



ChinaTD30: An annual 30 m tree density dataset for China (1985-2022)

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Abstract. Accurate information on tree density and its long-term dynamics is essential for understanding forest demography, ecosystem restoration, and terrestrial carbon cycling. However, existing tree-density products for China are generally limited by coarse spatial resolution, restricted temporal coverage, or a focus only on forested areas. Here, we developed a 30 m tree-density dataset for China (ChinaTD30) spanning 1985–2022 by integrating four cycles of the National Forest Inventory (NFI), each comprising 670,279 plot observations, with long-term satellite observations, forest attributes, land-cover information, and environmental variables. Three modelling strategies were evaluated to balance prediction accuracy and temporal consistency, and a temporally unified model was adopted for the reconstruction of the released product. The resulting dataset characterizes tree density in both forest and non-forest ecosystems and resolves substantial spatial heterogeneity across China. Comparison with existing tree-density products showed large discrepancies in densely forested regions, partly reflecting differences in training data, spatial resolution, and model structure. The reconstructed time series reveals a pronounced long-term increase in China's tree population. Forest trees increased from approximately 106 billion in 1985 to about 182 billion in 2022, an increase of approximately 72%, while trees outside forests increased from about 2.3 billion to 5.1 billion. Tree number increases were evident not only across northern restoration regions but also in densely forested southeastern China. Tree density exhibited distinct age-related patterns between natural and planted forests, with densities generally peaking in young-to-middle-aged stands before declining in older stands. This dataset provides a spatially detailed and temporally consistent basis for investigating forest dynamics, ecological restoration, tree mortality, carbon cycling, and the contribution of trees outside forests across China. The dataset is available at <https://doi.org/10.5281/zenodo.23100944> (Xian et al., 2026a), with the nine associated part records detailed in the Data availability section.



1 Introduction

Tree density, defined as the number of tree stems per unit area, is a basic descriptor of forest stand structure. Together with tree size distribution and basal area, it provides information on stand stocking, structural development, competition for resources, and potential biomass accumulation (Wang et al., 2024). Changes in tree density reflect demographic processes such as recruitment and mortality, as well as the effects of disturbance and forest management. These processes are increasingly being altered by climate change. For example, comparisons between historical and contemporary forest inventories in California revealed a shift toward higher stem densities and smaller trees, accompanied by a decline in basal area (McIntyre et al., 2015). At broader scales, changes in climate and disturbance regimes are altering forest recruitment, growth, and mortality, with growing evidence that these demographic changes can shift forests toward younger and shorter-statured stands (McDowell et al., 2020; Senf et al., 2021), although the direction and magnitude of these responses vary among forest biomes. Such changes in forest demography and structure have important implications for terrestrial carbon storage and uptake. Global forests have maintained a substantial carbon sink over the past three decades, despite pronounced regional differences in sink strength and dynamics (Pan et al., 2024). In China, large-scale ecological restoration and afforestation programs have also contributed substantially to increases in ecosystem carbon stocks (Lu et al., 2018). Quantifying long-term changes in tree density is therefore important for understanding how forest restoration, stand development, and climate-related stress jointly affect forest structure and its associated carbon dynamics.

Field inventories provide direct and standardized measurements of tree abundance and remain indispensable for characterizing forest structure and calibrating remote-sensing products. However, their high costs and spatially discrete sampling make it difficult to characterize spatially continuous tree-density patterns over large regions and extended periods. Geospatial modelling and remote sensing have therefore been increasingly used to upscale plot measurements. Crowther et al. (2015) produced the first spatially continuous global tree-density map at approximately 1 km resolution using 429,775 ground-based observations and biome-level regression models with a negative-binomial error structure. This work established an important global baseline, but its relatively coarse spatial resolution and static representation limit its applicability to stand-scale structural assessment and temporal change analysis. More recently, Cheng et al. (2025) produced a 100 m tree-density map for China for the year 2020 by integrating extensive LiDAR-derived reference data with multi-source environmental information and ensemble learning. This dataset represents an important advance in national-scale tree-density mapping, but it focuses on forested regions and provides a single-year estimate, limiting its ability to characterize trees in low-cover or transitional landscapes and to resolve long-term changes in forest structure. In addition, uncertainties in large-scale tree-density products can be particularly pronounced in environmentally heterogeneous regions. For example, Song et al. (2025) showed that existing tree-density products substantially underestimated tree abundance in the mountainous regions of Northeast China. More generally, remote-sensing retrievals of forest structural attributes can lose sensitivity in dense canopies because of spectral or backscatter saturation, while topographic effects and canopy heterogeneity introduce additional uncertainties (Lu,



2006; Zhao et al., 2016). Consequently, a high-resolution, spatially continuous, and temporally consistent record of tree density
65 that can resolve multi-decadal forest structural changes is still lacking for China.

Addressing these limitations requires both complementary information from multiple remote-sensing sources and models
capable of representing complex relationships between remotely sensed signals and forest structure. Optical observations
provide information on canopy spectral properties and vegetation condition, radar observations are sensitive to canopy and
woody structure as well as moisture conditions, and LiDAR measurements provide direct information on forest vertical
70 structure. The complementary information provided by different sensor types has therefore become increasingly important for
large-scale retrievals of forest structural attributes (Fassnacht et al., 2014). Machine-learning approaches are particularly
suitable for integrating these heterogeneous and high-dimensional predictors. Among them, Random Forest (RF) has been
widely applied in remote-sensing studies because it can accommodate nonlinear relationships and interactions among
predictors, is relatively insensitive to overfitting, and does not require strict assumptions about the statistical distribution of
75 explanatory variables (Belgiu and Drăguț, 2016). Nevertheless, RF and other empirical regression approaches often compress
the predicted range of forest structural variables, leading to overestimation at the lower end and underestimation at the upper
end of the observed distribution. Similar patterns have been widely reported in remote-sensing retrievals of forest biomass and
other structural attributes (Réjou-Méchain et al., 2019; Rodríguez-Veiga et al., 2019), and can be further amplified when
predictor variables become saturated in structurally dense forests. For tree-density mapping, reducing such biases requires
80 reference observations that adequately represent the full density gradient, predictors that retain sensitivity across contrasting
stand conditions, and explicit treatment of residual spatial biases.

Here, we develop a 30 m spatial-resolution tree-density dataset for China spanning 1985–2022 (ChinaTD30). Although each
30 m grid cell covers only 900 m², tree abundance was standardized to stems per hectare (stems ha⁻¹) to facilitate consistent
and intuitive comparisons. The reconstruction is based on 670,279 field sample plots and integrates multi-source remote-
85 sensing, topographic, and climatic predictors within an optimized RF framework. The extensive reference dataset improves
the representation of forest conditions across a broad tree-density gradient, while the multi-decadal reconstruction enables the
characterization of spatial and temporal changes in forest structure beyond the single-year snapshots provided by existing
products. The resulting dataset can support investigations of forest demographic and structural change, assessments of
ecological restoration and forest management, and analyses of the relationships between forest structure and terrestrial carbon
90 dynamics. Long-term and spatially explicit information on forest demographic structure can also provide empirical constraints
for the representation and evaluation of vegetation demographic processes in Earth system models (Fisher et al., 2018).



2 Data and methods

2.1 Study Area

The field inventory dataset covers ten climatic regions across China, representing a broad environmental gradient from tropical to cold temperate and alpine environments (Fig. 1, Zheng et al., 2010). To characterize the spatial coverage and sampling density of the inventory dataset, all plot locations were aggregated into 50 km hexagonal grids (plots with no trees were not included for display). The spatial distribution of plots shows strong heterogeneity, largely corresponding to China's major vegetation zones and regional differences in forest distribution. High-density sampling areas (>160 plots per hexagon) are primarily located in eastern and southern China, particularly within the mid-subtropical, north subtropical, and warm temperate regions, where extensive evergreen broadleaved, deciduous broadleaved, and coniferous forests occur.

The dataset also includes extensive sampling across western and high-elevation regions, including the Qinghai–Tibet Plateau and northwestern China. The alpine region (Zone 10) contains the largest number of inventory records (392,804 plots), followed by the temperate region (Zone 6; 105,651 plots) (Fig. 1b). However, many plots in these regions contained no trees, particularly those situated in non-forest ecosystems such as alpine meadows, grasslands, steppes, and deserts. This comprehensive spatial representation enables the dataset to capture both forested and non-forested landscapes, reducing uncertainties associated with spatial extrapolation in large-scale tree-density mapping.

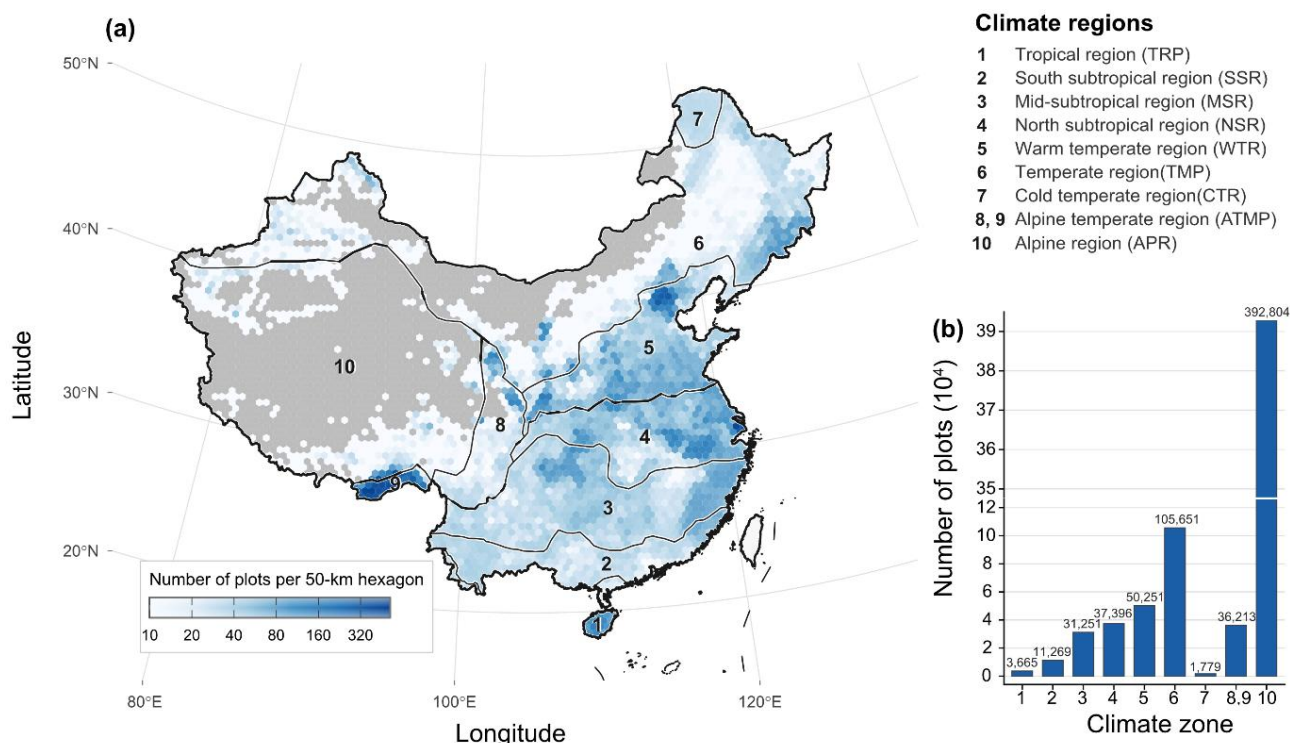


Figure 1: Inventory plots and study area across different climate regions. In panel (a), plots with tree density below 10 stems ha^{-1} were not displayed. Trees with a diameter at breast height (DBH) below 5 cm were not recorded in the inventory data.



110 2.2 Data Sources and Processing

2.2.1 Field inventory data

Field observations used in this study were obtained from the National Forest Inventory (NFI), a systematic sample-based forest resource monitoring program conducted on a five-year cycle (Zeng et al., 2015). We compiled plot records from four consecutive inventory cycles spanning 1999–2018, corresponding to the 6th (1999–2003), 7th (2004–2008), 8th (2009–2013),
 115 and 9th (2014–2018) NFIs. After excluding the 1,766 plots with missing coordinates, each NFI cycle contained 670,279 plot observations, with plot areas ranging from 0.0667 to 0.08 ha. Within each plot, trees with a diameter at breast height (DBH, measured at 1.3 m above ground) of at least 5 cm were recorded. Tree density for each plot was calculated as the number of recorded stems divided by the corresponding plot area and expressed as stems per hectare (stems ha⁻¹):

$$D_i = \frac{N_i}{A_i}, \quad (1)$$

120 where D_i is tree density (stems ha⁻¹) for plot i , N_i is the number of trees with DBH ≥ 5 cm recorded within the plot, and A_i is the plot area in hectares. Plots containing no trees above the DBH threshold were assigned as 0 stems ha⁻¹.

2.2.2 Remote sensing and ancillary datasets

To support annual tree-density mapping, we assembled a suite of remotely sensed observations and ancillary geospatial datasets describing vegetation condition, forest structure, land cover, stand age, climate, topography, and soil conditions (Table
 125 1). The datasets differed substantially in their native spatial and temporal resolutions and were therefore harmonized to a common spatial grid prior to model development.

Annual optical information was obtained from the 30 m seamless leaf-on Landsat composite data cube for China developed by Cai et al. (2025). The dataset provides temporally consistent annual composites from 1985 onward and contains six spectral bands (see Section 2.3.1). For this study, annual composites corresponding to the 1985–2022 reconstruction period were used.
 130 Spectral indices, including NDVI and EVI, were subsequently calculated from the annual Landsat composites. These optical variables characterize differences in vegetation greenness, canopy condition, and spectral properties among forest stands. The optical observations were complemented with the Global 25 m PALSAR/PALSAR-2 annual mosaics produced by the Japan Aerospace Exploration Agency (JAXA). We used the HH- and HV-polarized L-band SAR backscatter as additional predictors of forest structural variation (Shimada et al., 2014). PALSAR observations are available for 2007–2010 and PALSAR-2
 135 observations from 2015 onward; therefore, no annual SAR observations are available for 1985–2006 or 2011–2014.

Several environmental covariates were included to represent broad-scale climatic and site controls on forest structure. Bioclimatic variables were obtained from WorldClim v2.1 at a spatial resolution of 30 arcsec (approximately 1 km at the Equator). These variables represent long-term climatic conditions averaged over 1970–2000 and were therefore treated as temporally invariant covariates rather than annual climate observations (Fick and Hijmans, 2017). The elevation was derived
 140 at 90 m spatial resolution (Farr et al., 2007; OpenTopography, 2013). Soil properties were obtained from Liu et al. (2022).



Together, these variables were used to account for persistent environmental differences in forest growing conditions across China.

Annual land-cover information was obtained from the China Land Cover Dataset (CLCD; Yang and Huang, 2021). CLCD data were used as covariates to represent land-use conditions during model training and were subsequently incorporated as constraints for the estimation of tree numbers across different land-use types. Forest stand age was obtained from China's Annual Forest Age dataset (CAFA V2.0), which provides annual forest-age estimates at 30 m resolution for 1986–2022 (Shang et al., 2025). Forest age was included as a predictor to represent differences in stand developmental stage that cannot be fully characterized by spectral and environmental variables alone. For years between 1985 and 1990, missing auxiliary data of CLCD and age maps were substituted by the nearest year data.

Table 1: Gridded data collected for tree density construction

Datasets	Temporal coverage	Spatial resolution	Reference
The annual 30 m tree canopy cover dataset for China from the 1970s to 2024 (ChinaTCC)	1985-2022	30m	Yu et al. (2026)
The 30m Seamless Annual Leaf-On Landsat Composite Data Cube for China	1985-2022	30m	Cai et al. (2025)
Global PALSAR-2/PALSAR Yearly Mosaic, versions 1& 2.5.0	2007-2010, 2015-2021	25m	Shimada et al., 2014
China Land Cover Dataset (CLCD), updated version, 1985–2022	1985, 1990-2022	30m	Yang and Huang (2021)
China's Annual Forest Age (CAFA V2.0)	1986-2022	30m	Shang et al. (2025)
WorldClim Bioclimatic variables	1970–2000 (climatology)	30 arcsec (~1 km)	Fick and Hijmans (2017)
SRTM GL3 90 m DEM	2000	90m	Farr et al. (2007); OpenTopography (2013)
National Soil Information Grids of China	2010-2018 (soil profile survey period)	90m	Liu et al. (2022)



2.3 Methodology

2.3.1 Predictor variable preparation and preprocessing

155 Candidate predictor variables were assembled from multiple sources to characterize forest spectral properties, canopy structure, stand development, land-cover conditions, and environmental constraints (Table 2). Because the temporal coverage of the available datasets differed substantially, particularly for the PALSAR/PALSAR-2 observations, the predictors were not assumed to be uniformly available throughout the entire reconstruction period. Instead, the temporal availability of each dataset was explicitly considered in the subsequent modeling strategy.

160 Optical predictors were derived from the 30 m Seamless Annual Leaf-On Landsat Composite Data Cube for China (Cai et al., 2025). Six surface-reflectance bands, including Blue, Green, Red, near-infrared (NIR), shortwave infrared 1 (SWIR1), and shortwave infrared 2 (SWIR2), were used. Additionally, two vegetation indices, the normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI), were derived from the annual Landsat composites. NDVI and EVI were included to complement the original spectral bands by describing variations in vegetation greenness and canopy condition
 165 (Huete et al., 2002; Tucker, 1979).

The SAR predictors consisted of the HH- and HV-polarized backscatter from the 25 m Global PALSAR/PALSAR-2 annual mosaics. The original digital numbers were converted to gamma-nought backscatter coefficients (γ^0) in decibels following the calibration specified by JAXA:

$$\gamma^0 = 10 \log_{10} (DN^2) - 83.0 \quad (2)$$

170 where (DN) denotes the digital number of the PALSAR/PALSAR-2 mosaic. The resulting HH and HV backscatter coefficients were used as complementary indicators of forest structural properties. Because L-band SAR is sensitive to woody vegetation and canopy structure, these variables provide information that is complementary to optical reflectance observations (Shimada et al., 2014).

Additional vegetation-related predictors included annual tree canopy cover, forest age, and land use/land cover (LULC). Tree
 175 canopy cover was obtained from Yu et al. (2026). Annual LULC information was obtained from the China Land Cover Dataset (CLCD; Yang and Huang, 2021), and forest age was obtained from China's Annual Forest Age dataset (CAFA V2.0; Shang et al., 2025). The latter provides annual forest-age estimates at 30 m resolution from 1986 to 2022 and was used to represent differences in stand developmental stage.

Long-term climatic conditions were represented using the 19 WorldClim v2.1 bioclimatic variables (Bio1–Bio19) at a native
 180 resolution of 30 arcsec (approximately 1 km at the Equator; Fick and Hijmans, 2017). Because these variables represent the 1970–2000 climatological baseline, they were treated as temporally invariant covariates describing broad spatial climatic gradients. Soil conditions were characterized using nine variables at 90 m spatial resolution, including soil pH, soil organic carbon (SOC), soil thickness, coarse-fragment content (CF), total nitrogen (TN), total phosphorus (TP), bulk density (BD), cation exchange capacity (CEC), and total potassium (TK) (Liu et al., 2022).



185 Given the discontinuous availability of PALSAR/PALSAR-2 observations and the four National Forest Inventory reference periods, three complementary modeling scenarios were subsequently designed to reconstruct tree-density dynamics at different temporal extents and levels of predictor availability.

Table 2: Candidate predictor variables used in the three data reconstruction scenarios.

Category	Variable	Resolution	Source	Scenario 1	Scenario 2	Scenario 3
SAR	HH (dB), HV (dB)	25m	Global PALSAR-2/PALSAR Yearly Mosaic, versions 1& 2.5.0	✓	–	–
Optical remote sensing	Blue, Green, Red, NIR, SWIR1, SWIR2, NDVI, EVI	30m	The 30m Seamless Annual Leaf-On Landsat Composite Data Cube for China	✓	✓	✓
Vegetation and land cover	Tree canopy cover	30m	The annual 30 m tree canopy cover dataset for China from the 1970s to 2024	✓	✓	✓
	Forest age	30m	China's Annual Forest Age	✓	✓	✓
	LULC	30m	The 30 m annual land cover dataset and its dynamics in China	✓	✓	✓
Climate	Bio1-19	30 arcsec (~1 km)	WorldClim Bioclimatic variables	✓	✓	✓
Soil	pH, SOC, Thickness, CF, TN, TP, BD, CEC, TK	90m	National Soil Information Grids of China	✓	✓	✓
Terrain	DEM	90m	SRTM GL3 90 m DEM	✓	✓	✓

190 **Note:** HH: horizontal transmit, horizontal receive; HV: horizontal transmit, vertical receive; NIR: near-infrared; SWIR1: short-wave infrared 1; SWIR2: short-wave infrared 2; NDVI: normalized difference vegetation index; EVI: enhanced vegetation index; LULC: land use and land cover; pH: soil pH; SOC: soil organic carbon; Thickness: soil thickness; CF: coarse fragments; TN: total nitrogen; TP: total phosphorus; BD: bulk density; CEC: cation exchange capacity; TK: total potassium



2.3.2 Reconstruction scenarios

195 To accommodate differences in predictor availability while retaining both temporal continuity and structural information, three complementary reconstruction scenarios were developed (Fig. 2). The scenarios differed primarily in the temporal organization of the NFI reference observations and in whether PALSAR/PALSAR-2 backscatter was included in the predictor set.

Scenario 1: SAR-enhanced multi-source reconstruction.

Scenario 1 was designed to maximize the structural information available from multi-source remote sensing. For NFI reference
 200 years that coincided with the availability of ALOS PALSAR or ALOS-2 PALSAR-2 observations, models were developed using the full predictor set, including Landsat spectral variables, PALSAR/PALSAR-2 HH and HV backscatter, forest and land-cover variables, and environmental covariates. Specifically, the 2008 NFI observations were used to construct the model for the 2007–2010 PALSAR period, whereas the 2018 NFI observations were used for the 2015–2021 PALSAR-2 period. Annual predictor layers were used to generate tree-density estimates for each year within the corresponding period. This
 205 scenario provides the most information-rich estimates because it combines optical and L-band SAR observations, but its temporal coverage is restricted by the availability of PALSAR/PALSAR-2 data.

Scenario 2: NFI-anchored reconstruction without SAR.

Scenario 2 was developed to examine temporal changes in tree density over the period surrounding each NFI reference year without relying on SAR observations. Four independent models were calibrated using the NFI observations associated with
 210 2003, 2008, 2013, and 2018. PALSAR/PALSAR-2 predictors were excluded, while Landsat observations and the available vegetation, climatic, topographic, and soil covariates were retained. The four models were applied to their respective temporal windows: 2001–2005, 2006–2010, 2011–2015, and 2016–2020. Within each window, the model calibrated from the corresponding NFI reference period was applied to annual predictor layers to reconstruct interannual variations in tree density. This design maintains a relatively close temporal correspondence between field observations and remotely sensed predictors
 215 while avoiding dependence on the discontinuous SAR record.

Scenario 3: full-period reconstruction.

Scenario 3 was designed to provide a temporally continuous and methodologically consistent tree-density record for the entire 1985–2022 period. PALSAR/PALSAR-2 predictors were excluded because comparable L-band SAR observations were not available throughout the full reconstruction period. The model therefore relied on predictors with sufficiently long temporal
 220 coverage, principally annual Landsat observations together with forest, land-cover, climatic, topographic, and soil covariates. To ensure representation of all four NFI periods while maintaining a consistent sampling proportion, 25% of the observations from each inventory period were randomly sampled and combined into a single pooled modeling dataset. A single RF model was developed using the pooled observations to establish a common relationship between tree density and the predictor variables across inventory periods. The trained model was subsequently applied, without changing the predictor configuration
 225 or modeling framework, to the annual predictor layers from 1985 to 2022. By using a single model based on observations from



all four inventory periods, Scenario 3 reduces methodological discontinuities among inventory cycles and provides the primary dataset for analyses requiring a continuous long-term tree-density record.

The three scenarios were designed for different but complementary purposes rather than as interchangeable estimates. Scenario 1 evaluates the additional information provided by L-band SAR during periods of data availability; Scenario 2 emphasizes
 230 temporal proximity between field calibration and annual predictions; and Scenario 3 prioritizes methodological consistency and complete temporal coverage. Comparisons among the overlapping periods of the three scenarios were subsequently used to assess the robustness of the reconstructed tree-density patterns and the influence of predictor configuration on model performance.

2.3.3 Feature extraction and predictor selection

235 Candidate predictors representing optical spectral characteristics, vegetation condition, radar backscatter, forest and land-cover attributes, climate, and soil properties were extracted for the NFI plots (Table 2). Because the predictor set contained variables derived from multiple sensors and environmental datasets, particular attention was given to the spatial correspondence between field observations and raster predictors before feature selection.

For Landsat-derived continuous predictors, including Landsat spectral bands and vegetation indices, predictor values were
 240 summarized within a 3×3 pixel neighborhood centered on each NFI plot location. The mean of the valid pixels within the approximately 90×90 m window was used as the plot-level predictor value. This neighborhood-based extraction was adopted to reduce sensitivity to small positional discrepancies between field plots and satellite imagery and to account for local pixel-scale heterogeneity. Such discrepancies can arise from uncertainties in plot coordinates and image geolocation and may affect the linkage between forest inventory observations and spatially explicit remote-sensing data (Halme and
 245 Tomppo, 2001; Sabor et al., 2007). The 3×3 window was therefore used as a spatial-support strategy rather than as a direct representation of the physical footprint of an NFI plot.

Categorical variables, such as LULC, were represented by the class of the pixel containing the plot center, rather than by arithmetic averaging. Other thematic raster covariates at or near the Landsat spatial resolution were likewise represented by the pixel containing the plot center, thereby preserving their original pixel-level representation. For environmental covariates
 250 with substantially coarser native resolutions, including the 90 m soil variables and 30-arcsec WorldClim bioclimatic variables, the value of the source grid cell containing the plot center was assigned to the corresponding field observation. These coarser variables were intended to represent site-level or regional environmental conditions rather than fine-scale variation within individual plots.

Following predictor extraction, recursive feature elimination with cross-validation (RFECV) was used to identify compact
 255 predictor subsets for model development. RFECV was implemented in Python using the scikit-learn library (Pedregosa et al., 2011), with a Random Forest regressor serving as the underlying estimator. Beginning with the complete candidate set available for a given model configuration, the estimator was fitted and predictors were ranked according to their Random



Forest feature importance. The least informative predictors were successively removed, and model performance was re-evaluated after each elimination step. Cross-validation scores across the resulting nested predictor subsets were then compared, and the subset yielding the highest mean validation performance was retained (Guyon et al., 2002).

Feature selection was conducted separately for the different model configurations because predictor availability differed among the three reconstruction scenarios. In particular, HH and HV backscatter were considered only for Scenario 1, whereas Scenarios 2 and 3 were restricted to predictors available independently of PALSAR/PALSAR-2. This procedure ensured that the selected predictor set reflected the information available to each reconstruction model rather than imposing a common feature subset across models with different temporal data availability.

To reduce the influence of spatial dependence during feature selection, RFECV was coupled with five-fold spatial-block cross-validation, while an independent 20% of the data was reserved as a spatial hold-out set for final model evaluation. The study area was partitioned using a 50 km regular grid, and all plots belonging to the same spatial block were assigned exclusively to either the hold-out set or one of the five cross-validation folds. The independent hold-out set was completely excluded from the RFECV procedure and all model training, ensuring that these observations had no influence on predictor selection or model fitting. Within the remaining 80% of the data, the same five predefined spatial folds were used throughout RFECV, such that plots within a given spatial block could not occur simultaneously in the training and validation subsets. This spatial grouping provides a more conservative assessment of predictor transferability than random plot-level partitioning when observations exhibit spatial dependence (Roberts et al., 2017). The final predictor subset was selected according to the mean RMSE across the five RFECV validation folds. After feature selection and model training had been completed using the 80% development dataset, the independent 20% hold-out set was used only for final model evaluation.

2.3.4 Model training, hyperparameter optimization, and validation

The study area was first divided into 50-km spatial grid cells to reduce spatial dependence between training and validation samples. Based on these spatial blocks, approximately 20% of the data were reserved a priori as an independent hold-out set, while the remaining 80% constituted the development dataset. The partitioning was stratified by climate zone to maintain similar relative proportions of samples from each climate zone in the hold-out and development datasets, while ensuring that samples from the same spatial grid cell remained within the same subset. The 80% development dataset was then further divided into five spatial folds. During five-fold cross-validation, each fold was used once as the validation set, while the remaining four folds were used for model training. This process yielded five fold-specific models and corresponding validation results.

To assess whether model performance was strongly dependent on the choice of machine-learning algorithm, we additionally compared RF with XGBoost and ExtraTrees using the same spatial cross-validation scheme. RF was retained as the primary modelling framework to ensure methodological consistency among the different model configurations and throughout the 1985–2022 reconstruction. XGBoost achieved the lowest cross-validated RMSE (161.12 ± 4.68 stems ha^{-1}) and a high R^2 (0.71



290 ± 0.01), followed closely by RF (RMSE = 165.18 ± 4.66 stems ha^{-1} ; $R^2 = 0.70 \pm 0.01$), whereas ExtraTrees showed slightly lower predictive performance (RMSE = 165.78 ± 4.72 stems ha^{-1} ; $R^2 = 0.70 \pm 0.01$). Nevertheless, the improvement of XGBoost over RF was small, corresponding to only an approximately 2.5 % reduction in RMSE and a negligible increase of R^2 . Given this limited improvement, we retained RF as the common modelling framework to maintain consistency among the different model configurations and avoid introducing additional variation associated with the choice of algorithm.

295 RF has been widely applied to multisource remote-sensing data because of its robustness to high-dimensional and correlated predictors and its relatively low sensitivity to overfitting (Belgiu and Drăguț, 2016; Bryan et al., 2018). In RF regression, predictions from individual trees are averaged to obtain the final estimate. The combination of bootstrap sampling and random predictor selection helps reduce variance among individual trees and allows RF to capture complex and nonlinear relationships between forest structure and remotely sensed and environmental predictors. RF has therefore been widely used in ecological
 300 and remote-sensing studies involving heterogeneous and high-dimensional predictor datasets (Belgiu and Drăguț, 2016; Cutler et al., 2007).

Because nearby inventory plots may share similar environmental conditions and remote-sensing characteristics, randomly partitioning individual plots may lead to overly optimistic estimates of model performance due to spatial autocorrelation and information leakage. We therefore adopted a spatially constrained data-partitioning strategy. Specifically, the study area was
 305 first divided into a regular 50 km grid, and all samples within the same grid cell were kept within the same data subset to avoid splitting spatially neighboring observations between training and validation data. Approximately 20% of the samples were reserved a priori as an independent spatial hold-out set and excluded from all subsequent feature selection, hyperparameter optimization, and model fitting. The remaining 80% of the samples constituted the development dataset and were further divided into five spatial folds for cross-validation, with each fold containing samples distributed across the country. The spatial
 310 partitioning was performed once and kept fixed throughout the analysis. The five-fold spatial cross-validation was used for model development and internal validation, whereas the independent 20% hold-out set was used only for final model evaluation. This spatial blocking strategy reduces the influence of spatial autocorrelation among neighboring samples and limits information leakage between model development and independent evaluation datasets, thereby providing a more robust assessment of model generalizability (Ploton et al., 2020; Roberts et al., 2017; Valavi et al., 2019).

315 Feature selection and hyperparameter optimization were conducted exclusively using the 80% development dataset. Specifically, the RFECV procedure described in Section 2.3.3 was performed using the five-fold spatial cross-validation scheme defined within this dataset. The independent 20% spatial hold-out set was not used during either feature selection or hyperparameter optimization and therefore had no influence on predictor selection or model fitting. Model performance during development was assessed across the five spatial cross-validation folds, whereas the independent hold-out set was used only
 320 for final model evaluation.



Following feature selection, RF hyperparameters were optimized using Optuna (Akiba et al., 2019). The Tree-structured Parzen Estimator (TPE) sampler was used to efficiently search the predefined hyperparameter space (Bergstra et al., 2011). Five RF hyperparameters were considered: the number of regression trees (`n_estimators`, 100–500), maximum tree depth (`max_depth`, 5–25), minimum number of samples required to split an internal node (`min_samples_split`, 2–20), minimum
325 number of samples required at a terminal leaf (`min_samples_leaf`, 1–15), and the number of predictors considered at each split (`max_features`, `sqrt` or `log2`). For each Optuna trial, model performance was evaluated using the same predefined five-fold spatial cross-validation scheme within the 80% development dataset, and the hyperparameter combination with the lowest mean RMSE across the five validation folds was retained. The independent 20% hold-out set was excluded from the entire hyperparameter optimization procedure. This spatially explicit tuning strategy reduced the likelihood that hyperparameter
330 selection was driven primarily by short-distance spatial similarity among samples.

For final model evaluation and spatial prediction, the five development folds were used in a fold-wise ensemble framework. In each iteration, four of the five development folds were used to train the RF model using the selected predictor subset and optimized hyperparameters, while the remaining fold was used for validation. This procedure resulted in five-fold-specific RF models. The independently reserved hold-out set remained excluded from model fitting, feature selection, and hyperparameter
335 optimization and was used only for independent evaluation. For Scenario 3, each of the five RF models was subsequently applied to the annual predictor layers from 1985 to 2022. For each pixel and year, the mean of the five predictions was used as the final ChinaTD30 tree-density estimate. The standard deviation among the five predictions was additionally calculated to quantify model-based prediction variability, representing the sensitivity of the estimated tree density to differences in the spatial composition of the training data.

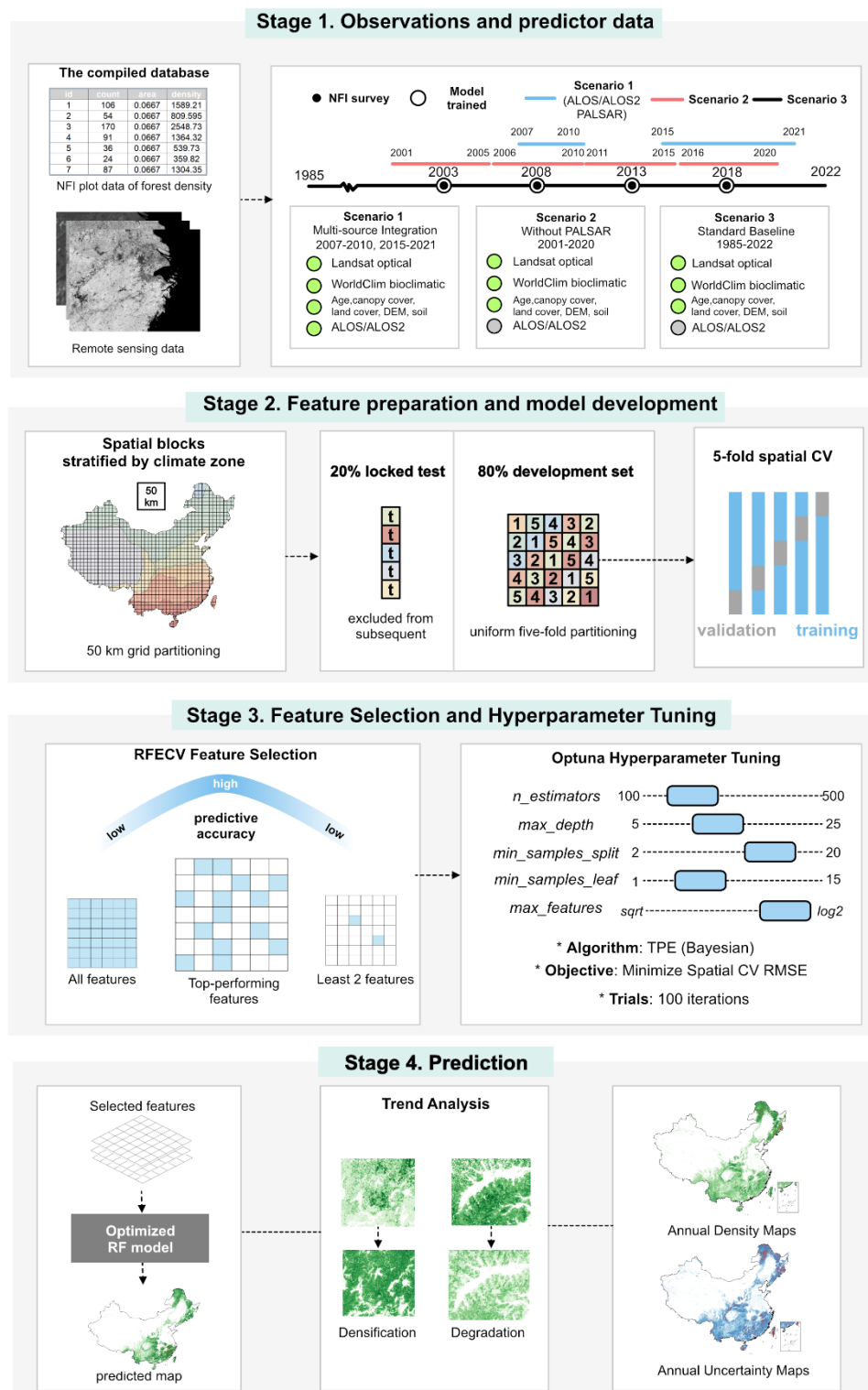




Figure 2. Overall methodological framework for the development of the long-term tree density product. The workflow is divided into four main stages: (Stage 1) Compilation of observations and predictor data, integrating National Forest Inventory (NFI) plot data with multi-source remote sensing covariates (Landsat optical, WorldClim bioclimatic, DEM, soil, and ALOS/PALSAR). Three distinct model configurations are designed to accommodate differences in satellite-data availability and model-training strategies from 1985 to 2022. (Stage 2) Feature preparation and spatial cross-validation design, utilizing a 50 km spatial grid stratified by climate zones. The dataset is geographically split into an 80% development set and a 20% independent hold-out set that is excluded from model training and parameter optimization. The 80% development set is further partitioned into five spatial folds, with each fold used once for validation while the remaining four folds are combined for model training. This procedure produces five-fold-specific models, while the independent 20% hold-out set is reserved for final validation. (Stage 3) Model optimization, applying Recursive Feature Elimination with Cross-Validation (RFECV) to identify the optimal feature subset, followed by Bayesian hyperparameter tuning using the Optuna framework (TPE algorithm) to optimize the Random Forest (RF) model by minimizing the spatial cross-validation RMSE. (Stage 4) Final prediction and trend analysis, where predictions from the five-fold-specific RF models are used to generate annual tree density maps, and the pixel-wise standard deviation among the five predictions is used to quantify spatial prediction uncertainty.

3 Results

3.1 Spatial patterns of field-observed tree density

Figure 3 shows the spatial distribution of tree density derived from the four NFI periods corresponding to 2003, 2008, 2013, and 2018. To reduce visual overlap among the large number of field observations, plot-level tree-density values were aggregated to 50 km hexagonal grids, with each grid cell representing the mean tree density of the plots located within that cell.

Tree density exhibited pronounced spatial heterogeneity across China in all four inventory periods (Fig. 3). High-density observations were consistently concentrated in northeastern China, where many hexagonal cells exceeded 1000 stems ha^{-1} and locally reached more than 1200 stems ha^{-1} . Relatively high tree densities were also observed across parts of southern and southeastern China. In contrast, lower-density observations occurred more frequently in northwestern China and along the western and high-elevation margins of the sampled forest distribution. Southwestern China showed a comparatively heterogeneous pattern, with both low- and high-density observations distributed across the region.

Despite local differences among the four inventory periods, the broad geographical pattern of tree density remained similar from 2003 to 2018, characterized by persistently high values in northeastern China and substantial spatial variation across southern and southwestern China. Changes in the magnitude and spatial extent of high-density cells were nevertheless evident among individual inventory periods. These four sets of field observations provided the reference data for model calibration, feature selection, and independent spatial validation in the subsequent tree-density reconstruction.

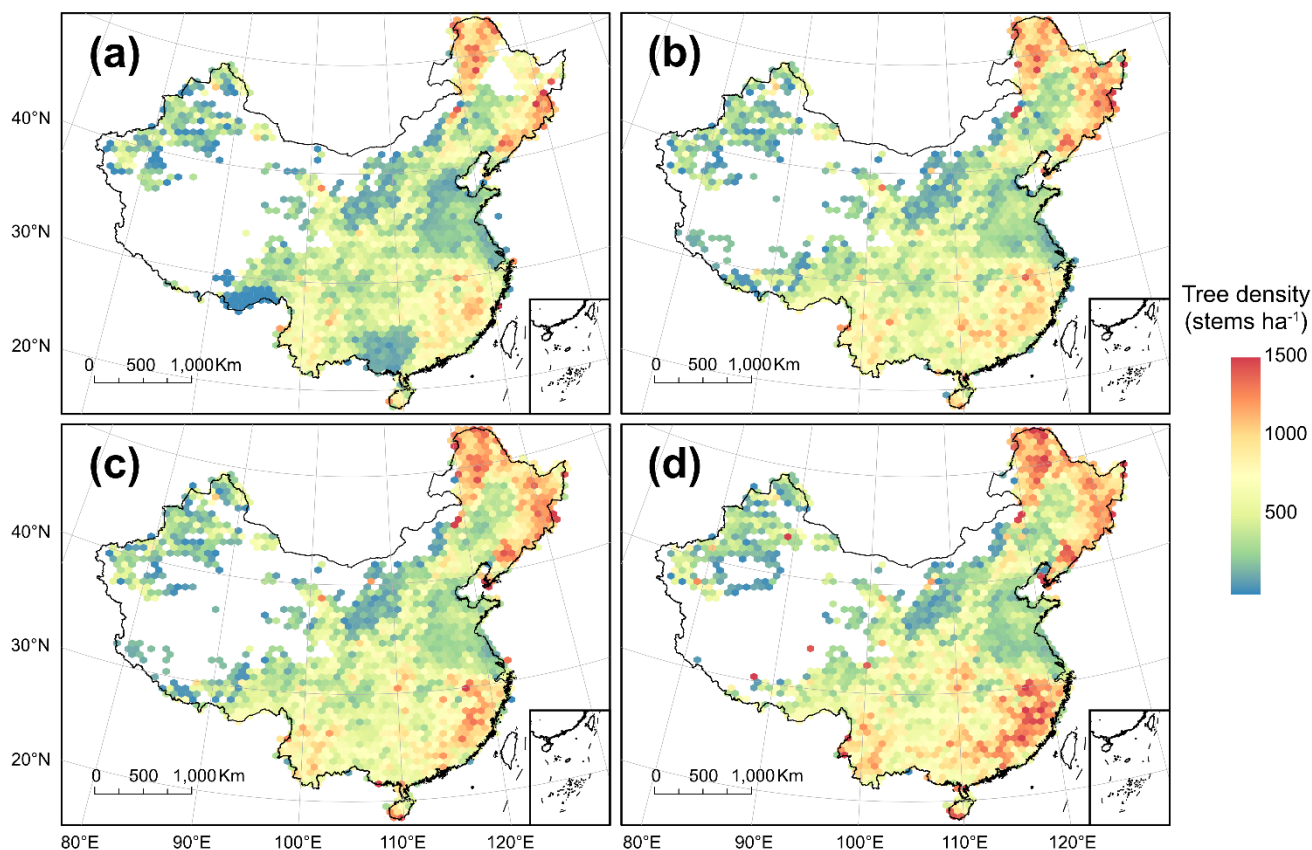


Figure 3: Spatial distribution of field-observed tree density during the four National Forest Inventory periods. Plot observations were aggregated into 50 km hexagonal grids, and the color of each hexagon represents the mean tree density (stems ha^{-1}) of the plots within that grid. Panels (a)–(d) correspond to 2003, 2008, 2013, and 2018, respectively.

375 To characterize the climatic distribution of tree density, observations from the 2018 National Forest Inventory (NFI) were projected onto the Whittaker climate–biome space defined by mean annual temperature (MAT) and mean annual precipitation (MAP), with tree density represented by color (Fig. 4; Whittaker, 1975). The observations covered a broad range of climatic conditions, extending from cold and dry environments to warm and humid regions and encompassing most major biome domains occurring in China. Tree density showed a distinct distribution along the climatic gradients. Relatively

380 low densities were predominant under cold and/or dry conditions, whereas higher densities occurred mainly under temperate to warm and relatively humid climates, particularly within the climatic space associated with temperate seasonal forest, temperate rain forest, and their transitional zones. Nevertheless, substantial variation in tree density was observed under similar MAT–MAP conditions, indicating that climatic controls alone cannot fully explain the spatial variability in stand density.

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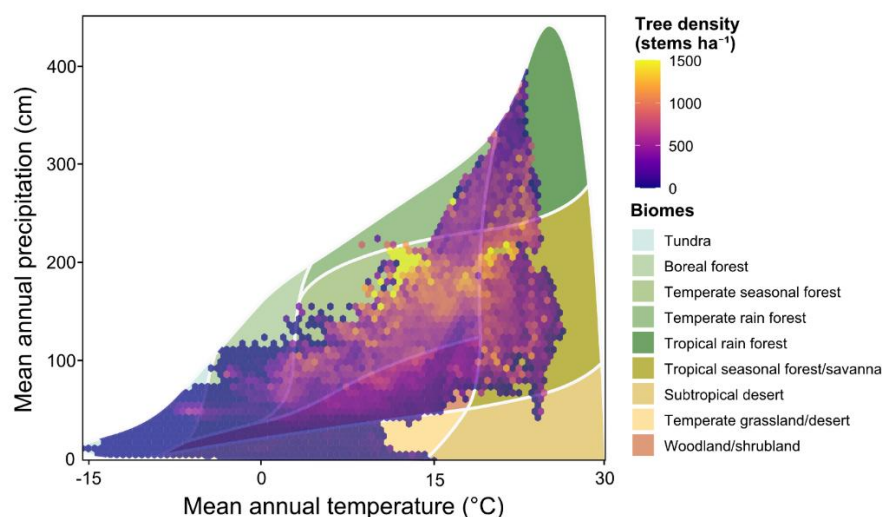


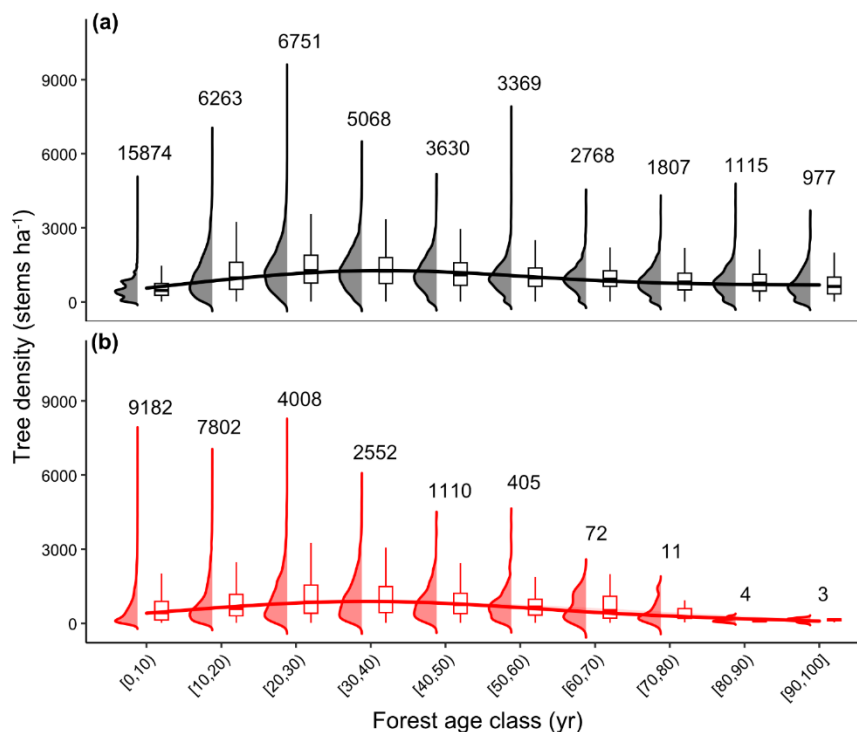
Figure 4: Distribution of stem density across China's 9th NFI plots in the Whittaker biome diagram. A total of 862 plots falling outside the Whittaker climate–biome space were not plotted.

Figure 5 summarizes the distribution of tree density across 10-year stand-age classes for natural and planted forests in the 9th NFI. Both forest origins were dominated by relatively young stands, although their age distributions differed markedly. For natural forests, the largest number of observations occurred in the 0–10 yr class ($n=15,874$), and sample availability generally declined toward older age classes. Nevertheless, natural forests retained substantial representation at older ages, with 10,036 observations older than 50 yr. Planted forests showed a much stronger concentration in the younger age classes: 9,182 and 7,802 observations occurred in the 0–10 and 10–20 yr classes, respectively, whereas only 495 observations were older than 50 yr. In particular, planted forests older than 70 yr were sparsely represented ($n=18$). This age structure is broadly consistent with national forest inventories showing a predominance of young and middle-aged forests in China and with previous assessments indicating a comparatively young age structure of China's planted forests (Yu et al., 2020; Zeng et al., 2015).

Tree density also varied systematically along the stand-age gradient (Fig. 5). Note that tree abundance was standardized to stems per hectare (stems ha^{-1}) to ensure consistent comparisons among plots of varying sizes across regions. For both natural and planted forests, median density increased from the youngest age class and reached relatively high values at approximately 20–30 yr, followed by an overall decline toward older stands. Natural forests generally exhibited higher median tree densities than planted forests across the intermediate age classes, with the contrast particularly apparent between approximately 20 and 40 yr. The distributions of natural forests also remained comparatively broad across older age classes, whereas the apparent narrowing of the planted-forest distributions after 60 yr largely coincided with the sharp reduction in



sample size. These results indicate clear differences in both the age structure and tree-density distributions of natural and planted forest observations used for subsequent model development.



410 **Figure 5: Distribution of field-observed tree density across stand-age classes for (a) natural forests and (b) planted forests in the 9th National Forest Inventory.** Half-violin plots show the distribution of tree density within each 10-year age class, and boxplots indicate the median and interquartile range. Values above each age class denote the number of field observations.

3.2 Model performance and predictor importance

415 Feature selection resulted in model-specific predictor subsets that varied according to data availability and reconstruction scenario (Fig. 6b). Rather than retaining a common predictor set for all models, RFECV selected the variables that provided the highest cross-validated predictive performance for each model configuration. The retained predictors represented a combination of forest attributes, optical and SAR observations, and environmental covariates, with the exact composition differing among the seven models.

420 The independent hold-out evaluation (Fig. 6a) and five-fold spatial cross-validation (Table 3) showed generally consistent predictive performance across the model configurations. In Fig. 6a, R^2 and RMSE were calculated from predictions for the independent 20% hold-out dataset, whereas Table 3 reports the mean $\pm$ SD of R^2 and RMSE across the five spatial cross-validation folds within the 80% development dataset. Among the models for which cross-validation statistics are reported in Table 3, R^2 ranged from 0.67 to 0.73. Model 1_2 achieved the highest R^2 (0.73 ± 0.01), whereas the four Scenario 2 models yielded R^2 values ranging from 0.67 to 0.72. The full-period Model 3 achieved an R^2 of 0.70 ± 0.01 . Corresponding RMSE



425 values ranged from 130.37 to 186.56 stems ha^{-1} . However, differences in RMSE among models representing different temporal periods should be interpreted in conjunction with differences in the observed tree-density distributions of their respective validation samples.

Across all model configurations, predicted tree density increased consistently with observed density, but the predicted range was narrower than the observed range (Fig. 6a). The fitted regression lines increasingly deviated below the 1:1 line toward the upper end of the density distribution, indicating systematic underestimation of high-density observations. This pattern was
 430 evident in both SAR-enhanced and non-SAR models, suggesting that it cannot be attributed solely to the availability of a particular remote-sensing sensor. Similar compression of predicted ranges has been reported in Random Forest retrievals of forest structural attributes, while reduced sensitivity of optical observations under dense forest conditions may further contribute to upper-range underestimation (Baccini et al., 2004; Zhao et al., 2016).

435 Stand age was consistently the highest-ranked predictor in all seven models, with importance values ranging from 0.24 to 0.34 (Fig. 6b). LULC (0.13–0.18) and tree canopy cover (0.11–0.13) also showed consistently high importance across model configurations. Together, these three variables accounted for a substantial proportion of the total predictor importance and remained prominent regardless of whether SAR observations were available. Among the Landsat-derived variables, NDVI was retained in all models, although its relative importance varied considerably (0.03–0.09). Soil pH and several bioclimatic
 440 variables were also repeatedly retained, but with lower individual importance values.

The contribution of SAR information differed between the two Scenario 1 models. HV backscatter was retained in both Model 1_1 and Model 1_2, but its relative importance increased from 0.03 in Model 1_1 to 0.12 in Model 1_2. In contrast, HH backscatter was not among the predictors retained in the final feature subsets shown in Fig. 6b. For Scenarios 2 and 3, which did not incorporate PALSAR/PALSAR-2 observations, the selected models relied on combinations of Landsat spectral
 445 variables, vegetation attributes, and environmental covariates. Despite differences in the selected feature sets, the four Scenario 2 models and the full-period Model 3 exhibited broadly comparable validation performance, indicating that a consistent level of predictive skill could be maintained across periods with different predictor configurations.

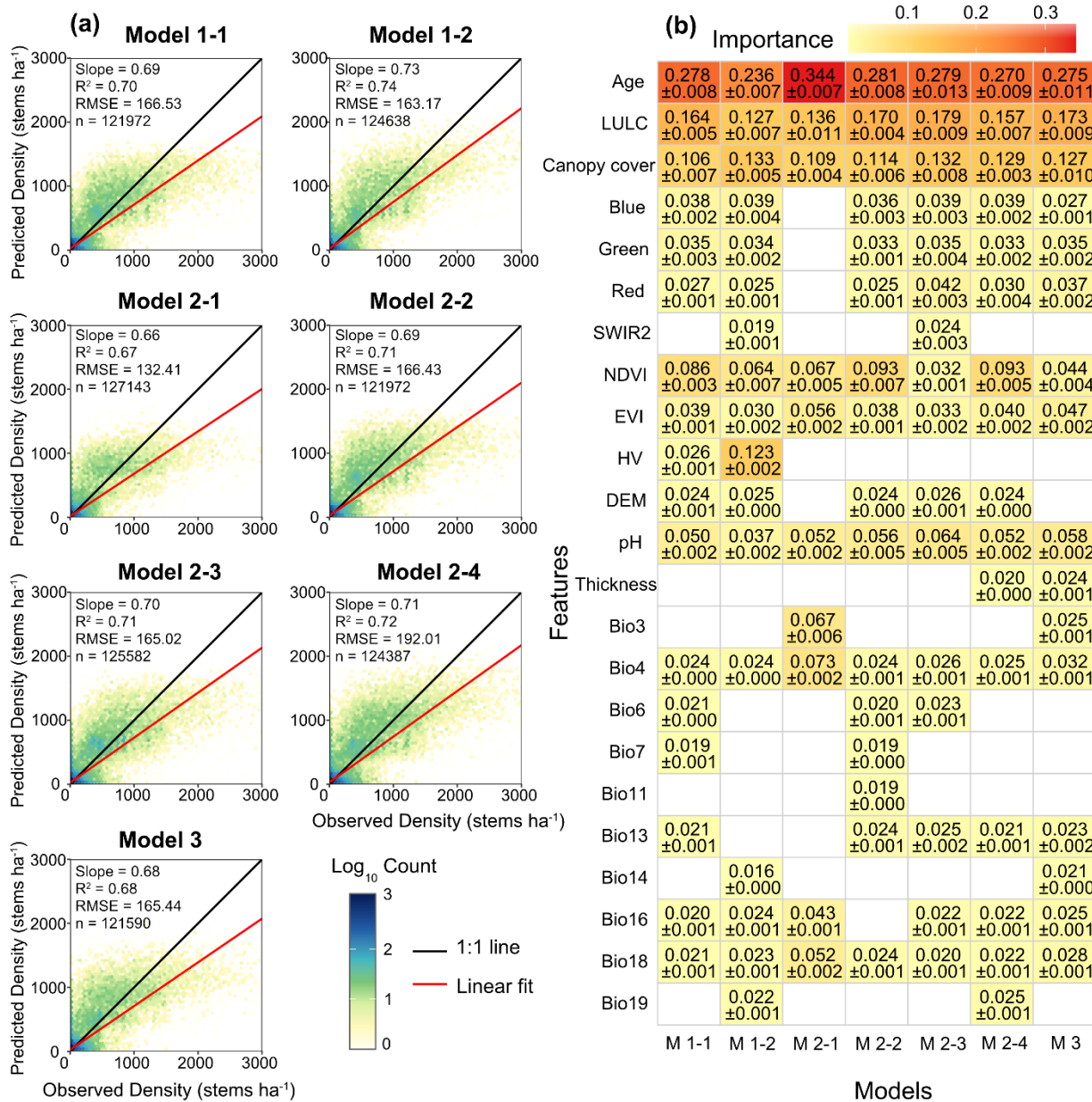


Figure 6. Scatter plots of independent hold-out validation and feature importance of the different models. Model 1 incorporates JAXA PALSAR HH and HV backscatter data and was therefore developed only for inventory periods with corresponding radar observations. Model 1-1 and Model 1-2 were trained using data from the 7th (2008) and 9th (2018) National Forest Inventories (NFIs), respectively. Model 2 excludes JAXA PALSAR data and comprises four independently trained models, with Model 2-1 to Model 2-4 corresponding to the 6th (2003), 7th (2008), 8th (2013), and 9th (2018) NFIs, respectively. Model 3 also excludes JAXA PALSAR data but was trained as a single model using the pooled observations from all four NFI periods (2003, 2008, 2013, and 2018). HH : horizontal transmit, horizontal receive; HV: horizontal transmit, vertical receive; NIR: near-infrared; SWIR1: short-wave infrared 1; SWIR2: short-wave infrared 2; NDVI: normalized difference vegetation index; EVI: enhanced vegetation index; LULC: land use and land cover; pH: soil pH; SOC: soil organic carbon; Thickness: soil thickness; CF: coarse fragments; TN: total nitrogen; TP: total phosphorus; BD: bulk density; CEC: cation exchange capacity; TK: total potassium.



460 **Table 3. Five-fold spatial cross-validation performance of the different models (R^2 and RMSE, mean $\pm$ SD).**

Model	R^2	RMSE (stems ha^{-1})
Model 1-1	0.70 ± 0.01	160.24 ± 3.67
Model 1-2	0.73 ± 0.01	164.66 ± 2.75
Model 2-1	0.67 ± 0.004	130.37 ± 6.70
Model 2-2	0.70 ± 0.01	160.38 ± 3.50
Model 2-3	0.71 ± 0.01	166.52 ± 4.42
Model 2-4	0.72 ± 0.01	186.56 ± 2.24
Model 3	0.70 ± 0.01	165.18 ± 4.66

Note: Model 1 incorporates JAXA PALSAR HH and HV backscatter data and was therefore developed only for inventory periods with corresponding radar observations. Model 1-1 and Model 1-2 were trained using data from the 7th (2008) and 9th (2018) National Forest Inventories (NFIs), respectively. Model 2 excludes JAXA PALSAR data and comprises four independently trained models, with Model 2-1 to Model 2-4 corresponding to the 6th (2003), 7th (2008), 8th (2013), and 9th (2018) NFIs, respectively. Model 3 also excludes JAXA PALSAR data but was trained as a single model using the pooled observations from all four NFI periods (2003, 2008, 2013, and 2018).
 465

3.3 Spatial-temporal distributions of stem density

For the comparison of tree-density dynamics between forest and non-forest areas, annual land-cover information from the CLCD dataset was used to classify pixels into the two categories (Yang and Huang, 2021). Forest areas were defined as pixels classified as forest in CLCD, whereas non-forest areas included cropland, shrubland, grassland, impervious surfaces, and
 470 wetlands. Tree density occurring within impervious-surface pixels was interpreted as urban tree density in this study. Other land-cover types were excluded from the forest–non-forest comparison.

The three modelling strategies showed broadly consistent long-term changes in tree density, but differed noticeably in their absolute estimates and temporal continuity (Fig. 7). For both Figs. 7 and 8, tree-number estimates were calculated based on the actual ground area represented by each pixel. On this basis, Model 3, which provided the continuous reconstruction for
 475 1985–2022, estimated that the total number of stems in forest areas increased from approximately $1,060 \times 10^8$ in 1985 to $1,818 \times 10^8$ in 2022, corresponding to an increase of approximately 72%. In forest areas, Model 1, which incorporated JAXA PALSAR HH and HV data, showed temporal patterns similar to those of Model 3 during the two periods for which the radar data were available, although its estimates were generally higher. In contrast, Model 2 showed clear discontinuities between the four independently trained models, despite a generally increasing tendency within each individual period. Model 3
 480 produced a much smoother and more continuous trajectory throughout 1985–2022.

A similar pattern was observed for non-forest areas. Model 3 estimates increased from approximately 23×10^8 stems in 1985 to a maximum of 59×10^8 stems in 2018, before declining to approximately 51×10^8 stems in 2022. Model 1 generally



produced slightly higher estimates than Model 3, whereas Model 2 showed distinct discontinuities among the four modelling periods. Nevertheless, all three modelling strategies showed higher tree abundance at the end of the study period than at the beginning in both forest and non-forest areas, although the non-forest trajectory showed a decline after its late-period peak.

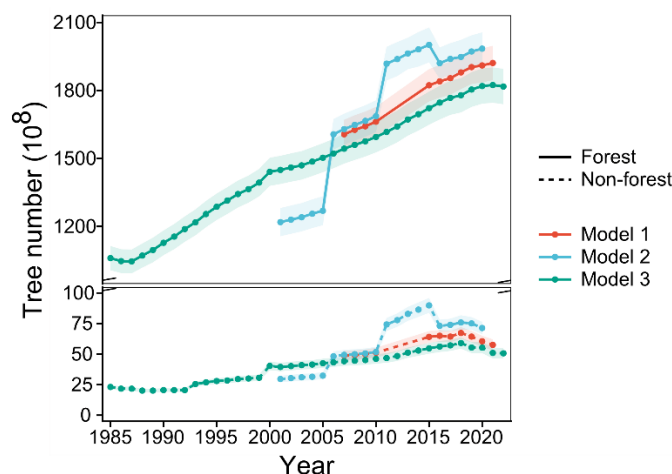


Figure 7: Statistics of forest and non-forest tree counts in China over time series. Temporal changes in the estimated number of stems in forest and non-forest areas under the three modelling strategies from 1985 to 2022. Model 1 includes JAXA PALSAR data and uses models trained with the 2008 and 2018 NFIs; Model 2 excludes PALSAR data and uses four independently trained models for the 2003, 2008, 2013, and 2018 NFIs; and Model 3 uses a single model trained with pooled observations from all four NFI periods. Forest and non-forest areas were identified using the LULC dataset of Yang and Huang (2021), with the latter comprising cropland, shrubland, grassland, urban, and wetland pixels. Shaded bands indicate ± 1 standard deviation across the five cross-validation models.

Further separation of the non-forest estimates by land-cover type showed clear differences in their contributions to the total number of trees (Fig. 8). Across all three modelling strategies, cropland contained substantially more trees than the other non-forest land-cover types, and this contrast was particularly pronounced in Model 1 (Fig. 8a). Grassland and urban areas generally made the next largest contributions, with relatively small differences between them, whereas shrubland contributed fewer trees and wetland consistently made the smallest contribution.

The differences among the three modelling strategies were also apparent within individual land-cover types. Model 2 again showed pronounced discontinuities between successive modelling periods (Fig. 8b), with particularly large changes in cropland and grassland estimates. In contrast, Model 3 produced substantially smoother trajectories for most non-forest land-cover types over the 1985–2022 period (Fig. 8c). Cropland tree numbers generally increased over the study period, with some variation in the trajectory around 2000, and reached a maximum around 2017–2018 before declining toward 2022. By comparison, urban areas showed a gradual increase during the later part of the time series, while grassland generally declined slightly and changes in shrubland and wetland were comparatively small.

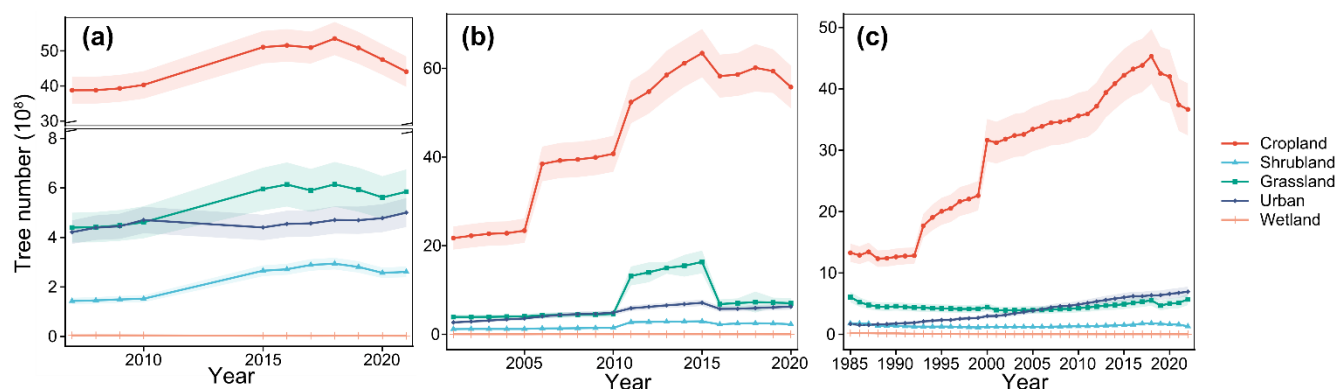


Figure 8: Tree counts in non-forest areas in China over the study period. Temporal changes in the estimated number of stems across five non-forest land-cover types under the three modelling strategies. Panels (a)–(c) represent Models 1–3, respectively. Model 1 includes JAXA PALSAR data, Model 2 comprises four independently trained models corresponding to the four NFI periods, and Model 3 uses a single model trained with pooled observations from all four NFI periods. Non-forest areas were classified as cropland, shrubland, grassland, urban, and wetland according to the LULC dataset of Yang and Huang (2021). Shaded bands indicate ± 1 standard deviation among the five cross-validation models. Tree numbers are expressed in units of 10^8 stems.

Model 3 produced temporally continuous tree-density maps for China from 1985 to 2022 (Fig. 9). Throughout the study period, moderate- to high-density tree stands were primarily distributed in northeastern China and across the humid southern and southeastern regions, whereas tree density remained low over most of northwestern China and the interior Tibetan Plateau. This broad geographical pattern was already evident in 1985 and changed progressively rather than through abrupt shifts between successive periods. From the mid-1990s onwards, areas with densities of approximately 500–1000 stems ha^{-1} became increasingly extensive and spatially continuous, with the clearest increases occurring in southern and southwestern China and along the eastern forest belt. High-density patches in northeastern China persisted throughout the time series, while southern China exhibited a more widespread increase after 2000. The frequency distributions further showed that the lowest-density class (A, 0–200 stems ha^{-1}) remained dominant throughout the study period, whereas the relative frequencies of intermediate- to high-density classes, particularly classes D–F (600–1200 stems ha^{-1}), generally increased over time. The spatial distributions in 2015, 2020, and 2022 were broadly similar, although locally higher densities were apparent in the two most recent maps.

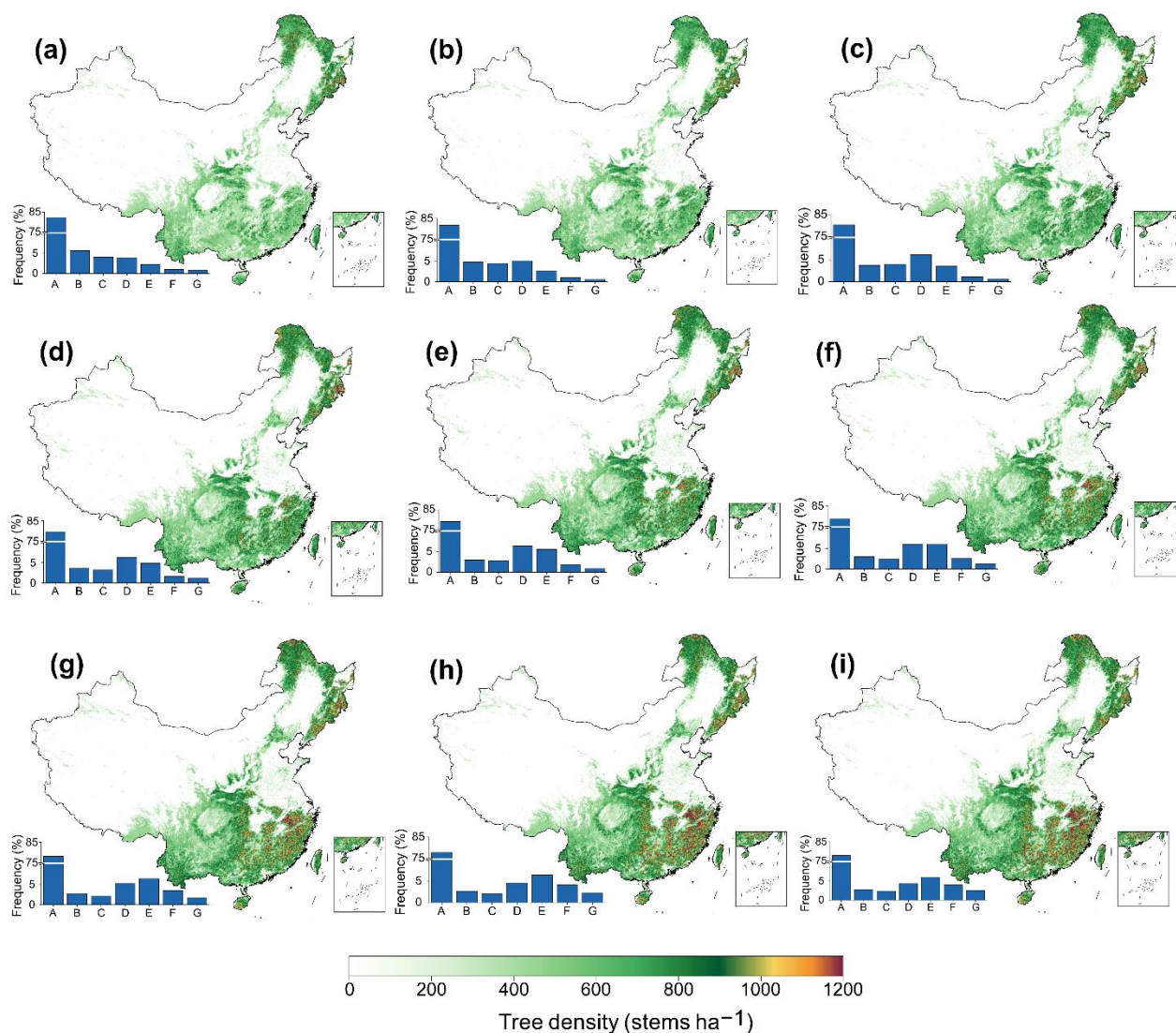


Figure 9: Temporal changes in the spatial distribution of tree density in China from 1985 to 2022. Panels (a)–(i) correspond to 1985, 1990, 1995, 2000, 2005, 2010, 2015, 2020, and 2022, respectively. The inset histograms show the frequency (%) of tree-density values within seven classes: A, 0–200; B, 200–400; C, 400–600; D, 600–800; E, 800–1000; F, 1000–1200; and G, ≥ 1200 stems ha^{-1} . Tree densities ≥ 1200 stems ha^{-1} are represented by the upper-end color of the map scale.

4 Discussion

4.1 Comparison with existing tree-density products

Despite differences in data sources, tree definitions, spatial resolution, and modelling approaches, our tree-density product shows broad spatial consistency with both the China tree-density map of Cheng et al. (2025) and the global tree-density product of Crowther et al. (2015) in several regions (Fig. 10). In the arid basins of northwestern China, much of the Tibetan Plateau,



the steppe regions of northern China, and parts of the Loess Plateau, differences among the three products are generally small. These regions are dominated by arid, semi-arid, alpine, or steppe environments, where extensive areas are non-forested or support only sparse and spatially fragmented tree cover. This spatial pattern is consistent with previous national-scale assessments showing generally low tree densities across northern and northwestern China (Cheng et al., 2025), while recent
 540 high-resolution forest mapping has also highlighted the sparse and fragmented distribution of forests in northern China, particularly on the Loess Plateau (Peng et al., 2024). The relatively close agreement among the three products in these low-density regions suggests that they capture similar broad-scale spatial constraints on tree occurrence. Relatively small differences are also observed in parts of northeastern, northern, and eastern China, indicating that the major spatial pattern of tree density in these areas is represented similarly among the three datasets (Fig. 10). Such agreement is notable given their
 545 substantial methodological differences: the product of Cheng et al. (2025) was developed specifically for China at 100 m resolution, whereas the product of Crowther et al. (2015) was produced within a global modelling framework using more than 400,000 ground-based tree-density observations worldwide.

More pronounced discrepancies occur in several other regions (Fig. 10). Relative to both the products of Cheng et al. (2025) and Crowther et al. (2015), our estimates are lower in parts of the southern and eastern Tibetan Plateau, southwestern China,
 550 northern China, and central and southern Taiwan. Outside these regions, however, the spatial patterns of disagreement differ substantially between the two reference products. Comparison with Crowther et al. (2015) reveals a strongly contrasting spatial pattern (Fig. 10a). Across extensive areas of northeastern China, our estimated tree densities are lower than those of Crowther et al. (2015), with differences in many locations reaching -500 stems ha^{-1} or less. In contrast, positive differences occur in several high-tree-density regions of eastern, central, and northern China, where our estimates exceed those reported by
 555 Crowther et al. (2015). These positive differences should not be interpreted directly as evidence of model underestimation in the Crowther et al. (2015) product because the two datasets differ in their definitions of counted trees and in several aspects of their underlying data and modelling frameworks. In particular, Crowther et al. (2015) defined trees as individuals with a diameter at breast height (DBH) of at least 10 cm, whereas the present study includes trees with $\text{DBH} \geq 5$ cm. The exclusion of smaller-diameter trees from the Crowther et al. (2015) dataset may therefore contribute to its lower tree-density values in
 560 some densely stocked forests, especially where small stems constitute a substantial fraction of the stand population. Compared with Cheng et al. (2025), our estimates are higher across much of the remaining forested area of China, with parts of southern China representing the principal exceptions (Fig. 10b). Overall, the comparison with Crowther et al. (2015) is characterized by extensive negative differences in northeastern China and positive differences in several high-density forest regions, whereas differences relative to Cheng et al. (2025) are more spatially coherent and predominantly positive across much of the country.
 565 The frequency distributions of pixel-level differences provide further support for these spatial patterns (Fig. 10c, d). In comparison with Crowther et al. (2015), most pixels fall within the 0 – 100 stems ha^{-1} interval (Fig. 10c), indicating that our estimates are only slightly higher across a large proportion of the compared area. Together with the spatial pattern shown in Fig. 10a, this suggests broad consistency between the two products at the regional scale. The remaining differences may partly



reflect their substantially different native spatial resolutions, as the Crowther et al. (2015) product was produced at an
 approximately 1-km spatial scale (30 arc-seconds), and spatial aggregation at coarser resolutions tends to reduce local
 variability and smooth fine-scale spatial heterogeneity (Nelson et al., 2009). In comparison with Cheng et al. (2025), most
 pixel-level differences are concentrated between 0 and 800 stems ha^{-1} , with the largest number of pixels occurring in the 400–
 600 stems ha^{-1} interval (Fig. 10d). Combined with the spatial pattern in Fig. 10b, this indicates that our product generally
 provides higher tree-density estimates across much of the forested area, although these positive differences are mostly below
 800 stems ha^{-1} .

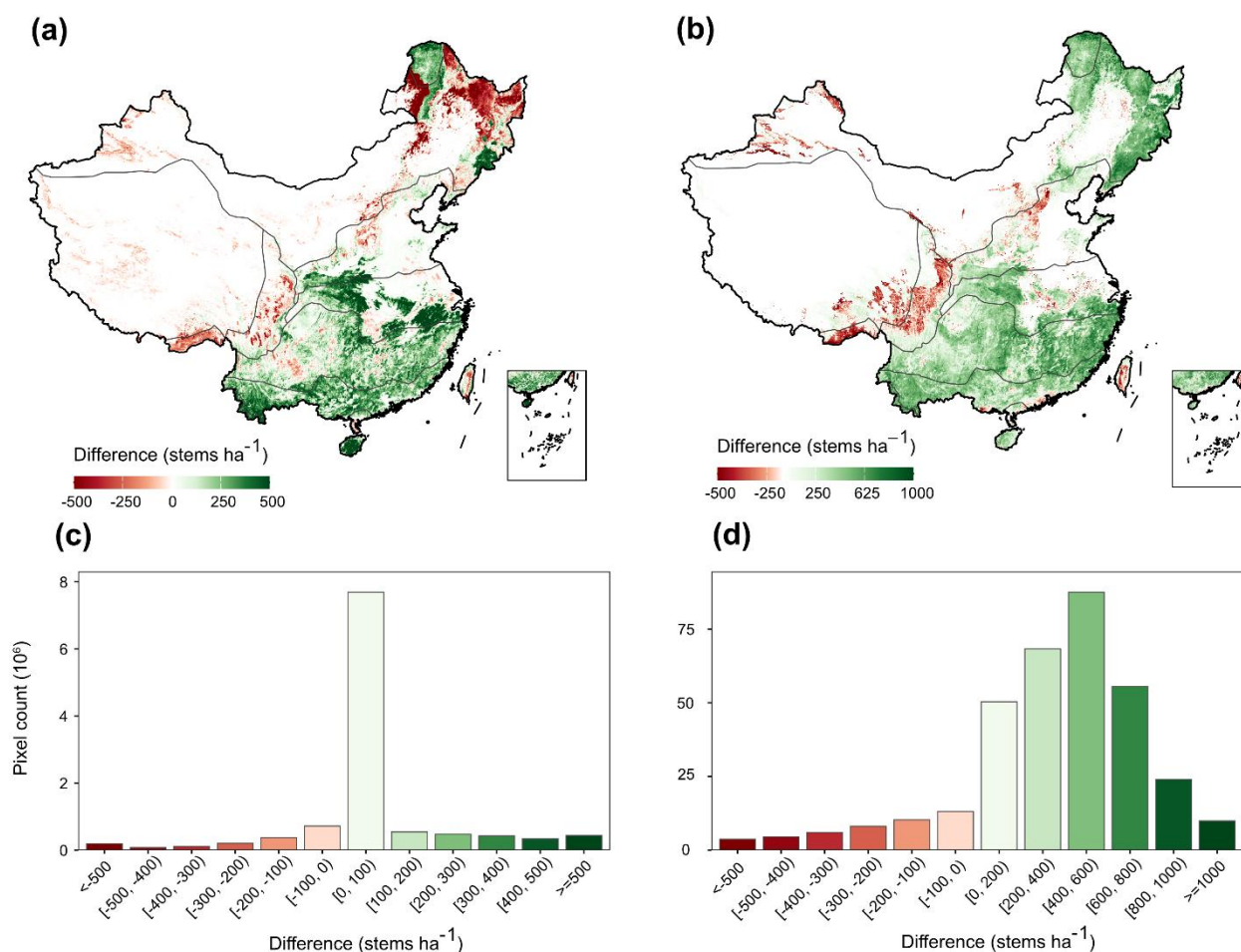


Figure 10: Spatial comparison of the Model 3 tree-density estimates with two existing tree-density products. Differences were calculated as the Model 3 estimate minus the corresponding reference product after harmonizing the coordinate system, spatial extent, grid, and units. (a) Difference between the Model 3 estimate (2015) and the global tree-density product of Crowther et al. (2015) at an approximately 1 km spatial resolution; (b) difference between the Model 3 estimate (2020) and the China forest tree-density product of Cheng et al. (2025) at an approximately 100 m spatial resolution. Green indicates that the Model 3 estimate is higher than the reference product, whereas red indicates that it is lower. Panels (c) and (d) show the counts of valid comparison pixels among tree-density difference intervals corresponding to panels (a) and (b), respectively. Only pixels classified as forest and containing valid estimates in both products were included. In panel (d), only valid pixels from the product of Cheng et al. (2025) were included in the analysis, with non-forest pixels designated as NoData excluded.



The comparison in climate space further reveals that the discrepancies among the three tree-density products are strongly dependent on environmental conditions rather than representing a uniform offset (Fig. 11). Relative to both Crowther et al. (2015) and Cheng et al. (2025), our product generally shows lower tree densities under tropical rain forest conditions, while a similar negative difference is also evident in the temperate rain forest domain when compared with the Crowther product. In contrast, the comparison with Cheng et al. (2025) shows predominantly positive differences across a broad range of mean annual precipitation between approximately 50 and 200 cm, suggesting that, outside the wettest and structurally most complex forests, tree densities estimated in this study are generally higher. This pattern is consistent with an important methodological distinction between the two products. Cheng et al. (2025) derived their training tree densities from individual-tree segmentation of UAV LiDAR data, whereas the present study directly uses forest inventory measurements as model reference data. The reported national mean tree density of 689 trees ha⁻¹ in Cheng et al. (2025) is substantially below the 1052 trees ha⁻¹ indicated by the 9th National Forest Resources Inventory. This underestimation is primarily attributed to the difficulty of identifying individual trees beneath overlapping crowns, particularly mid-storey and understorey individuals in dense forests. Direct calibration against inventory measurements avoids introducing this intermediate tree-segmentation error into the response variable and may therefore partly explain the generally higher densities obtained here (Cheng et al., 2025). Nevertheless, the negative differences that persist in rain forest environments indicate that inventory-based calibration cannot completely overcome the limited sensitivity of remote-sensing predictors to vertically complex, multilayered forest structure.

In comparison, a different pattern emerges between our estimations and Crowther et al. (2015). Specifically, clear positive differences are largely concentrated in relatively warm and dry climate space, approximately where mean annual precipitation is below 200 cm and mean annual temperature exceeds 10 °C, whereas no equally coherent difference is apparent under colder and drier conditions. This climate-dependent divergence is unsurprising given that the Crowther product was developed primarily to reproduce tree-density patterns at global and biome scales using biome-level models and ~1 km spatial covariates; its accompanying data descriptor explicitly cautions against interpreting the product as a precise local- or pixel-scale estimate (Crowther et al., 2015; Glick et al., 2016). The higher densities obtained here in some warm and relatively dry regions may additionally reflect locally heterogeneous afforestation and forest-management effects in China, which can modify tree abundance independently of broad climatic controls and may consequently be smoothed in a globally calibrated model (Bryan et al., 2018; Cao et al., 2011). These comparisons suggest that the main advantage of the present inventory-calibrated product is most evident across low- to intermediate-precipitation environments, whereas very humid, structurally complex forests remain a major source of uncertainty for remotely sensed tree-density estimation. Besides, the ground-based observations available for mainland China were relatively sparse in Crowther et al. (2015), in which the Global Index of Vegetation-Plot Databases (GIVD; Dengler et al., 2011) used has only approximately 330 plots located within China. Such a global framework was designed primarily to capture broad biome- and global-scale patterns rather than fine-scale variation within individual countries, and may therefore inadequately represent the regional characteristics and spatial heterogeneity of tree density across China.

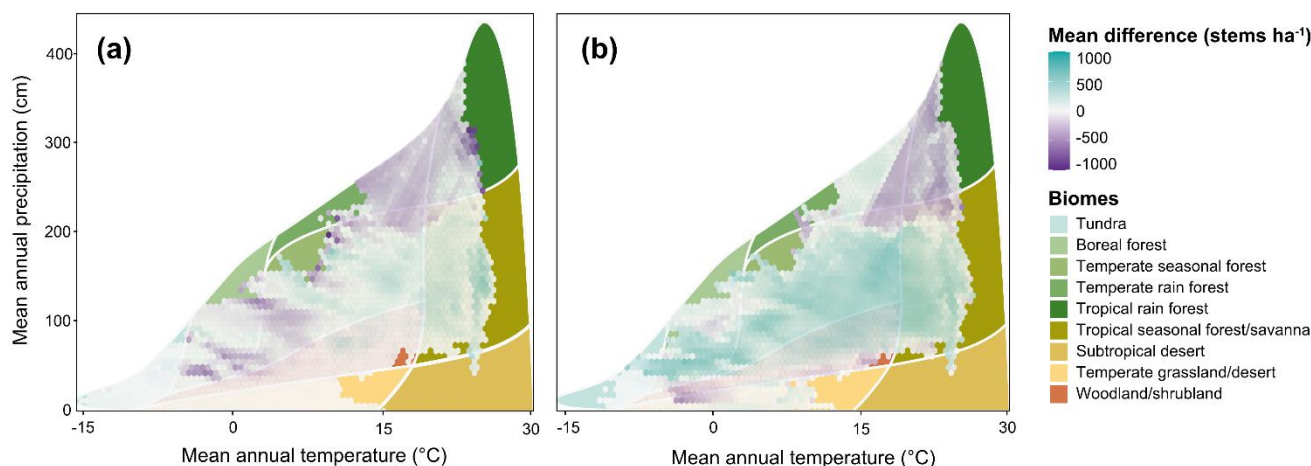


Figure 11: Distribution of inter-product differences in forest tree density across Whittaker climate–biome space. Mean tree-density differences were calculated as the 2015 Model 3 estimate minus (a) the global tree-density product of Crowther et al. (2015), and the 2020 Model 3 estimate minus (b) the China tree-density product of Cheng et al. (2025). Each hexagonal bin represents the mean difference among spatially overlapping valid forest pixels falling within the corresponding combination of mean annual temperature and mean annual precipitation. Cyan colors indicate higher tree density in Model 3, purple colors indicate lower density in Model 3, and near-white colors indicate close agreement between products. Background polygons represent the principal terrestrial biomes defined in Whittaker climate space (Whittaker, 1975). All tree-density products were harmonized to consistent units, spatial extent and grid alignment before comparison. In panel (a), 14,390 pixels (0.12%), and in panel (b), 1,029,783 pixels (0.30%), fell outside the Whittaker climate–biome space and were therefore not plotted.

Another important advantage of the present product lies in its finer spatial resolution and more complete representation of tree populations across different land-cover types. The 30 m spatial resolution is substantially finer than the previous products. More importantly, both reference products were developed primarily to characterize tree density within forested areas, whereas our product explicitly extends tree-density estimation to non-forest landscapes. This distinction is important because a considerable number of trees in China occur outside conventionally defined forests. Our results show that croplands contain by far the largest proportion of non-forest trees, while trees are also widely distributed across shrublands, grasslands, impervious surfaces, and wetlands. Trees outside forests are increasingly recognized as an important component of terrestrial ecosystems because they contribute to carbon storage, microclimate regulation, soil and water conservation, and landscape resilience (Skole et al., 2021). A recent nationwide assessment further estimated that trees in non-forest ecosystems account for 20.8–32.9 % of China’s above-ground carbon, with particularly substantial contributions from cropland trees (Su et al., 2026). The combination of 30 m resolution and coverage across both forest and non-forest land therefore enables the present product to better resolve fragmented forests, shelterbelts, scattered trees, and heterogeneous agricultural and urban landscapes that are difficult to characterize using coarser forest-oriented tree-density products.

Additionally, the present dataset is advantaged in its multi-decadal temporal coverage (1985 to 2022). This temporal dimension makes it possible to move beyond a snapshot of contemporary tree distribution and to examine long-term changes in tree



abundance at both national and regional scales. In particular, the dataset enables changes within existing forests, newly established forests, and trees outside forests to be examined within a common framework, thereby providing a basis for investigating long-term forest dynamics, land-management effects, and ecological restoration.

4.2 Spatiotemporal patterns of tree stem density

The reconstructed time series reveals a clear long-term increase in tree abundance across China from 1985 to 2022, although this increase was neither spatially uniform nor temporally monotonic. The overall trajectory is broadly consistent with the profound transition in forest management that has occurred in China over the past four decades, during which forest policy shifted progressively from timber production toward large-scale afforestation, ecological restoration, and the protection and recovery of existing forests. The Three-North Shelter Forest Program, initiated in 1978 across northern, northeastern, and northwestern China, represented the earliest of these large-scale restoration efforts and was followed by a series of national programs that further accelerated forest recovery, particularly after 2000 (Lu et al., 2018; Yue et al., 2024). The ecological mechanisms through which these policies influence tree abundance, however, are not identical. Afforestation programs such as the Three-North Shelter Forest Program directly increase tree numbers by establishing new stands in formerly sparsely wooded landscapes, whereas the Natural Forest Protection Program, initiated in 1998, substantially reduced timber extraction from natural forests and therefore promoted the persistence, regeneration, and structural development of existing stands. In contrast, the Grain for Green Program, initiated in 1999, promoted the conversion of croplands and other marginal lands into forest and other perennial vegetation, thereby contributing primarily to forest expansion and the establishment of young stands (Cheng et al., 2024; Liu et al., 2008; Yue et al., 2024). These different pathways are reflected in the spatial patterns detected by our dataset. Increasing tree abundance is evident across parts of northern China within the broad implementation region of the Three-North program, but substantial increases also occur in the already forest-rich regions of southeastern China. The latter pattern is important because it indicates that the national increase cannot be explained by the establishment of new forests alone. Independent Landsat-based analyses have shown that planting campaigns during the 1990s were particularly prominent in southeastern China, while forests established around 2000 subsequently underwent rapid canopy development and densification during the following decade (Tong et al., 2023). Consistently, Cheng et al. (2024) found that the area of planted forests in China nearly doubled between 1990 and 2020, with expansion accelerating after 2000. Thus, the increasing tree abundance reconstructed here likely represents a combination of forest expansion, through the establishment of new planted forests, and stand densification and recovery, through tree recruitment and reduced disturbance within existing forests. This distinction is ecologically important because an increase in forest area does not necessarily imply a proportional increase in tree abundance or stand structural development, whereas tree-density trajectories provide complementary information on changes occurring within forest stands themselves. At the same time, these trends should not be interpreted as the consequence of restoration policy alone. Forest development is also regulated by stand age, climate variability, water availability, disturbance, and management intensity; for example, improved climatic conditions contributed to the rapid densification of



some southern Chinese forests during the 2010s (Tong et al., 2023). Consequently, the long-term increase observed in our dataset can be viewed as the integrated outcome of large-scale ecological restoration, forest protection, stand development, and environmental variability rather than as a simple response to afforestation alone.

The stand-age structure recorded by the 9th National Forest Inventory provides an independent demographic perspective on the long-term forest changes described above (Fig. 5). Among the 47,622 natural-forest observations, 15,874 plots (33.3%) belong to the <10-year age class, indicating a substantial representation of recently regenerated natural forests by 2018. Although the proportion of inventory plots should not be interpreted directly as an equivalent proportion of national forest area, the prominence of this youngest cohort is consistent with continued natural regeneration and forest recovery during approximately 2008–2018, following decades of strengthened protection and reduced disturbance of natural forests. A second notable feature is the relatively large number of natural-forest plots in the 20–30-year class ($n = 6751$), exceeding those in both the 10–20-year ($n = 6263$) and 30–40-year ($n = 5068$) classes. This local peak indicates a substantial cohort of natural forests regenerated approximately between 1988 and 1998. Because these stands are classified as natural forests, however, this pattern is more appropriately interpreted as evidence of natural regeneration and secondary-forest recruitment rather than as a direct consequence of tree planting. Independent Landsat-based evidence nevertheless shows that the late twentieth century and the period around 2000 represented an important phase of forest recovery in southeastern China, followed by pronounced forest densification in subsequent decades (Tong et al., 2023).

The age structure of planted forests is even more strongly skewed toward recent decades. Of the 25,149 planted-forest observations, 20,992 (83.5%) are younger than 30 years, whereas only 90 plots (0.36%) are older than 60 years. In particular, the 10–20-year class accounts for 31.0% of the planted-forest observations and corresponds approximately to stands established during 1998–2008, broadly coinciding with the rapid expansion of large-scale restoration and afforestation programs after the late 1990s, especially the Grain for Green Program. The presence of a substantial 30–40-year cohort is likewise temporally compatible with earlier afforestation efforts initiated in the late 1970s, including the Three-North Shelter Forest Program, although the national age distribution alone cannot assign individual stands to specific restoration programs. Cheng et al. (2024) independently showed that China's planted-forest area increased by 94.3% between 1990 and 2020 and that most existing planted forests remain in young or middle age classes, while both area expansion and the subsequent growth of young plantations have contributed substantially to the increase in planted-forest carbon storage. The scarcity of old planted-forest plots therefore likely reflects a combination of the relatively recent expansion of China's plantation resource and management processes such as harvesting and rotation, rather than simply an absence of long-lived planted stands. More broadly, this age structure is consistent with the demographic changes reported by Dong et al. (2023) using the NFI plots from the 6th to 9th NFIs: tree populations increased substantially in both natural and planted forests from 1998 to 2018, with particularly pronounced increases in planted forests.

In parts of southern China, tree-density changes are relatively heterogeneous, particularly in regions where forest harvesting and regeneration are frequent (Fig. 9). Satellite-based studies have reported widespread timber harvesting in southern China



during 2002–2017, together with substantial forest regrowth following disturbance (Tong et al., 2020). Therefore, some of the spatial and temporal variation observed in these regions may partly reflect harvesting and subsequent regeneration. At a broader scale, the overall increase in tree abundance is consistent with the continued expansion and growth of planted forests in eastern and southern China over recent decades (Cheng et al., 2024).

715 4.3 Uncertainties and potential improvements

Prediction uncertainty was quantified as the pixel-wise standard deviation of predictions from the five models generated through five-fold spatial cross-validation. This standard deviation reflects the variability among the five model predictions and was used to characterize the spatial distribution of prediction uncertainty for each year. The spatial pattern of prediction uncertainty is relatively consistent throughout the time series, although high-uncertainty areas become somewhat more pronounced in the later years. Low to moderate standard deviations occur across most of China, whereas higher values are mainly concentrated in the more densely forested regions of southeastern China and central and southern Taiwan, with additional localized patches in northeastern and southern China (Fig. 12). The frequency distributions further show that lower-uncertainty classes consistently account for the largest proportions of pixels, and the frequency generally decreases toward the higher-uncertainty classes. Pixels with the highest standard deviations represent only a relatively small fraction of the mapped area, although their proportion increases slightly in the later part of the time series. This suggests that high prediction uncertainty is spatially concentrated rather than widespread across the product.

When considered together with the model evaluation results, which show an increasing tendency to underestimate observations toward the upper end of the tree-density range, the high-uncertainty areas occurring in dense forests are likely to be more susceptible to underestimation. One probable reason is the relatively limited representation of extremely high-density stands in the forest inventory data. Random-forest regression combines predictions from multiple regression trees, and estimates near the extremes of the response distribution are consequently sensitive to the availability of representative training samples (Breiman, 2001). Similar behaviour has been reported in forest remote-sensing applications, where random-forest models tended to underestimate high forest attributes while overestimating low values (Duncanson et al., 2017). The same mechanism may therefore lead to some overestimation at the lower end of the tree-density distribution, particularly in sparse or fragmented forests and in transition areas surrounding denser forests. The standard-deviation maps alone cannot determine whether predictions are biased upward or downward, because they describe variation among model predictions rather than the direction of prediction error. Spatial patterns of potential bias should be evaluated together with the predicted tree-density maps and model residuals.

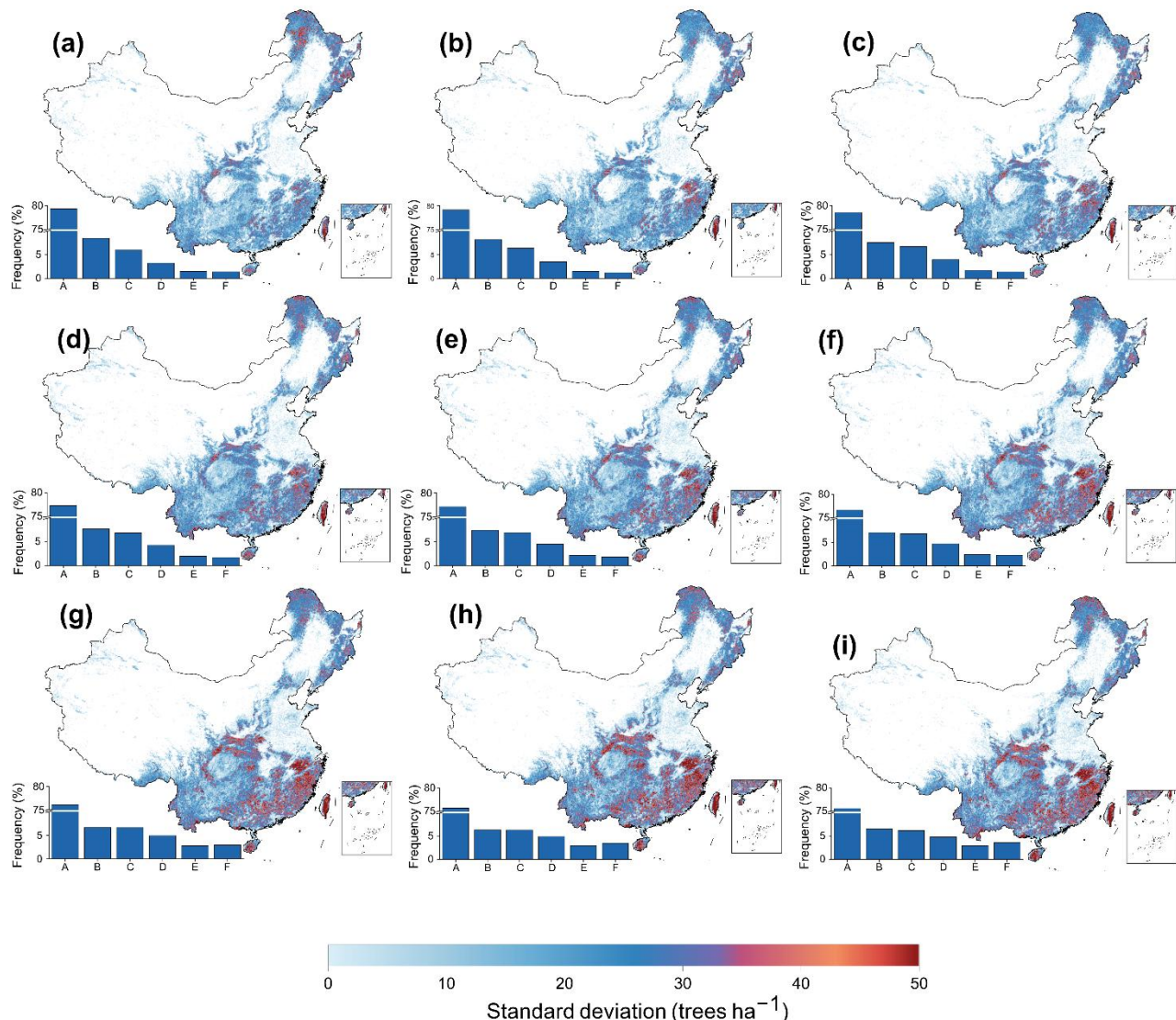


Figure 12. Prediction uncertainty in tree density from 1985 to 2022, quantified as the pixel-wise standard deviation among predictions from the five models generated through five-fold spatial cross-validation. (a) 1985; (b) 1990; (c) 1995; (d) 2000; (e) 2005; (f) 2010; (g) 2015; (h) 2020; (i) 2022. The inset histograms show the percentage of pixels in six standard-deviation classes: A, [0, 10); B, [10, 20); C, [20, 30); D, [30, 40); E, [40, 50); and F, ≥ 50 stems ha^{-1} .

The feature-importance analysis further suggests that some of the most influential predictors may themselves contribute to the underestimation of very high tree densities. Stand age is consistently the most important predictor, but its relationship with tree density is inherently non-unique. During stand establishment and regeneration, recruitment can increase the number of established trees, whereas increasing competition after canopy closure eventually induces density-dependent mortality and



self-thinning. Consequently, stem density may reach a maximum during stand development and subsequently decline as
 750 surviving trees increase in size. The timing and magnitude of this trajectory vary with species, initial stocking, site conditions,
 and climate (Walker et al., 2020), implying that stands of different ages can have similar stem densities and stands of the same
 age can differ substantially in density. Although random forests can accommodate such nonlinear relationships, this ecological
 ambiguity limits the amount of information that stand age alone can provide. A more direct limitation arises from tree canopy
 cover, which is consistently among the three most important predictors. Canopy cover represents the horizontal proportion of
 755 ground occupied by vertically projected tree crowns; once crown cover approaches complete closure, additional stems beneath
 the upper canopy or further crown overlap produce little or no corresponding increase in this variable. This saturation therefore
 reduces sensitivity to differences among very dense stands. Similar limitations apply to optical predictors. NDVI is well known
 to asymptotically saturate under high-biomass conditions, whereas EVI retains greater sensitivity in dense vegetation but still
 primarily responds to upper-canopy spectral and structural properties rather than directly resolving the number of subcanopy
 760 stems (Huete et al., 2002). The HH and HV radar variables included in Model 1 provide complementary sensitivity to woody
 and vertical forest structure and can therefore partly compensate for the limitations of optical observations. However, radar
 backscatter remains an indirect proxy for forest structure rather than a direct measurement of stem abundance, and its response
 varies with forest type, scattering geometry, vegetation and surface moisture, and environmental conditions; it can also become
 progressively saturated at high biomass levels (Yu and Saatchi, 2016). Taken together, the non-unique age–density relationship
 765 and the progressive saturation of canopy-cover, optical, and radar signals reduce the contrast among the densest stands and
 likely contribute to the systematic underestimation observed at the upper end of the tree-density range.

Methodological uncertainty also arises from the trade-off between period-specific model performance and temporal
 comparability. Among the three modelling scenarios, Scenario 2, in which an independent model was trained for each of the
 four NFI cycles, produced the largest discontinuities in the reconstructed national tree-density trajectory. Although fitting
 770 separate models allows each inventory period to be optimized against its contemporaneous observations, differences between
 successive estimates may reflect not only actual changes in tree abundance but also changes in training-sample composition
 and the fitted model response. Consequently, estimates generated by different period-specific models are less suitable for direct
 temporal comparison. This issue is particularly important in long-term remote-sensing reconstruction, as temporal changes in
 model–predictor relationships can introduce biases into estimated trends even when individual models perform well within
 775 their respective calibration periods (Filippelli et al., 2024). Scenario 1, which additionally incorporated HH and HV radar
 backscatter, alleviates the optical signal saturation in producing stem-density maps, but its restricted temporal coverage
 prevented reconstruction on a consistent basis over the full 1985–2022 period. Scenario 3 therefore represents a compromise
 between predictive performance and temporal consistency. For this reason, Scenario 3 was adopted for the final product in this
 study.

780 Several avenues could further improve the accuracy and reliability of future tree-density reconstructions. Although RF
 provided satisfactory performance in the present study, alternative machine-learning approaches, such as XGBoost and



CatBoost, might have better performance in other regions. Besides, deep-learning approaches may provide an additional opportunity when high-resolution imagery is available. For example, individual tree crowns have been successfully delineated directly from sub-meter satellite imagery over very large areas (Brandt et al., 2020). More importantly, future models could incorporate more direct measurements of vertical forest structure. Space-borne LIDAR observations from GEDI and ICESat-2 provide canopy-height and vertical-structure information that is complementary to optical canopy-cover indices, and the fusion of GEDI with Sentinel-2 imagery has already enabled global canopy-height retrieval at 10 m resolution (Lang et al., 2023). For temporal reconstruction, recently developed 30 m annual vegetation-height products covering 2000–2022 also provide a potentially useful structural constraint, although their temporal consistency and dependence on other satellite inputs should be carefully considered before integration (Hunter et al., 2025). Improvements to the reference data may ultimately be equally important, particularly by better representing extremely dense stands and ensuring close temporal correspondence between inventory plots and satellite observations.

Data availability

The ChinaTD30 dataset is publicly available on Zenodo through the master record at <https://doi.org/10.5281/zenodo.23100944> (Xian et al., 2026a). Owing to the large data volume, the complete dataset is organized into nine part records. The corresponding DOIs and data citations are provided in Table 4.

Table 4. DOIs and corresponding citations for the ChinaTD30 dataset.

Record	DOI	Citation
Master	10.5281/zenodo.23100944	Xian et al. (2026a)
Part 1	10.5281/zenodo.23108775	Xian et al. (2026b)
Part 2	10.5281/zenodo.23109771	Xian et al. (2026c)
Part 3	10.5281/zenodo.23109786	Xian et al. (2026d)
Part 4	10.5281/zenodo.23109796	Xian et al. (2026e)
Part 5	10.5281/zenodo.23109804	Xian et al. (2026f)
Part 6	10.5281/zenodo.23109810	Xian et al. (2026g)
Part 7	10.5281/zenodo.23109820	Xian et al. (2026h)
Part 8	10.5281/zenodo.23109826	Xian et al. (2026i)
Part 9	10.5281/zenodo.23109833	Xian et al. (2026j)



800 **Author contributions**

Ziyi Xian: Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing, Visualization. **Zhen Yu:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Writing – original draft, Writing – review & editing, Visualization. **Jinge Yu:** Resources, Software, Visualization. **Shirong Liu:** Resources, Funding acquisition.

805 **Competing interests**

Zhen Yu is a member of the Editorial Board for Earth System Science Data but had no role in the peer review, editorial management, or final decision regarding this manuscript.

Ethics approval and consent to participate

Not applicable.

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815 **Declaration of Generative AI and AI-assisted Technologies**

During the preparation of this manuscript, the authors used ChatGPT (OpenAI) to assist with language editing and improve the readability and clarity of the text. The authors reviewed and edited the output as necessary and take full responsibility for the content of this publication. The use of these tools did not influence the scientific content, interpretation, conclusions, or authorship of the work.

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