



A High-Resolution Gridded Dataset of Vertically Resolved Fine Root Biomass Across China

Wenlu Zheng¹, Min Zhao¹, Woheng Li¹, Deshuai Zhang¹, Weihua Tang¹, Junshen Luo¹, Shuning Jiao¹, Fengtai Li¹, Haicheng Zhang¹

¹ Carbon-Water Research Station in Karst Regions of Northern Guangdong, School of Geography and Planning, Sun Yat-sen University, 510006, China

Correspondence to: Haicheng Zhang (zhanghch59@mail.sysu.edu.cn)

Abstract. Fine root plays a critical role in ecosystem biogeochemical cycles, serving as the primary organs for water and nutrient uptake and exhibiting rapid turnover. However, a spatially explicit dataset of fine root biomass (FRB) across soil profiles and vegetation types remains lacking. To address this knowledge gap, we compiled 2,311 in-situ measurements of woody FRB and 3,580 measurements of herbaceous FRB from peer-reviewed studies across China. Using these observations, we developed random forest models to estimate surface-layer (0–20 cm) FRB and the vertical attenuation coefficient (k) of FRB for woody and herbaceous ecosystems, respectively. By integrating the predicted surface-layer FRB and vertical distribution functions, we finally generated a gridded dataset of FRB across 0–2 m soil depth (at 20 cm intervals) at 1 km spatial resolution for all woody and herbaceous ecosystems in China for 2005–2025. Model evaluation showed that our models explain approximately 86% and 81% of the observed variations in surface FRB across woody and herbaceous ecosystems, respectively, and reasonably capture the interannual dynamics of observed FRB. Model predictions reveal substantial spatial and vertical variations in both woody and herbaceous FRB across China. Woody FRB density was generally higher in southern China than in central and northern China, whereas herbaceous FRB density was highest on the Qinghai–Tibet Plateau. Woody plants exhibit deeper root distributions in arid regions, whereas herbaceous species show consistently surface-concentrated rooting patterns across climate zones. The environmental controls of FRB also differed between vegetation types, with woody FRB being more strongly influenced by root traits and nutrient availability, whereas herbaceous FRB was more closely associated with climatic conditions. This dataset provides an observation-constrained, spatially explicit benchmark for quantifying belowground carbon stocks and dynamics, and it is archived and publicly available at <https://doi.org/10.6084/m9.figshare.32353257> (Zheng et al., 2026).

1 Introduction

Plant roots constitute a critical interface linking biological communities with soil, water, and the atmosphere, mediating the exchange of matter and energy in terrestrial ecosystem (Brunner et al., 2013). They play a central role in water and nutrient acquisition, thereby exerting profound influences on terrestrial biogeochemical cycles and ecosystem sustainability (Bardgett et al., 2014). While many studies have focused on aboveground litterfall, fine roots—typically defined as roots with a diameter



35 ≤ 2 mm—also contribute substantial inputs of labile carbon to soils through continuous growth, turnover, and rhizodeposition
 (Helfenstein, 2010; Nurse et al., 2013). Annual fine root production and turnover are estimated to account for approximately
 14–27% of global net primary productivity (NPP) (Iversen et al., 2017; Jackson et al., 1997; McCormack et al., 2015; Mitchell
 et al., 2010). These processes stimulate rhizosphere microbial activity, thereby regulating the formation and decomposition of
 soil organic carbon (Kuzyakov and Blagodatskaya, 2015; Sokol and Bradford, 2019). Consequently, an accurate and spatially
 explicit database of fine root biomass (FRB) is essential for benchmarking terrestrial carbon cycle models and improving
 predictions of ecosystem responses to climate change (Hayashi et al., 2023; Kuzyakov and Blagodatskaya, 2015; Ma et al.,
 2025; Malhotra et al., 2025; Pausch and Kuzyakov, 2018).

40 In addition to the total FRB, a reliable database of its vertical distribution is crucial for explicitly representing terrestrial
 biogeochemical cycles. The vertical profile of FRB determines the depth at which carbon inputs enter the soil, thereby
 influencing carbon residence time and stabilization processes (Jobbágy and Jackson, 2000; Rasse et al., 2005). Compared with
 surface inputs, debris derived from deeper roots is more likely to be stabilized through mineral associations or physical
 protection from microbial protection, highlighting the importance of deep fine roots in long-term carbon sequestration
 (Freschet et al., 2021; Lorenz and Lal, 2005; Rumpel and Kögel-Knabner, 2011). Moreover, vertical FRB profiles also reflect
 45 plant adaptive strategies to gradients in water and nutrient availability, particularly in arid and semi-arid regions (Canadell et
 al., 1996; Fan et al., 2017; Maeght et al., 2013). Datasets describing vertical FRB profiles are thus essential for improving our
 understanding of vegetation adaptation to environmental conditions and for more accurately simulating the terrestrial carbon
 cycle. However, the large-scale spatial variation in FRB vertical distribution remains poorly constrained (Finér et al., 2011;
 Iversen et al., 2017; Schenk and Jackson, 2002b).

50 Furthermore, a comprehensive understanding in the environmental controls of FRB and its vertical profile is critical for
 accurately projecting the responses of vegetation growth and the soil carbon cycle to future climate change. Many studies have
 investigated the controlling factors of FRB and its vertical profile (Chen et al., 2019; Finér et al., 2011; Saha et al., 2023).
 Among all environmental factors, climate is widely recognized as a primary control. Warming experiments show that fine root
 production and turnover are generally higher in warmer than in colder regions (Gill and Jackson, 2000; Yuan and Chen, 2010).
 55 Precipitation further regulates FRB by controlling water availability. Increased precipitation can enhance FRB and its turnover
 (Cordeiro et al., 2020; Wang et al., 2020). Hydrological processes also play an important role. Evapotranspiration influences
 the vertical distribution of FRB by regulating subsurface water dynamics (Desborough, 1997; Zeng, 2001). Drought stress
 typically alters root traits, accelerates root mortality, and reduces root biomass (Xiao et al., 2020; Zhou et al., 2018), although
 some drought-tolerant species may increase root investment to cope with water limitation (Shan et al., 2015). Topographic
 60 factors indirectly regulate FRB through their effects on hydrothermal conditions and soil development (Davis et al., 2004;
 Karki et al., 2021; Ma et al., 2010; Moser et al., 2010). Biological factors and soil properties further modulate both FRB and
 its profile. Plant diversity generally promotes FRB, although their effects depend on environmental context and soil depth
 (Barry et al., 2019; Peng and Chen, 2021). Soil texture and nutrient availability, particularly nitrogen and phosphorus, strongly
 influence FRB and its turnover and profile across ecosystems (Chang et al., 2012; Geng et al., 2021; Huang et al., 2019;



65 Kulmatiski et al., 2017; Yuan and Chen, 2012). For example, nitrogen addition may promote FRB in deeper soil layers while
 suppressing it in surface soils (Geng et al., 2021). Overall, FRB and its vertical distribution are jointly regulated by multiple
 environmental factors, often exhibiting strong nonlinear responses. Differences in resource acquisition and adaptive strategies
 between herbaceous and woody plants further lead to contrasting responses of FRB to climate change. However, existing
 studies have largely focused on single factors or local scales. A systematic investigation on the controlling factors of FRB and
 70 its vertical distribution patterns remains lacking, particularly with respect to differences between woody and herbaceous
 vegetation.

In this study, we aimed to develop a reliable, high-resolution dataset of FRB across soil profiles and vegetation types in China,
 and to identify the key environmental controls on FRB and its vertical distribution in woody and herbaceous ecosystems. Using
 in-situ observation data of FRB across soil layers, we fitted an exponential function describing the decline of FRB with soil
 75 depth for each site and extracted the vertical attenuation coefficient (k) to characterize root distribution profiles (see Materials
 and Methods). We then developed random forest models to predict surface-layer (0–20 cm) FRB and the corresponding k
 values for woody and herbaceous ecosystems. By integrating these models, we generated a gridded dataset of FRB across 0–
 2 m soil depth (at 20 cm intervals) at 1 km spatial resolution for the period 2005–2025. In addition, we applied SHapley
 Additive exPlanations (SHAP) to quantify the relative importance of environmental drivers controlling FRB and its vertical
 80 distribution. This dataset fills a critical gap in large-scale datasets of FRB and its vertical structure and provides an
 observationally constrained basis for understanding belowground carbon allocation across vegetation types and their responses
 to environmental change. It also offers valuable constraints for improving terrestrial ecosystem model parameterization and
 carbon cycle assessments.

2 Materials and Methods

85 2.1 Study area

China spans a vast geographic extent across multiple climatic zones and ecological regions, characterized by pronounced
 climatic gradients and complex topography (Fig. 1). Mean annual temperature across different regions of China ranges from
 –5 °C to 25 °C, while annual precipitation increases from less than 100 mm in the northwestern inland regions to over 2000
 mm in the southeastern coastal areas (Piao et al., 2010). These environmental gradients support a wide range of vegetation
 90 formations (Ni, 2000), which in this study are categorized into two functional types: woody and herbaceous vegetation. The
 interaction between climatic gradients and topographic complexity generates substantial heterogeneity in vegetation types and
 soil properties, which strongly influence FRB and vertical distribution (Shangguan et al., 2014). This environmental diversity
 provides an ideal natural setting for investigating FRB and its vertical distribution across woody and herbaceous ecosystems.

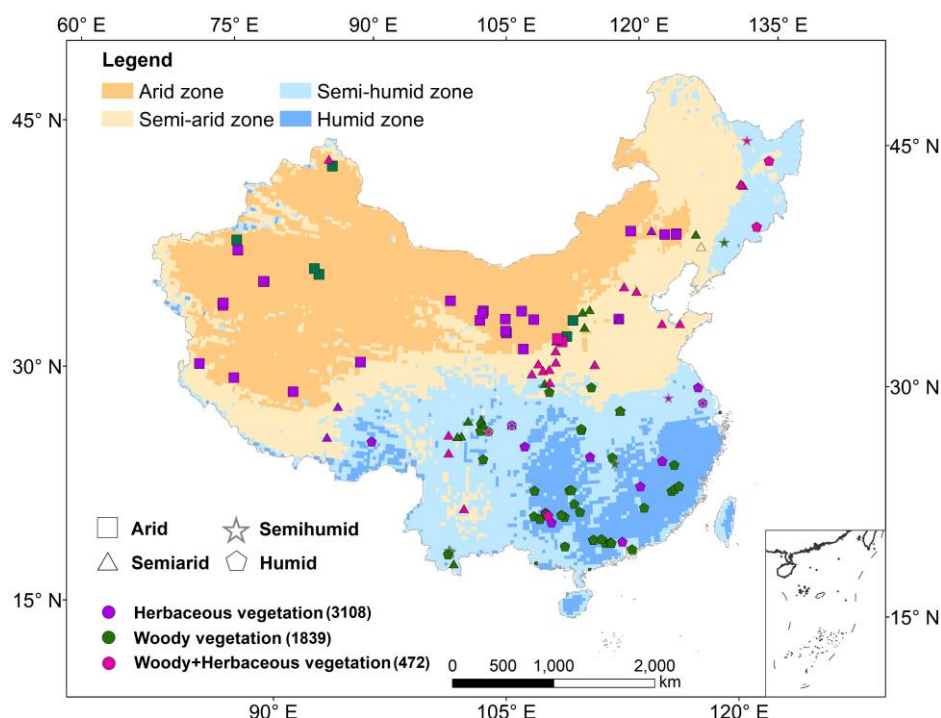


Figure 1. Spatial distribution of sampling sites for woody and herbaceous fine roots across China.

2.2 Collection of FRB profile data

We compiled a comprehensive root biomass database from 109 peer-reviewed studies retrieved from the Web of Science, Google Scholar, and China National Knowledge Infrastructure. The literature search was conducted using the keywords “root biomass”, “fine root”, “root depth”, “root depth distribution”, and “maximum rooting depth”. Because of inconsistencies in fine root classification criteria across studies, only studies reporting measurements of live roots (diameter ≤ 5 mm) were included, while those containing dead root data were excluded. After removing duplicate records and studies that reported only total FRB across the entire soil profile without depth-resolved measurements, the final database comprised 5,419 root biomass observations from 256 sites across China (Fig. 1), spanning a wide range of topographic, climatic, and soil conditions. Of these, 2,311 samples from 98 sites corresponded to woody plants, while 3,580 samples from 177 sites represented herbaceous plants. Some sampling sites included both woody and herbaceous vegetation samples. The dataset covers measurements collected during 1989–2023, with most FRB measurements confined to the upper 2 m of the soil profile.

To evaluate the environmental representativeness the ground-based observations across forests and grasslands in China, we analyzed the ranges and distributions of annual total precipitation (ATP), mean annual temperature (MAT), elevation (DEM), and enhanced vegetation index (EVI) across all observation sites. These variables represent the most important conditions of local climate, topography, and vegetation. We then assessed the extent to which the observations represented environmental conditions across forests and grasslands in China. A grid cell was considered environmentally represented by the observations



when its values of all four variables fell within the corresponding observed ranges. Our analysis shows that the observational samples broadly captured the major environmental gradients across China, with substantial overlap between the sampled and national distributions of ATP, MAT, DEM, and EVI (Figs. 2b & d). Overall, 87.5% of the national prediction domain was environmentally represented by the woody observations, compared with 71.3% for herbaceous observations (Figs. 2a & c). Areas not represented by the observations were mainly concentrated in high-elevation, extremely arid, and sparsely vegetated regions, particularly for herbaceous vegetation. These results indicate broad environmental coverage of the observations for national-scale FRB modelling.

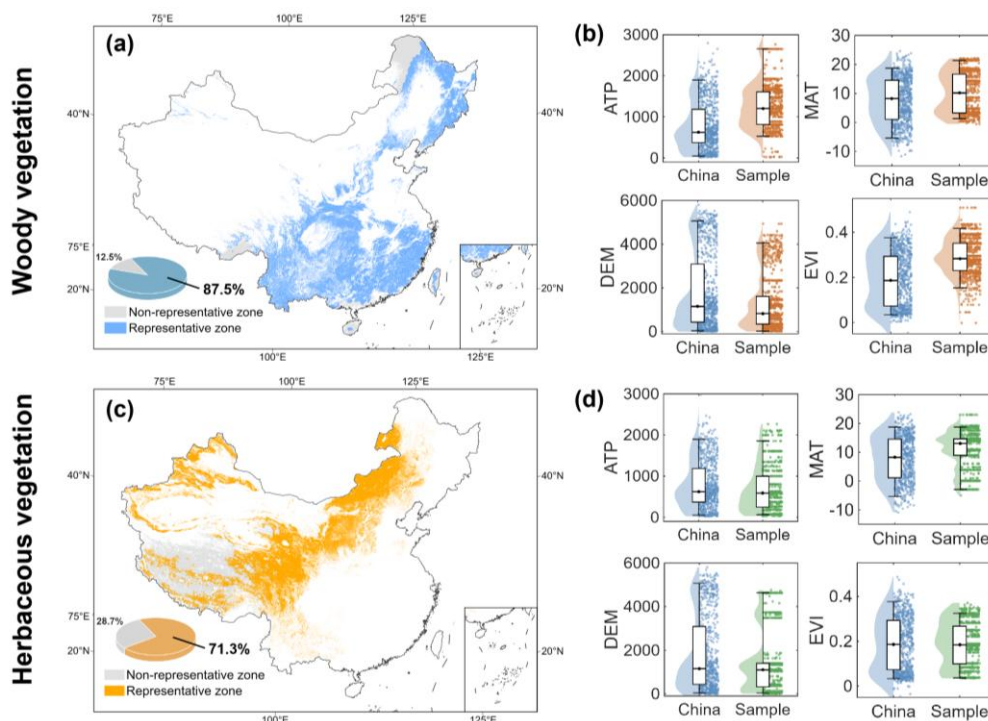


Figure 2. Environmental representativeness of ground-based FRB observations across China. Spatial distributions of representative and non-representative areas for (a) woody and (c) herbaceous vegetation, together with comparisons between the distributions of ATP, MAT, DEM, and EVI across China and at the sampling locations.

2.3 Quantifying the vertical attenuation coefficient of FRB

To characterize the vertical profile of FRB, field measurements of FRB at each site for each plant community were normalized by setting the biomass of the topsoil layer to unity and expressing the biomass of deeper layers as ratios relative to the top layer. This normalization facilitates cross-site comparisons of vertical root distribution patterns independent of absolute biomass differences. The FRB mostly decreases exponentially with increasing soil depth (Jackson et al., 1996; Schenk and Jackson, 2002b; Vogt et al., 1998). In this study, a negative exponential equation of soil depth (Eq. 1) was fitted to each normalized FRB profile, from which a key parameter—the vertical attenuation coefficient (k)—was derived to quantify the rate at which root biomass declines with depth. The equation is expressed as follows:



$$f_{FRB_i} = 1 - e^{-k \times d_i} \quad (1)$$

where f_{FRB_i} (0–1, dimensionless) represents the ratio of FRB (g m^{-2}) in soil layer i to FRB in the surface soil layers. d_i (cm) denotes the depth to middle of soil layer i . A higher k value indicates that root biomass is more concentrated near the soil surface, whereas a lower k value reflects a deeper root distribution.

135 2.4 Machine-learning modelling of surface FRB and vertical FRB profiles

To generate a spatially explicit dataset of FRB across soil profiles in China, we developed separate Random Forest (RF) models to predict surface-layer (0–20 cm) FRB and the vertical attenuation coefficient (k), respectively. RF uses bootstrap resampling to build multiple decision trees, which effectively reduces variance and minimizes overfitting. In addition, RF can capture complex nonlinear relationships and interactions among predictors without requiring strict assumptions about data distribution,
 140 a feature that is particularly important for ecological systems driven by multiple interacting factors. It is also robust to noise and outliers, as the ensemble structure reduces the influence of individual observations. Compared with boosting algorithms (e.g., eXtreme Gradient Boosting and Light Gradient Boosting Machine), RF is less sensitive to parameter tuning and less prone to overfitting under limited sample sizes and relatively high feature dimensionality. Consequently, RF provides a more reliable framework for characterizing the relationships between environmental factors and both the FRB decay parameter (k)
 145 and surface FRB.

We selected 27 potential environmental factors as predictors for the RF model based on a comprehensive review of potential factors known to influence surface-layer (0–20 cm) FRB and the vertical attenuation coefficient (k). These predictors encompass climatic, topographical, and soil physicochemical properties (Table 1). For factors not reported in the original publications, we extracted corresponding values from global gridded datasets based on the geographic coordinates of each
 150 sampling site. In specific, these potential predictors includes six climatic variables—annual total precipitation (ATP), mean annual temperature (MAT), minimum temperature (Tmin), maximum temperature (Tmax), evapotranspiration (ET), and aridity index (AI); two topographic variables—elevation (DEM) and slope (Slope); four vegetation variables—leaf area index (LAI), enhanced vegetation index (EVI), species richness (SRich), and root diameter (RDiam); and fifteen soil variables—total nitrogen (TN), total phosphorus (TP), total potassium (TK), available nitrogen (AN), available phosphorus (AP), available
 155 potassium (AK), silt content (Silt), clay content (Clay), sand content (Sand), gravel content (Gravel), soil pH, soil moisture (SM), bulk density (BD), soil organic matter (SOM) and soil depth (LDep). Detailed descriptions of the environmental variables and their sources are provided in Table 1.

Prior to model training, we first conducted an initial multicollinearity screening using the Pearson correlation coefficients and the variance inflation factors (VIF). Recursive feature elimination (Guyon et al., 2002) was then applied separately to each
 160 response variable to identify the optimal subset of predictors, resulting in distinct sets of explanatory variables for the RF models of surface-layer (0–20 cm) FRB and the vertical attenuation coefficient (k) (Figs. 4 & 6). This process helps reduce model complexity, improve computational efficiency, optimize model fitting, and eliminate redundant variables that may negatively affect model performance. Recursive feature elimination is a model-based backward feature selection method that



iteratively trains a model, ranks variables according to their importance, and progressively removes features with low
 165 contributions, thereby identifying the optimal subset of predictors.

Because the vertical distribution and controlling factors of woody plant roots differ substantially from those of herbaceous
 plants (Freschet et al., 2021; Mokany et al., 2006), separate RF models were developed for woody and herbaceous ecosystems.
 Ultimately, nine key variables were retained for woody vegetation, while eight key variables were retained for herbaceous
 vegetation (Fig. 4a).

170 Consistent with the prediction of surface (0–20 cm) FRB, a total of 27 candidate variables encompassing climate, topography,
 vegetation, and soil properties were initially considered for modeling the attenuation coefficient (k) of FRB. Through
 multicollinearity screening and recursive feature elimination, redundant variables exhibiting high collinearity and low
 contribution were removed, resulting in optimal factor subsets for predicting the vertical attenuation coefficients of woody and
 herbaceous plants, respectively (Fig. 6a).

175 Bayesian optimization was applied to determine the optimal model parameter values, resulting in a modeling framework that
 balances high predictive accuracy with strong interpretability. Model performance was evaluated using ten-fold cross-
 validation. In each fold, 90% of the samples were used for training, while the remaining 10% for testing. Hyperparameters
 were optimized via Bayesian optimization. Model performance was assessed using the root mean square error (RMSE) and
 the coefficient of determination (R^2) between observed and predicted values.

180 The trained RF models against all observational data were then applied at a national scale to generate annual spatially-resolved
 maps of k values and surface-layer (0–20 cm) FRB at a spatial resolution of 1 km for the period 2005–2025. Based on the
 predicted k -values, we further derived the vertical FRB profile for each 1 km $\times$ 1 km grid cell across China (Eq. 1). By
 integrating the surface-layer FRB with the vertical profiles, we produced a gridded dataset of FBD across 0–2 m soil depth (at
 20 cm intervals) at 1 km spatial resolution for both woody and herbaceous ecosystems in China over the period 2005–2025.

185 Note that, in arid regions where FRB does not decrease exponentially with soil depth (Fig. 1), the RF models for k were not
 applied. Instead, vertical FRB distributions in these regions were calculated directly as the ratio of FRB in subsurface soil
 layers to that in the surface layer.

To quantify the prediction uncertainty, we used the 10 independent models generated during the 10-fold cross-validation
 (Kohavi, 1995). The complete observational dataset was divided into 10 mutually exclusive subsets, with nine subsets (90%
 190 of the observations) used for model training, and the remaining subset (10%) withheld for validation in each fold. This
 procedure produced 10 independently trained models for surface RFB density and 10 models for the vertical attenuation
 coefficient (k) for each vegetation type.

Each model was applied to the same spatial predictor datasets for 2005–2025 to predict surface-layer FRB (0–20 cm) and the
 vertical attenuation coefficient (k). These predictions were then combined using the negative exponential relationship to
 195 reconstruct FRB throughout the 0–200 cm soil profile at 20 cm intervals. For each year, soil-depth interval, and grid cell, the
 standard deviation of predictions from different models generated during the 10-fold cross-validation were calculated as



absolute prediction uncertainty, respectively. Relative uncertainty was expressed as the ratio of the standard deviation to the ensemble mean. The annual, depth-resolved ensemble predictions of FRB and associated uncertainty estimates were archived and made available through Figshare.

200 **Table 1. Selected potential environmental variables controlling fine-root biomass and vertical distribution profiles.**

Category	Variable	Description	Unit	Period	Reference
Soil property	pH	Soil pH	\	\	(Shangguan et al., 2013)
	Silt	Silt content	%	\	
	Sand	Sand content	%	\	
	Clay	Clay content	%	\	
	Gravel	Gravel content	%	\	
	TN	Total soil nitrogen content	g kg ⁻¹	\	
	TK	Total soil potassium content	g kg ⁻¹	\	
	TP	Total soil phosphorus content	g kg ⁻¹	\	
	AN	Available soil nitrogen content	mg kg ⁻¹	\	
	AK	Available soil potassium content	mg kg ⁻¹	\	
	AP	Available soil phosphorus content	mg kg ⁻¹	\	
	SOM	Soil organic matter	%	\	
	BD	Soil bulk density	g cm ⁻³	\	
	LDep	Soil layer depth	cm	\	
	SM	Soil Moisture	m ³ m ⁻³	2005–2025	(Muñoz-Sabater et al., 2021)
Climate	MAT	Mean annual temperature	°C	2005–2025	(Muñoz-Sabater et al., 2021)
	Tmax	Annual maximum monthly mean temperature	°C	2005–2025	
	Tmin	Annual minimum monthly mean temperature	°C	2005–2025	
	ATP	Annual total precipitation	mm yr ⁻¹	2005–2025	
	AI	Aridity Index	\	2005–2025	
	ET	Evapotranspiration	mm	2005–2025	
Topography	DEM	Elevation	m	\	(Farr et al., 2007)
	Slope	Slope	%	\	
Vegetation	LAI	Leaf area index	m ² m ⁻²	2005–2025	(Myneni et al., 2021)



EVI	Enhanced vegetation index	\	2005–2025	(Didan, K., 2021)
SRich	Species Richness	n	\	Corresponding
RDiam	Root Diameter	mm	\	references

2.5 Temporal validation and leave-one-year-out cross-validation

To assess whether the model captures temporal variability in FRB, we conducted a temporal validation using field observations with recorded sampling years. This provides an complementary assessment to spatial cross-validation by evaluating whether the learned relationships in trained models can capture the interannual FRB dynamics. In this temporal validation, observed and predicted FRB were grouped into consecutive temporal intervals, and mean values were calculated for each interval. Uncertainty in the observed means was quantified from within-group variability and sample size, with confidence intervals used to represent the uncertainty of the temporal means. Observed and predicted trajectories were then compared in terms of their overall direction, magnitude, and temporal changes. Years without field observations were excluded rather than assigned zero values; therefore, the resulting trajectories represent only periods with available observations and do not imply continuous annual observations.

In addition, we also performed a Leave-One-Year-Out (LOYO) cross-validation to explicitly assess temporal transferability and generalization of the trained models (Filippelli et al., 2024; Tredennick et al., 2021). In each LOYO iteration, all observations collected in a given year were completely withheld as an independent temporal test set, while observations from all other available years were used exclusively for model training.

2.6 Identifying Key Environmental Factors

We employed an advanced machine learning interpretability framework, SHapley Additive exPlanations (SHAP) (Lundberg et al., 2020), in combination with Recursive Feature Elimination (Guyon et al., 2002) to identify the key controlling factors of variability in FRB density. SHAP is grounded in cooperative game theory and quantifies the marginal contribution of each feature to model predictions by evaluating different combinations of feature subsets, thereby generating feature attribution values for each variable. The relative importance of environmental variables in predicting surface-layer (0–20 cm) FRB and the vertical attenuation coefficient (k) of FRB was quantified using the SHAP analysis, respectively. Furthermore, by leveraging the local interpretability of SHAP values, we analyzed the nonlinear response of surface-layer FRB and its vertical attenuation rate to major environmental drivers.

3 Results and Discussion

3.1 Vertical profiles of FRB density

The FRB of woody vegetation generally decreased markedly from surface to deeper soil layers, with attenuation rates increasing from arid to humid zones (Fig. 3). In arid and semi-arid regions, a relatively larger proportion (36%–68%) of fine roots is distributed in deeper soil layers compared with humid regions (22%–25%), indicating a shift toward deeper rooting



strategies under water-limited conditions. Previous studies have shown that woody plants allocate more biomass to deeper roots to access more stable subsurface water resources, thereby enhancing drought resistance (Fan et al., 2017; Schenk and Jackson, 2002a).

In contrast, in humid and semi-humid regions, FRB of woody vegetation is predominantly concentrated in the upper soil layers, with a reduced contribution from deeper layers. This shallow distribution reflects sufficient water availability near the surface and higher nutrient concentrations in topsoil, which reduce the need for deep rooting. Root distribution patterns are strongly influenced by the vertical distribution of soil resources, with nutrient-rich surface layers generally favoring shallow root systems (Jobbágy and Jackson, 2000; Ma et al., 2021). Overall, woody vegetation exhibits considerable plasticity in root distribution across aridity zones, shifting from shallow to deeper rooting strategies with increasing aridity (Fan et al., 2017).

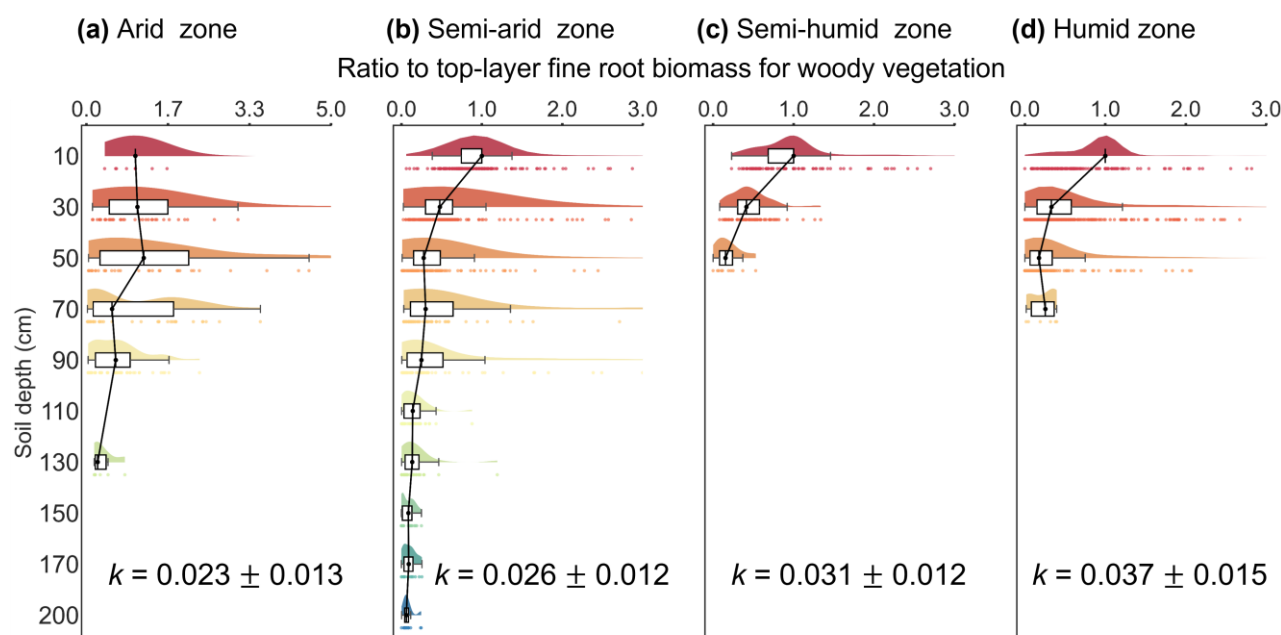


Figure 3. Vertical distribution of FRB in woody ecosystems across different aridity zones (AI is aridity index. Arid: $AI < 0.2$; Semi-arid: $0.2 \leq AI < 0.5$; Semi-humid: $0.5 \leq AI < 0.65$; Humid: $AI \geq 0.65$). k denotes the vertical FRB attenuation rate.

Compared with woody plants, herbaceous plants exhibit a more rapid decline in FRB with increasing soil depth, indicating a stronger concentration of roots in shallow soil layers. Across all aridity zones, most (63%–90%) fine roots of herbaceous plants are confined to the upper soil layers (e.g., 0–20 cm), with relatively limited distribution in deeper soils. This pattern reflects a greater reliance on surface soil moisture and is consistent with the typically shallow rooting systems and rapid resource acquisition strategies of herbaceous plants (Freschet et al., 2021; He et al., 2023). In arid and semi-arid regions, the proportion of roots in deeper soil layers increases slightly, suggesting some degree of adaptive response to water limitation. However, this increase is much less pronounced than that observed in woody vegetation, indicating a more limited capacity for deep root development. In humid and semi-humid regions, herbaceous roots are almost entirely restricted to surface soils, reflecting the



abundant availability of water and nutrients in the upper soil layers. Overall, herbaceous vegetation shows relatively consistent
 250 shallow rooting patterns across aridity zones, with only modest adjustments under increasing aridity (Fan et al., 2017; Freschet
 et al., 2021; Jobbágy and Jackson, 2001; Lyu et al., 2025).

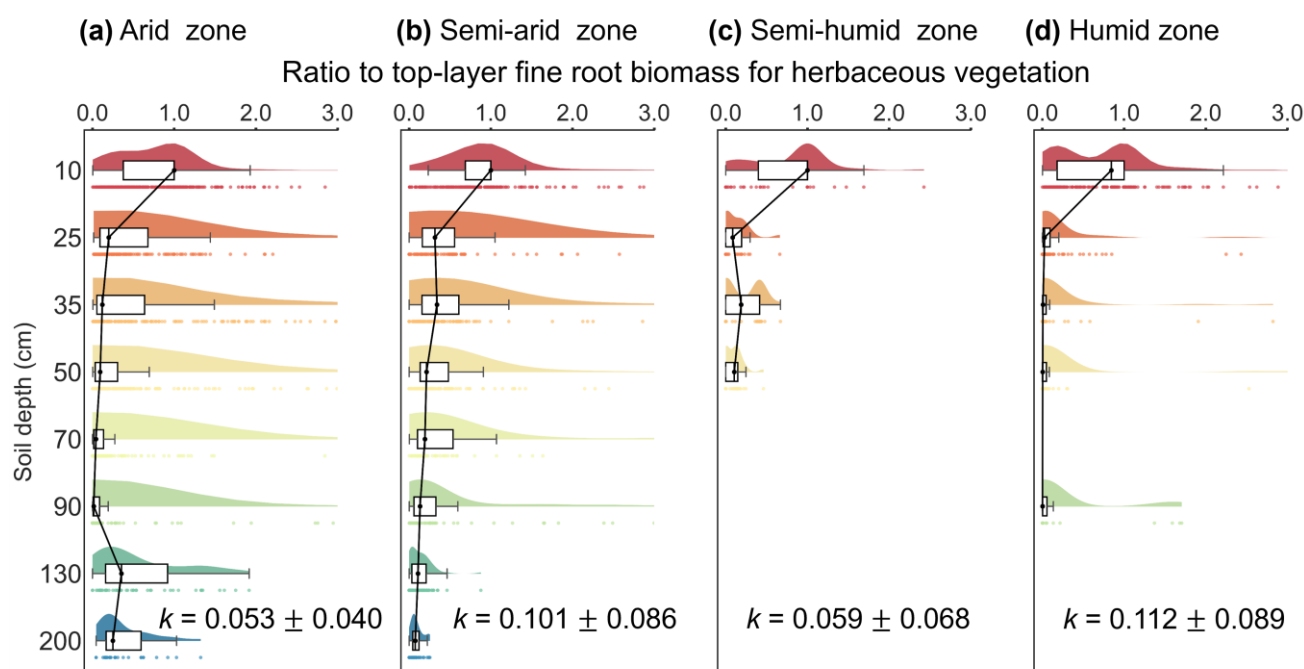


Figure 4. Vertical distribution of fine root biomass in herbaceous ecosystems across different aridity zones (AI is aridity index. Arid: AI < 0.2; Semi-arid: 0.2 ≤ AI < 0.5; Semi-humid: 0.5 ≤ AI < 0.65; Humid: AI ≥ 0.65). k denotes the vertical FRB attenuation rate.

255 3.2 Environmental controls of surface-layer FRB density

The trained RF models in this study largely explain the variation in surface-layer (0–20 cm) FRB (Figs. 5a & c). For woody
 plants, the model achieved a R^2 of 0.86, indicating that it explains most of the spatial variation in woody FRB. For herbaceous
 plants, the trained RF model explains 81% of the spatial FRB variation, also demonstrating high predictive accuracy. The
 trained RF model can also well capture the interannual variability in FRB across observation sites included in this study (Figs.
 260 6a & b). Moreover, Leave-One-Year-Out (LOYO) cross-validation showed that the models maintained predictive skill across
 the tested years for both vegetation types, demonstrating their temporal transferability and generalization across sampling years
 (Figs. 6c & d).

Analysis using SHapley Additive exPlanations (SHAP) reveals marked differences in the key controlling factors of surface-
 layer FRB between woody and herbaceous plants (Figs. 6a & c). In woody systems, root diameter (RDiam) is the most
 265 important predictor, with larger root diameters promoting higher FRB (Figs. 6a & b), particularly when RDiam is larger than
 2 mm (Fig. 6a). Following root diameter, soil total nitrogen (TN) and potassium (TK) also strongly regulate FRB density. FRB
 decreases sharply with increasing soil total nitrogen content when TN is lower than 0.25%, and then remains relatively stable



as TN continues to increase (Fig. 6b). This pattern suggests that under extremely nutrient-poor conditions, woody plants may substantially increase FRB to enhance nutrient acquisition.

FRB shows a nonlinear relationship with local temperature (Fig. 6c), with relatively lower FRB observed in temperate regions where mean annual temperature (MAT) ranged from 5 to 18 °C. In cooler regions ($\text{MAT} < 5^\circ\text{C}$), plants tend to develop substantial fine roots to rapidly acquire water and nutrients during the relatively short growing season (Finér et al., 2011; Yuan and Chen, 2010). In warmer regions ($\text{MAT} > 18^\circ\text{C}$), plants also tend to allocate more biomass belowground to enhance nutrient acquisition, while higher biodiversity may further contribute to increased FRB (Niu et al., 2010; Tilman et al., 2001). Additionally, soil gravel content (Gravel) and bulk (BD) are also key controls on FRB, reflecting the constraining effects of soil physical properties on root growth and resource acquisition. High gravel content and soil compaction may restrict root penetration and reduce access to water and nutrients, thereby strongly influencing fine-root biomass distribution.

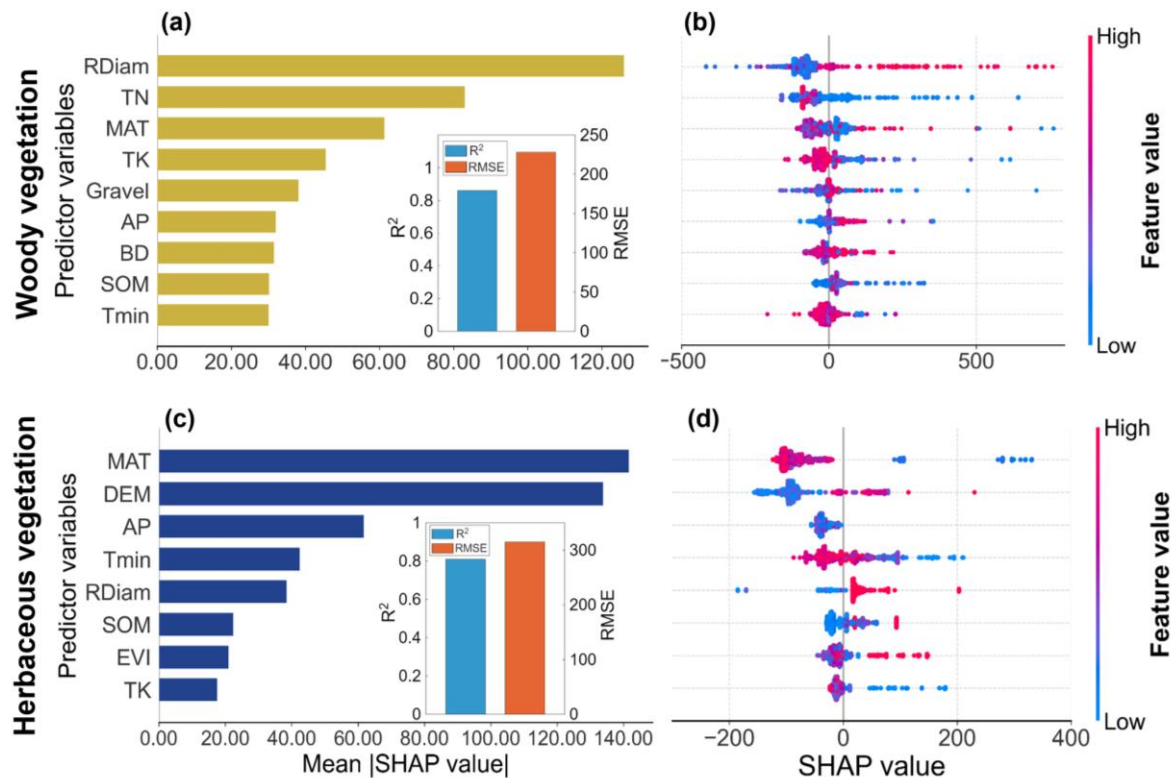
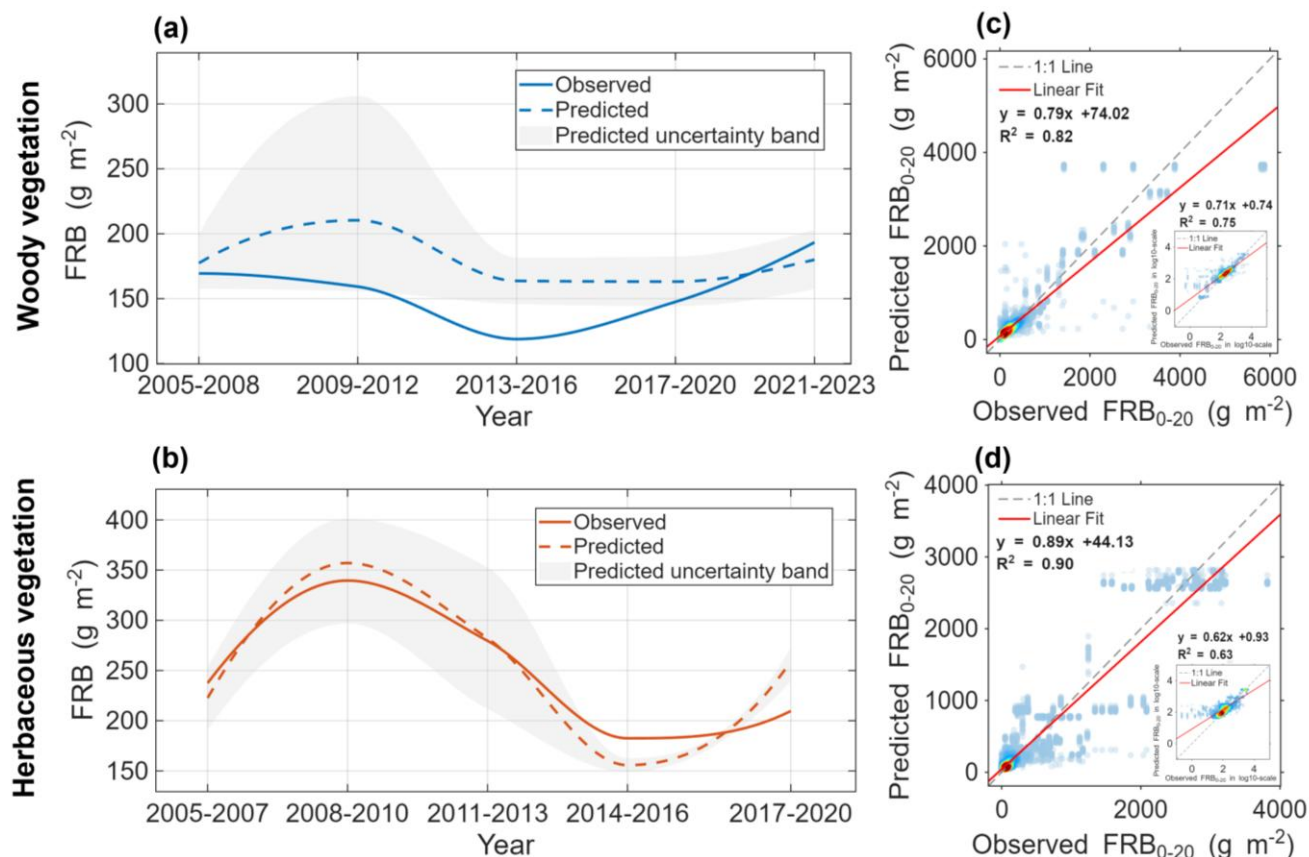


Figure 5. Key environmental controls of the FRB in the 0–20 cm surface layer for woody and herbaceous vegetation. Panels (a) and (c) present the importance rankings of environmental factors controlling woody and herbaceous surface-layer FRB densities, respectively. In the inserted bar plots, blue bar denotes the coefficient of determination (R^2) of regression function between observed and simulated surface-layer FRB densities, and orange bar represents the root mean square error (RMSE) of the simulated surface-layer FRB densities. Panels (b) and (d) show the corresponding SHAP beeswarm plots. Explanations of the environmental variables are provided in Table 1.



285 **Figure 6. Comparison of observed and predicted interannual dynamics of fine root biomass (FRB) and leave-one-year-out (LOYO) cross-validation of the trained models.** Panels (a) and (b) Observed and predicted temporal trajectories for woody and herbaceous vegetation, respectively. Panels (c) and (d) LOYO validation for woody and herbaceous vegetation, respectively. Shaded areas in panels (a) and (b) indicate uncertainty bands calculated as standard deviation. Dashed gray lines in panels (c) and (d) indicate 1:1 relationships.

In contrast, herbaceous FRB is most strongly influenced by mean annual temperature (MAT), with higher mean annual
 290 temperature promoting higher FRB (Figs. 6d & 7d). This finding highlights the high sensitivity of herbaceous fine roots to cold stress. Elevation (DEM) and available soil phosphorus content (AP) ranked next in feature importance, indicating that nutrient availability and topographic conditions jointly regulate herbaceous FRB in surface soils (Figs. 6d, 7e & 7f).

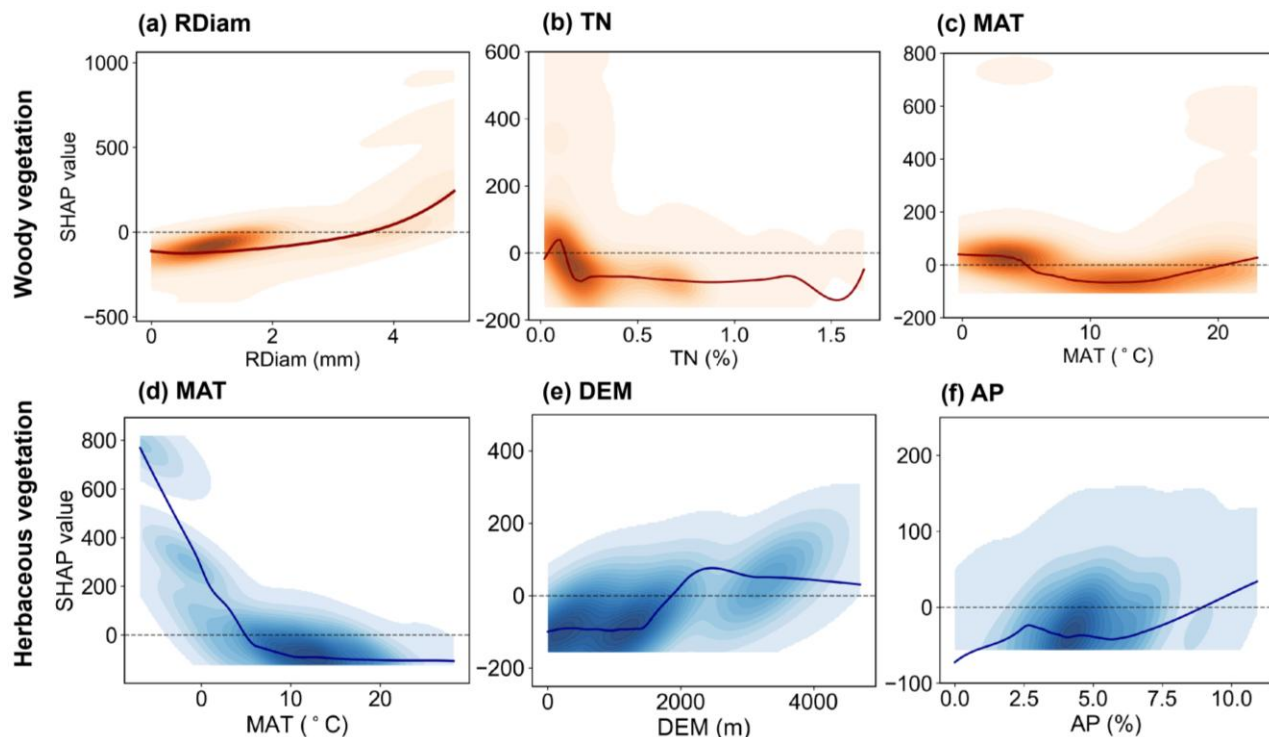


Figure 7. Relationships between surface-layer (0–20 cm) FRB and key environmental controls based on SHAP interaction analysis. RDiam is root diameter; TN is total soil nitrogen content; MAT is mean annual temperature; DEM is elevation; AP is available soil phosphorus content. Orange represents woody vegetation, and blue represents herbaceous vegetation. Darker colors indicate higher point density, reflecting a greater concentration of samples in the corresponding value range.

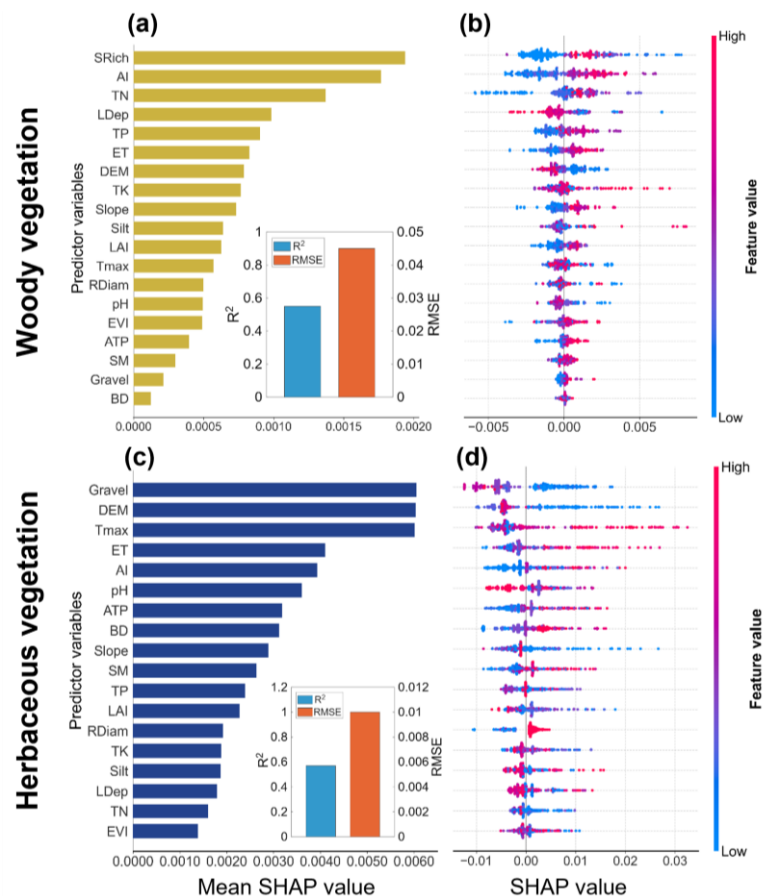
3.3 Environmental controls of vertical fine root profile

In this study, the trained RF model effectively explained variations in the k coefficient describing the vertical FRB distribution (Figs. 8a & c). For woody vegetation, the trained RF model explains 57% of the spatial variation in its coefficient k , while for herbaceous vegetation, the trained model explains 55%.

SHapley Additive exPlanations (SHAP) analysis further revealed substantial differences in the key predictors of vertical FRB distribution between woody and herbaceous systems (Figs. 8a & c). For woody vegetation, species richness (SRich) emerged as the most important predictor. The vertical attenuation coefficient (k) increases initially when SRich was below 5 and then decreases gradually with further increases in species richness, indicating that the shallowest FRB distribution occurred when species richness was around 5 (Figs. 8b & 9a). Higher species richness likely promotes fine root concentration in surface soils through intensified competition for nutrient-rich topsoil resources and enhanced interspecific niche complementarity (Ma and Chen, 2017). Following species richness, both the aridity index (AI) and soil total nitrogen (TN) strongly regulated vertical FRB distribution. The k value increased continuously with increasing AI (Fig. 9b), suggesting that wetter conditions are associated with greater root concentration in surface soils. In addition, TN exerted a negative effect on k when TN was below 0.14%, whereas a relatively stable positive effect was observed when TN exceeded 0.15% (Fig. 9c). This pattern suggests that



under combined water and nutrient limitations, woody plants may allocate more roots to deeper soil layers to enhance water and nutrient acquisition (Finér et al., 2011; Niu et al., 2010; Yuan and Chen, 2010).



315 **Figure 8. Key environmental controls of the vertical fine-root distribution pattern (k) for woody and herbaceous vegetation.** Panels
(a) and (c) present the importance rankings of environmental factors controlling woody and herbaceous surface-layer FRB densities,
respectively. In the inserted bar plots, blue bars denote the coefficient of determination (R^2) of regression function between observed and
simulated k -values, and orange bars represent the root mean square error (RMSE) of the simulated k -values. Panels (b) and (d) show the
corresponding SHAP beeswarm plots. Explanations of the environmental variables are provided in Table 1.

320 Conversely, the vertical distribution of FRB in herbaceous vegetation is most strongly influenced by soil gravel content
(Gravel), elevation (DEM), and annual maximum monthly mean temperature (Tmax). With increasing soil gravel content, the
vertical attenuation coefficient (k) of herbaceous FRB declines continuously, particularly when Gravel is lower than 30% (Figs.
8d & 9d). This indicates that FRB is more strongly concentrated in surface soils under conditions of lower gravel content,
whereas higher gravel content promoted deeper root distribution. DEM shows the second strongest influence on herbaceous
325 FRB profile (Fig. 8d). In regions with elevations lower than 1,800 m, k declines linearly with increasing elevation (Fig. 9e),
whereas k remained relatively stable when elevation exceeds 1,800 m. This pattern indicates that herbaceous FRB is more
strongly concentrated in surface soils in low-elevation regions than in middle and high-elevation regions, while the vertical
FRB profiles in areas above 1,800 m were generally similar.



Tmax does not exert a strong influence on herbaceous FRB profiles when it is lower than 20 °C. However, when Tmax exceeds 20°C, increasing temperature promotes greater FRB concentration in surface soil layers (Figs. 8d & 9f). Moreover, evapotranspiration (ET) and aridity index (AI) rank next in feature importance, suggesting that moisture availability also plays an important regulatory role in shaping the vertical distribution of herbaceous FRB (Fig. 8d).

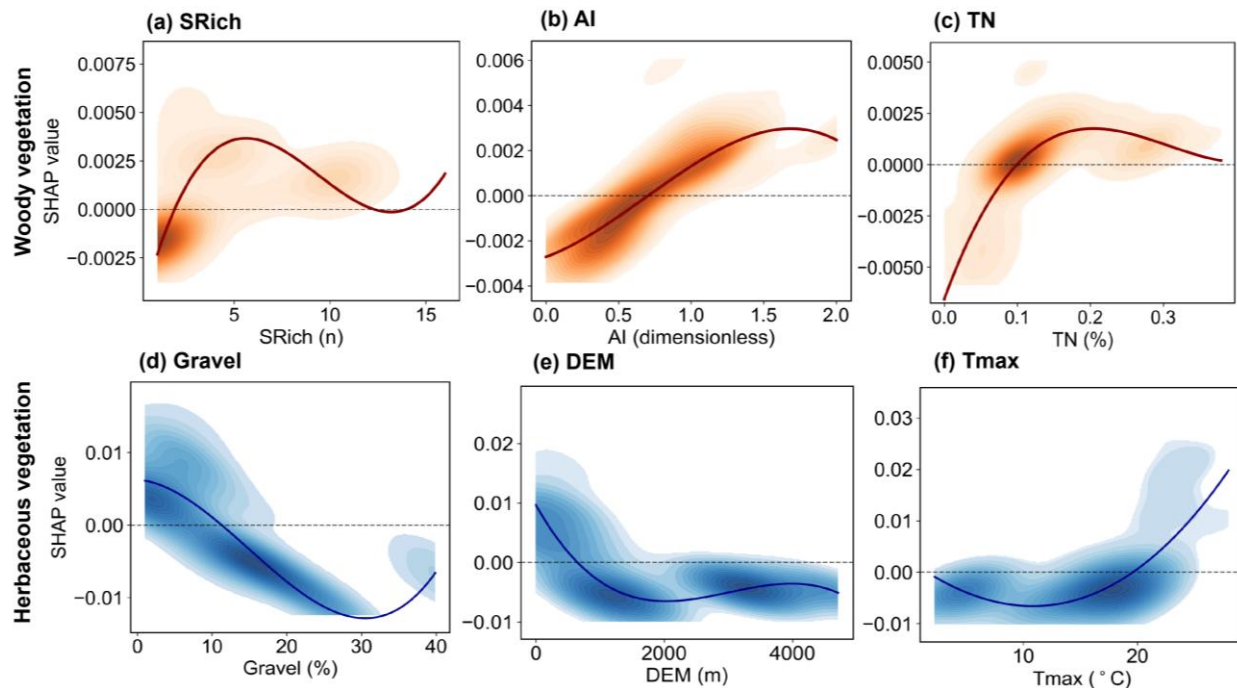


Figure 9. Relationships between vertical FRB attenuation coefficients (k) and key environmental controls based on SHAP interaction analysis. SRich is species richness; AI is aridity index; TN is total soil nitrogen content; Gravel is soil gravel content; DEM is elevation; Tmax is annual maximum monthly mean temperature. Orange represents woody vegetation, and blue represents herbaceous vegetation. Darker colors indicate higher point density, reflecting a greater concentration of samples in the corresponding value range.

3.5 Spatial variation in FRB and profile across China

Application of the RF models developed in this study across China indicates that the total FRB within the 0–2 m soil profile amounts to 3.0 Pg C for herbaceous vegetation and 1.4 Pg C for woody vegetation (Fig. 10). Both woody and herbaceous FRB exhibit substantial spatial variation across China. High woody FRB is primarily distributed in the mountainous regions of northeastern and southern China, where forest cover is extensive and ecosystems are strongly influenced by the monsoon climate. These regions generally provide favourable hydrothermal conditions and high productivity, which support greater belowground fine root growth. In contrast, herbaceous vegetation is mainly distributed in northwestern China, with particularly high FRB concentrated on the Qinghai-Tibet Plateau, followed by the Loess Plateau and Inner Mongolia Plateau. This spatial pattern highlights the dominant role of elevation in regulating herbaceous FRB, likely through its combined effects on temperature, moisture availability, and vegetation communities (Kattge et al., 2020; Pan et al., 2025). Moreover, comparison of the FRB predictions generated by the trained models during 10-fold cross-validation showed that the relative uncertainty in



simulated woody FRB was generally below 20%, with higher uncertainties mainly concentrated in southern China. In contrast, the relative uncertainty in simulated herbaceous FRB was overall higher than that of woody FRB, with high uncertainties primarily distributed across northern China. The mean relative uncertainty was approximately $11 \pm 0.5\%$ for woody FRB and $15 \pm 0.5\%$ for herbaceous FRB (Figs. 10c & d).

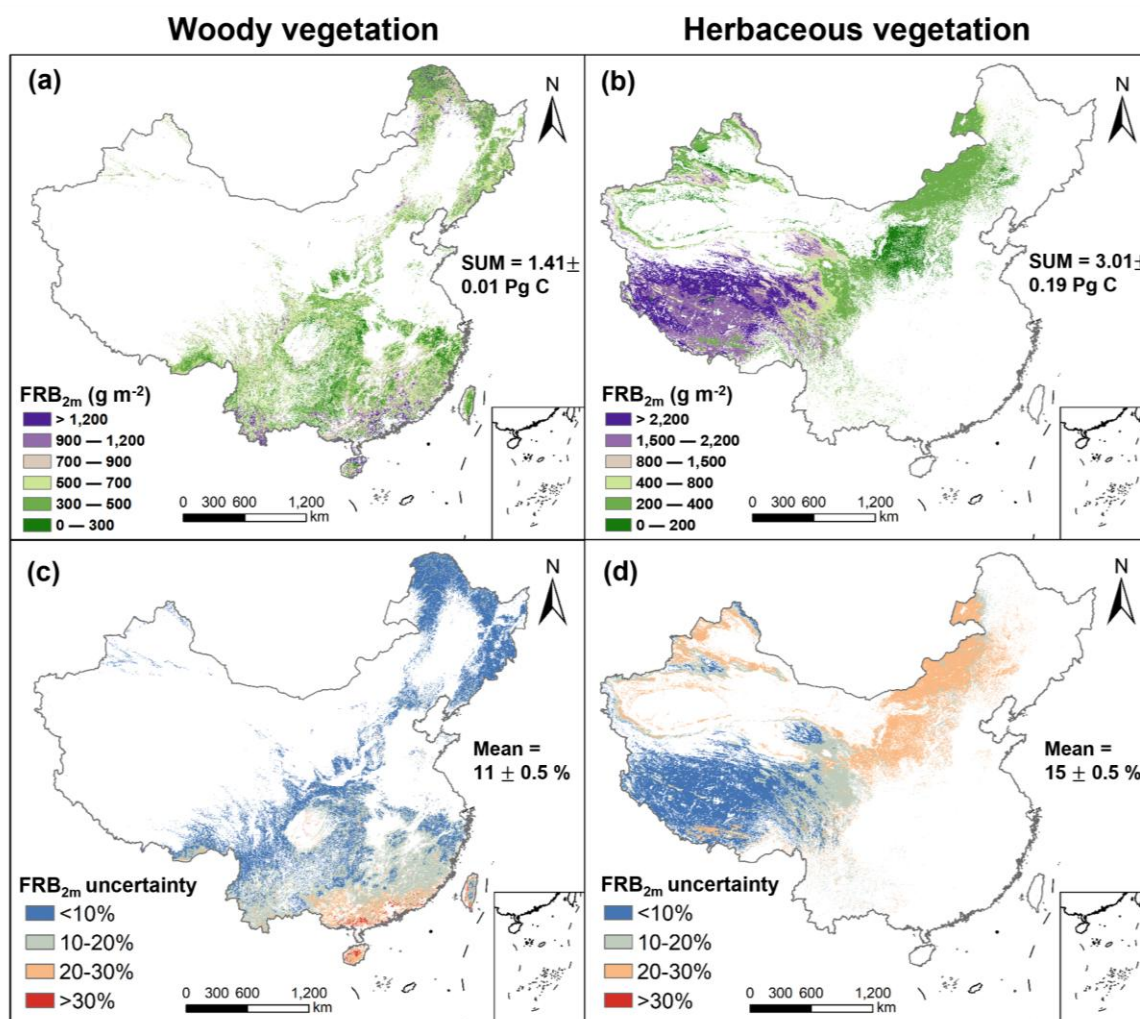


Figure 10. Spatial patterns of FRB within 0–2 m soil profile for woody and herbaceous vegetation across China during 2005–2025. SUM is the total FRB within 0–2 m soil profile (FRB_{2m}) across China.

Pronounced differences are also observed in the vertical FRB profiles of woody and herbaceous plants (Figs. 11a & c). For woody vegetation, FRB declines relatively gradually with soil depth, with the surface 0–20 cm soil layer accounting for $49 \pm 6\%$ of the total FRB within the 0–2 m soil profile. In contrast, herbaceous vegetation exhibits a more surface-concentrated distribution pattern, with FRB in the surface 0–20 cm soil layer accounting for $77 \pm 7\%$ of the total FRB.



In addition, the proportion of surface-layer (0–20 cm) FRB relative to total FRB (F value) varied substantially across China for both woody and herbaceous vegetation (Figs. 11b & d). For woody vegetation, FRB is more strongly concentrated in the surface soil layers in the mountainous regions of northeastern, central, and southwestern China, as well as in Taiwan Province (Fig. 11b). These regions generally have shallower soil profiles than other parts of China due to carbonate bedrock in southwestern China, slower rock weathering rates caused by low temperatures in northeastern China, and high soil erosion associated with steep slopes and intense rainfall in central and southern China. The spatial pattern of surface-layer FRB proportion in herbaceous vegetation differed notably from that of woody vegetation. Herbaceous fine roots were less concentrated in the surface soil layers of the Qinghai-Tibet Plateau than in other regions of China. This indicates a relatively deeper vertical distribution of herbaceous roots in alpine regions, likely reflecting an adaptive strategy to access more stable soil moisture and nutrients under cold, dry, and high-altitude environmental conditions.

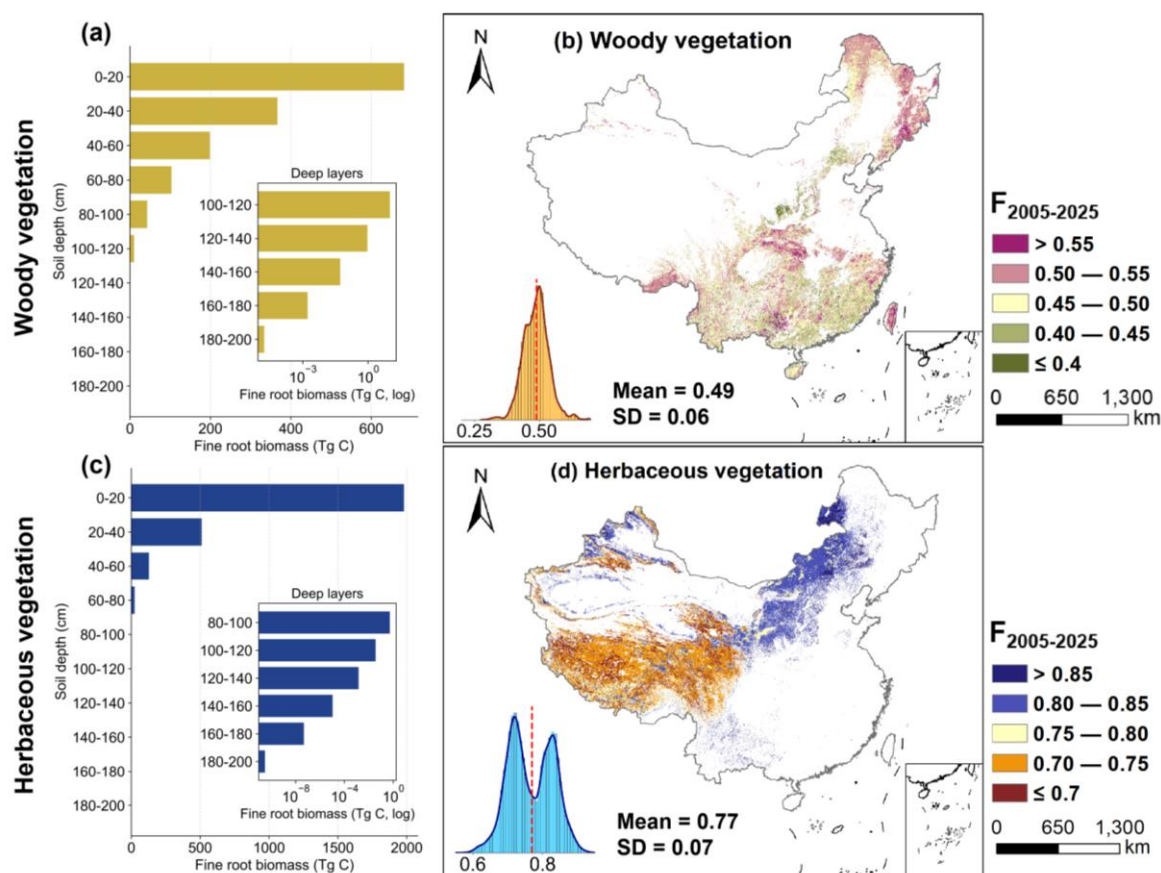


Figure 11. Total fine-root biomass (FRB) in different soil layers across China (a, c) and the spatial patterns of the ratios of surface-layer (0–20 cm) FRB to total FRB within the 0–2 m soil profile (b, d). The insets in panels (b) and (d) present frequency distribution histograms of FRB for woody and herbaceous vegetation types, respectively. Mean and SD in panels (b) and (d) represent the mean value and standard deviation across different grid cells, respectively. $F_{2005-2025}$ is the proportion of FRB in the surface layer (0–20 cm) relative to the total FRB of the whole soil profile during 2005–2025.



3.6 Historical changes in FRB and profile across China

Application of the trained RF models indicates that the total FRB (0–2 m) for both woody and herbaceous vegetation across China declined significantly ($p < 0.01$) over the period 2005–2025 (Figs. 12a & c). From 2005 to 2025, total woody FRB declined by approximately 20%, which is substantially greater than the decrease in in total herbaceous FRB (approximately 2%).

The changes in FRB from 2005 to 2025 for both woody and herbaceous vegetation varied substantially across China. Although woody FRB increased across most regions of China during this period, numerous mountainous regions in southern, central, and northeastern China—where FRB were generally higher than in other regions (Fig. 12a)—experienced notable declines in woody FRB (Fig. 12b). In contrast to woody vegetation, herbaceous FRB decreased markedly across the Qinghai-Tibet Plateau, while increasing across the semi-arid belt extending from northeastern to southwestern China (Fig. 12d). Because FRB declined in regions with initially high FRB while increasing in regions with relatively low FRB, the overall spatial heterogeneity of FRB for both woody and herbaceous vegetation decreased over the past two decades.

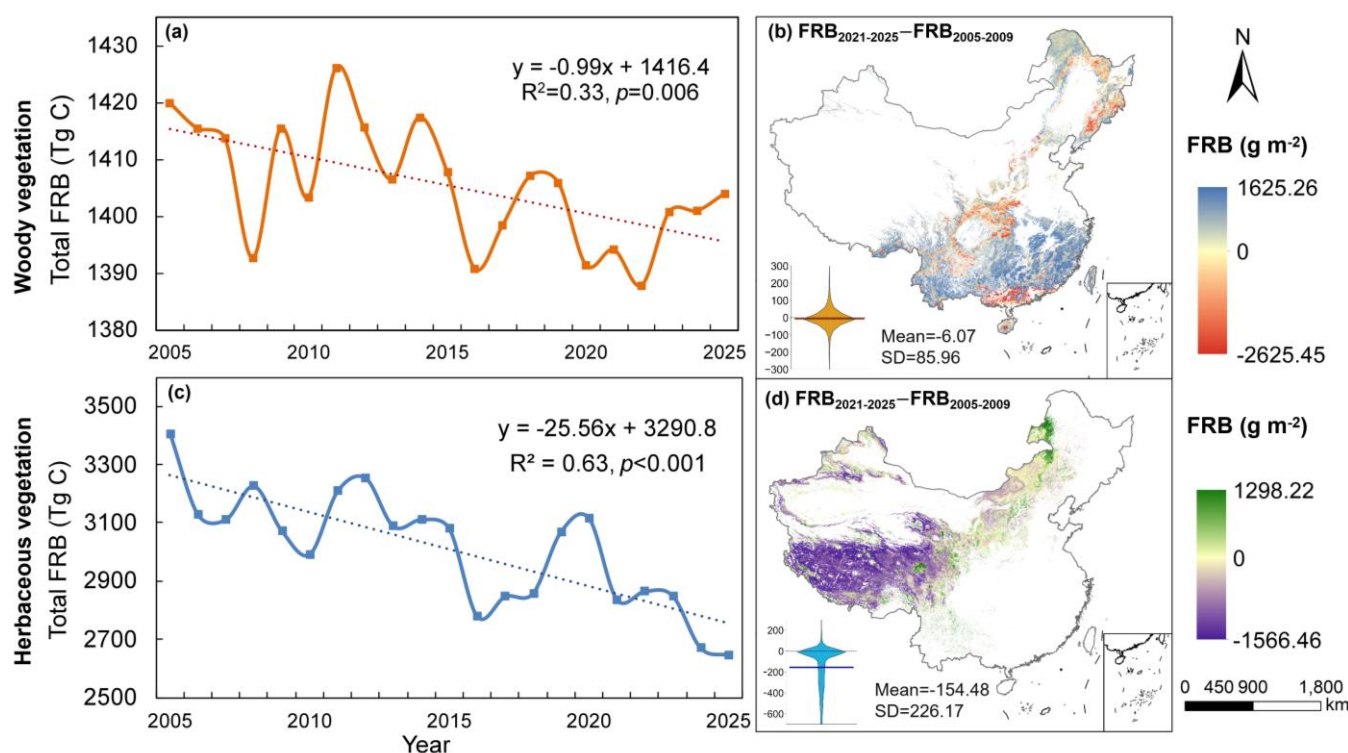


Figure 12. Spatiotemporal dynamics of fine-root biomass (FRB) in China during 2005–2025. Panel (a), (c) temporal variation in total mean fine-root biomass (FRB) in China from 2005 to 2025. Panel (b), (d) spatial distribution of changes in mean FRB between 2020–2025 and 2005–2010. Mean and SD in panels (b) and (d) represent the mean value and standard deviation across different grid cells, respectively.

Our simulation results further reveal that environmental change over the past two decades significantly ($p < 0.01$) increased the proportion of FRB in the surface (0–20 cm) soil layer relative to FRB (F value) within the 0–2 m soil profile (Fig. 13). For



woody vegetation, the mean proportion of surface-layer to whole-profile FRB increased from less than 48% in 2005 to more
 395 than 49% in 2025 (Fig. 13a), while for herbaceous vegetation, the proportion increased from approximately 76.5% to more
 than 78% (Fig. 13c). The proportion of surface-layer to whole-profile FRB in woody vegetation increased across most regions
 of China over the past two decades, with decreases mainly occurring in southwestern China. For herbaceous vegetation, this
 proportion also increased across most regions of China, except for limited areas of the Qinghai-Tibet Plateau. These changes
 in vertical FRB distribution patterns may further influence soil biogeochemical cycling and alter vegetation responses to future
 400 climate change.

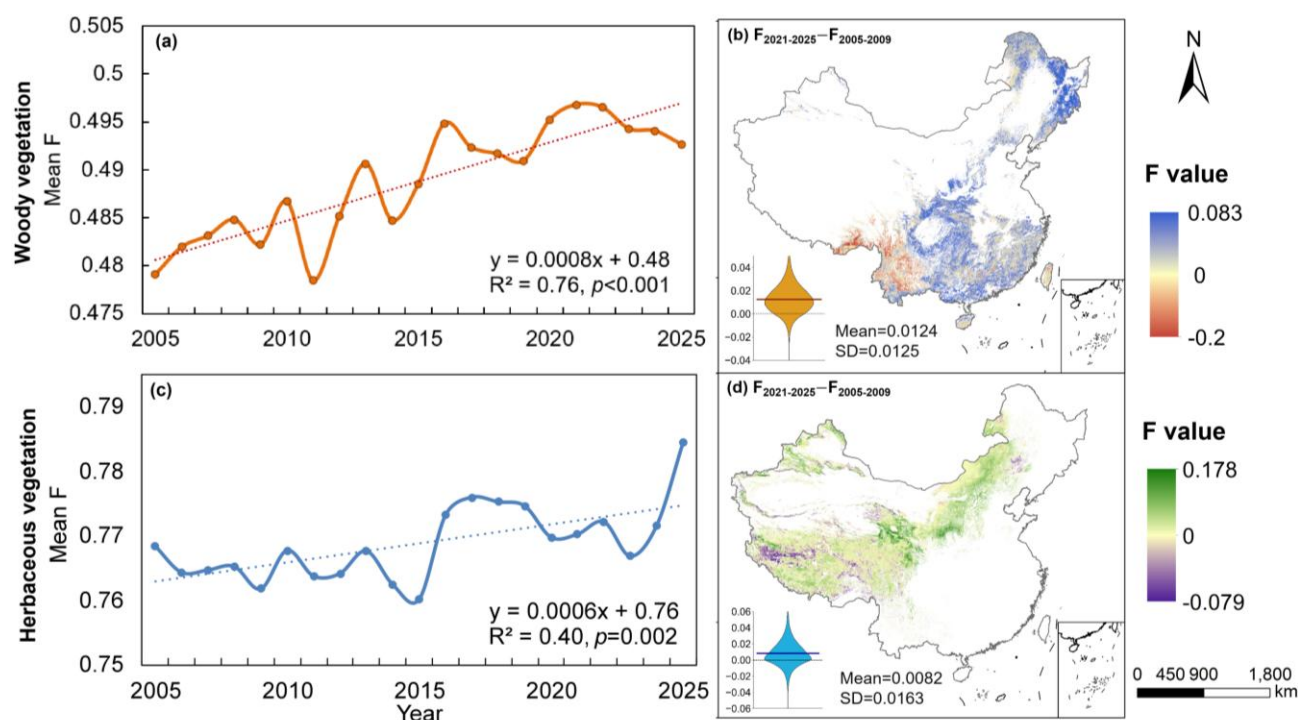


Figure 13. Spatiotemporal changes in the proportion of fine-root biomass (FRB) in the surface soil layer (0–20 cm) relative to total FRB (0–2 m) in China during 2005–2025. Panels (a) and (c) temporal variations in F (the surface (0–20 cm) soil layer relative to FRB within the 0–2 m soil profile). Panels (b) and (d) spatial changes in F between 2005–2010 and 2020–2025. Mean and SD in panels (b) and
 405 (d) represent the mean value and standard deviation across different grid cells, respectively.

4 Conclusions

Based on 2,311 in-situ measurements of woody FRB and 3,580 measurements of herbaceous FRB collected from peer-
 reviewed studies across China, we established separate RF models to estimate surface-layer (0–20 cm) FRB and the vertical
 attenuation coefficient (k) for woody and herbaceous ecosystems. Model validation showed strong predictive performance,
 410 explaining approximately 86% and 81% of the variation in surface-layer FRB for woody and herbaceous vegetation,
 respectively. Temporal validation further indicated that the models were able to reproduce the observed temporal variability



in FRB, while leave-one-year-out validation demonstrated that the models retained predictive skill when applied to years excluded from model training. Together, these complementary validation results provide evidence that the models captured not only spatial variation but also part of the temporal variability in observed FRB. The drivers of FRB differed substantially between vegetation types. Surface-layer FRB in woody vegetation was mainly regulated by root morphological traits and soil nutrient availability, whereas herbaceous FRB was more strongly constrained by climatic factors, particularly temperature. For vertical root distribution, woody vegetation was primarily influenced by species richness and aridity, while herbaceous vegetation was more sensitive to soil texture, elevation, and thermal conditions. These results highlight distinct belowground resource allocation strategies between woody and herbaceous plant communities.

By integrating the trained RF models, we produced a gridded dataset of FRB across 0–2 m soil depth (at 20 cm intervals) at 1 km spatial resolution for woody and herbaceous ecosystems across China during 2005–2025. The results showed that total FRB within the 0–2 m soil profile reached 1.4 Pg C for woody vegetation and 3.0 Pg C for herbaceous vegetation. Uncertainty analysis showed that the mean relative uncertainty in simulated woody and herbaceous FRB across China are $11 \pm 0.5\%$ and $15 \pm 0.5\%$, respectively. Higher uncertainties in simulated woody FRB mainly concentrated in southern China, whereas high uncertainties in simulated herbaceous FRB primarily distributed across northern China. Both FRB and vertical distribution exhibited pronounced spatial heterogeneity across climate zones and vegetation types. Over the past two decades, total FRB in the 0–2 m soil profile declined significantly ($p < 0.01$) for both woody and herbaceous vegetation, while fine roots of both vegetation types showed an increasing tendency to concentrate in surface soil layers. This upward shift in root distribution may have important implications for soil carbon cycling, nutrient turnover, and ecosystem responses to future climate change.

Overall, the dataset developed in this study provides a valuable national-scale benchmark for investigating belowground carbon dynamics, improving the parameterization and validation of terrestrial ecosystem models, and enhancing predictions of vegetation responses to ongoing environmental change.

Code and data availability

The gridded dataset of FRB across 0–2 m soil depth (at 20 cm intervals) at 1 km spatial resolution for all woody and herbaceous ecosystems in China over the period 2005–2025 is available at <https://doi.org/10.6084/m9.figshare.32353257> (Zheng et al., 2026).

Supplement link

The supplementary material is provided as a separate file published with this article.



Author contributions

440 HZ conceived and designed the study and secured funding support. WZ compiled the fine-root biomass dataset, conducted model development, training, and evaluation, performed the simulations and data analysis, and wrote the initial manuscript. HZ and WZ jointly interpreted the results, designed the figures, and revised the manuscript. All co-authors contributed substantially to environmental data collection, model development, and manuscript revision.

Competing interests

445 The contact author has declared that none of the authors has any competing interests.

Disclaimer

Publisher's note: Copernicus Publications remains neutral with regard to jurisdictional claims made in the text, published maps, institutional affiliations, or any other geographical representation in this paper. While Copernicus Publications makes every effort to include appropriate place names, the final responsibility lies with the authors. Views expressed in the text are those
450 of the authors and do not necessarily reflect the views of the publisher.

Acknowledgements

Besides the author's statement of gratitude to and recognition of the people and institutions that helped the author's research and writing, authors are also asked to include relevant research infrastructure they have benefitted from during their research, where research was conducted or data/resources were used. Examples are Field Stations and Marine Laboratories (FSMLs).

455 Financial support

This work was supported by the Young Scientists Project of the National Key R&D Program of China (Grant No. 2024YFF0811000), the National Natural Science Foundation of China (Grant No. 42301020), and the High-Level Young Talent Program (Grant Nos. 2024HYSPT1105, 24hytd001).

References

460 Bardgett, R. D., Mommer, L., and Vries, F. T. D.: Going underground: Root traits as drivers of ecosystem processes, Trends Ecol. Evol., 29, 692–699, <https://doi.org/10.1016/j.tree.2014.10.006>, 2014.



- Barry, K. E., Mommer, L., Van Ruijven, J., Wirth, C., Wright, A. J., Bai, Y., Connolly, J., De Deyn, G. B., De Kroon, H., Isbell, F., Milcu, A., Roscher, C., Scherer-Lorenzen, M., Schmid, B., and Weigelt, A.: The future of complementarity: Disentangling causes from consequences, *Trends Ecol. Evol.*, 34, 167–180, <https://doi.org/10.1016/j.tree.2018.10.013>, 2019.
- 465 Brunner, I., Bakker, M. R., Björk, R. G., Hirano, Y., Lukac, M., Aranda, X., Børja, I., Eldhuset, T. D., Helmisaari, H. S., Jourdan, C., Konôpka, B., López, B. C., Miguel Pérez, C., Persson, H., and Ostonen, I.: Fine-root turnover rates of european forests revisited: An analysis of data from sequential coring and ingrowth cores, *Plant Soil*, 362, 357–372, <https://doi.org/10.1007/s11104-012-1313-5>, 2013.
- Canadell, J., Jackson, R. B., Ehleringer, J. B., Mooney, H. A., Sala, O. E., and Schulze, E.-D.: Maximum rooting depth of
 470 vegetation types at the global scale, *Oecologia*, 108, 583–595, <https://doi.org/10.1007/BF00329030>, 1996.
- Chang, R., Fu, B., Liu, G., Yao, X., and Wang, S.: Effects of soil physicochemical properties and stand age on fine root biomass and vertical distribution of plantation forests in the loess plateau of China, *Ecol. Res.*, 27, 827–836, <https://doi.org/10.1007/s11284-012-0958-0>, 2012.
- Chen, G., Hobbie, S. E., Reich, P. B., Yang, Y., and Robinson, D.: Allometry of fine roots in forest ecosystems, *Ecol. Lett.*,
 475 22, 322–331, <https://doi.org/10.1111/ele.13193>, 2019.
- Cordeiro, A. L., Norby, R. J., Andersen, K. M., Valverde-Barrantes, O., Fuchslueger, L., Oblitas, E., Hartley, I. P., Iversen, C. M., Gonçalves, N. B., Takeshi, B., Lapola, D. M., and Quesada, C. A.: Fine-root dynamics vary with soil depth and precipitation in a low-nutrient tropical forest in the central amazonia, *Plant-environ. Interact.*, 1, 3–16, <https://doi.org/10.1002/pei3.10010>, 2020.
- 480 Davis, J. P., Haines, B., Coleman, D., and Hendrick, R.: Fine root dynamics along an elevational gradient in the southern appalachian mountains, USA, *For. Ecol. Manage.*, 187, 19–33, [https://doi.org/10.1016/S0378-1127\(03\)00226-3](https://doi.org/10.1016/S0378-1127(03)00226-3), 2004.
- Desborough, C. E.: The impact of root weighting on the response of transpiration to moisture stress in land surface schemes, *Mon. Wea. Rev.*, 125, 1920–1930, [https://doi.org/10.1175/1520-0493\(1997\)125%3C1920:TIORWO%3E2.0.CO;2](https://doi.org/10.1175/1520-0493(1997)125%3C1920:TIORWO%3E2.0.CO;2), 1997.
- Earth Science Data Systems, N.: MODIS/terra+aqua leaf area index/FPAR 4-day L4 global 500m SIN grid V061 | NASA
 485 earthdata, <https://www.earthdata.nasa.gov/data/catalog/lpcloud-mcd15a3h-061> (last access: 21 April 2026a), 2025.
- Earth Science Data Systems, N.: MODIS/terra net evapotranspiration 8-day L4 global 500m SIN grid V061 | NASA earthdata, <https://www.earthdata.nasa.gov/data/catalog/lpcloud-mod16a2-061> (last access: 21 April 2026b), 2025.
- Earth Science Data Systems, N.: MODIS/terra vegetation indices 16-day L3 global 250m SIN grid V061 | NASA earthdata, <https://www.earthdata.nasa.gov/data/catalog/lpcloud-mod13q1-061> (last access: 21 April 2026c), 2025.
- 490 Fan, Y., Miguez-Macho, G., Jobbágy, E. G., Jackson, R. B., and Otero-Casal, C.: Hydrologic regulation of plant rooting depth, *Proceedings of the National Academy of Sciences*, 114, 10572–10577, <https://doi.org/10.1073/pnas.1712381114>, 2017.
- Farr, T. G., Rosen, P. A., Caro, E., Crippen, R., Duren, R., Hensley, S., Kobrick, M., Paller, M., Rodriguez, E., Roth, L., Seal, D., Shaffer, S., Shimada, J., Umland, J., Werner, M., Oskin, M., Burbank, D., and Alsdorf, D.: The shuttle radar topography mission, *Rev. Geophys.*, 45, <https://doi.org/10.1029/2005RG000183>, 2007.



- 495 Filippelli, S. K., Schleeweis, K., Nelson, M. D., Fekety, P. A., and Vogeler, J. C.: Testing temporal transferability of remote sensing models for large area monitoring, *Science of Remote Sensing*, 9, 100119, <https://doi.org/10.1016/j.srs.2024.100119>, 2024.
- Finér, L., Ohashi, M., Noguchi, K., and Hirano, Y.: Factors causing variation in fine root biomass in forest ecosystems, *For. Ecol. Manage.*, 261, 265–277, <https://doi.org/10.1016/j.foreco.2010.10.016>, 2011.
- 500 Freschet, G. T., Roumet, C., Comas, L. H., Weemstra, M., Bengough, A. G., Rewald, B., Bardgett, R. D., De Deyn, G. B., Johnson, D., Klimešová, J., Lukac, M., McCormack, M. L., Meier, I. C., Pagès, L., Poorter, H., Prieto, I., Wurzbarger, N., Zadworny, M., Bagniewska-Zadworna, A., Blancaflor, E. B., Brunner, I., Gessler, A., Hobbie, S. E., Iversen, C. M., Mommer, L., Picon-Cochard, C., Postma, J. A., Rose, L., Ryser, P., Scherer-Lorenzen, M., Soudzilovskaia, N. A., Sun, T., Valverde-Barrantes, O. J., Weigelt, A., York, L. M., and Stokes, A.: Root traits as drivers of plant and ecosystem functioning: Current
- 505 understanding, pitfalls and future research needs, *New Phytol.*, 232, 1123–1158, <https://doi.org/10.1111/nph.17072>, 2021.
- Geng, Q., Ma, X., Liao, J., Wu, W., Niu, S., Luo, Y., and Xu, X.: Contrasting nutrient-mediated responses between surface and deep fine root biomass to N addition in poplar plantations on the east coast of China, *For. Ecol. Manage.*, 490, 119152, <https://doi.org/10.1016/j.foreco.2021.119152>, 2021.
- Gill, R. A. and Jackson, R. B.: Global patterns of root turnover for terrestrial ecosystems, *The New Phytologist*, 147, 13–31, <https://doi.org/10.1046/j.1469-8137.2000.00681.x>, 2000.
- 510 Guyon, I., Weston, J., Barnhill, S., and Vapnik, V.: Gene Selection for Cancer Classification using Support Vector Machines, <https://link.springer.com/article/10.1023/A:1012487302797>, 2002.
- Hayashi, R., Maie, N., Wagai, R., Hirano, Y., Matsuda, Y., Makita, N., Mizoguchi, T., Wada, R., and Tanikawa, T.: An increase of fine-root biomass in nutrient-poor soils increases soil organic matter but not soil cation exchange capacity, *Plant Soil*, 482, 89–110, <https://doi.org/10.1007/s11104-022-05675-z>, 2023.
- 515 He, W., Mäkiranta, P., Straková, P., Ojanen, P., Penttilä, T., Bhuiyan, R., Minkinen, K., and Laiho, R.: Fine-root production in boreal peatland forests: Effects of stand and environmental factors, *For. Ecol. Manage.*, 550, 121503, <https://doi.org/10.1016/j.foreco.2023.121503>, 2023.
- Helfenstein, P.: Tectonic overturn on enceladus, *Nature Geosci*, 3, 75–76, <https://doi.org/10.1038/ngeo763>, 2010.
- 520 Huang, J., Liu, L., Qi, K., Yang, T., Yang, B., Bao, W., and Pang, X.: Differential mechanisms drive changes in soil C pools under N and P enrichment in a subalpine spruce plantation, *Geoderma*, 340, 213–223, <https://doi.org/10.1016/j.geoderma.2019.01.027>, 2019.
- Iversen, C. M., McCormack, M. L., Powell, A. S., Blackwood, C. B., Freschet, G. T., Kattge, J., Roumet, C., Stover, D. B., Soudzilovskaia, N. A., Valverde-Barrantes, O. J., van Bodegom, P. M., and Violle, C.: A global fine-root ecology database to
- 525 address below-ground challenges in plant ecology, *New Phytol.*, 215, 15–26, <https://doi.org/10.1111/nph.14486>, 2017.
- Jackson, R. B., Canadell, J., Ehleringer, J. R., Mooney, H. A., Sala, O. E., and Schulze, E. D.: A global analysis of root distributions for terrestrial biomes, *Oecologia*, 108, 389–411, <https://doi.org/10.1007/BF00333714>, 1996.



- Jackson, R. B., Mooney, H. A., and Schulze, E.-D.: A global budget for fine root biomass, surface area, and nutrient contents, *Proc. Natl. Acad. Sci. U.S.A.*, 94, 7362–7366, <https://doi.org/10.1073/pnas.94.14.7362>, 1997.
- 530 Jobbágy, E. G. and Jackson, R. B.: The vertical distribution of soil organic carbon and its relation to climate and vegetation, *Ecol. Appl.*, 10, 423–436, [https://doi.org/10.1890/1051-0761\(2000\)010%5B0423:TVDOSO%5D2.0.CO;2](https://doi.org/10.1890/1051-0761(2000)010%5B0423:TVDOSO%5D2.0.CO;2), 2000.
- Jobbágy, E. G. and Jackson, R. B.: The distribution of soil nutrients with depth: Global patterns and the imprint of plants, *Biogeochemistry*, 53, 51–77, <https://doi.org/10.1023/A:1010760720215>, 2001.
- Karki, H., Bargali, K., and Bargali, S. S.: Spatial and seasonal pattern of fine root biomass and turnover rate in different land
 535 use systems in central himalaya, India, *Russ. J. Ecol.*, 52, 36–48, <https://doi.org/10.1134/S1067413621010070>, 2021.
- Kattge, J., Bönisch, G., Díaz, S., Lavorel, S., Prentice, I. C., Leadley, P., Tautenhahn, S., Werner, G. D. A., Aakala, T., Abedi, M., Acosta, A. T. R., Adamidis, G. C., Adamson, K., Aiba, M., Albert, C. H., Alcántara, J. M., Alcázar C, C., Aleixo, I., Ali, H., Amiaud, B., Ammer, C., Amoroso, M. M., Anand, M., Anderson, C., Anten, N., Antos, J., Apgaua, D. M. G., Ashman, T., Asmara, D. H., Asner, G. P., Aspinwall, M., Atkin, O., Aubin, I., Baastrop-Spohr, L., Bahalkeh, K., Bahn, M., Baker, T.,
 540 Baker, W. J., Bakker, J. P., Baldocchi, D., Baltzer, J., Banerjee, A., Baranger, A., Barlow, J., Barneche, D. R., Baruch, Z., Bastianelli, D., Battles, J., Bauerle, W., Bauters, M., Bazzato, E., Beckmann, M., Beeckman, H., Beierkuhnlein, C., Bekker, R., Belfry, G., Belluau, M., Beloiu, M., Benavides, R., Benomar, L., Berdugo-Lattke, M. L., Berenguer, E., Bergamin, R., Bergmann, J., Bergmann Carlucci, M., Berner, L., Bernhardt-Römermann, M., Bigler, C., Bjorkman, A. D., Blackman, C., Blanco, C., Blonder, B., Blumenthal, D., Bocanegra-González, K. T., Boeckx, P., Bohlman, S., Böhning-Gaese, K., Boisvert-
 545 Marsh, L., Bond, W., Bond-Lamberty, B., Boom, A., Boonman, C. C. F., Bordin, K., Boughton, E. H., Boukili, V., Bowman, D. M. J. S., Bravo, S., Brendel, M. R., Broadley, M. R., Brown, K. A., Bruelheide, H., Brumnich, F., Bruun, H. H., Bruy, D., Buchanan, S. W., Bucher, S. F., Buchmann, N., Buitenwerf, R., Bunker, D. E., Bürger, J., Burrascano, S., Burslem, D. F. R. P., Butterfield, B. J., Byun, C., Marques, M., Scalón, M. C., Caccianiga, M., Cadotte, M., Cailleret, M., Camac, J., Camarero, J. J., Company, C., Campetella, G., Campos, J. A., Cano-Arboleda, L., Canullo, R., Carbognani, M., Carvalho, F., Casanoves, F., Castagneyrol, B., Catford, J. A., Cavender-Bares, J., Cerabolini, B. E. L., Cervellini, M., Chacón-Madrigal, E., Chapin, K.,
 550 Chapin, F. S., Chelli, S., Chen, S., Chen, A., Cherubini, P., Chianucci, F., Choat, B., Chung, K., Chytrý, M., Ciccarelli, D., Coll, L., Collins, C. G., Conti, L., Coomes, D., Cornelissen, J. H. C., Cornwell, W. K., Corona, P., Coyea, M., Craine, J., Craven, D., Croomsigt, J. P. G. M., Cseceserits, A., Cufar, K., Cuntz, M., Da Silva, A. C., Dahlin, K. M., Dainese, M., Dalke, I., Dalle Fratte, M., Dang-Le, A. T., Danihelka, J., Dannoura, M., Dawson, S., De Beer, A. J., De Frutos, A., De Long, J. R.,
 555 Dechant, B., Delagrange, S., Delpierre, N., Derroire, G., Dias, A. S., Diaz-Toribio, M. H., Dimitrakopoulos, P. G., Dobrowolski, M., Doktor, D., Dřevojan, P., Dong, N., Dransfield, J., Dressler, S., Duarte, L., Ducouret, E., Dullinger, S., Durka, W., Duursma, R., Dymova, O., E-Vojtkó, A., Eckstein, R. L., Ejtehadi, H., Elser, J., Emilio, T., Engemann, K., Erfanian, M. B., Erfmeier, A., Esquivel-Muelbert, A., Esser, G., Estiarte, M., Domingues, T. F., Fagan, W. F., Fagúndez, J., Falster, D. S., Fan, Y., Fang, J., Farris, E., Fazlioglu, F., Feng, Y., Fernandez-Mendez, F., Ferrara, C., Ferreira, J., Fidelis, A., Finegan,
 560 B., Firn, J., Flowers, T. J., Flynn, D. F. B., Fontana, V., Forey, E., Forgiarini, C., François, L., Frangipani, M., Frank, D., Frenette-Dussault, C., Freschet, G. T., Fry, E. L., Fyllas, N. M., Mazzochini, G. G., Gachet, S., Gallagher, R., Ganade, G.,



Ganga, F., García-Palacios, P., Gargaglione, V., Garnier, E., Garrido, J. L., De Gasper, A. L., Gea-Izquierdo, G., Gibson, D., Gillison, A. N., Girollo, A., Glasenhardt, M., Gleason, S., Gliesch, M., Goldberg, E., Göldel, B., Gonzalez-Akre, E., Gonzalez-Andujar, J. L., González-Melo, A., González-Robles, A., Graae, B. J., Granda, E., Graves, S., Green, W. A., Gregor, T., Gross, N., Guerin, G. R., Günther, A., Gutiérrez, A. G., Haddock, L., Haines, A., Hall, J., Hambuckers, A., Han, W., Harrison, S. P., Hattingh, W., Hawes, J. E., He, T., He, P., Heberling, J. M., Helm, A., Hempel, S., Hentschel, J., Hérault, B., Hereş, A., Herz, K., Heuertz, M., Hickler, T., Hietz, P., Higuchi, P., Hipp, A. L., Hirons, A., Hock, M., Hogan, J. A., Holl, K., Honnay, O., Hornstein, D., Hou, E., Hough-Snee, N., Hovstad, K. A., Ichie, T., Igić, B., Illa, E., Isaac, M., Ishihara, M., Ivanov, L., Ivanova, L., Iversen, C. M., Izquierdo, J., Jackson, R. B., Jackson, B., Jactel, H., Jagodzinski, A. M., Jandt, U., Jansen, S., Jenkins, T., Jentsch, A., Jespersen, J. R. P., Jiang, G., Johansen, J. L., Johnson, D., Jokela, E. J., Joly, C. A., Jordan, G. J., Joseph, G. S., Junaedi, D., Junker, R. R., Justes, E., Kabzems, R., Kane, J., Kaplan, Z., Kattenborn, T., Kavelenova, L., Kearsley, E., Kempel, A., Kenzo, T., Kerkhoff, A., Khalil, M. I., Kinlock, N. L., Kissling, W. D., Kitajima, K., Kitzberger, T., Kjoller, R., Klein, T., Kleyer, M., Klimešová, J., Klipel, J., Kloeppel, B., Klotz, S., Knops, J. M. H., Kohyama, T., Koike, F., Kollmann, J., Komac, B., Komatsu, K., König, C., Kraft, N. J. B., Kramer, K., Kreft, H., Kühn, I., Kumarathunge, D., Kuppler, J., Kurokawa, H., Kurosawa, Y., Kuyah, S., Laclau, J., Lafleur, B., Lallai, E., Lamb, E., Lamprecht, A., Larkin, D. J., Laughlin, D., Le Bagousse-Pinguet, Y., Le Maire, G., Le Roux, P. C., Le Roux, E., Lee, T., Lens, F., Lewis, S. L., Lhotsky, B., Li, Y., Li, X., Lichstein, J. W., Liebergesell, M., Lim, J. Y., Lin, Y., Linares, J. C., Liu, C., Liu, D., Liu, U., Livingstone, S., Llusà, J., Lohbeck, M., López-García, Á., Lopez-Gonzalez, G., Lososová, Z., Louault, F., Lukács, B. A., Lukeš, P., Luo, Y., Lussu, M., Ma, S., Maciel Rabelo Pereira, C., Mack, M., Maire, V., Mäkelä, A., Mäkinen, H., Malhado, A. C. M., Mallik, A., Manning, P., Manzoni, S., Marchetti, Z., Marchino, L., Marcilio-Silva, V., Marcon, E., Marignani, M., Markesteijn, L., Martin, A., Martínez-Garza, C., Martínez-Vilalta, J., Mašková, T., Mason, K., Mason, N., Massad, T. J., Masse, J., Mayrose, I., McCarthy, J., McCormack, M. L., McCulloh, K., McFadden, I. R., McGill, B. J., McPartland, M. Y., Medeiros, J. S., Medlyn, B., Meerts, P., Mehrabi, Z., Meir, P., Melo, F. P. L., Mencuccini, M., Meredieu, C., Messier, J., Mészáros, I., Metsaranta, J., Michaletz, S. T., Michelaki, C., Migalina, S., Milla, R., Miller, J. E. D., Minden, V., Ming, R., Mokany, K., Moles, A. T., Molnár, A., Molofsky, J., Molz, M., Montgomery, R. A., Monty, A., Moravcová, L., Moreno-Martínez, A., Moretti, M., Mori, A. S., Mori, S., Morris, D., Morrison, J., Mucina, L., Mueller, S., Muir, C. D., Müller, S. C., Munoz, F., Myers-Smith, I. H., Myster, R. W., Nagano, M., Naidu, S., Narayanan, A., Natesan, B., Negoita, L., Nelson, A. S., Neuschulz, E. L., Ni, J., Niedrist, G., Nieto, J., Niinemets, Ü., Nolan, R., Nottebrock, H., Nouvellon, Y., Novakovskiy, A., The Nutrient Network, Nystuen, K. O., O'Grady, A., O'Hara, K., O'Reilly-Nugent, A., Oakley, S., Oberhuber, W., Ohtsuka, T., Oliveira, R., Öllerer, K., Olson, M. E., Onipchenko, V., Onoda, Y., Onstein, R. E., Ordonez, J. C., Osada, N., Ostonen, I., Ottaviani, G., Otto, S., Overbeck, G. E., Ozinga, W. A., Pahl, A. T., Paine, C. E. T., Pakeman, R. J., Papageorgiou, A. C., Parfionova, E., Pärtel, M., Patacca, M., Paula, S., Paule, J., Pauli, H., Pausas, J. G., Peco, B., Penuelas, J., Perea, A., Peri, P. L., Petisco-Souza, A. C., Petraglia, A., Petritan, A. M., Phillips, O. L., Pierce, S., Pillar, V. D., Pisek, J., Pomogaybin, A., Poorter, H., Portsmouth, A., Poschlod, P., Potvin, C., Pounds, D., Powell, A. S., Power, S. A., Prinzing, A., Puglielli, G., Pyšek, P., Raevel, V., Rammig, A., Ransijn, J., Ray, C. A., Reich, P. B., Reichstein, M., Reid, D. E. B., Réjou-Méchain, M., De Dios, V. R., Ribeiro, S., Richardson, S., Riibak, K., Rillig, M. C.,



- Riviera, F., Robert, E. M. R., Roberts, S., Robroek, B., Roddy, A., Rodrigues, A. V., Rogers, A., Rollinson, E., Rolo, V., Römermann, C., Ronzhina, D., Roscher, C., Rosell, J. A., Rosenfield, M. F., Rossi, C., Roy, D. B., Royer-Tardif, S., Rüger, N., Ruiz-Peinado, R., Rumpf, S. B., Rusch, G. M., Ryo, M., Sack, L., Saldaña, A., Salgado-Negret, B., Salguero-Gomez, R., Santa-Regina, I., Santacruz-García, A. C., Santos, J., Sardans, J., Schamp, B., Scherer-Lorezen, M., Schleuning, M., Schmid, B., Schmidt, M., Schmitt, S., Schneider, J. V., Schowanek, S. D., Schrader, J., Schrod, F., Schuldt, B., Schurr, F., Selaya Garvizu, G., Semchenko, M., Seymour, C., Sfair, J. C., Sharpe, J. M., Sheppard, C. S., Sheremetiev, S., Shiodera, S., Shipley, B., Shovon, T. A., Siebenkäs, A., Sierra, C., Silva, V., Silva, M., Sitzia, T., Sjöman, H., Slot, M., Smith, N. G., Sodhi, D., Soltis, P., Soltis, D., Somers, B., Sonnier, G., Sørensen, M. V., Sosinski, E. E., Soudzilovskaia, N. A., Souza, A. F., Spasojevic, M., Sperandii, M. G., Stan, A. B., Stegen, J., Steinbauer, K., Stephan, J. G., Sterck, F., Stojanovic, D. B., Strydom, T., Suarez, M. L., Svenning, J., Svitková, I., Svitok, M., Svoboda, M., Swaine, E., Swenson, N., Tabarelli, M., Takagi, K., Tappeiner, U., Tarifa, R., Tauougeurdeau, S., Tavsanoğlu, C., Te Beest, M., Tedersoo, L., Thiffault, N., Thom, D., Thomas, E., Thompson, K., Thornton, P. E., Thuiller, W., Tichý, L., Tissue, D., Tjoelker, M. G., Tng, D. Y. P., Tobias, J., Török, P., Tarin, T., Torres-Ruiz, J. M., Tóthmérész, B., Treurnicht, M., Trivellone, V., Trolliet, F., Trotsiuk, V., Tsakalos, J. L., Tsiripidis, I., Tysklind, N., Umehara, T., Usoltsev, V., Vadeboncoeur, M., Vaezi, J., Valladares, F., Vamosi, J., Van Bodegom, P. M., Van Breugel, M., Van Cleemput, E., Van De Weg, M., Van Der Merwe, S., Van Der Plas, F., Van Der Sande, M. T., Van Kleunen, M., Van Meerbeek, K., Vanderwel, M., Vanselow, K. A., Vårhammar, A., Varone, L., Vasquez Valderrama, M. Y., Vassilev, K., Vellend, M., Veneklaas, E. J., Verbeeck, H., Verheyen, K., Vibrans, A., Vieira, I., Villacís, J., Violle, C., Vivek, P., Wagner, K., Waldram, M., Waldron, A., Walker, A. P., Waller, M., Walther, G., Wang, H., Wang, F., Wang, W., Watkins, H., Watkins, J., Weber, U., Weedon, J. T., Wei, L., Weigelt, P., Weiher, E., Wells, A. W., Wellstein, C., Wenk, E., Westoby, M., Westwood, A., White, P. J., Whitten, M., Williams, M., Winkler, D. E., Winter, K., Womack, C., Wright, I. J., Wright, S. J., Wright, J., Pinho, B. X., Ximenes, F., Yamada, T., Yamaji, K., Yanai, R., Yankov, N., Yguel, B., Zanini, K. J., Zanne, A. E., Zelený, D., Zhao, Y., Zheng, J., Zheng, J., Ziemińska, K., Zirbel, C. R., Zizka, G., Zo-Bi, I. C., Zotz, G., and Wirth, C.: TRY plant trait database – enhanced coverage and open access, *Global Change Biology*, 26, 119–188, <https://doi.org/10.1111/gcb.14904>, 2020.
- Kohavi, R.: A study of cross-validation and bootstrap for accuracy estimation and model selection, in: *Proceedings of the 14th international joint conference on Artificial intelligence - Volume 2*, 1137–1143, <https://www.ijcai.org/Proceedings/95-2/Papers/016.pdf>, 1995.
- Kulmatiski, A., Sprouse, S. R. C., and Beard, K. H.: Soil type more than precipitation determines fine-root abundance in savannas of kruger national park, south africa, *Plant Soil*, 417, 523–533, <https://doi.org/10.1007/s11104-017-3277-y>, 2017.
- Kuzyakov, Y. and Blagodatskaya, E.: Microbial hotspots and hot moments in soil: Concept & review, *Soil Biology and Biochemistry*, 83, 184–199, <https://doi.org/10.1016/j.soilbio.2015.01.025>, 2015.
- Lorenz, K. and Lal, R.: The depth distribution of soil organic carbon in relation to land use and management and the potential of carbon sequestration in subsoil horizons, in: *Advances in Agronomy*, vol. 88, Elsevier, 35–66, [https://doi.org/10.1016/S0065-2113\(05\)88002-2](https://doi.org/10.1016/S0065-2113(05)88002-2), 2005.



- Lundberg, S. M., Erion, G., Chen, H., DeGrave, A., Prutkin, J. M., Nair, B., Katz, R., Himmelfarb, J., Bansal, N., and Lee, S.-
 630 I.: From local explanations to global understanding with explainable AI for trees, *Nat Mach Intell*, 2, 56–67,
<https://doi.org/10.1038/s42256-019-0138-9>, 2020.
- Lyu, J., Zhang, Y., Dai, T., Wang, W., and Sang, S.: Eco-engineering effects of *setaria viridis* and *panicum bisulcatum* thunb
 roots on slope stability under controlled moisture conditions, *Sci. Rep.*, 15, 40456, [https://doi.org/10.1038/s41598-025-24096-](https://doi.org/10.1038/s41598-025-24096-3)
 3, 2025.
- 635 Ma, H., Mo, L., Crowther, T. W., Maynard, D. S., Van Den Hoogen, J., Stocker, B. D., Terrer, C., and Zohner, C. M.: The
 global distribution and environmental drivers of aboveground versus belowground plant biomass, *Nat. Ecol. Evol.*, 5, 1110–
 1122, <https://doi.org/10.1038/s41559-021-01485-1>, 2021.
- Ma, N., Li, S., McCormack, M. L., Freschet, G. T., Ciais, P., Wang, H., Niu, S., Reich, P. B., Zhang, M., Zhao, R., Zhao, B.,
 Gao, D., Gessler, A., Huang, Y., Gu, J., Fu, X., Dai, X., Meng, S., Zheng, J., Yang, F., and Kou, L.: Substantial forest soil
 640 carbon accrual from absorptive fine roots over decadal timescales, *Nat. Geosci.*, 18, 1020–1026,
<https://doi.org/10.1038/s41561-025-01790-5>, 2025.
- Ma, W., Shi, P., Li, W., He, Y., Zhang, X., Shen, Z., and Chai, S.: Changes in individual plant traits and biomass allocation in
 alpine meadow with elevation variation on the qinghai-tibetan plateau, *Sci. China Life Sci.*, 53, 1142–1151,
<https://doi.org/10.1007/s11427-010-4054-9>, 2010.
- 645 Ma, Z. and Chen, H. Y. H.: Effects of species diversity on fine root productivity increase with stand development and
 associated mechanisms in a boreal forest, *Journal of Ecology*, 105, 237–245, <https://doi.org/10.1111/1365-2745.12667>, 2017.
- Maeght, J.-L., Rewald, B., and Pierret, A.: How to study deep roots—and why it matters, *Front. Plant Sci.*, 4,
<https://doi.org/10.3389/fpls.2013.00299>, 2013.
- Malhotra, A., Moore, J. A. M., Weintraub-Leff, S., Georgiou, K., Berhe, A. A., Billings, S. A., de Graaff, M.-A., Fraterrigo,
 650 J. M., Grandy, A. S., Kyker-Snowman, E., Lu, M., Meier, C., Pierson, D., Tumber-Dávila, S. J., Lajtha, K., Wieder, W. R.,
 and Jackson, R. B.: Fine root and soil carbon stocks are positively related in grasslands but not in forests, *Commun. Earth
 Environ.*, 6, 497, <https://doi.org/10.1038/s43247-025-02486-9>, 2025.
- McCormack, M. L., Dickie, I. A., Eissenstat, D. M., Fahey, T. J., Fernandez, C. W., Guo, D., Helmisaari, H.-S., Hobbie, E.
 A., Iversen, C. M., Jackson, R. B., Leppälammi-Kujansuu, J., Norby, R. J., Phillips, R. P., Pregitzer, K. S., Pritchard, S. G.,
 655 Rewald, B., and Zadworny, M.: Redefining fine roots improves understanding of below-ground contributions to terrestrial
 biosphere processes, *New Phytol.*, 207, 505–518, <https://doi.org/10.1111/nph.13363>, 2015.
- Mitchell, N. J., Allendorf, F. W., Keall, S. N., Daugherty, C. H., and Nelson, N. J.: Demographic effects of temperature-
 dependent sex determination: Will tuatara survive global warming?, *Global Change Biol.*, 16, 60–72,
<https://doi.org/10.1111/j.1365-2486.2009.01964.x>, 2010.
- 660 Mokany, K., Raison, R. J., and Prokushkin, A. S.: Critical analysis of root : Shoot ratios in terrestrial biomes, *Global Change
 Biology*, 12, 84–96, <https://doi.org/10.1111/j.1365-2486.2005.001043.x>, 2006.



- Moser, G., Leuschner, C., Röderstein, M., Graefe, S., Soethe, N., and Hertel, D.: Biomass and productivity of fine and coarse roots in five tropical mountain forests stands along an altitudinal transect in southern ecuador, *Plant Ecology & Diversity*, 3, 151–164, <https://doi.org/10.1080/17550874.2010.517788>, 2010.
- 665 Muñoz-Sabater, J., Dutra, E., Agustí-Panareda, A., Albergel, C., Arduini, G., Balsamo, G., Boussetta, S., Choulga, M., Harrigan, S., Hersbach, H., Martens, B., Miralles, D. G., Piles, M., Rodríguez-Fernández, N. J., Zsoter, E., Buontempo, C., and Thépaut, J.-N.: ERA5-land: A state-of-the-art global reanalysis dataset for land applications, *Earth Syst. Sci. Data*, 13, 4349–4383, <https://doi.org/10.5194/essd-13-4349-2021>, 2021.
- Ni, J.: A simulation of biomes on the tibetan plateau and their responses to global climate change, *Mountain Research and*
 670 *Development*, 20, 80–89, <https://www.jstor.org/stable/3674211>, 2000.
- Niu, S., Wu, M., Han, Y., Xia, J., Zhang, Z., Yang, H., and Wan, S.: Nitrogen effects on net ecosystem carbon exchange in a temperate steppe, *Global Change Biology*, 16, 144–155, <https://doi.org/10.1111/j.1365-2486.2009.01894.x>, 2010.
- Nurse, P., Treisman, R., and Smith, J.: Building better institutions, *Science*, 341, 10–10, <https://doi.org/10.1126/science.1242307>, 2013.
- 675 Pan, Y.-L., Tang, H.-P., Liu, D., and Ma, Y.-G.: Geographical patterns and drivers of plant productivity and species diversity in the qinghai-tibet plateau, *Plant Diversity*, 47, 908–919, <https://doi.org/10.1016/j.pld.2023.06.007>, 2025.
- Pausch, J. and Kuzyakov, Y.: Carbon input by roots into the soil: Quantification of rhizodeposition from root to ecosystem scale, *Global Change Biol.*, 24, 1–12, <https://doi.org/10.1111/gcb.13850>, 2018.
- Peng, S. and Chen, H. Y. H.: Global responses of fine root biomass and traits to plant species mixtures in terrestrial ecosystems, *Global Ecol. Biogeogr.*, 30, 289–304, <https://doi.org/10.1111/geb.13205>, 2021.
- 680 Piao, S., Ciais, P., Huang, Y., Shen, Z., Peng, S., Li, J., Zhou, L., Liu, H., Ma, Y., Ding, Y., Friedlingstein, P., Liu, C., Tan, K., Yu, Y., Zhang, T., and Fang, J.: The impacts of climate change on water resources and agriculture in China, *Nature*, 467, 43–51, <https://doi.org/10.1038/nature09364>, 2010.
- Rasse, D. P., Rumpel, C., and Dignac, M.-F.: Is soil carbon mostly root carbon? Mechanisms for a specific stabilisation, *Plant*
 685 *Soil*, 269, 341–356, <https://doi.org/10.1007/s11104-004-0907-y>, 2005.
- Rumpel, C. and Kögel-Knabner, I.: Deep soil organic matter—a key but poorly understood component of terrestrial C cycle, *Plant Soil*, 338, 143–158, <https://doi.org/10.1007/s11104-010-0391-5>, 2011.
- Saha, S., Huang, L., Khoso, M. A., Wu, H., Han, D., Ma, X., Poudel, T. R., Li, B., Zhu, M., Lan, Q., Sakib, N., Wei, R., Islam, Md. Z., Zhang, P., and Shen, H.: Fine root decomposition in forest ecosystems: An ecological perspective, *Front. Plant Sci.*,
 690 14, 1277510, <https://doi.org/10.3389/fpls.2023.1277510>, 2023.
- Schenk, H. J. and Jackson, R. B.: Rooting depths, lateral root spreads and below-ground/above-ground allometries of plants in water-limited ecosystems, *J. Ecol.*, 90, 480–494, <https://www.jstor.org/stable/3072232>, 2002a.
- Schenk, H. J. and Jackson, R. B.: The global biogeography of roots, *Ecol. Monogr.*, 72, 311–328, [https://doi.org/10.1890/0012-9615\(2002\)072%5B0311:TGBOR%5D2.0.CO;2](https://doi.org/10.1890/0012-9615(2002)072%5B0311:TGBOR%5D2.0.CO;2), 2002b.



- 695 Shan, L., Yang, C., Li, Y., Duan, Y., Geng, D., Li, Z., Zhang, R., Duan, G., and Васильевич, Ж. А.: Effects of drought stress on root physiological traits and root biomass allocation of reaumuria soongorica, *Acta Ecol. Sin.*, 35, 155–159, <https://doi.org/10.1016/j.chnaes.2015.06.010>, 2015.
- Shangguan, W., Dai, Y., Liu, B., Zhu, A., Duan, Q., Wu, L., Ji, D., Ye, A., Yuan, H., Zhang, Q., Chen, D., Chen, M., Chu, J., Dou, Y., Guo, J., Li, H., Li, J., Liang, L., Liang, X., Liu, H., Liu, S., Miao, C., and Zhang, Y.: A China data set of soil properties
700 for land surface modeling, *James*, 5, 212–224, <https://doi.org/10.1002/jame.20026>, 2013.
- Shangguan, W., Dai, Y., Duan, Q., Liu, B., and Yuan, H.: A global soil data set for earth system modeling, *James*, 6, 249–263, <https://doi.org/10.1002/2013MS000293>, 2014.
- Sokol, N. W. and Bradford, M. A.: Microbial formation of stable soil carbon is more efficient from belowground than aboveground input, *Nat. Geosci.*, 12, 46–53, <https://doi.org/10.1038/s41561-018-0258-6>, 2019.
- 705 Tilman, D., Reich, P. B., Knops, J., Wedin, D., Mielke, T., and Lehman, C.: Diversity and productivity in a long-term grassland experiment, *Science*, 294, 843–845, <https://doi.org/10.1126/science.1060391>, 2001.
- Tredennick, A. T., Hooker, G., Ellner, S. P., and Adler, P. B.: A practical guide to selecting models for exploration, inference, and prediction in ecology, *Ecology*, 102, e03336, <https://doi.org/10.1002/ecy.3336>, 2021.
- Vogt, K. A., Vogt, D. J., and Bloomfield, J.: Analysis of some direct and indirect methods for estimating root biomass and
710 production of forests at an ecosystem level, in: *Root Demographics and Their Efficiencies in Sustainable Agriculture, Grasslands and Forest Ecosystems*, edited by: Box, J. E., Springer Netherlands, Dordrecht, 687–720, https://doi.org/10.1007/978-94-011-5270-9_61, 1998.
- Wang, P., Huang, K., and Hu, S.: Distinct fine-root responses to precipitation changes in herbaceous and woody plants: A meta-analysis, *New Phytol.*, 225, 1491–1499, <https://doi.org/10.1111/nph.16266>, 2020.
- 715 Wenlu Zheng, Min Zhao, Woheng Li, Deshuai Zhang, Weihua Tang, Junshen Luo, Shuning Jiao, Fengtai Li, Haicheng Zhang: A high-resolution gridded dataset of vertically resolved fine root biomass from 2005 to 2025 across China, <https://doi.org/10.6084/m9.figshare.32353257.v1>, 2026.
- Xiao, S., Liu, L., Zhang, Y., Sun, H., Zhang, K., Bai, Z., Dong, H., and Li, C.: Fine root and root hair morphology of cotton under drought stress revealed with RhizoPot, *J. Agron. Crop Sci.*, 206, 679–693, <https://doi.org/10.1111/jac.12429>, 2020.
- 720 Yuan, Z. Y. and Chen, H. Y. H.: Fine root biomass, production, turnover rates, and nutrient contents in boreal forest ecosystems in relation to species, climate, fertility, and stand age: Literature review and meta-analyses, *Crit. Rev. Plant Sci.*, 29, 204–221, <https://doi.org/10.1080/07352689.2010.483579>, 2010.
- Yuan, Z. Y. and Chen, H. Y. H.: A global analysis of fine root production as affected by soil nitrogen and phosphorus, *Proc Biol Sci*, 279, 3796–3802, <https://doi.org/10.1098/rspb.2012.0955>, 2012.
- 725 Zeng, X.: Global vegetation root distribution for land modeling, https://journals.ametsoc.org/view/journals/hydr/2/5/1525-7541_2001_002_0525_gvrdf1_2_0_co_2.xml, 2001.



Zhou, G., Zhou, X., Nie, Y., Bai, S. H., Zhou, L., Shao, J., Cheng, W., Wang, J., Hu, F., and Fu, Y.: Drought-induced changes in root biomass largely result from altered root morphological traits: Evidence from a synthesis of global field trials, *Plant Cell Environ.*, 41, 2589–2599, <https://doi.org/10.1111/pce.13356>, 2018.

730