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Enhanced CO_2 Response and Aging-Related Dynamics Drive a Greater Leaf Area Index Increase in China's Planted Forests in Comparison to Natural Forests

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Abstract China's forests have experienced a notable increase in leaf area, driven by planted forest expansion and natural forest conservation. However, how planted and natural forests respond differently to environmental changes remains unclear. Using leaf area index (LAI) data, propensity score matching (PSM), and machine learning, we compared these forest types under similar conditions. We show that planted forests increased their leaf area 65.8% faster than natural forests nationally. Even when comparing forests of similar age and growing conditions, planted forests grew 4.6% faster—especially in mixed and evergreen forests, where they showed stronger responses to rising CO_2. This CO_2-driven advantage declines markedly after age 40. Although natural forests eventually surpass planted forests in age-related LAI growth, planted forests' initial advantage is stronger due to their younger age (34 vs. 57 years) and greater CO_2 sensitivity. Our findings highlight planted forests' role in carbon sequestration and could help inform improvements in ecosystem models.

Plain Language Summary China has experienced a notable increase in the density of its forest foliage, largely due to planted forest expansion and natural forest conservation. However, it has remained uncertain how planted and natural forests respond differently to global environmental changes (e.g., rising CO_2), as the former grow and the latter age. Here, we used satellite data, propensity score matching, and machine learning to compare planted and natural forests under similar environmental conditions. We found that planted forests increased their leaf area about ~2/3 faster than natural forests across China. Even when comparing forests of similar age and growing conditions, planted forests still grew 4.6% faster. This difference was largest in mixed and evergreen forests, mainly because planted forests responded more to higher CO_2. However, this extra CO_2-driven growth decreases noticeably after about 40 years of age. While natural forests eventually catch up in some growth measures—typically between 21 and 53 years—planted forests exhibit a stronger initial advantage due to their younger age (34 vs. 57 years) and greater sensitivity to CO_2. These findings highlight how planted forests help absorb carbon from the air and support climate action. They also provide useful insights for improving climate and ecosystem models in the future.

Key Points:

- Planted forests exhibit a 4.6% stronger LAI trend than their natural counterparts after controlling for environmental and age differences
- A younger age structure and enhanced CO_2 response act in synergy as the drivers of the greater LAI trend in planted forests
- The CO_2 fertilization effect on greening peaks in mid-aged stands (~30–40 years)

Supporting Information:

Supporting Information may be found in the online version of this article.

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1. Introduction

Forests constitute a key component of global climate regulation and ecosystem service delivery (Gamfeldt et al., 2013; Grassi et al., 2018). Against the background of the continued decline in natural forest cover, the expansion of planted forests has been widely promoted as a key strategy to achieve the United Nations' global forest targets, which aim to reverse forest cover loss and enhance forest-based benefits (Payn et al., 2015; Peters et al., 2023; UNDESA, 2021). However, planted and natural forests differ markedly in greening rates, biodiversity conservation, and long-term stability (Fan et al., 2024; Gao et al., 2023). Planted forests exhibit rapid growth due to management and selective species cultivation (Dangal et al., 2017; Zhu et al., 2022), but their simplified structure may accelerate age-related functional decline (He et al., 2012; Jin et al., 2024). In contrast, natural forests show greater resilience, attributed to biodiversity-mediated complexity and adaptive capacity (Liu et al., 2024; Ma et al., 2025). Despite these differences, international policy frameworks (e.g., Reducing Emissions from Deforestation and Forest Degradation–REDD+) and ecosystem models (e.g., Dynamic Global Vegetation Models–DGVMs) treat all forests uniformly (Chini et al., 2021; Pauly and Tosteson (2022)), disregarding distinct growth characteristics (Braakhekke et al., 2019; Cheng, Chen, et al., 2024; Tian et al., 2024). Such oversimplification not only masks regional forest growth dynamics but also propagates biases in global-

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scale assessments of carbon sequestration potential and climate feedbacks, given the widespread distribution of planted forests.

China, as the country with the world's largest planted forest area, has achieved remarkable success in ecological restoration (Erbaugh et al., 2020; Yao et al., 2024; Zhang et al., 2025). By 2020, planted forests covered 90.31 million hectares, accounting for 36.6% of the nation's total forest land (Cheng, Yang, et al., 2024). These large-scale afforestation programs have substantially contributed to the global increase in forest cover (Chen et al., 2019; Li et al., 2025; Tong et al., 2018), with substantial implications for hydrological processes, energy dynamics, and carbon cycling within the terrestrial biosphere (Liu et al., 2023; Park et al., 2023; Zhang et al., 2025). While natural forests in China show higher aboveground carbon accumulation during early establishment (Cheng et al., 2025), it remains unclear whether this advantage persists compared to planted forests (Fan et al., 2024; Gao et al., 2023). Addressing this question requires comparing the long-term vegetative dynamics between the two forest types. Leaf area index (LAI), as an integrative measure of canopy productivity and a key driver of carbon uptake, provides a suitable metric for such comparison. However, direct comparison is confounded by differences in environment and stand age (Alkama et al., 2022; Guo and Ren (2014); Zhu et al., 2016), which obscure forest-type effects (Zhong et al., 2021). Furthermore, state-of-the-art ecosystem models often neglect forest age effects, leading to biases in capturing these dynamics (Piao et al., 2020; Yue et al., 2018). Consequently, accurately investigating the distinctions and relative advantages between natural and planted forests requires approaches that can isolate the contribution of forest type from confounding environmental and age-related factors.

Here, we assess LAI divergence between planted and natural forests across China (Figure 1). Using propensity score matching (PSM), we pair stable planted and natural forest pixels to compare LAI trends (2000–2022) under comparable conditions (Cheng, Yang, et al., 2024; Fan et al., 2024). We then apply explainable machine learning to quantify the roles of forest age, type, and environmental drivers (Li et al., 2025). An innovation of our study lies in isolating how the LAI response to rising CO_2 and climate change is modulated by forest age and management history. We further benchmark these data-driven results against an ensemble of DGVMs, revealing biases in current model representations of age-mediated processes. This study aims to investigate the distinct responses of LAI dynamics in planted and natural forests to stand age and environmental conditions, thereby providing a basis for improving next-generation ecosystem models and informing evidence-based forest governance.

2. Materials and Methods

2.1. Data Sets and Preprocessing Procedures

We employed Sensor-Independent LAI data (500 m spatial resolution) at half-month temporal resolution from 2000 to 2022 (Pu et al., 2024). Annual mean LAI was calculated for trend analysis. We reconstructed China's 2020 forest age map by integrating three independent age products through gap-filling and ensemble averaging (Xu et al., 2023; Shang et al., 2023; Cheng, Chen, et al., 2024; Figure S1 in Supporting Information S1).

We utilized the data set developed by Cheng, Yang, et al. (2024), which provides maps of planted and natural forest distribution in China at 1 km resolution at five-year intervals from 1990 to 2020. A categorical classification scheme was applied to examine transitions between planted and natural forests over the period 2000–2020 (Figure S2 in Supporting Information S1). Our analysis focused on stable forest pixels. For the LAI trend analysis through 2022, we assumed these pixels remained largely unchanged during 2020–2022.

Environmental drivers included temperature, precipitation, solar radiation, vapor pressure deficit (VPD), and soil moisture derived from ERA5 and TerraClimate; elevation and slope from Copernicus DEM; human pressure from the Human Footprint Index; and atmospheric CO_2 concentration from the Keeling Curve. To integrate data sets with varying spatial resolutions into a unified analytical framework, all spatial data sets were resampled to a common 1 km resolution.

2.2. Controlling Covariates in LAI Trends Through Matching Method

To isolate the effect of forest type on LAI trends, we employed PSM to construct comparable groups of planted and natural forest pixels by balancing their environmental and structural characteristics. Propensity score matching is a statistical technique that reduces bias in observational studies by matching treatment and control units with similar probabilities of receiving the treatment, given a set of covariates (Wolf et al., 2021). Here, the

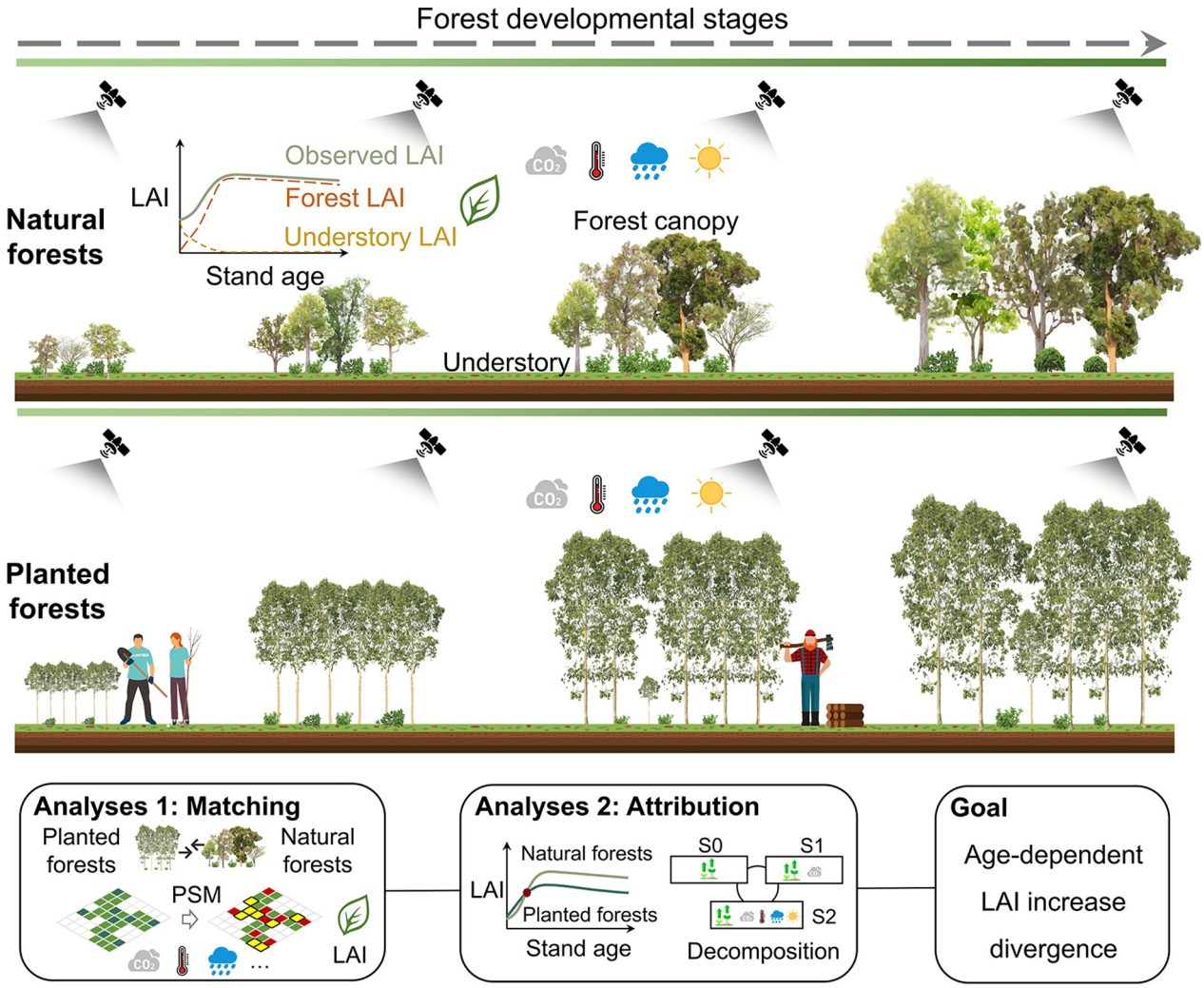

Figure 1. A conceptual diagram showing divergent leaf area index (LAI) trends between planted and natural forests induced by differential growth responses. Using propensity score matching and machine learning, we compared LAI trends between forest types while disentangling the effects of age, rising CO_2, and climate change on LAI dynamics.

"treatment" was defined as being a planted forest pixel, and the "control" as a natural forest pixel. The propensity score—the conditional probability of being a planted forest given the covariates—was estimated using a logistic regression model.

We included 13 biophysical covariates to capture the environmental and structural context of each forest pixel: forest age; plant diversity; plant functional type (PFT); human footprint index (HFP); elevation; slope; linear trends (2000–2022) of precipitation, temperature, soil moisture, solar radiation, and VPD; mean LAI; and ecoregion (Figure S3 in Supporting Information S1). Categorical covariates (ecoregion and PFT) were used as exact matching constraints to ensure that matched pixels came from the same ecoregion and functional type.

Given that natural forests cover 2.7 times more area than planted forests, we adopted a many-to-one matching design, where each planted forest pixel was matched to multiple natural forest pixels with similar propensity scores. Specifically, we applied nearest-neighbor matching within a caliper distance of 0.25 to balance proximity and match quality. Multiple planted pixels were allowed to match to the same natural pixel when no other suitable control was available, which maximizes the use of the larger natural forest pool while maintaining covariate balance. This design ensures that each planted pixel is compared to a set of environmentally similar natural pixels.

Matching quality was evaluated using several diagnostics (Figure S4 and S5; Table S1 and S2 in Supporting Information S1). First, we compared the distributions of propensity scores and forest age between the treatment

and control groups before and after matching to assess overall balance. Second, we computed standardized mean differences (SMD) for all covariates, with an absolute SMD < 0.1 considered acceptable balance. Third, we visualized covariate balance using a love plot, which displays SMDs before and after matching. Additionally, we conducted a sensitivity analysis for hidden bias using Rosenbaum's framework implemented in the "rbounds" *R* package (Rosenbaum, 2002). The sensitivity parameter Γ quantifies the degree of deviation from random assignment; at $\Gamma = 1$, the inference is insensitive to unmeasured confounding.

The PSM procedure successfully generated 641,541 matched pairs of planted and natural forest pixels with well-balanced covariates. Final comparative analyses of LAI trends were conducted using paired difference tests on the matched samples.

2.3. Attribution of Drivers Using Machine Learning

2.3.1. XGBoost Model and Partial Dependence Analysis

To understand LAI drivers, we used XGBoost (eXtreme Gradient Boosting) regression with partial dependence plots (PDPs) to analyze relationships between LAI and 13 variables across four domains: vegetation (diversity, functional type, age), climate (CO_2, temperature, precipitation, soil moisture, radiation, VPD), terrain (elevation, slope), and anthropogenic factors (human footprint index, establishment mode).

XGBoost builds an ensemble of decision trees to model complex nonlinear relationships (Glidden et al., 2024). Using R packages "xgboost," "DALEX," and "DALEXtra," we trained and validated the model via spatiotemporal cross-validation (3 spatial folds $\times$ 3 temporal blocks), stratifying by vegetation type and splitting into three longitudinal zones and three temporal periods (2000–2007, 2008–2015, 2016–2022). Hyperparameters (eta = 0.08, max_depth = 7, subsample = 0.7, colsample_bytree = 0.7) were selected via cross validation to minimize loss, and model performance was evaluated accordingly (Figure S6 in Supporting Information S1). Variable importance and partial dependencies were assessed using "'vivo::global_variable_importance" and "DALEX::model_profile".

A scenario-based decomposition isolated the effects of age, rising CO_2, and climate change on LAI. Scenarios included: S1 (constant year-2000 CO_2 and climate), S2 (historical CO_2 increase, constant climate), and S3 (all drivers as observed). Contributions were quantified via differential analysis (S2−S1 for CO_2; S3−S2 for climate). We further examined how CO_2 effects vary with forest age and assessed management influences by comparing planted and natural forests.

2.3.2. Analysis of the Marginal Effect of Forest Age

We employed partial dependence (PD) analysis to quantify the marginal effects of forest age on LAI across plant functional types (PFTs), comparing planted and natural forests (Bai et al., 2024). The marginal effect is defined as the change in LAI per additional year of forest age. Stratified XGBoost models by PFT and forest origin captured nonlinear age–LAI relationships, with PD plots isolating age-mediated responses. We identified "crossover age" thresholds where natural forests surpass planted forests in marginal LAI increase. We then projected age-mediated LAI contributions to 2060—a time horizon aligned with China's carbon neutrality goal and the mid-century target of many climate mitigation scenarios—by integrating marginal effects and areal distributions.

2.3.3. Quantification of Future LAI Trends and Their Driving Factors

We projected future LAI trends and attributed contributions from rising CO_2 and climate change using a multi-scenario, multi-model framework based on Coupled Model Intercomparison Project Phase 6 (CMIP6) Earth system models under three Shared Socioeconomic Pathways (SSP1-2.6, SSP2-4.5, and SSP5-8.5). The analysis comprised three steps (Text 4 in Supporting Information S1).

First, we estimated the CO_2 fertilization effect using the 1% per year increasing CO_2 experiment (1pctCO_2) from seven CMIP6 models (Table S3 in Supporting Information S1). For each model, we derived a CO_2-LAI response function for planted and natural forests by matching forest pixels to model grids via nearest-neighbor interpolation, which was then applied to the CO_2 trajectories of the three SSP scenarios. To account for age modulation, we adjusted the CO_2-induced LAI increment using age-dependent scaling factors derived from the XGBoost model's PD analysis (Text 5 in Supporting Information S1).

Second, we quantified climate change contributions using a factorial simulation approach with the pre-trained XGBoost model. The XGBoost model was pre-trained using historical data (2000–2022) with the 13 variables from Section 2.3.1 (vegetation, climate, terrain, and anthropogenic factors). Using this trained model, we quantified climate change contributions via a factorial simulation approach. For each SSP scenario, we constructed two input sets: S1 (CO_2 follows the SSP trajectory, climate fixed) and S2 (both CO_2 and climate follow the SSP trajectory). Climate variables were obtained from 13 CMIP6 models (Table S3 in Supporting Information S1). The climate contribution was calculated as the LAI difference between S2 and S1, with future projections anchored to the 2022 historical baseline to ensure continuity.

Third, we synthesized CO_2 and climate contributions to estimate total LAI trends over 2000–2060. For each SSP scenario and forest type, we computed multi-model ensemble means (MMEM) across the CMIP6 models to capture inter-model uncertainty. LAI trends were calculated via linear regression for five overlapping periods (2000–2020, 2010–2030, 2020–2040, 2030–2050, and 2040–2060), with results area-weighted by forest pixel weights for national-scale representativeness.

2.4. Comparison With DGVM Simulations

We evaluated LAI trend drivers using 14 TRENDY DGVMs (CABLE-POP, CLASSIC, CLM5.0, ED, ELM, IBIS, ISBACTRIP, JSBACH, JULES, LPJ-GUESS, LPJml, OCN, ORCHIDEE, and SDGVM). All model outputs were extracted at monthly resolution for the period 2000–2022, regridded to a common 0.5° spatial resolution, and aggregated to annual mean LAI for consistency with observations. Contributions of natural growth, rising CO_2, and climate change were quantified (Figures S7−S9 in Supporting Information S1) using three scenarios: S0 (constant CO_2, climate, land cover), S1 (rising CO_2 only), and S2 (combined CO_2 and climate forcing). Driver contributions were isolated by differential analysis (S1−S0 for CO_2; S2−S1 for climate), with MMEM compared against XGBoost attributions.

3. Results

3.1. Matched Comparison Reveals Enhanced LAI Trends in Planted Forests

Based on Sensor-Independent LAI products from 2000 to 2022, we found that at the national scale, the rate of LAI increase in stable planted forest areas (0.297 $m^2\ m^{-2}\ decade^{-1}$) was significantly higher than that in natural forests (0.179 $m^2\ m^{-2}\ decade^{-1}$; Figures 2a and 2b; Figures S2 and S10 in Supporting Information S1). However, the mean age of planted forests was 34.1-year-old (Figure 2d), younger than that of natural forests (56.9-year-old).

A PSM framework establishes comparable cohorts of stable planted and natural forest pixels with matched environmental and age characteristics. PSM reveals significant LAI trend differences in LAI trends between China's planted and natural forests. Spatially, the differences range from −0.137 to +0.634 $m^2\ m^{-2}\ decade^{-1}$ across China (Figure 2c). Planted forests in Sichuan, Yunnan, and Guangdong exhibited markedly higher rates of LAI increase than their natural counterparts, whereas those in Fujian showed lower trends relative to similar natural forests (Figure S11 in Supporting Information S1).

At the national scale, planted forests exhibited a 4.6% (0.013 $m^2\ m^{-2}\ decade^{-1}$, $p < 0.01$, T-test; Figure 2e) higher mean rate of LAI increase compared to their natural forest counterparts (0.283 $m^2\ m^{-2}\ decade^{-1}$), with particularly pronounced differences observed in planted mixed forest (MXF, 14.0%), followed by evergreen needleleaf forests (ENF, 8.9%) and evergreen broadleaf forests (EBF, 8.7%). Contrary to this general pattern, natural deciduous forests (both broadleaf and needleleaf) displayed slightly higher rates of LAI increase compared to planted deciduous forests.

3.2. Amplified CO_2 Response in Planted Forests Mediated by Management

PDPs show a nonlinear relationship between forest age and LAI, conforming to the classical "growth-maturity-decline" trajectory of forest development (Figure S12 in Supporting Information S1). We further quantified the relative contributions of major drivers (i.e., rising CO_2, climate change, and forest growth) to the observed LAI trends. The XGBoost attribution analysis indicated that elevated CO_2 concentration explained 88.5% (0.267 $m^2\ m^{-2}\ decade^{-1}$, $p < 0.05$) of the observed LAI increase in planted forests versus 74.5% (0.142 $m^2\ m^{-2}\ decade^{-1}$, $p < 0.05$) in natural forests (Figure S13 in Supporting Information S1). In contrast, the MMEM of DGVMs generally underestimated the magnitude of LAI trends (Figure S9 and S14 in Supporting

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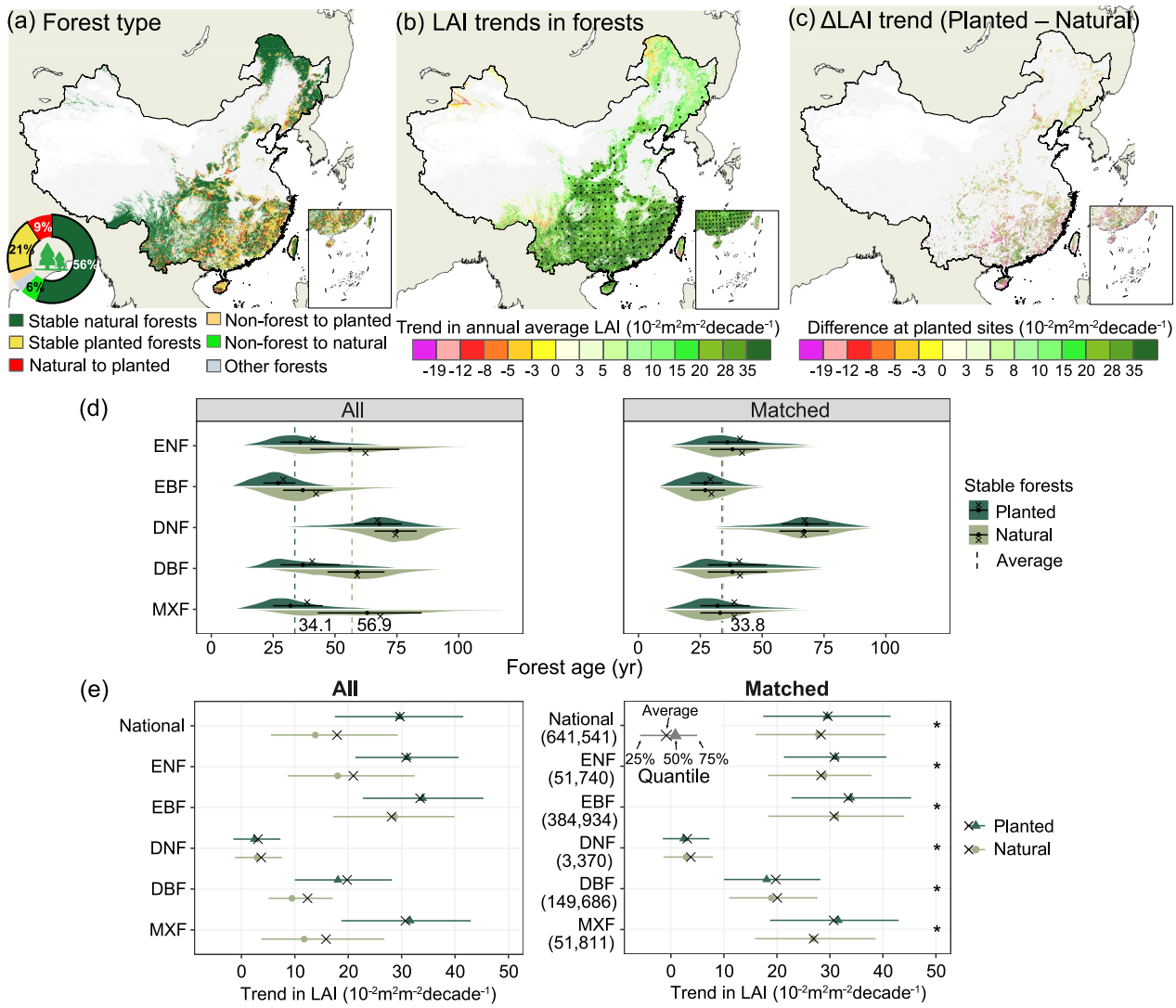

Figure 2. Leaf area index (LAI) trend Differences Between Natural and Planted Forests. (a) Spatiotemporal patterns of planted and natural forests. (b) Map of trends in annual average forest LAI; regions denoted by dots have statistically significant trends ($p < 0.05$). (c) Spatial distribution of LAI trend differences between planted forests and their matched natural forest counterparts. For each matched pair, the difference (planted forest LAI trend minus natural forest LAI trend) is mapped to the location of the planted forest pixel. Comparative analysis of forest age (d) and LAI trends (e) between stable planted and natural forests using propensity score matching. Forest age distribution changes before and after matching, with dashed lines indicating mean ages. "×" symbols denote mean values. In the right of panel (e), the value on the vertical axis shows the count of matched 1-km pixel pairs.

Information S1). We further reveal that, 11 out of 14 DGVMs represent a greater contribution of the CO_2 fertilization effect to LAI trends in planted forests than in natural forests, although these models generally underestimate the difference between the two forest types in this effect.

Regarding climate change effects, the XGBoost model attributed 5.8% (0.018 m^2 m^{-2} $decade^{-1}$) of the observed LAI increase in planted forests to climate change, compared with 3.8% (0.007 m^2 m^{-2} $decade^{-1}$) in natural forests (Figure 3a). In contrast, the MMEM of the DGVMs simulated a slight negative effect of climate change on LAI trends with a slightly stronger negative impact on planted forests (−0.010 m^2 m^{-2} $decade^{-1}$) than on natural forests (−0.009 m^2 m^{-2} $decade^{-1}$). However, among individual DGVMs, three models—CLASSIC, ISBA-CTRIP, and OCN—supported the machine learning-based attribution results, showing a weak positive effect of climate change on LAI increase, with a stronger effect in planted forests than in natural forests. Notably, despite these contrasting directional signals, the magnitude of climate contributions remains small across both approaches, and both consistently identify rising CO_2 as the dominant driver of LAI trends.

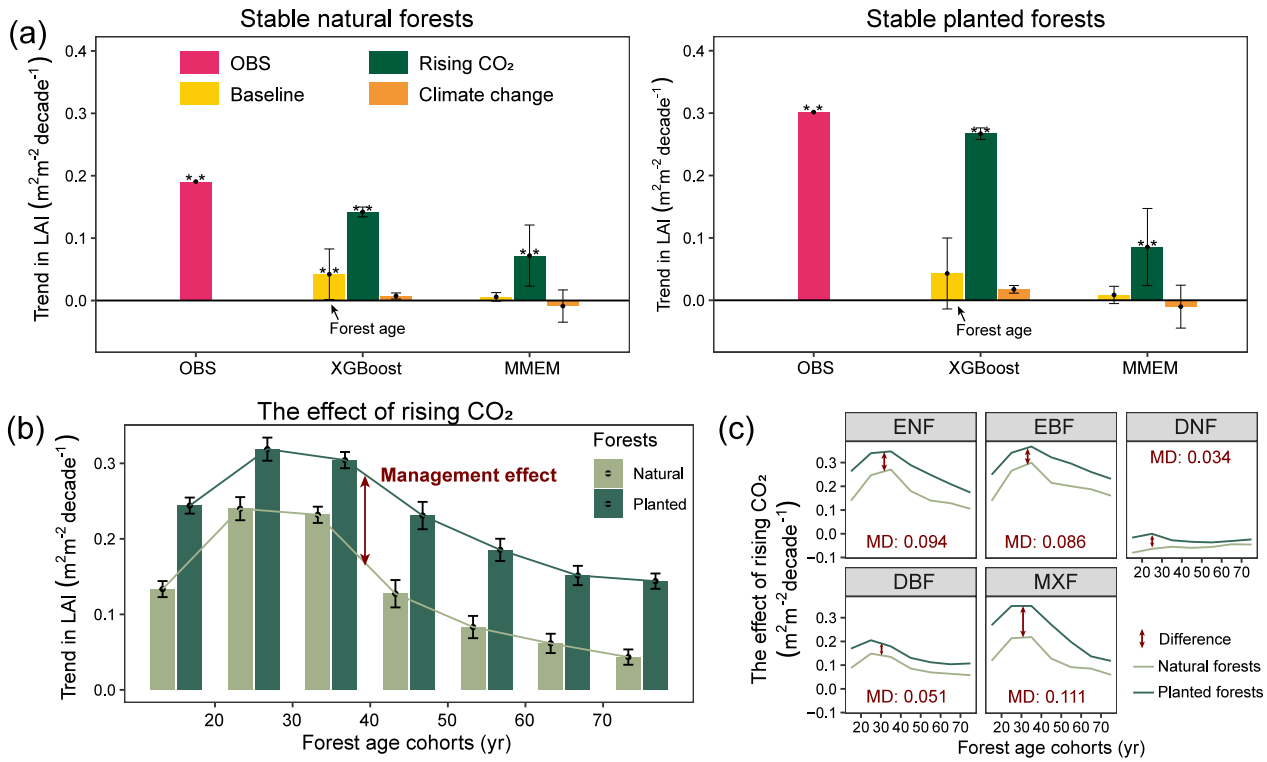

Figure 3. Drivers of leaf area index (LAI) trends in planted versus natural forests. (a) Contributions of forest age (natural growth), rising CO_2, and climate change to LAI trends derived from XGBoost and DGVM analyses. Error bars represent modeling uncertainties from XGBoost or DGVMs. (b) Age-dependent variation in the effects of rising CO_2 on LAI trends, with land-use management effects quantified as the differential CO_2 response between planted and natural forests. The forest age of 2010 was adopted for cohort division. (c) Breakdown of the age-dependent CO_2 fertilization effect on LAI trends by plant functional types (PFT). The mean difference of the effect was calculated for each PFT.

To isolate the effect of forest growth (i.e., age-related development), we held CO_2 concentrations (369.71 ppm) and climate conditions (2000 annual mean values) constant at year-2000 levels in the XGBoost framework. This analysis revealed that forest growth accounted for 14.2% (0.043 m^2 m^{-2} $decade^{-1}$, $p = 0.26$) of the observed LAI increase in planted forests and 22.1% (0.042 m^2 m^{-2} $decade^{-1}$, $p < 0.05$) in natural forests, suggesting the substantial role of intrinsic forest development in vegetation dynamics. Notably, the underestimation of LAI trends by current DGVMs, particularly in regions with young and fast-growing forests (Figure S7 in Supporting Information S1). Over the study period, atmospheric CO_2 concentrations increased from 369.71 ppm to 418.53 ppm. We revealed distinct responses of rising CO_2 on the rate of LAI increase across different age classes of planted and natural forests (Figure 3b). The magnitude of LAI increase during the period of rising CO_2 varied with forest age, exhibiting a single-peaked pattern, with the strongest response observed in mid-aged stands (30–40-year-old). Planted forests were found to substantially amplify this CO_2-associated effect, with particularly pronounced enhancement in mature stands (>40-year-old). This CO_2-associated enhancement was consistently greater in planted forests across all plant functional types (PFTs; Figure 3c). Notably, the mean difference in CO_2 fertilization effects between planted and natural forests on enhancing LAI trends was most pronounced in evergreen and mixed forests, thereby explaining the diverging results derived from PSM results.

3.3. Limited Temporal Sustainability of LAI Growth Potential in Planted Forests

We identified a consistent pattern across all PFTs wherein the marginal effect of age on LAI increase in planted forests was ultimately surpassed by that in natural forests (Figure 4a; Figure S15 in Supporting Information S1). The quantitative assessment revealed distinct crossover thresholds—defined as the age at which natural forests surpass planted forests in terms of age-related LAI increase—occurring at 23, 21, 30, 53, and 48-year-old for ENF, EBF, DNF, DBF, and MXF, respectively.

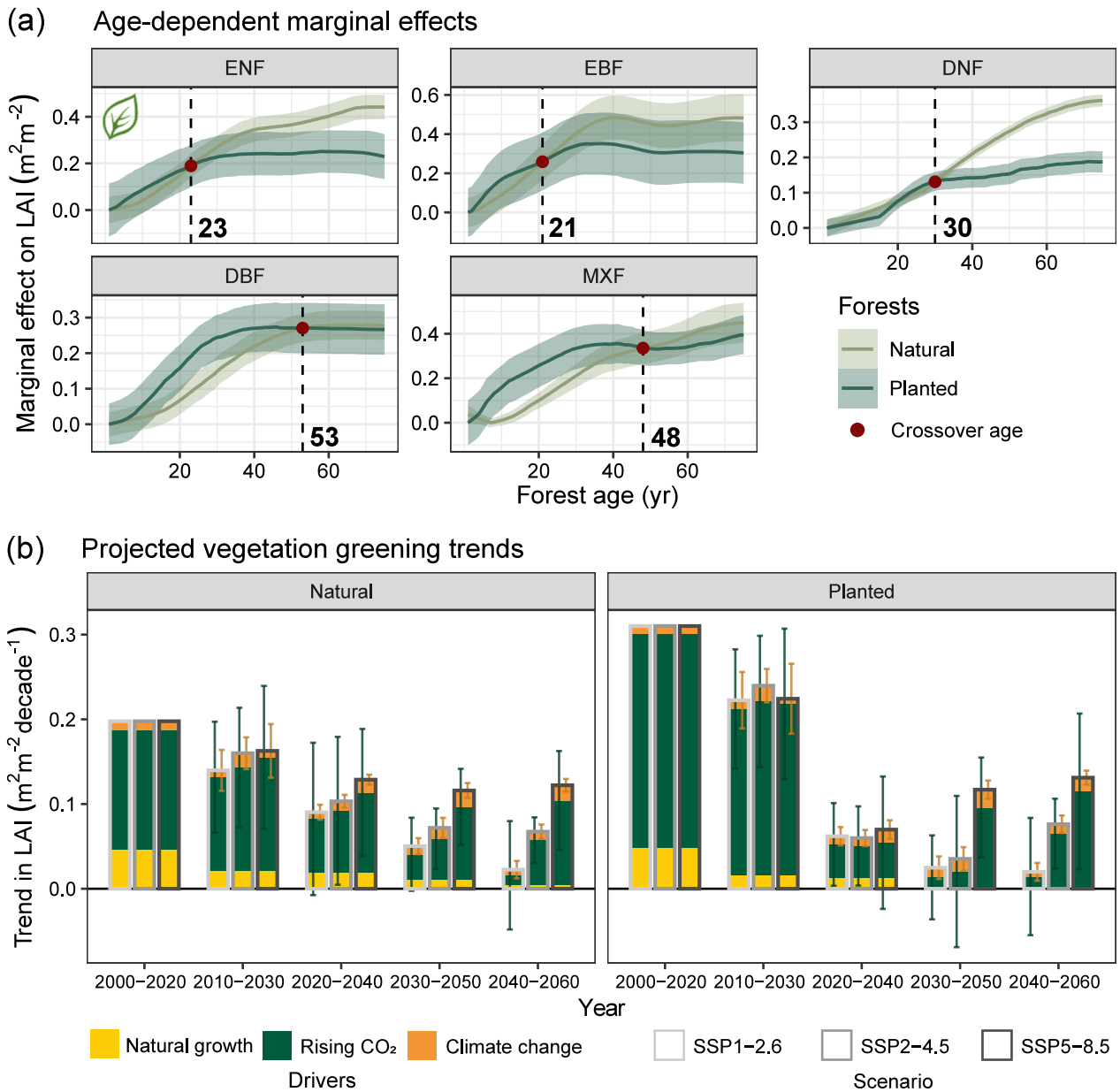

Figure 4. Drivers of leaf area index (LAI) trends in planted and natural forests (2000–2060). (a) Marginal effects of forest age on LAI increase in planted forests versus natural forests. (b) Projected LAI trends and their drivers in planted and natural forests from 2000 to 2060, derived from the CMIP6 1pctCO_2 experiment, climate simulations under shared socioeconomic pathways scenarios, and the machine learning model. All contributions represent multi-model ensemble means, and error bars indicate the inter-model variability among Earth system models.

Under all SSP scenarios, planted forests have higher LAI trends than natural forests only before 2030 (Figure 4b); thereafter, trends became comparable. Under the SSP5-8.5 scenario, the CO_2 fertilization effect dominates the LAI trend, with its influence gradually weakening toward 2060; under the SSP1-2.6 and SSP2-4.5 scenarios, this effect diminishes more markedly (Figure S16 and S17 in Supporting Information S1). Climate change contributes only modestly across most scenarios, accounting for less than 20% of the total LAI trend (Figure S18 and S19 in Supporting Information S1). After 2030, natural growth contributes negligibly to LAI increases in planted forests, whereas natural forests sustain positive contributions throughout the projection period. Compared with the period 2000–2020, under the SSP2-4.5 scenario, the rate of LAI increase during 2040–2060 is projected to decline by 75.4% in planted forests and by 65.9% in natural forests.

4. Discussion

China's planted forests have exhibited faster LAI increase since 2000 and are projected to sustain this advantage in the near term, corroborating previous studies on land-use management (Chen et al., 2019). This reflects a younger age structure and stronger CO_2 response. We also show that although the age-marginal effect of LAI increase saturates rapidly in planted forests (Shan et al., 2025)—likely due to ecological constraints in monoculture systems (Ullah et al., 2024; Xu et al., 2020)—they exhibit a pronounced response to rising CO_2 (Braakhekke et al., 2019; Leng et al., 2024), enabling sustained LAI increases. This reflects interactions between forest management and global change drivers (Davis et al., 2022; Terrer et al., 2019). In contrast, natural forests show stronger long-term age-mediated LAI increase due to biodiversity-supported complexity (Tian et al., 2024), yet their CO_2 response remains weaker than that of planted forests.

The enhanced CO_2 responsiveness and rapid leaf area expansion of planted forests position them as a climate change mitigation tool (Li et al., 2025), stemming from biological traits and management interventions (Chen et al., 2019; Luyssaert et al., 2014). Fast-growing, photosynthetically efficient species (e.g., Eucalyptus, Paulownia) and intensive practices (e.g., density optimization, resource supplementation) jointly maximize CO_2 fertilization effects (Jin et al., 2024). Additionally, the young age structure of planted forests (mean: 34 years) enhances their role as robust carbon sinks (Cheng, Chen, et al., 2024). Notably, within the same age cohorts, the stronger CO_2 fertilization effect in planted evergreen and mixed forests aligns with evidence that evergreen trees exhibit more sustained CO_2 responses than deciduous species (Dusenge et al., 2020; Franklin et al., 2009). Several mechanisms may explain this pattern. First, evergreen species have longer leaf lifespans, integrating CO_2 benefits over multiple growing seasons, whereas deciduous leaves are rebuilt annually, limiting cumulative responses (Marqués et al., 2023; Norby et al., 2003). Second, evergreen trees have slower fine-root turnover, buffering against progressive nitrogen limitation by reducing nitrogen demand for root production (Franklin et al., 2009). Third, anatomical traits such as mesophyll conductance and chloroplast distribution enhance photosynthetic capacity in evergreens under elevated CO_2 (Sun et al., 2023). These mechanisms help explain why planted evergreen forests, combining favorable leaf traits with intensive management, show the largest CO_2-driven LAI advantages.

Interestingly, the LAI response to elevated CO_2 varies with forest age, peaking in mid-aged stands (30–40 years)—a pattern corroborated by field-based analyses showing peak instantaneous LAI increase at 20–40 years (Leng et al., 2024; Xu et al., 2020), particularly in deciduous broadleaf, subtropical coniferous, and EBF (Figures S20–S22 in Supporting Information S1). While this attenuation of the LAI trend beyond 40 years is consistent with a constrained CO_2 fertilization effect, it also reflects a shift in carbon allocation priorities alongside physiological limitations. In aging forests with high canopy closure, trees prioritize carbon investment in maintenance and belowground storage over leaf production (Norby et al., 2010)—a shift that may coincide with constraints such as decreased Rubisco Activase content in senescing leaves (Keenan et al., 2023). Concurrently, as forests mature, progressive nitrogen and phosphorus limitation often develops (Norby et al., 2010; Terrer et al., 2019). Older trees may allocate more carbon belowground to access nutrients—mature forest Free-Air CO2 Enrichment experiments show that under elevated CO_2, old oak trees increased fine root branching by 73% and root exudation by 63% (Reay et al., 2025), stimulating microbial nutrient mineralization and fungal partnerships (Foyer et al., 2025). Thus, the age-dependent decline in CO_2-driven LAI increase beyond 40 years likely reflects both physiological limitations and ecological trade-offs.

However, state-of-the-art ecosystem models fail to incorporate the critical role of young forests (<40 years) in LAI dynamics (Piao et al., 2020). This omission likely contributes to DGVM underestimation of LAI trends in regions with the highest proportion of young forests, notably Brazil and China (Figure S23 in Supporting Information S1), although other structural differences may also play a role. The relationship between underestimation magnitude and forest age implicates age-related processes as a fundamental source of simulation bias (Leng et al., 2024; Ma et al., 2022; Yue et al., 2018). Our study demonstrates the value of integrating multi-source remote sensing data—sensor-independent LAI, forest age maps, and forest type classifications—to mechanistically dissect drivers of LAI trends, a capability previously unattainable with single-sensor or non-age-adjusted analyses (Maltman et al., 2023; Musavi et al., 2017). The systematic underestimation of LAI trends by DGVMs in young forests, diagnosed by our framework, underscores the urgent need to assimilate satellite-derived age and structure parameters into next-generation ecosystem models (Piao et al., 2020).

Planted forests exhibit higher LAI trends than natural forests, an advantage projected to persist due to younger age and stronger CO_2 response (Keenan et al., 2023; Reich et al., 2024). However, monoculture practices involve trade-offs, including reduced biodiversity and simplified ecosystem structures (Abbasi et al., 2023). Mixed-species plantations and close-to-nature forestry offer promising pathways to balance canopy development with ecological benefits (Feng et al., 2022). Natural forests remain irreplaceable for long-term ecosystem stability and biodiversity preservation due to their complex community structures and self-sustaining processes (Moreno-Mateos et al., 2020). Replacing natural forests with plantations is ill-advised; a balanced approach integrating well-designed planted forests with natural forest conservation is essential for coordinated climate and ecosystem objectives.

5. Conclusions

China's leading role in global leaf area expansion places its managed ecosystems at the forefront of land-use science. Here, we show that China's planted forests exhibit higher LAI increase rates than natural forests, driven by their younger age structure and stronger CO_2 responsiveness. Using PSM, we quantify a 4.6% higher national LAI increase rate in planted forests, with the strongest CO_2 fertilization effects in mid-aged stands (30–40 years). However, this advantage wanes with age, as natural forests surpass planted forests in marginal LAI gains beyond critical crossover ages. These findings underscore the importance of forest age and management history—dimensions currently overlooked in major ecosystem models, leading to systematic underestimation of LAI increase in young forest regions.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

This study makes use of publicly available data. The atmospheric CO_2 concentration records were obtained from the Keeling Curve (https://keelingcurve.ucsd.edu/). The land surface meteorological data are provided by TerraClimate (https://www.climatologylab.org/terraclimate.html). The temperature data is provided by ERA5-Land (https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land-monthly-means?tab=overview). The elevation data is provided by the GMTED2010 data set (https://www.usgs.gov/coastal-changes-and-impacts/gmted2010). Ecoregions 2017 © $^{\text{Resolve}}$ is downloaded at https://ecoregions.appspot.com. Plant functional type (PFT) classification was derived from the HYBMAP global hybrid land-cover product (https://zenodo.org/records/10488191). The newly developed 1-km resolution data set of China's forest age in 2020 and the codes written in *R* are available via Luo (2026).

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