in ~~forest~~forests, shrublands and grasslands in China.

| Vegetation type group | Vegetation type | Area ($10^6$ ha) | N pool (~~$10^6$ Mg~~Tg) | | | | P pool (~~$10^6$ Mg~~Tg) | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Vegetation | Soil | Litter | Ecosystem | Vegetation | Soil | Litter | Ecosystem |
| Forest | EBF | ~~45.59~~40.6 | ~~13.08~~18.0 | ~~587.48~~476.4 | 1.~~93~~7 | ~~608.73~~496.1 | 1.~~89~~7 | ~~193.27~~154.8 | 0.~~10~~1 | ~~195.26~~156.6 |
| | DBF | ~~91.14~~66.3 | 43.~~43~~1 | ~~665.60~~811.3 | ~~4.25~~3.7 | ~~713.29~~858.1 | ~~8.37~~6.9 | ~~277.61~~346.5 | 0.~~74~~4 | ~~286.71~~353.8 |
| | ENF | ~~99.97~~83.8 | ~~34.93~~28.4 | ~~1074.18~~952.8 | ~~3.58~~2.8 | ~~1112.69~~984.0 | ~~5.59~~3.7 | ~~377.27~~349.2 | 0.~~23~~2 | ~~383.08~~353.1 |
| | DNF | ~~19.79~~11.5 | ~~7.53~~5.6 | ~~84.76~~177.7 | ~~1.73~~0.5 | ~~94.03~~183.8 | ~~4.61~~1.5 | ~~123.33~~73.6 | 0.~~75~~1 | ~~128.70~~75.2 |
| | MF | ~~13.25~~9.6 | 4.6~~.47~~ | ~~96.95~~107.6 | 0.~~65~~5 | ~~104.07~~112.8 | ~~1.38~~0.9 | ~~42.08~~41.5 | 0.~~13~~1 | ~~43.59~~42.4 |
| | ***subtotal*** | ***~~269.75~~211.9*** | ***~~111.69~~99.8*** | ***~~2508.98~~2525.8*** | ***~~12.14~~9.3*** | ***~~2632.80~~2634.9*** | ***~~21.84~~14.6*** | ***~~1013.55~~965.6*** | ***~~1.96~~0.9*** | ***~~1037.34~~981.1*** |
| Shrubland | EBS | ~~21.65~~18.7 | 2.1~~.56~~ | ~~160.54~~213.6 | 0.~~61~~5 | ~~162.70~~216.2 | 0.~~20~~2 | ~~52.95~~80.9 | < 0.~~03~~1 | ~~53.18~~81.1 |
| | DBS | ~~63.94~~48.7 | 5.~~30~~5 | ~~598.39~~570.9 | 1.~~40~~2 | ~~605.09~~577.6 | 0.~~58~~5 | ~~220.48~~233.6 | 0.~~09~~1 | ~~221.15~~234.2 |
| | ENS | 1.~~36~~0 | 0.~~06~~1 | ~~13.29~~12.4 | < 0.~~01~~1 | ~~13.36~~12.5 | < 0.~~008~~1 | ~~5.40~~4.9 | < 0.~~0006~~1 | ~~5.41~~4.9 |
| | SS | ~~17.35~~11.9 | 0.~~22~~5 | ~~48.~~66.1 | 0.~~21~~1 | ~~49.10~~66.7 | < 0.~~02~~1 | ~~81.85~~61.6 | < 0.~~01~~1 | ~~81.88~~61.6 |
| | ***subtotal*** | ***~~104.31~~80.3*** | ***~~7.14~~8.1*** | ***~~820.88~~863.0*** | ***~~2.23~~1.8*** | ***~~830.24~~873.0*** | ***0.~~80~~7*** | ***~~360.69~~381.0*** | ***0.~~13~~1*** | ***~~361.62~~381.8*** |

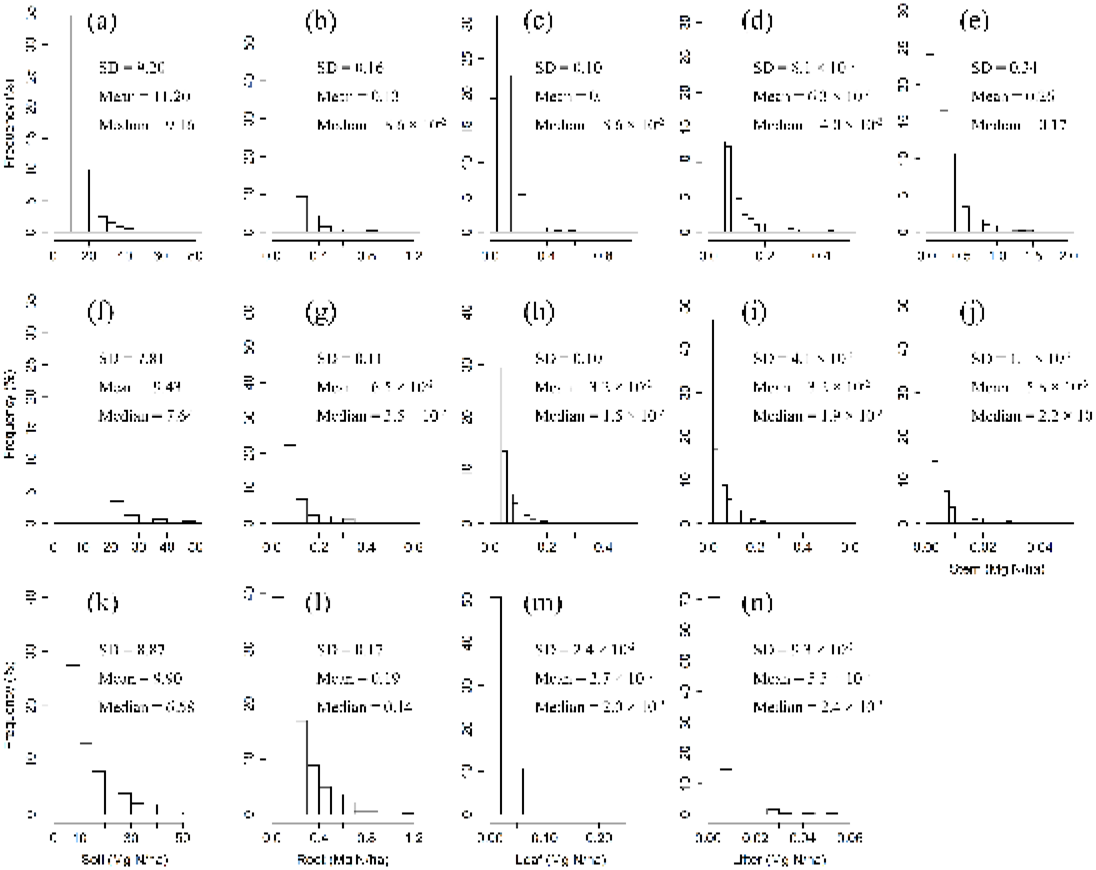
| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Grassland | ME | ~~59.62~~44.2 | ~~17.87~~11.6 | ~~994.70~~806.9 | 0.~~13~~1 | ~~1012.70~~818.5 | ~~1.33~~0.9 | ~~217.20~~247.2 | < 0.~~005~~1 | ~~218.54~~248.0 |
| | ST | ~~190.08~~137.4 | ~~36.31~~21.3 | ~~1562.94~~1348.5 | 0.~~22~~3 | ~~1599.47~~1370.1 | ~~2.32~~1.5 | ~~569.27~~573.1 | < 0.~~02~~1 | ~~571.61~~574.6 |
| | TU | ~~24.39~~22.8 | 2.~~39~~3 | ~~171.02~~230.4 | 0.~~10~~1 | ~~173.51~~232.8 | 0.~~26~~2 | ~~84.44~~112.9 | < 0.~~01~~1 | ~~84.71~~113.2 |
| | SG | ~~139.27~~103.8 | ~~40.78~~13.6 | ~~1376.02~~860.6 | 0.~~09~~1 | ~~1416.89~~874.4 | ~~2.33~~0.9 | ~~1576.48~~506.3 | < 0.~~02~~1 | ~~1578.83~~507.2 |
| | ***subtotal*** | ***~~413.35~~308.2*** | ***~~97.35~~48.8*** | ***~~4104.68~~3246.4*** | 0.~~55~~6 | ***~~4202.58~~3295.8*** | ***~~6.24~~3.5*** | ***~~2447.41~~1439.5*** | < 0.~~05~~1 | ***~~2453.70~~1443.0*** |
| Total | | ***~~787~~600.4*** | ***~~216.17~~156.7*** | ***~~7434.53~~6635.2*** | ***~~14.92~~11.7*** | ***~~7665.62~~6793.1*** | ***~~28.88~~18.8*** | ***~~3821.64~~2786.1*** | ***~~2.14~~1.0*** | ***~~3852.66~~2806.0*** |

EBF, evergreen broadleaf forest; DBF, deciduous broadleaf forest; ENF, evergreen needle-leaf forest; DNF, deciduous needle-leaf forest; MF, broadleaf and needle-leaf forest; EBS, evergreen broadleaf shrub; DBS, deciduous broadleaf shrub; ENS, evergreen needle-leaf shrub; SS, sparse shrub; ME, meadow; ST, steppe; TU, tussock; and SG, sparse grassland.

**Table.2.** N and P stocks of plant organs (leaf, stem and root) in ~~forest~~forests, shrublands and grasslands in China.

| Vegetation type group | Vegetation type | Area ($10^6$ ha) | N pool (~~$10^6$ Mg~~Tg) | | | P pool (~~$10^6$ Mg~~Tg) | | |
|---|---|---|---|---|---|---|---|---|
| | | | Leaf | Stem | Root | Leaf | Stem | Root |
| Forest | EBF | ~~45.59~~40.6 | 3.~~849~~9 | 10.~~863~~1 | 4.~~614~~0 | 0.~~273~~3 | 1.~~308~~0 | 0.~~313~~3 |
| | DBF | ~~91.14~~66.3 | 6.~~820~~1 | ~~23.289~~26.6 | ~~13.322~~10.5 | 0.~~555~~6 | 4.~~680~~6 | ~~3.133~~1.6 |
| | ENF | ~~99.97~~83.8 | ~~10.185~~8.6 | ~~17.090~~13.4 | ~~7.653~~6.4 | ~~1.256~~0.9 | ~~3.205~~2.0 | ~~1.125~~0.8 |
| | DNF | ~~19.79~~11.5 | 1.~~661~~3 | ~~4.336~~2.9 | 1.~~535~~4 | 0.~~292~~2 | ~~3.691~~0.9 | 0.~~631~~3 |
| | MF | ~~13.25~~9.6 | 1.~~326~~0 | ~~3.714~~2.6 | 1.~~428~~0 | 0.~~117~~1 | 0.~~931~~7 | 0.~~328~~2 |
| | ***subtotal*** | ***~~269.75~~211.9*** | ***~~23.841~~21.0*** | ***~~59.293~~55.5*** | ***~~28.552~~23.4*** | ***2.~~493~~1*** | ***~~13.814~~9.2*** | ***~~5.531~~3.3*** |
| Shrubland | EBS | ~~21.65~~18.7 | 0.~~632~~6 | 0.~~051~~7 | 0.~~872~~7 | < 0.~~045~~1 | 0.~~074~~1 | 0.~~083~~1 |
| | DBS | ~~63.94~~48.7 | 1.~~682~~4 | ~~0.205~~1.4 | ~~3.413~~2.7 | 0.~~124~~1 | 0.~~164~~1 | 0.~~290~~2 |
| | ENS | 1.~~36~~0 | < 0.~~037~~1 | < 0.~~001~~1 | < 0.~~022~~1 | < 0.~~005~~1 | < 0.~~0001~~1 | < 0.~~003~~1 |
| | SS | ~~17.35~~11.9 | 0.~~070~~1 | 0.~~021~~1 | 0.~~129~~3 | < 0.~~005~~1 | < 0.~~005~~1 | < 0.~~006~~1 |
| | ***subtotal*** | ***~~104.31~~80.3*** | ***2.~~420~~1*** | ***~~0.279~~2.3*** | ***~~4.436~~3.8*** | ***0.~~179~~2*** | ***0.~~243~~2*** | ***0.~~382~~2*** |
| eGrassland | ME | ~~59.62~~44.2 | ~~1.181~~0.9 | 0.0 | ~~16.687~~10.7 | 0.~~121~~1 | 0.0 | ~~1.213~~0.8 |
| | ST | ~~190.08~~137.4 | 2.~~818~~2 | 0.0 | ~~33.492~~19.2 | 0.~~261~~2 | 0.0 | ~~2.055~~1.3 |
| | TU | ~~24.39~~22.8 | 0.~~559~~5 | 0.0 | 1.~~830~~7 | 0.~~058~~1 | 0.0 | 0.~~201~~2 |
| | SG | ~~139.27~~103.8 | 1.~~573~~1 | 0.0 | ~~39.211~~12.5 | 0.~~244~~1 | 0.0 | ~~2.084~~0.8 |
| | ***subtotal*** | ***~~413.35~~308.2*** | ***~~6.132~~4.7*** | 0.0 | ***~~91.220~~44.1*** | 0.~~685~~4 | 0.0 | ***~~5.553~~3.1*** |
| Total | | ***~~787~~600.4*** | ***~~32.394~~27.7*** | ***~~59.571~~57.8*** | ***~~124.209~~71.2*** | ***~~3.357~~2.7*** | ***~~14.057~~9.4*** | ***~~11.466~~6.7*** |

See table 1 for abbreviations.


(a)
(b)
(c)
(d)
(e)
(f)
(g)
(h)
(i)
(j)
(k)
(l)
(m)
(n)
Stem (Mg N/ha)
Soil (Mg N/ha)
Root (Mg N/ha)
Leaf (Mg N/ha)
Litter (Mg N/ha)

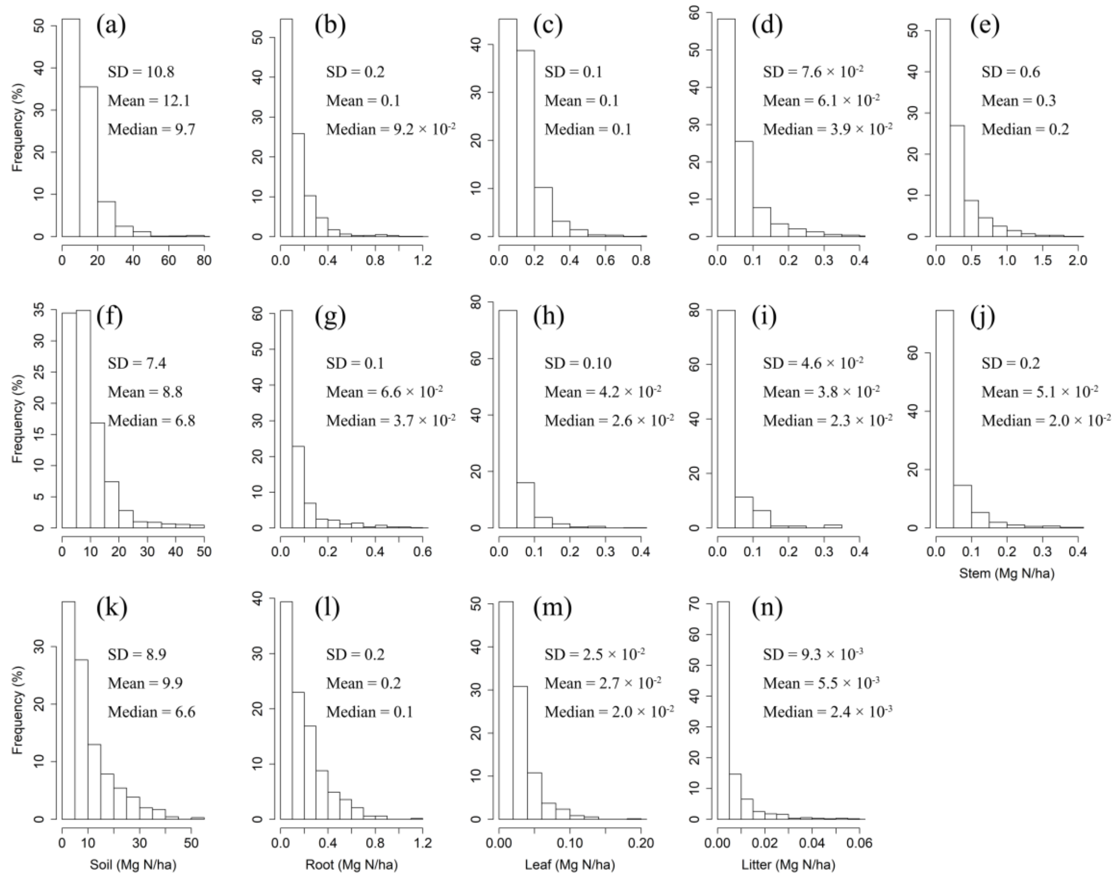
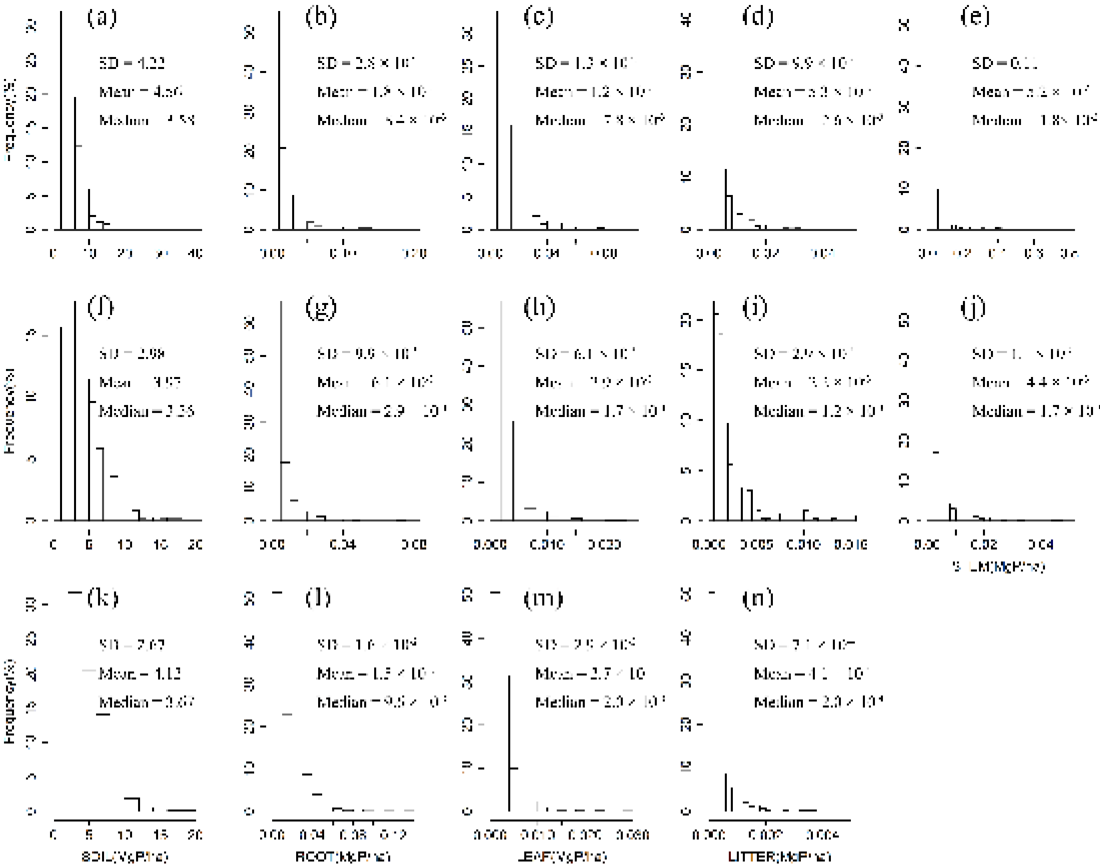



**Fig. 1.** Frequency distributions of N densities in soil, roots, leaves, litter and woody stems in forests (a–e), shrublands (f–j) and grasslands (k–n) in China.


(a)
(b)
(c)
(d)
(e)
(f)
(g)
(h)
(i)
(j)
(k)
(l)
(m)
(n)

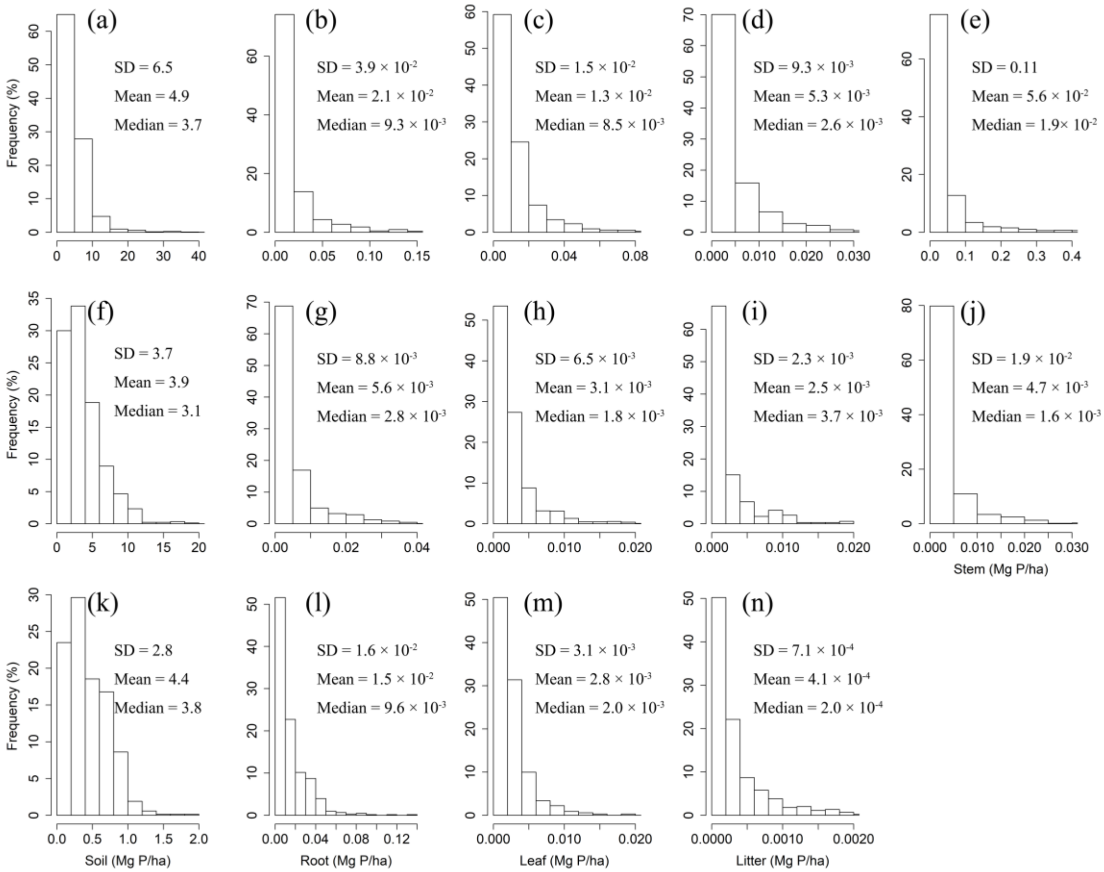
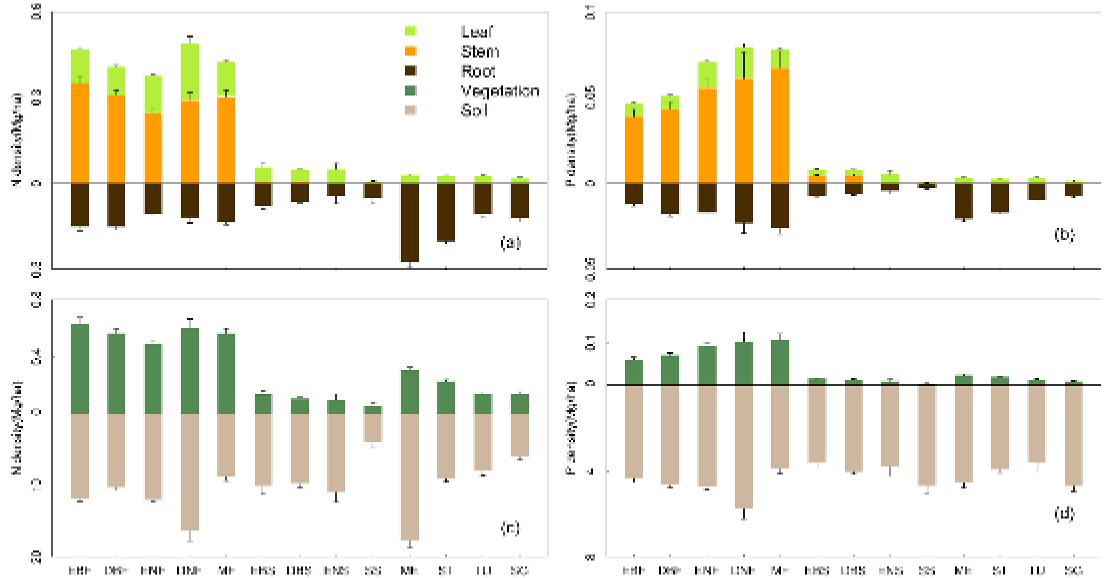



**Fig. 2.** Frequency distributions of P densities in soil, roots, leaves, litter and woody stems in forests (a–e), shrublands (f–j) and grasslands (k–n) in China.



Leaf
Stem
Root
Vegetation
Soil
(a)
(b)
(c)
(d)

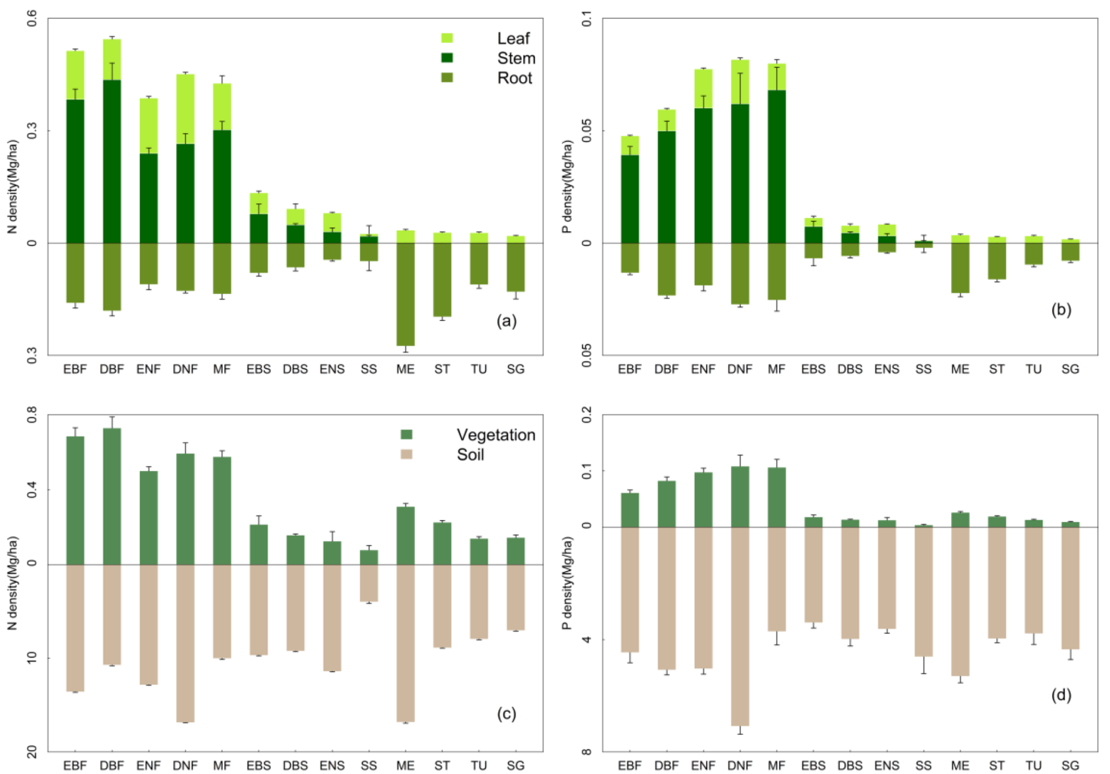
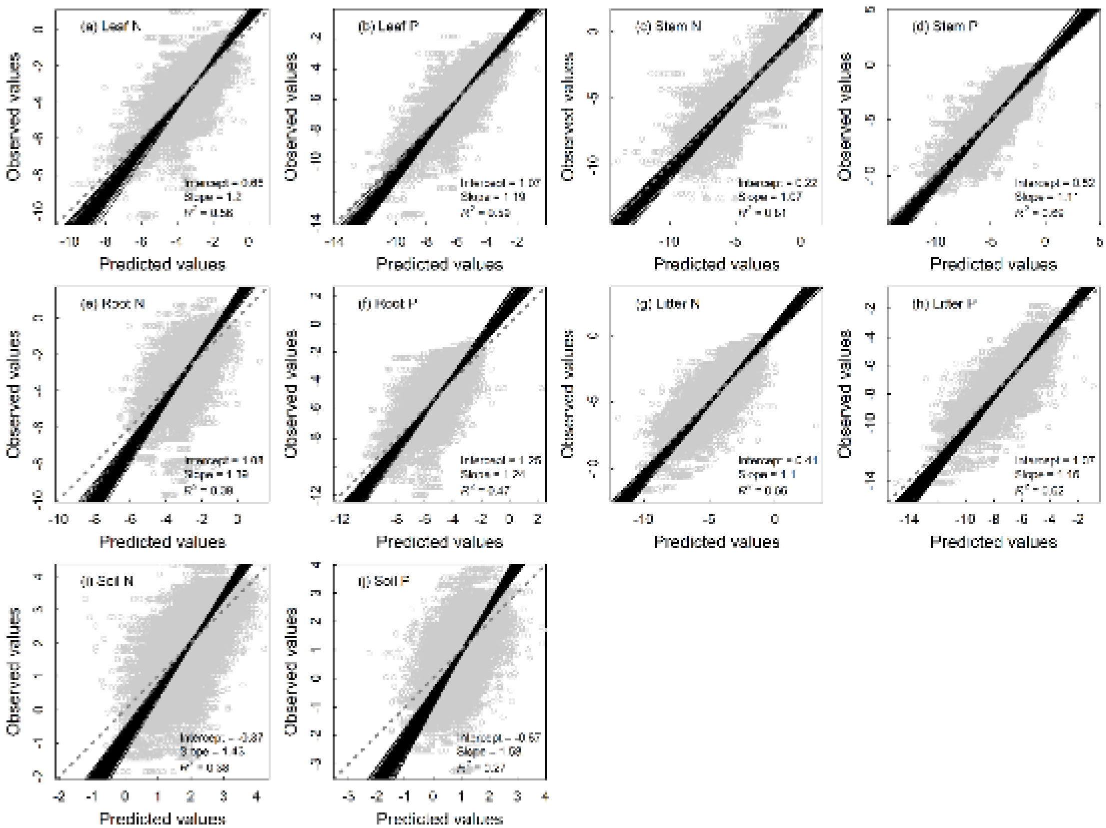



**Fig. 3.** N and P density allocations among leaf, stem and root (a & b) and between vegetation and soil (c & d) in 13 Vegetation types. See table 1 for abbreviations. The error bar represents standard error. Notice that the y axes above and below zero are disproportionate.



(a) Leaf N
(b) Leaf P
(c) Stem N
(d) Stem P
(e) Root N
(f) Root P
(g) Litter N
(h) Litter P
(i) Soil N
(j) Soil P
Observed values
Predicted values

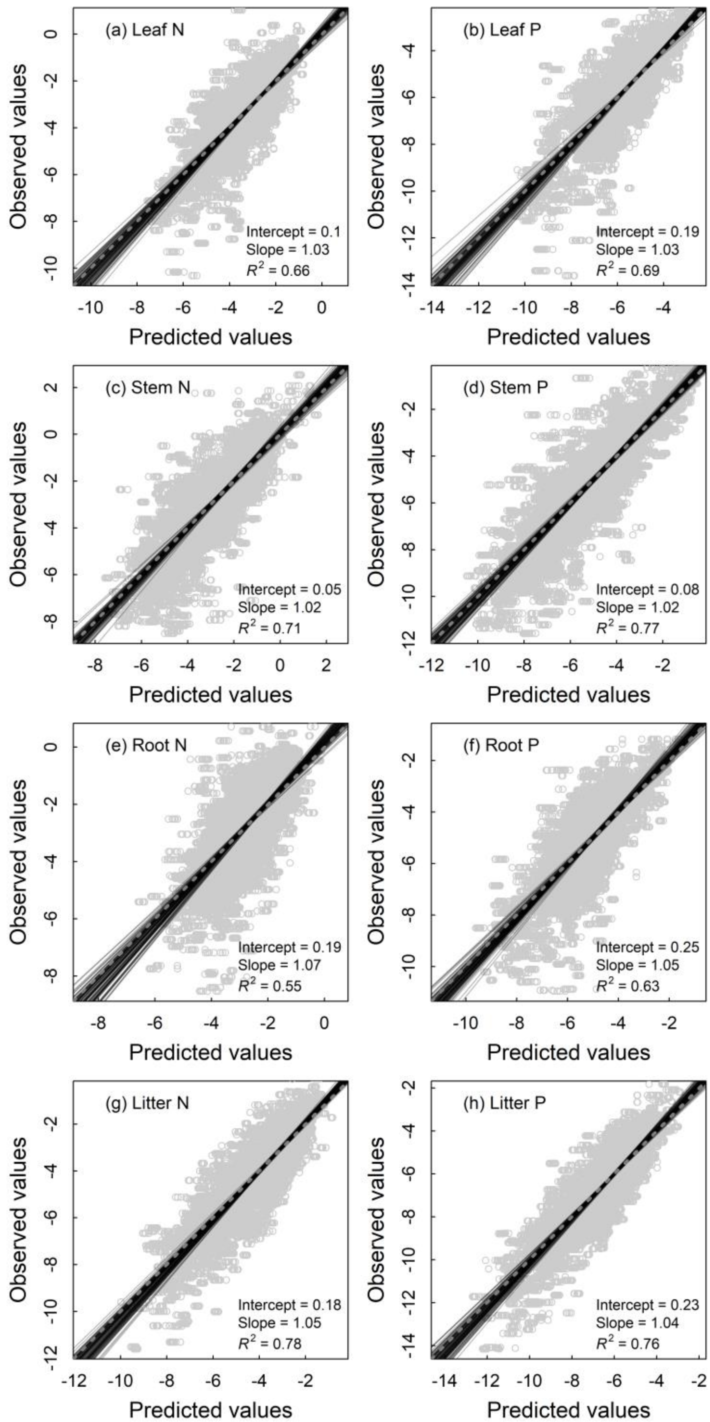
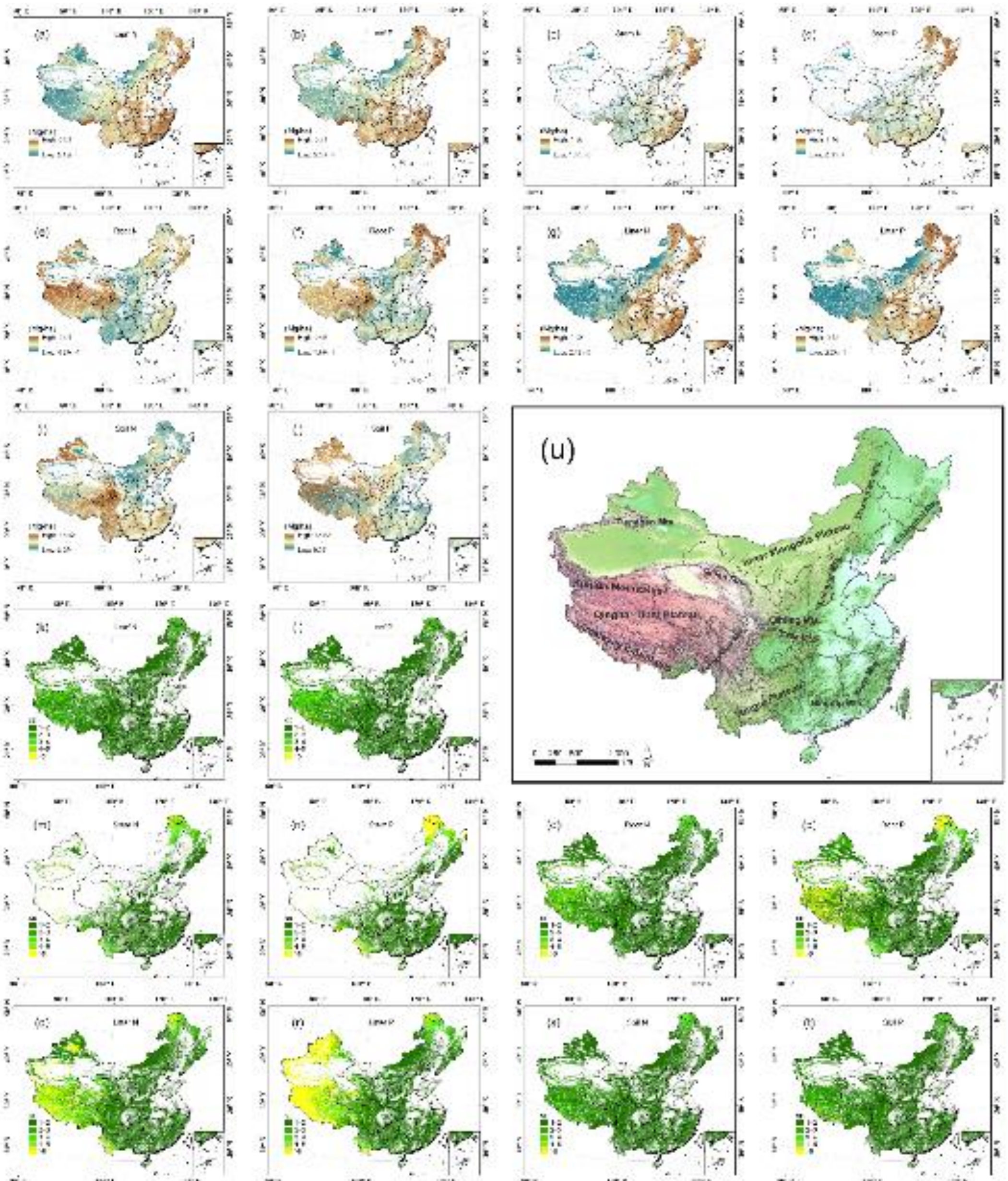
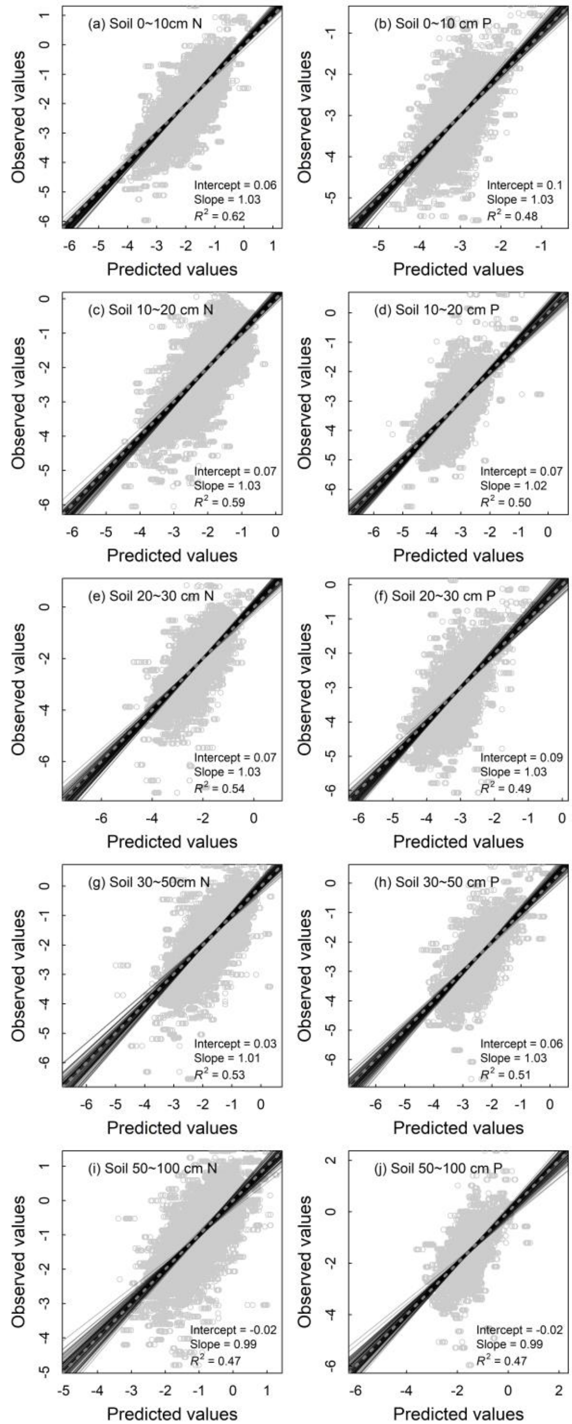
716 
(a) Leaf N
Intercept = 0.1
Slope = 1.03
$R^2$ = 0.66
(b) Leaf P
Intercept = 0.19
Slope = 1.03
$R^2$ = 0.69
(c) Stem N
Intercept = 0.05
Slope = 1.02
$R^2$ = 0.71
(d) Stem P
Intercept = 0.08
Slope = 1.02
$R^2$ = 0.77
(e) Root N
Intercept = 0.19
Slope = 1.07
$R^2$ = 0.55
(f) Root P
Intercept = 0.25
Slope = 1.05
$R^2$ = 0.63
(g) Litter N
Intercept = 0.18
Slope = 1.05
$R^2$ = 0.78
(h) Litter P
Intercept = 0.23
Slope = 1.04
$R^2$ = 0.76
Observed values
Predicted values

**Fig. 4.** Fitting performance of ~~artificial neural network~~random forest models for ~~different components~~nutrient densities of leaves (a & b), woody stems (c & d), roots (e & f) and litter (g & h) of terrestrial ecosystems in China based on 100 times of replications with the 10% validation data. Solid lines represent all the fitting lines~~ by standard major axis regression~~, and the displayed parameters stand for the average conditions. The dashed line denotes the 1:1 line.


(u)
Tianshan Mts
Qinling Mts


(a) Soil 0~10cm N
Intercept = 0.06
Slope = 1.03
$R^2$ = 0.62
(b) Soil 0~10 cm P
Intercept = 0.1
Slope = 1.03
$R^2$ = 0.48
(c) Soil 10~20 cm N
Intercept = 0.07
Slope = 1.03
$R^2$ = 0.59
(d) Soil 10~20 cm P
Intercept = 0.07
Slope = 1.02
$R^2$ = 0.50
(e) Soil 20~30 cm N
Intercept = 0.07
Slope = 1.03
$R^2$ = 0.54
(f) Soil 20~30 cm P
Intercept = 0.09
Slope = 1.03
$R^2$ = 0.49
(g) Soil 30~50cm N
Intercept = 0.03
Slope = 1.01
$R^2$ = 0.53
(h) Soil 30~50 cm P
Intercept = 0.06
Slope = 1.03
$R^2$ = 0.51
(i) Soil 50~100 cm N
Intercept = -0.02
Slope = 0.99
$R^2$ = 0.47
(j) Soil 50~100 cm P
Intercept = -0.02
Slope = 0.99
$R^2$ = 0.47
Predicted values
Observed values

~~Fig. 5.~~

**Fig. 5.** Fitting performance of random forest models for nutrient densities of 0–10 cm (a & b), 10–20 cm (c & d), 20–30 cm (e & f), 30–50 cm (g & h) and 50–100 cm (i & j) soil layers of terrestrial ecosystems in China based on 100 times of replications with the 10% validation data. Solid lines represent all the fitting lines, and the displayed parameters stand for the average conditions. The dashed line denotes the 1:1 line.

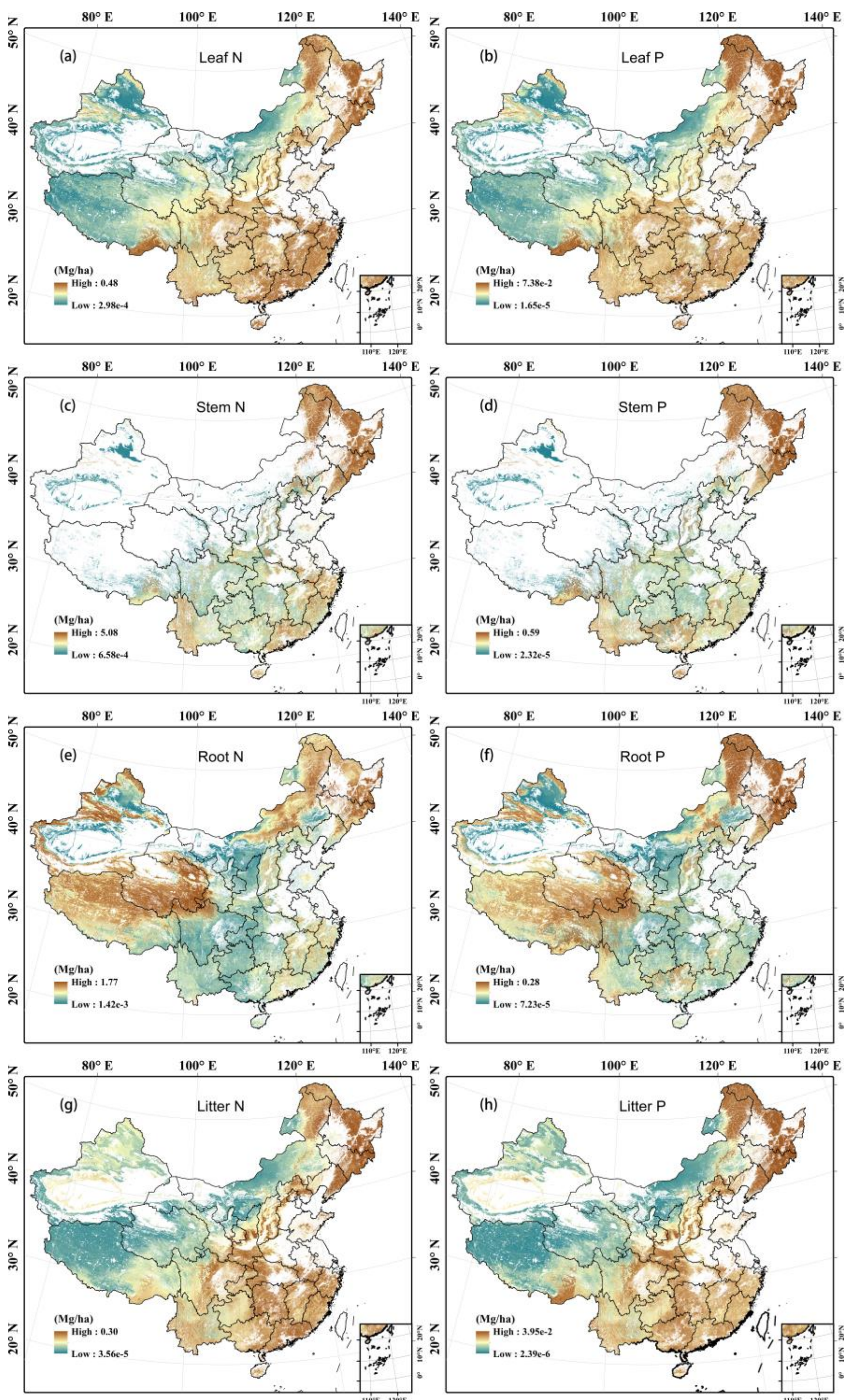
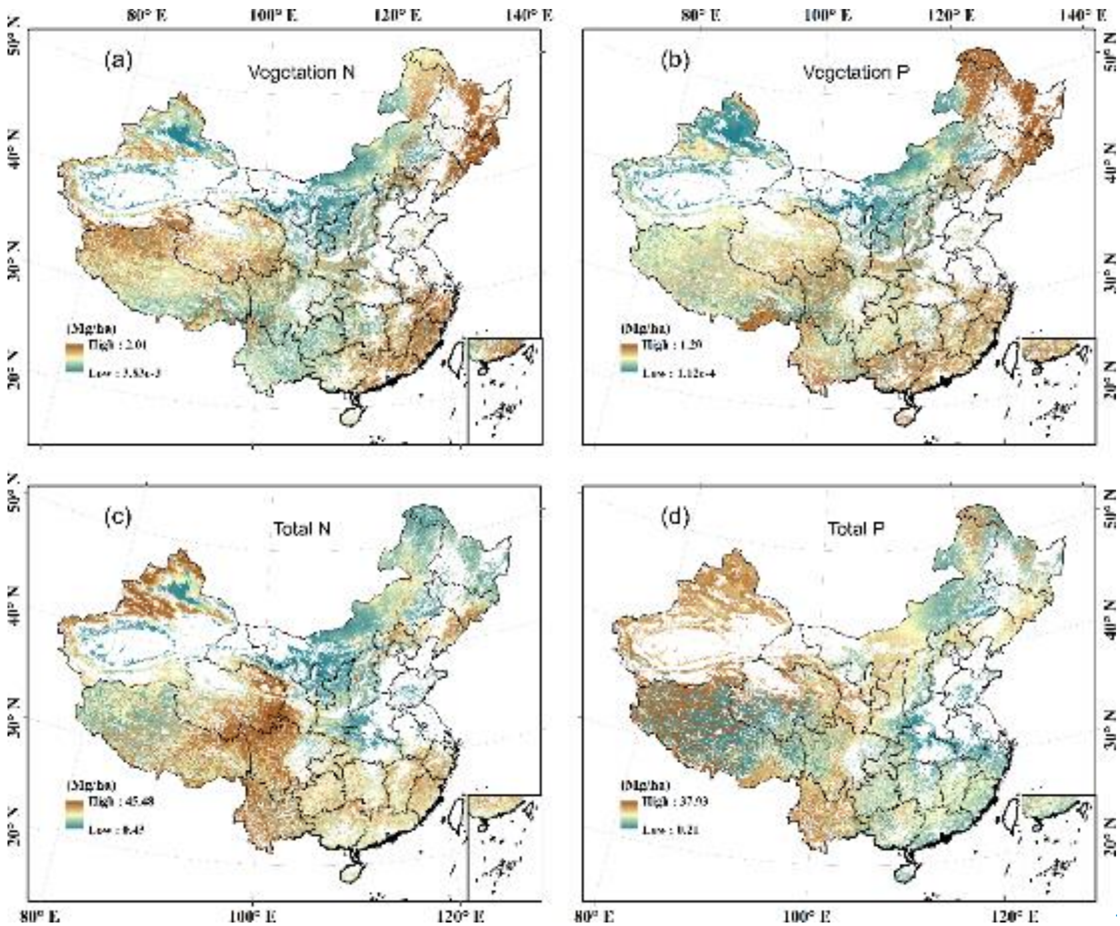
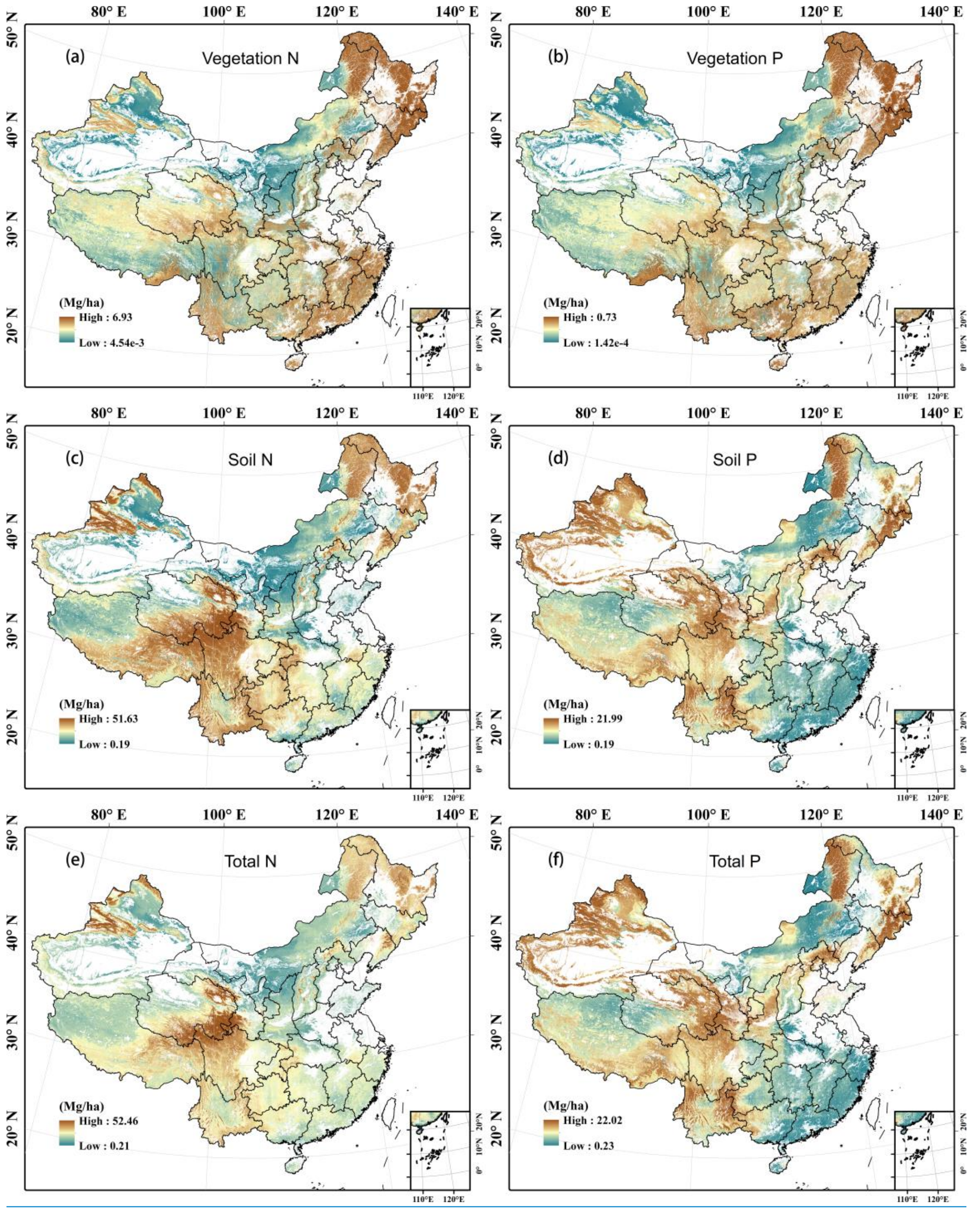

(a) Leaf N
(Mg/ha)
High : 0.48
Low : 2.98e-4
(b) Leaf P
(Mg/ha)
High : 7.38e-2
Low : 1.65e-5
(c) Stem N
(Mg/ha)
High : 5.08
Low : 6.58e-4
(d) Stem P
(Mg/ha)
High : 0.59
Low : 2.32e-5
(e) Root N
(Mg/ha)
High : 1.77
Low : 1.42e-3
(f) Root P
(Mg/ha)
High : 0.28
Low : 7.23e-5
(g) Litter N
(Mg/ha)
High : 0.30
Low : 3.56e-5
(h) Litter P
(Mg/ha)
High : 3.95e-2
Low : 2.39e-6
80° E
100° E
120° E
140° E
50° N
40° N
30° N
20° N

**Fig. 6.** Predicted spatial patterns of N and P densities with a resolution of 1 km (a–j) in leaves (a & b), woody stems (c & d), roots (e & f) and ~~their prediction standard deviations (SDs) (k–t) in each component~~litter (g & h) of terrestrial ecosystems in ~~China based on 100 replications. The topographic map of~~ China ~~(u) is also shown.~~.


(a)
Vegetation N
(Mg/ha)
High : 2.01
Low : 3.53e-3
(b)
Vegetation P
(Mg/ha)
High : 1.29
Low : 1.12e-4
(c)
Total N
(Mg/ha)
High : 45.48
Low : 0.45
(d)
Total P
(Mg/ha)
High : 37.93
Low : 0.21
80° E
100° E
120° E
140° E
20° N
30° N
40° N
50° N



80° E
100° E
120° E
140° E
50° N
40° N
30° N
20° N
(a)
Vegetation N
(Mg/ha)
High : 6.93
Low : 4.54e-3
(b)
Vegetation P
(Mg/ha)
High : 0.73
Low : 1.42e-4
(c)
Soil N
(Mg/ha)
High : 51.63
Low : 0.19
(d)
Soil P
(Mg/ha)
High : 21.99
Low : 0.19
(e)
Total N
(Mg/ha)
High : 52.46
Low : 0.21
(f)
Total P
(Mg/ha)
High : 22.02
Low : 0.23
110°E
120°E
20°N
10°N
0°

**Fig.** ~~**6.** Spatial~~**7.** Predicted spatial patterns of N and P densities with a resolution of 1 km in vegetation (a & b, the sum of leaves, stems and roots), soil (c & d, the sum of five layers) and ecosystems (~~c and d~~e & f, the sum of ~~leaves, stems, roots~~vegetation, litter and soil) of terrestrial ecosystems in China.

## **Supplement**

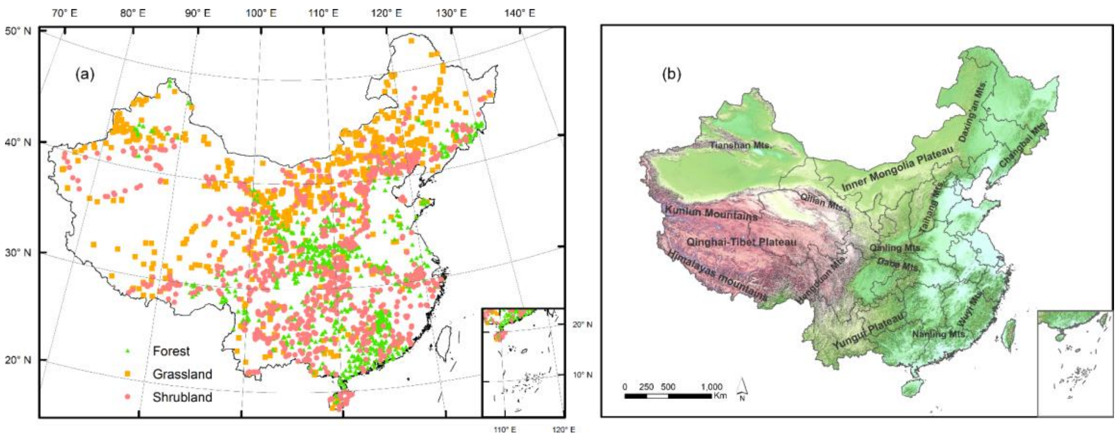



**Fig. S1.** The spatial distributions of sampling sites (a) and the topographic map of China (b).

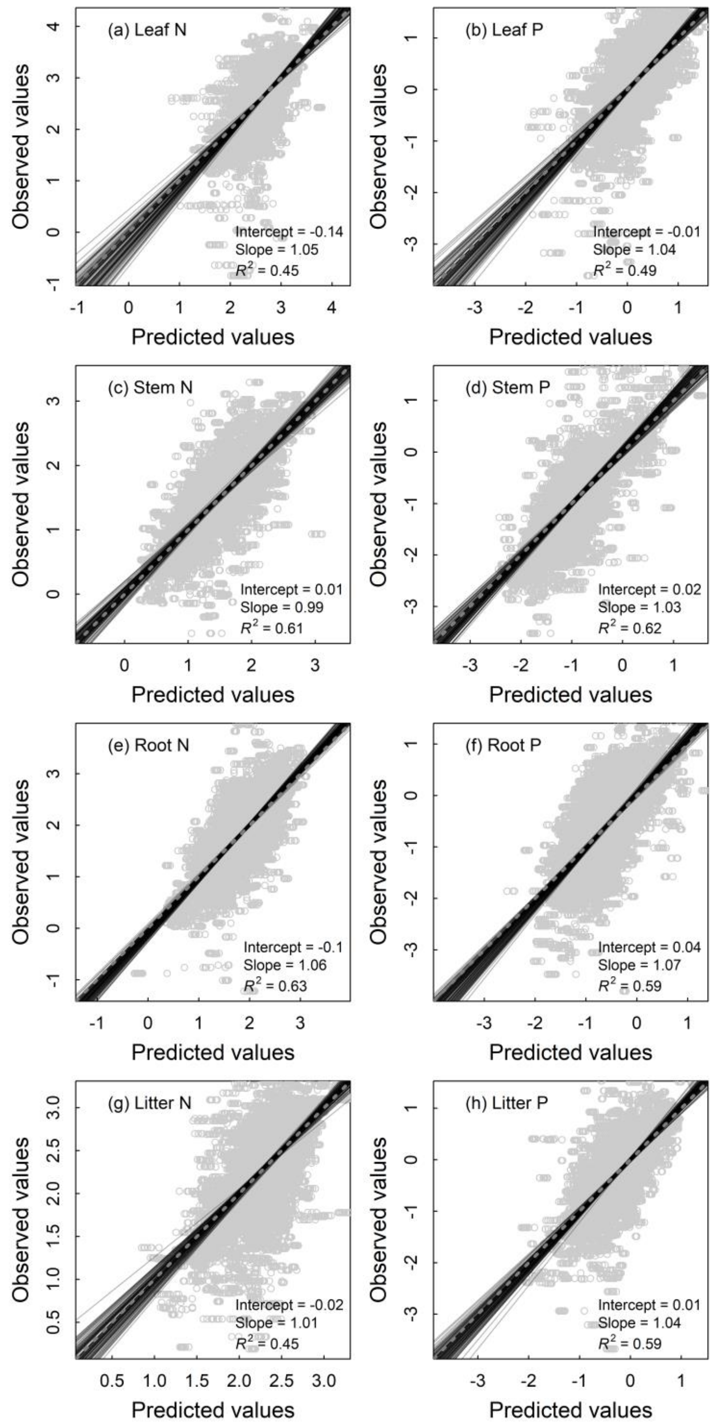

(a) Leaf N
Intercept = -0.14
Slope = 1.05
$R^2$ = 0.45
(b) Leaf P
Intercept = -0.01
Slope = 1.04
$R^2$ = 0.49
(c) Stem N
Intercept = 0.01
Slope = 0.99
$R^2$ = 0.61
(d) Stem P
Intercept = 0.02
Slope = 1.03
$R^2$ = 0.62
(e) Root N
Intercept = -0.1
Slope = 1.06
$R^2$ = 0.63
(f) Root P
Intercept = 0.04
Slope = 1.07
$R^2$ = 0.59
(g) Litter N
Intercept = -0.02
Slope = 1.01
$R^2$ = 0.45
(h) Litter P
Intercept = 0.01
Slope = 1.04
$R^2$ = 0.59
Observed values
Predicted values

**Fig. S2.** Fitting performance of random forest models for nutrient concentrations of leaves (a & b), woody stems (c & d), roots (e & f) and litter (g & h) of terrestrial ecosystems in China based on 100 times of replications with the 10% validation data. Solid lines represent all the fitting lines, and the displayed parameters stand for the average conditions. The dashed line denotes the 1:1 line.

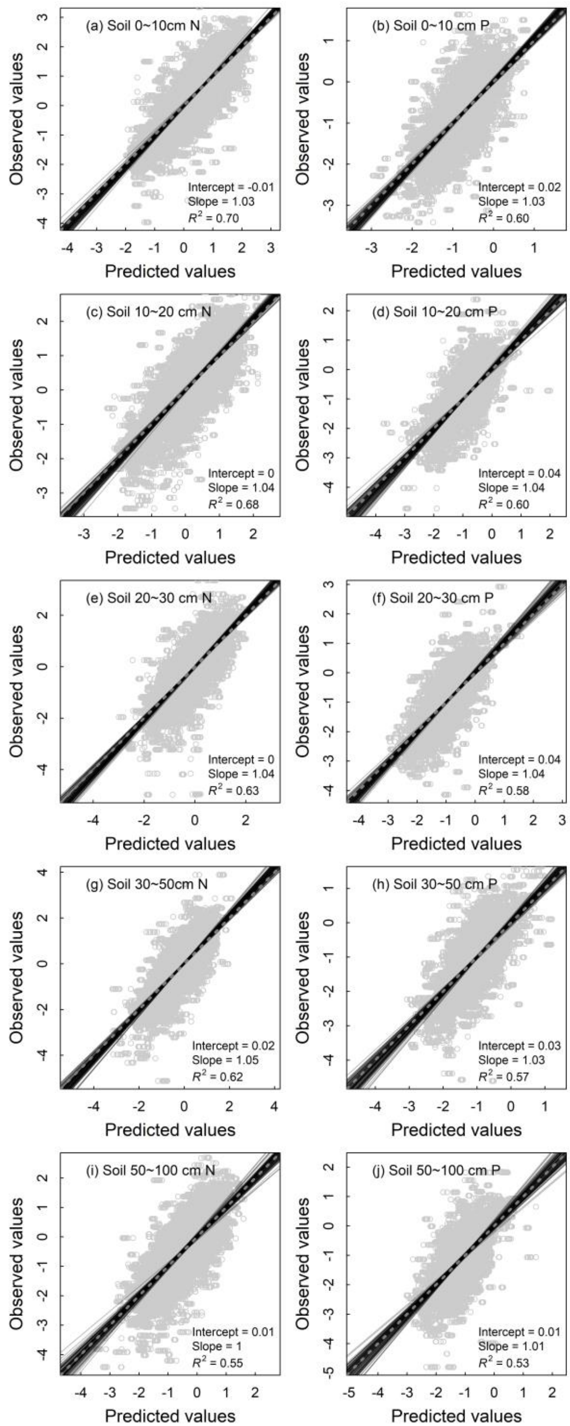

(a) Soil 0~10cm N
Intercept = -0.01
Slope = 1.03
$R^2$ = 0.70
(b) Soil 0~10 cm P
Intercept = 0.02
Slope = 1.03
$R^2$ = 0.60
(c) Soil 10~20 cm N
Intercept = 0
Slope = 1.04
$R^2$ = 0.68
(d) Soil 10~20 cm P
Intercept = 0.04
Slope = 1.04
$R^2$ = 0.60
(e) Soil 20~30 cm N
Intercept = 0
Slope = 1.04
$R^2$ = 0.63
(f) Soil 20~30 cm P
Intercept = 0.04
Slope = 1.04
$R^2$ = 0.58
(g) Soil 30~50cm N
Intercept = 0.02
Slope = 1.05
$R^2$ = 0.62
(h) Soil 30~50 cm P
Intercept = 0.03
Slope = 1.03
$R^2$ = 0.57
(i) Soil 50~100 cm N
Intercept = 0.01
Slope = 1
$R^2$ = 0.55
(j) Soil 50~100 cm P
Intercept = 0.01
Slope = 1.01
$R^2$ = 0.53
Observed values
Predicted values

**Fig. S3.** Fitting performance of random forest models for nutrient concentrations of 0–10 cm (a & b), 10–20 cm (c & d), 20–30 cm (e & f), 30–50 cm (g & h) and 50–100 cm (i & j) soil layers of terrestrial ecosystems in China based on 100 times of replications with the 10% validation data. Solid lines represent all the fitting lines, and the displayed parameters stand for the average conditions. The dashed line denotes the 1:1 line.

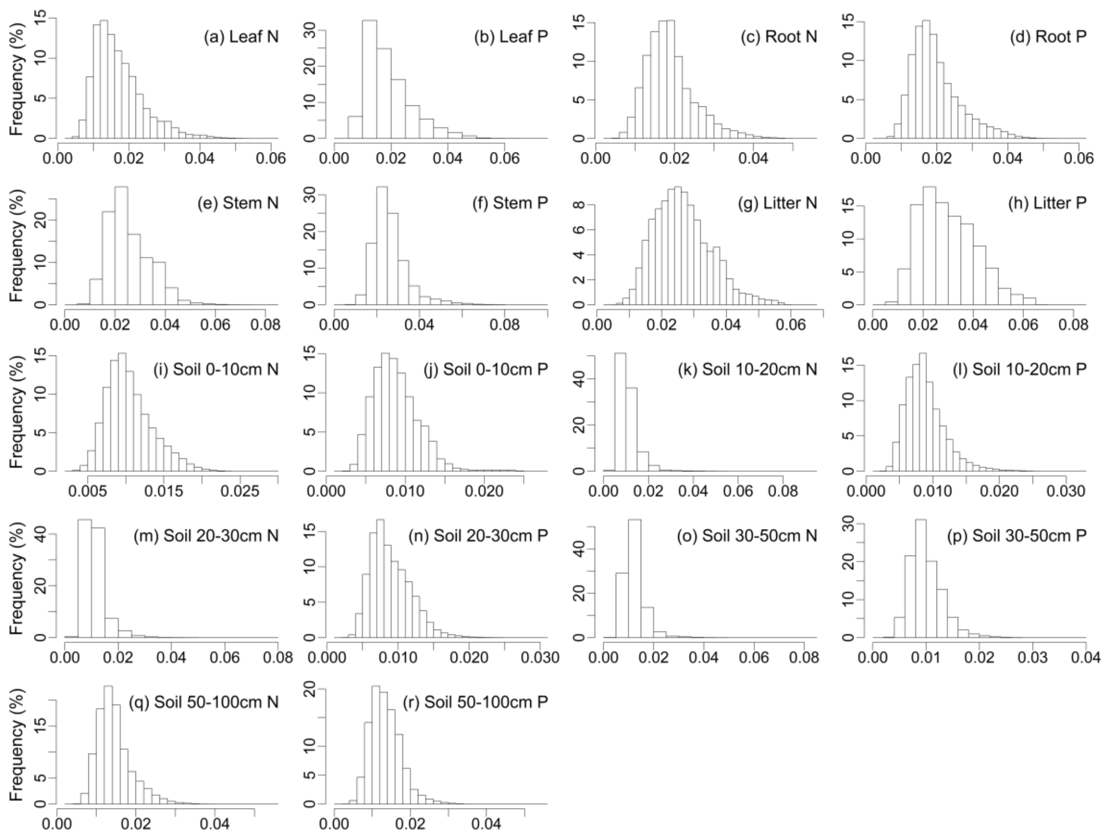



**Fig. S4.** Frequency distributions of standard deviations of the predictions in models for N and P densities in different components.

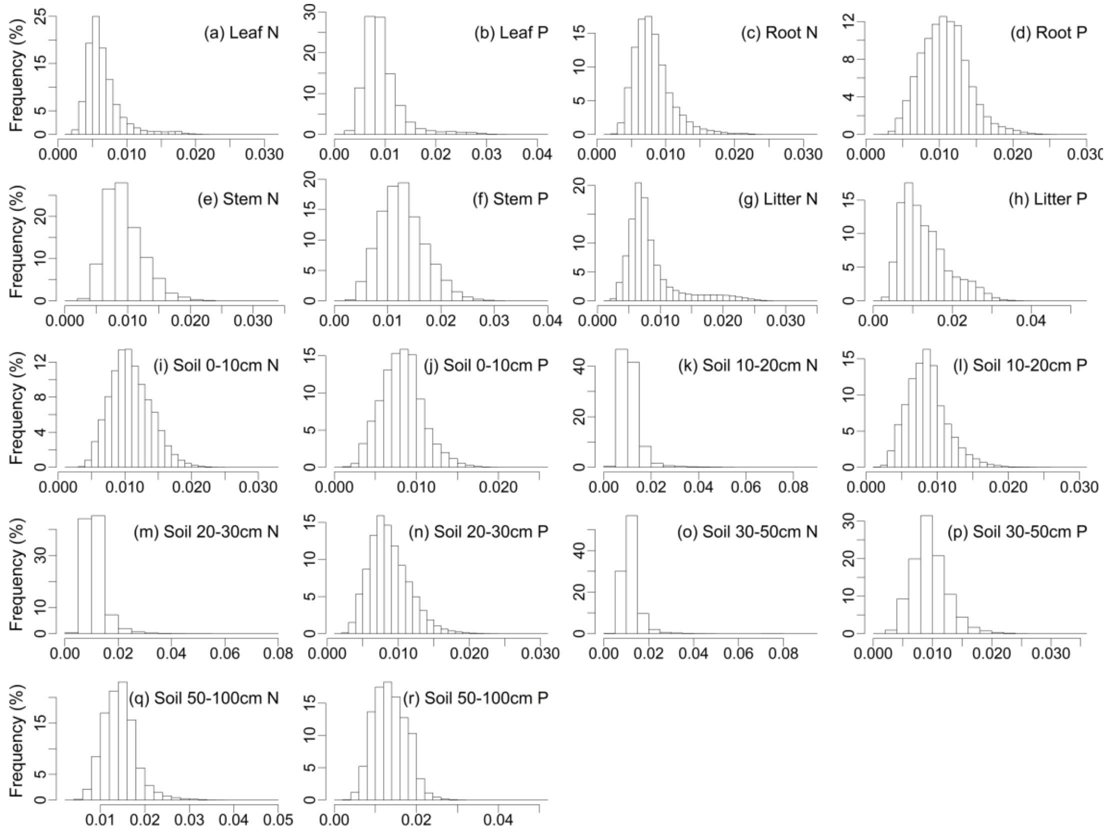



**Fig. S5.** Frequency distributions of standard deviations of the predictions in models for N and P concentrations in different components.

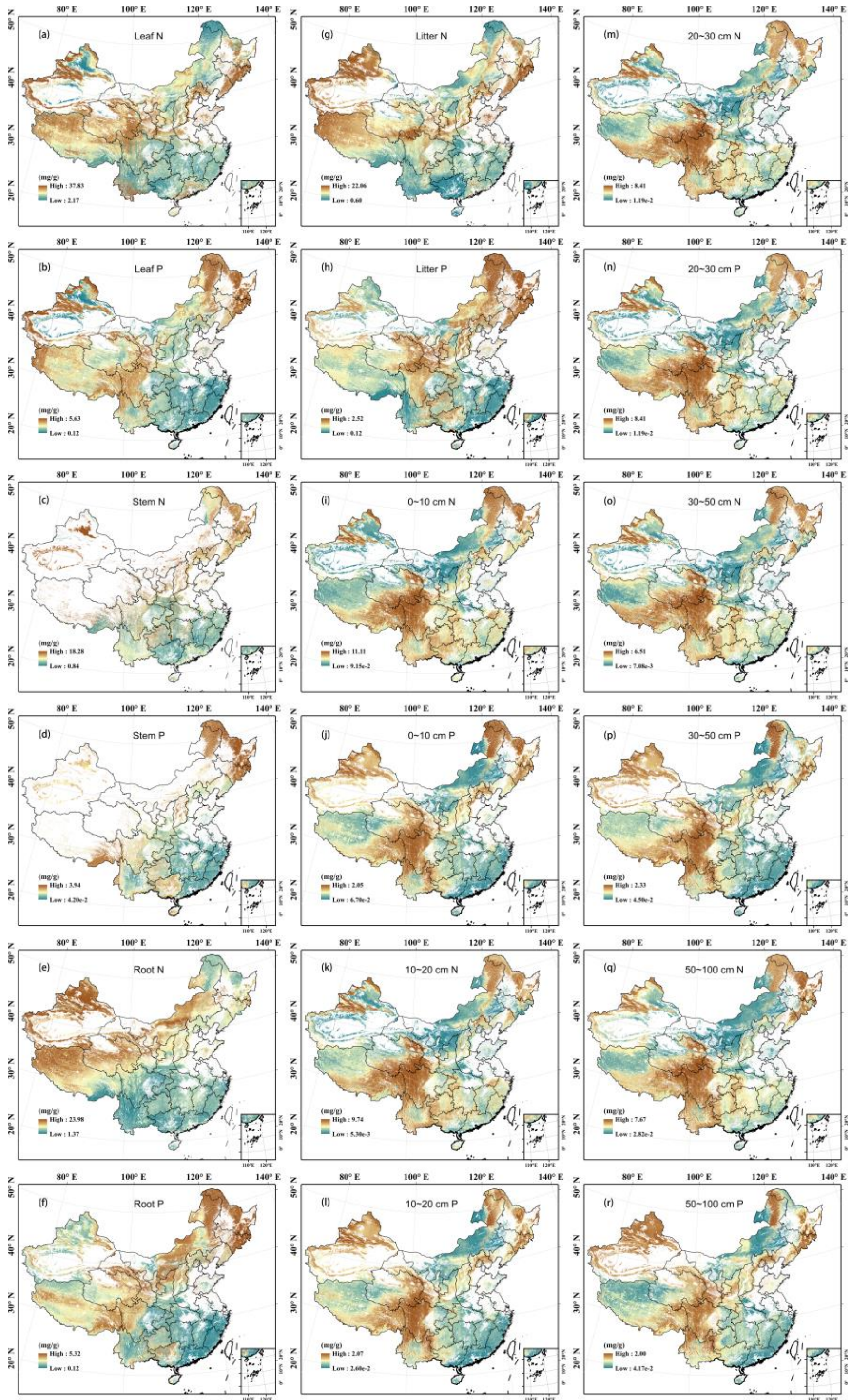

(a) Leaf N
(mg/g)
High : 37.83
Low : 2.17
(b) Leaf P
(mg/g)
High : 5.63
Low : 0.12
(c) Stem N
(mg/g)
High : 18.28
Low : 0.84
(d) Stem P
(mg/g)
High : 3.94
Low : 4.20e-2
(e) Root N
(mg/g)
High : 23.98
Low : 1.37
(f) Root P
(mg/g)
High : 5.32
Low : 0.12
(g) Litter N
(mg/g)
High : 22.06
Low : 0.60
(h) Litter P
(mg/g)
High : 2.52
Low : 0.12
(i) 0~10 cm N
(mg/g)
High : 11.11
Low : 9.15e-2
(j) 0~10 cm P
(mg/g)
High : 2.05
Low : 6.70e-2
(k) 10~20 cm N
(mg/g)
High : 9.74
Low : 5.30e-3
(l) 10~20 cm P
(mg/g)
High : 2.07
Low : 2.60e-2
(m) 20~30 cm N
(mg/g)
High : 8.41
Low : 1.19e-2
(n) 20~30 cm P
(mg/g)
High : 8.41
Low : 1.19e-2
(o) 30~50 cm N
(mg/g)
High : 6.51
Low : 7.08e-3
(p) 30~50 cm P
(mg/g)
High : 2.33
Low : 4.50e-2
(q) 50~100 cm N
(mg/g)
High : 7.67
Low : 2.82e-2
(r) 50~100 cm P
(mg/g)
High : 2.00
Low : 4.17e-2
80° E
100° E
120° E
140° E
50° N
40° N
30° N
20° N

**Fig. S6.** Predicted spatial patterns of N and P concentrations with a resolution of 1 km (a–j) in plant organs (a–f), litter (g & h), and soil layers (i–r) of terrestrial ecosystems in China.

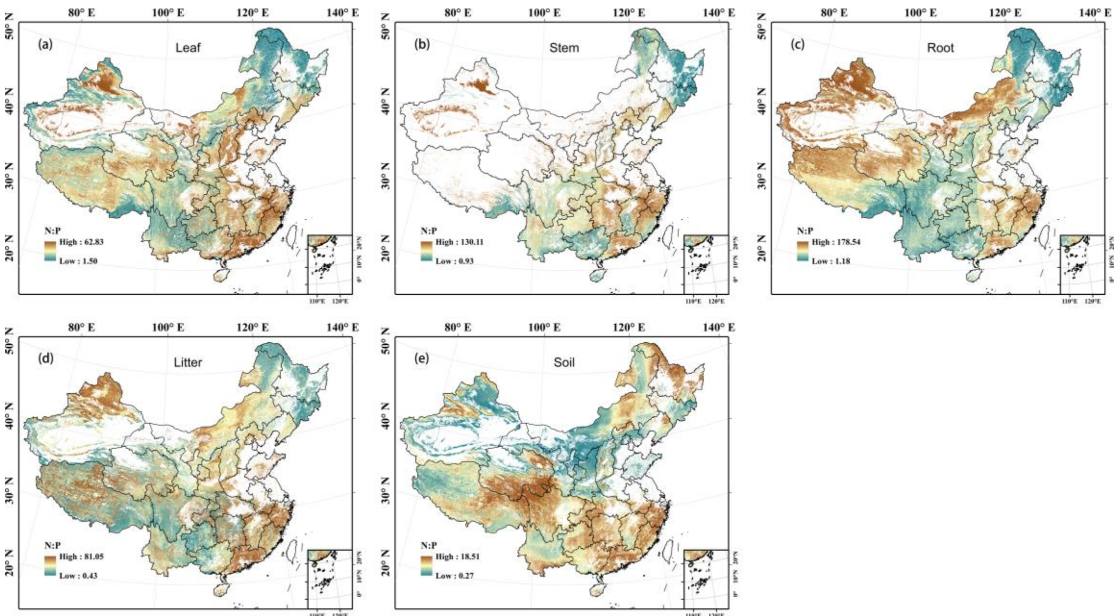



**Fig. S7.** Predicted spatial patterns of N:P ratios with a resolution of 1 km (a–j) in leaves (a), woody stems (b), roots (c), litter (d) and soil (e) of terrestrial ecosystems in China.

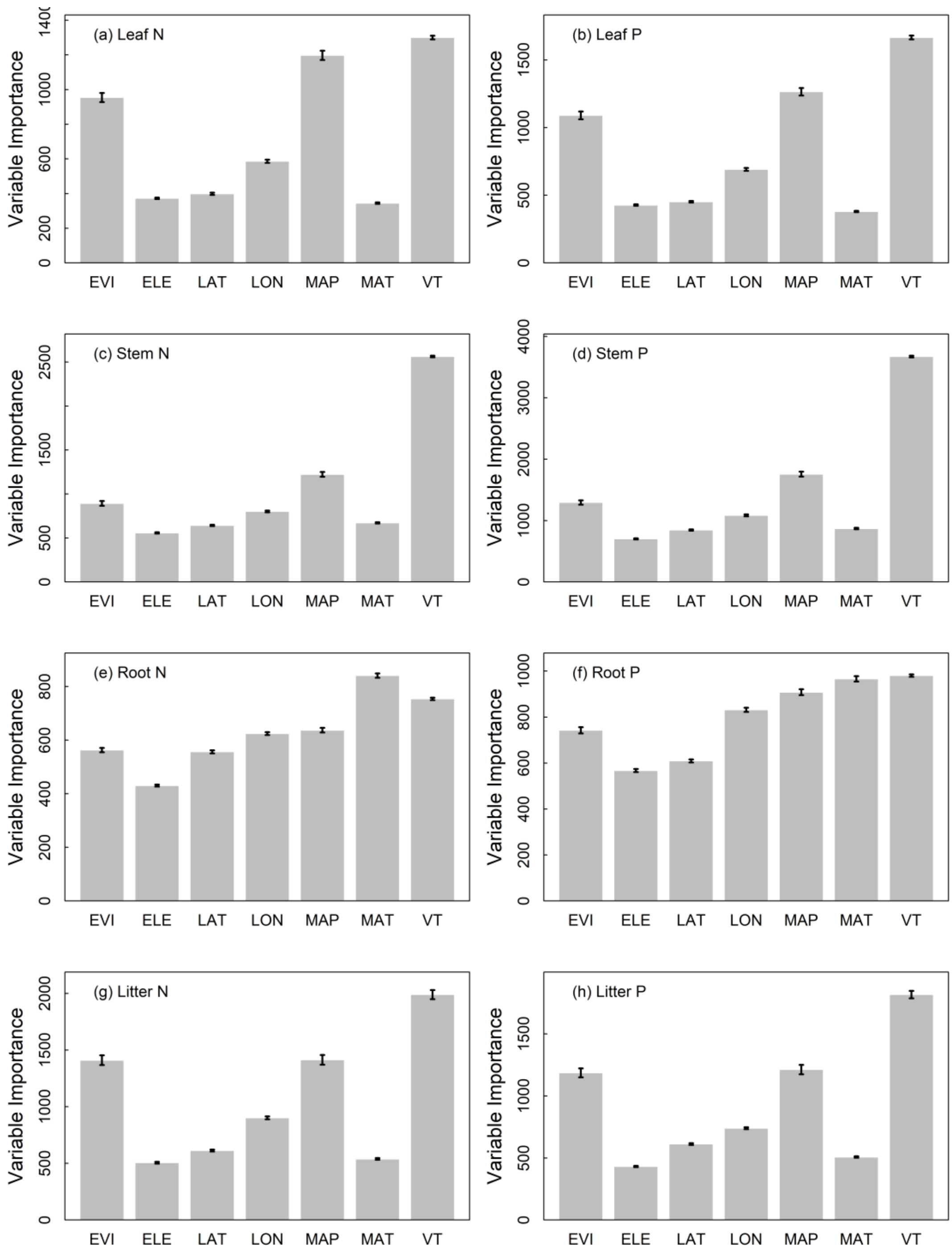

(a) Leaf N
(b) Leaf P
(c) Stem N
(d) Stem P
(e) Root N
(f) Root P
(g) Litter N
(h) Litter P
Variable Importance
EVI
ELE
LAT
LON
MAP
MAT
VT

**Fig. S8.** The relative importance of variables in random forest models of N and P densities for leaf (a & b), stem (c & d), root (e & f) and litter (g & h).

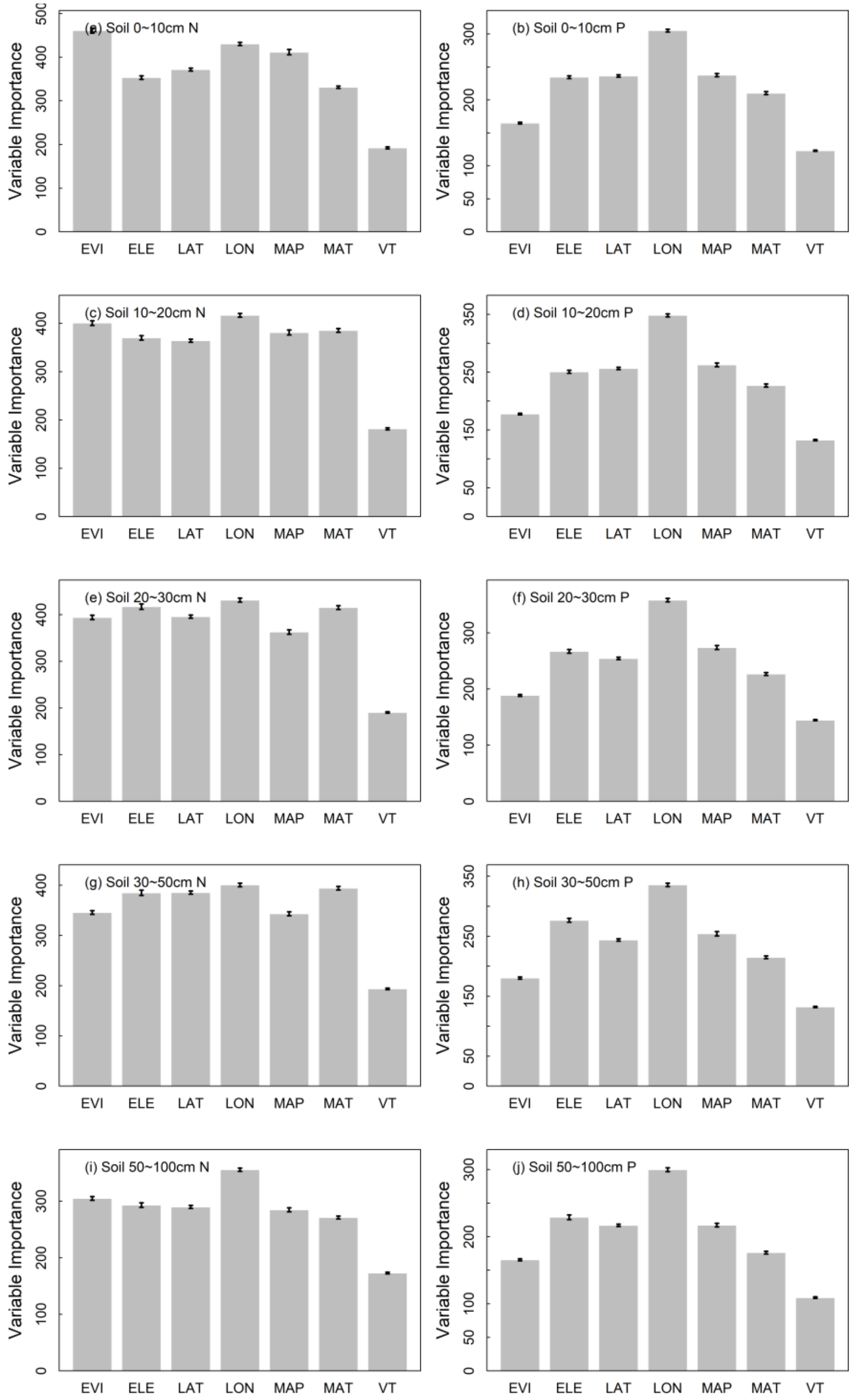

(a) Soil 0~10cm N
(b) Soil 0~10cm P
(c) Soil 10~20cm N
(d) Soil 10~20cm P
(e) Soil 20~30cm N
(f) Soil 20~30cm P
(g) Soil 30~50cm N
(h) Soil 30~50cm P
(i) Soil 50~100cm N
(j) Soil 50~100cm P
Variable Importance
EVI
ELE
LAT
LON
MAP
MAT
VT

**Fig. S9.** The relative importance of variables in random forest models of N and P densities for 0-10 cm (a & b), 10-20 cm (c & d),20-30 cm (e & f) 30-50 cm (g & h) and 50-100 cm (i & j) soil layers.

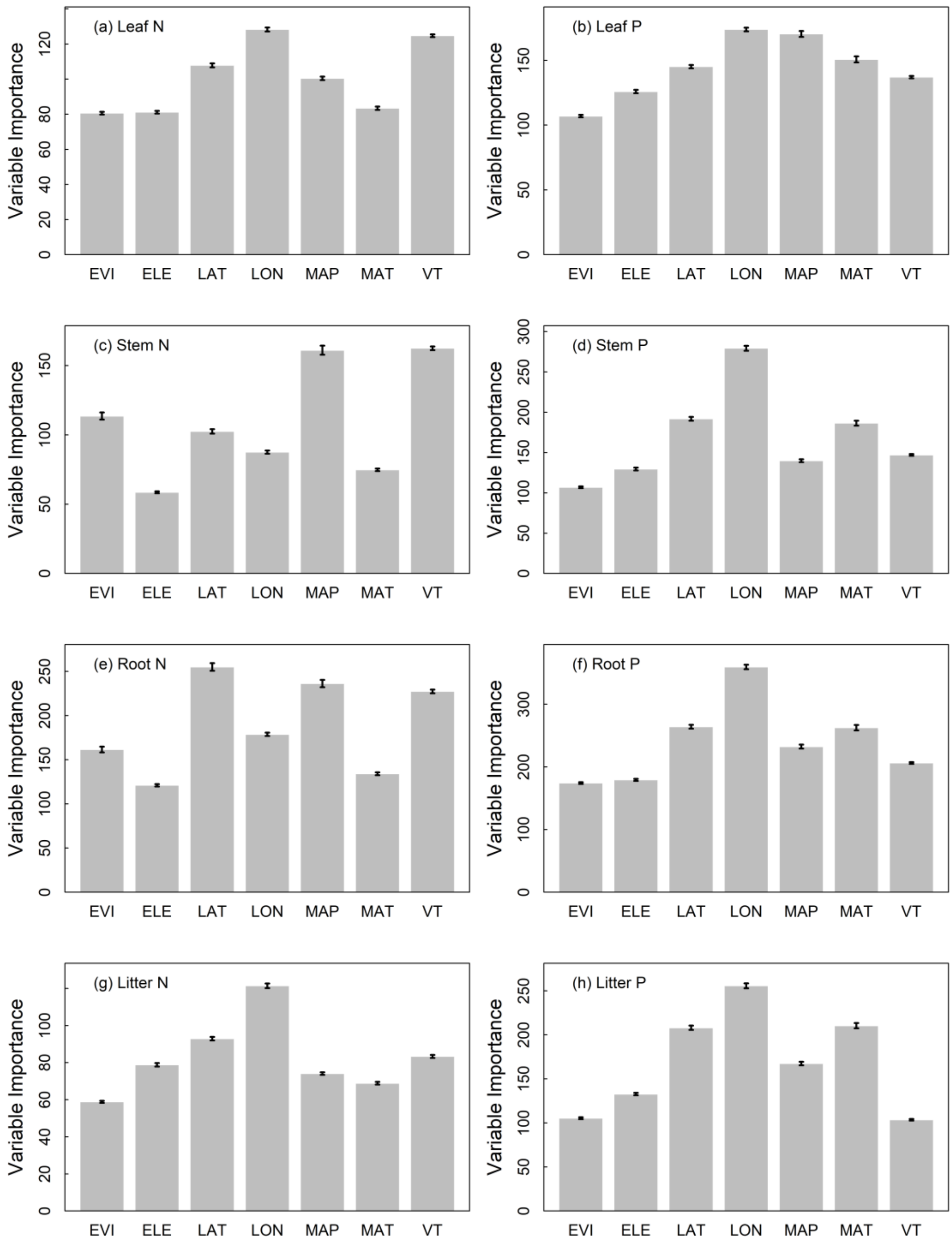

(a) Leaf N
(b) Leaf P
(c) Stem N
(d) Stem P
(e) Root N
(f) Root P
(g) Litter N
(h) Litter P
Variable Importance
EVI
ELE
LAT
LON
MAP
MAT
VT
0
20
40
60
80
100
120
50
150
200
250
300

**Fig. S10.** The relative importance of variables in random forest models of N and P concentrations for leaf (a & b), stem (c & d), root (e & f) and litter (g & h).

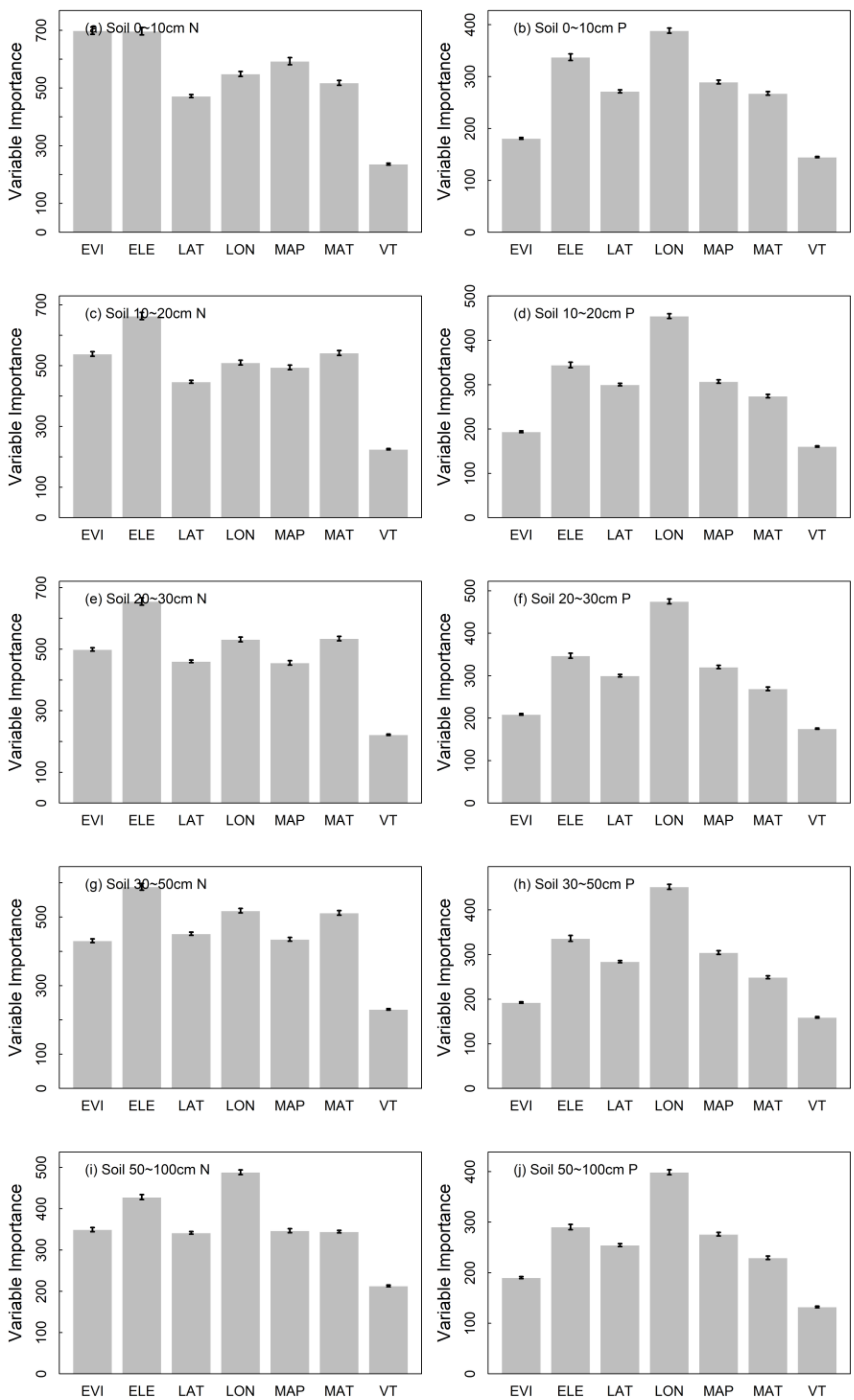

(a) Soil 0~10cm N
(b) Soil 0~10cm P
(c) Soil 10~20cm N
(d) Soil 10~20cm P
(e) Soil 20~30cm N
(f) Soil 20~30cm P
(g) Soil 30~50cm N
(h) Soil 30~50cm P
(i) Soil 50~100cm N
(j) Soil 50~100cm P
Variable Importance
EVI ELE LAT LON MAP MAT VT

**Fig. S11.** The relative importance of variables in random forest models of N and P concentrations for 0-10 cm (a & b), 10-20 cm (c & d),20-30 cm (e & f) 30-50 cm (g & h) and 50-100 cm (i & j) soil layers.