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A spatially explicit dynamic biomass baseline for forest-management carbon projects in China

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Abstract

Forest carbon credits reward gains above a counterfactual baseline—the carbon stock expected without a project. Low baselines overstate additional mitigation, whereas high baselines can obscure real gains. Here we develop a spatially explicit, dynamic baseline framework for China using 24,237 forest-plot records and national forest datasets. We estimate pixel-level attainable potential maximum biomass from mature, low-disturbance forests and couple this ceiling to age-dependent growth curves. We project three no-project scenarios that progressively incorporate historical management rotations and observed biomass-loss regimes. A spatially varying biomass ceiling is sufficient for most forest strata; unconstrained growth produces consistently higher

baselines than management-constrained scenarios, especially in intensively managed southern plantations. Incorporating observed biomass-loss events has little effect on national averages but alters local trajectories. Uncertainty is dominated by the attainable biomass ceiling rather than loss-event parameters. The framework provides an auditable and updateable basis for comparing counterfactual trajectories in forest carbon projects.

Introduction

Forest carbon projects issue credits for climate benefits generated by activities including afforestation, avoided deforestation and improved forest management (IFM). In an IFM project, the credited benefit is calculated as the difference between the forest carbon storage with the project and the amount that would have been stored without it, as defined by a counterfactual baseline. Therefore, the choice of baseline directly affects estimates of additionality and the number of credits that can be issued. By the end of 2022, 293 IFM projects had generated about 193 million credits, or 11% of credits in the voluntary carbon market, largely under protocols used by the American Carbon Registry, Climate Action Reserve and Verified Carbon Standard.¹ Forest carbon projects in China developed from early Clean Development Mechanism afforestation and reforestation activities to Chinese Certified Emission Reduction forest- and bamboo-management projects,^{2–4} making credible baseline setting increasingly important for both environmental integrity and market confidence.^{5–7}

Baseline bias has direct consequences. A baseline below the true no-project trajectory credits carbon accumulation that would have occurred anyway and overstates mitigation; a baseline above that trajectory can understate genuine project gains.^{8–9} Static reference levels and coarse regional averages are especially vulnerable. Since forest biomass changes with historical management practices, stand-age development, site conditions, and natural disturbance processes.^{10–12} Independent remote-sensing, matching and synthetic-control evaluations have shown that project-reported baselines can differ substantially from empirically reconstructed counterfactuals, sometimes producing systematic over-crediting.^{5,13–15} A useful counterfactual baseline must therefore describe annual biomass development before project outcomes are observed, while remaining transparent enough to audit and update.

In order to calculate the reasonable counterfactual trajectories, it's necessary to consider the by three related processes. First, stand age controls the expected phase of biomass accumulation. Second, historical management can impose rotations, harvests or biomass resets that prevent indefinite growth along an unconstrained curve. Third, observed biomass losses can alter local trajectories. Such losses may reflect management, fire, storms, drought, pests or other processes; the biomass time series used here identifies the loss event but does not attribute its cause. Climate-driven losses are also an increasing integrity concern because carbon-crediting protocols and pooled risk provisions may not fully represent their magnitude or spatial covariance.^{16–17} We therefore treat age, historical management and empirically observed biomass-loss regimes as separate inputs rather than labelling all detected losses as natural disturbance.

Methodological progress has provided important foundations at both the project and the regional-to-national levels. At the project level, matching, remote-sensing-based independent assessment, statistical matching for constructing comparable controls, synthetic-control methods for reconstructing counterfactual trajectories, and state-space frameworks linking ex-ante and ex-post baselines have improved the detection of bias in existing project baselines.^{13–15,18} At regional and national level, national forest type, origin, age, biomass, planted-forest expansion, forest management type variation datasets favor describing long-term growth and carbon-stock patterns in reality.^{19–22} However, ex-post matching assessment designs are valuable for review but cannot by themselves provide a standardised baseline at project registration phase.^{23–24} Furthermore, national growth studies are usually designed for aggregate carbon accounting rather than parcel-scale annual reference trajectories.^{25–28} A national ex-ante counterfactual baseline framework must connect these scales by representing age-dependent growth, spatial biomass potential, historical management and observed loss risk in the same projection system.

Here we develop a dynamic counterfactual baseline framework for IFM projects across China. We stratify 24,237 plot records by vegetation zone, forest type and origin (155 ecological strata, please see supplementary section 1 and 3) to estimate age–biomass curve shapes, then build the coupled growth-curve framework, which replace each curve's average asymptote with a spatial estimate of attainable potential maximum biomass. Annual counterfactual trajectories are projected under three scenarios: unconstrained continued growth (BAU),

continuation of historical management rotations (S1), and continuation of empirically observed biomass-loss probabilities and severities (S2). We compare differences of baselines under three scenarios and evaluated systematic biases introduced by the rotation and disturbance assumptions. The resulting database provides a national reference for baseline setting and supports consistent application of IFM methodologies, enabling accurate, credible quantification of climate mitigation outcomes and efficient credit issuance.

Results

Spatial biomass potential model and reliability of the coupled growth-curve framework

To capture the heterogeneity in forest biomass accumulation and support counterfactual baseline projection, we built the final growth-curve library contained 67 curves: 35 Logistic, 25 Richards and 7 Weibull functions (Supplementary Table 5). A 1,000-resample Monte Carlo analysis showed that uncertainty in the fitted growth curves was driven mainly by their asymptotic biomass term. The coefficient of variation in national total tree biomass (TB) was 2.77%: forest-age uncertainty contributed 1.02%, and fitted-curve parameters contributed 2.57%. Within the fitted-parameter component, the asymptotic biomass and growth-rate terms accounted for normalised shares of 65.9% and 34.1%, respectively, in one-at-a-time runs (Supplementary Fig. 4). This dominance of the asymptote motivated its replacement with an independently predicted spatial biomass ceiling.

We estimated the attainable near-natural biomass ceiling (B_{eco}) from mature, low-disturbance forest pixels using an ensemble of 50 Random Forest models driven by environmental covariates (Supplementary Table 6). Spatial block cross-validation across 19,110 training pixels gave an R^2 of 0.39, showing that environmental predictors captured part of the spatial variation in potential near-natural biomass, even without tree-specific attributes or management variables. Climate variables accounted for 45.8% of total predictor importance; monthly temperature range was the strongest individual predictor (18.47%). Soil and topographic variables contributed 22.9% and 17.2%, respectively, distance to protected areas contributed 13.9%, and tree cover contributed 0.19% (Fig. 1c). These patterns support the model's intended role as an environmental ceiling rather than a predictor of realised biomass under particular management.

For the 2000 initialisation, mean national B_{eco} was 207.9 Mg ha⁻¹, and the mean pixel-level half-width of the 95% ensemble interval was 16.7 Mg ha⁻¹ (8.0% of the prediction). Potential B_{eco} was highest in the humid southwest and lower in northeastern and northwestern China (Fig. 1a,b). Tropical and subtropical evergreen broad-leaved forests formed the principal high-value regions, whereas lower values occurred in northern typical deciduous broad-leaved and birch forests in the northern warm-temperate region and fir–spruce forests in northwestern temperate desert region. National mean B_{eco} remained near 207–208 Mg ha⁻¹ across the 2000–2020 initialisation years (Fig. 1d,e).

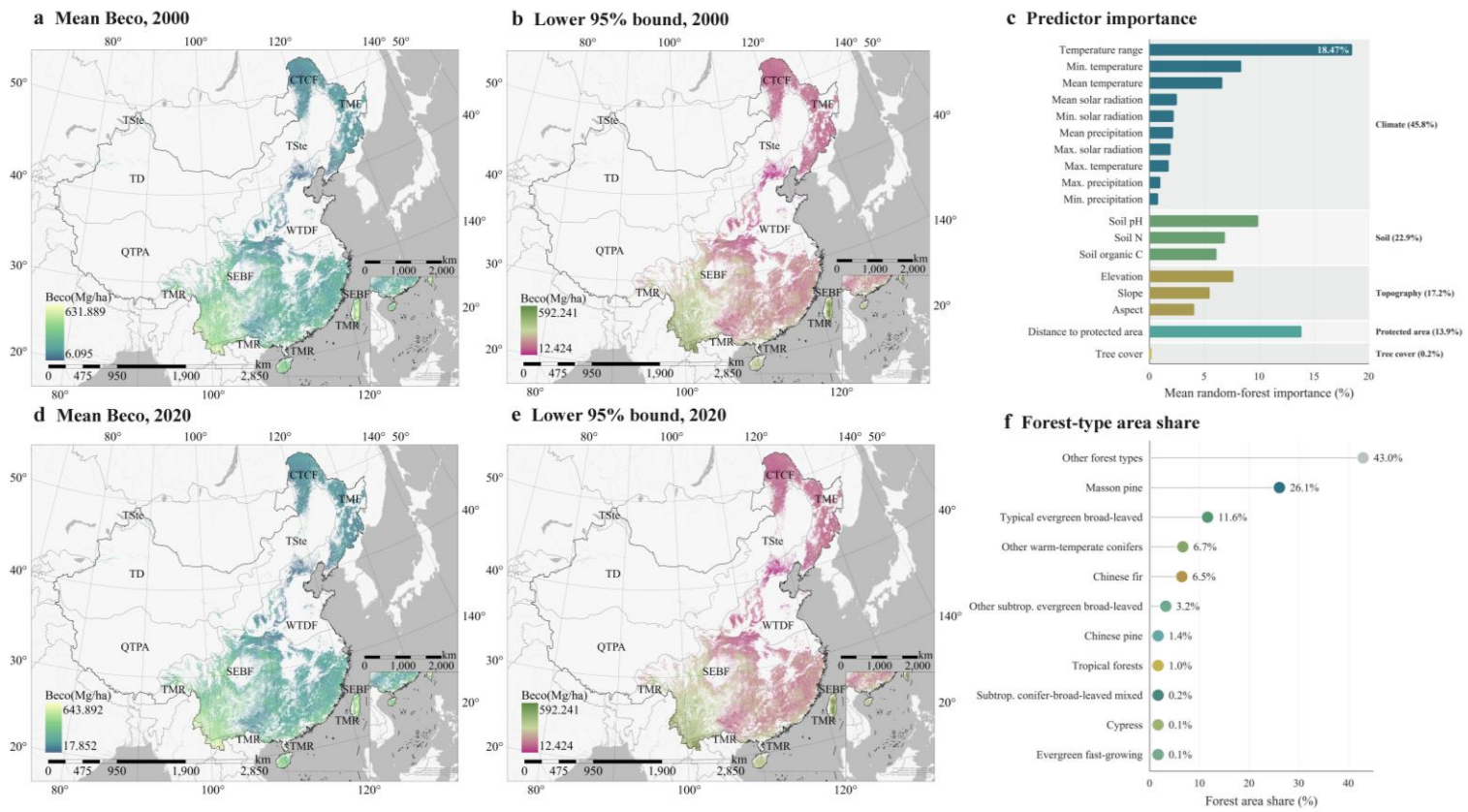


Figure 1. Spatial distribution, prediction interval and predictor importance of the pixel-level B_{eco} model. a,d, Mean pixel-level attainable near-natural biomass (B_{eco}) for the 2000 and 2020 initialisation years. b,e, Corresponding lower bounds of the 95% Random Forest ensemble interval. c, Mean predictor importance of the random forest model, grouped by climate, soil, topography, distance to protected areas and tree cover. f, Forest-type area shares among strata contributing most to the 20-year absolute difference between the management-constrained (S1) and unconstrained (BAU) baselines for the 2020 initialisation. CTCF, cold-temperate coniferous forest; TMF, temperate mixed forest; TSt, temperate steppe; TD, temperate desert; QTPA, Qinghai–Tibet Plateau alpine vegetation; WTDF, warm-temperate deciduous broad-leaved forest; TMR, tropical monsoon and rainforest; SEBF, subtropical evergreen broad-leaved forest.

Simply replacing the asymptotic biomass term in the growth curve with B_{eco} (M_0) allowed the coupled growth curve model to hold at the national scale. In 30 representative strata covering 85.4% of national forest area and

84.3% of biomass, an alternative model (M_1) that also allowed growth rate to covary with B_{eco} reduced relative RMSE by a median of 0.2% and a mean of 2.3%; improvement was below 5% in 24 strata (Supplementary Fig. 5). The 6 more sensitive strata were concentrated in subtropical coniferous forests and one tropical planted-forest strata. For a 2000 initialisation under unconstrained continued growth, using the alternative model (M_1) only in these 6 strata changed 10- and 20-year biomass by -0.45% to $+2.72\%$ and -0.93% to $+1.93\%$, respectively (Table 1). Area-weighted changes across the 6 strata were 1.62% and 1.21%, and results were similarly small for other initialisation years (Supplementary Table 7). We therefore used the M_0 as the national model.

Table 1. Relative changes in the 6 sensitive strata under M_1 for the 2000 initialisation BAU scenario.

Plant zone	Forest type	Origin	RMSE (%)	variation	ΔTB in 10 years (%)	ΔTB in 20 years (%)
Tropical monsoon and rain forest region	Tropical forest	Planted	18.17		-0.45	-0.93
Subtropical evergreen broad-leaved forest region	Chinese fir forest	Planted	14.05		-0.25	-0.22
Subtropical evergreen broad-leaved forest region	Other warm coniferous forest	Natural	7.30		0.01	-0.09
Subtropical evergreen broad-leaved forest region	Fir-spruce forest	Natural	5.54		1.35	1.40
Subtropical evergreen broad-leaved forest region	Masson pine forest	Natural	5.07		2.72	1.93
Subtropical evergreen broad-leaved forest region	Chinese fir forest	Natural	5.03		-0.40	-0.29

Note: Relative change = $(TB_{M1} - TB_{M0}) / TB_{M0} \times 100\%$.

Divergence of counterfactual baseline trajectories

The 3 counterfactual scenarios separated mainly according to whether historical management was continued. The unconstrained baseline (BAU) allowed stands to age without harvest or biomass reset and therefore formed an upper-envelope trajectory. The management-constrained baseline (S1) continued class-specific rotation resets, while the observed-loss baseline (S2) additionally applied empirically estimated probabilities and biomass-retention ratios for detected loss events. The spatially dynamic baseline database based on the coupled models contained the temporal variations of TBs in each pixels from 2000 to 2020. For a 2000 initialisation, the BAU scenario produced larger areas with high 20-year relative temporal variability than S1 and S2, as shown by the

coefficient of variation maps (Fig. 2a, c-f). The national mean BAU–S1 difference increased from 9.98 Mg ha⁻¹ after 10 years to 14.40 Mg ha⁻¹ after 20 years. For a 2020 initialisation, it reached 29.30 and 36.99 Mg ha⁻¹, respectively. S1 and S2 produced broadly similar baseline trajectories. their national mean 20-year difference was below 0.01 Mg ha⁻¹ for the 2000 initialisation and 0.22 Mg ha⁻¹ for 2020. Observed loss events changed local timing and temporal variability more than the national mean (Fig. 2b).

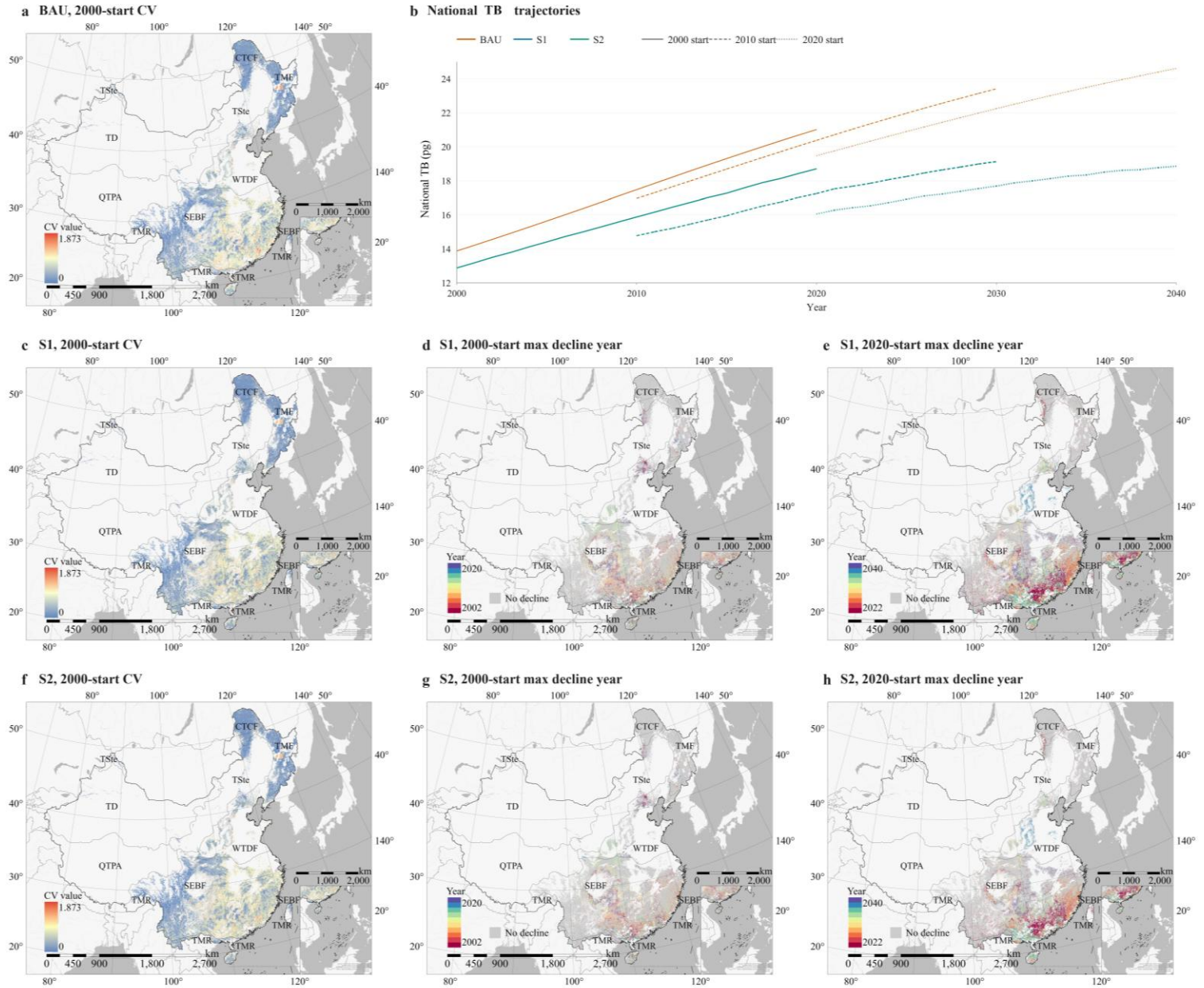


Figure 2. Counterfactual baseline trajectories and spatial variability. a,c,f, Pixel-level coefficient of variation over the 20-year trajectory for the 2000-start BAU, S1 and S2 scenarios. b, National mean total-tree-biomass trajectories for 2000, 2010 and 2020 initialisations. d,g, Year of maximum annual biomass decline for 2000-start S1 and S2. e,h, Corresponding decline year for 2020-start S1 and S2. Grey pixels had no decline during the projection period. The initialisation-year raster is the calculated starting state and predictions begin in the following year. Declines are assigned to the later year of each annual difference; the earliest mapped years are

therefore 2002 and 2022 for the 2000 and 2020 initialisations, respectively. BAU, unconstrained continued growth; S1, continuation of historical management rotations; S2, S1 plus empirically observed biomass-loss probability and severity.

Further decomposition of national mean differences revealed clear hierarchical patterns across management type, origin and region. At the management-type level, the largest BAU–S1 differences for both 2000 and 2020 initialisation years over the 20-year horizon occurred, in descending order, in short-rotation plantations, oil palm, agroforestry, long-rotation plantations, managed natural forests and unmanaged natural forests. For the 2020 initialisation year, the corresponding differences were 70.47, 68.16, 52.34, 38.72, 28.60 and 24.19 Mg ha⁻¹ (Fig. 3a). Management types with explicit rotation or biomass-reset characteristics were therefore more likely to produce overly high continuous-growth trajectories when these constraints were ignored under BAU. At the origin level, planted forests consistently showed larger differences than natural forests. Over the 20-year horizon, the BAU–S1 differences for natural and planted forests were 11.52 and 23.09 Mg ha⁻¹ for the 2000 start year and increased to 28.35 and 63.12 Mg ha⁻¹ for the 2020 start year (Fig. 3b).

Spatially, larger BAU–S1 gaps were concentrated in southern provinces with high growth potential and strong management activity, including Hainan, Guangdong, Guangxi, Fujian, Chongqing, Guizhou, Jiangxi and Yunnan (Fig. 3c). For the 2020 start year over the 20-year horizon, provincial BAU–S1 differences reached 132.48, 121.91, 87.76 and 83.91 Mg ha⁻¹ in Hainan, Guangdong, Guangxi and Fujian, respectively, and 62.70, 62.15 and 54.31 Mg ha⁻¹ in Chongqing, Guizhou and Jiangxi. Tianjin, Qinghai and Shandong also showed locally high values. Their limited pixel extent or distinctive type composition gave them only a small contribution to national differences (Fig. 3c).

At the ecological-stratum level, a small number of widespread combinations accounted for most of the national difference. The 6 leading ecological strata—natural Masson pine forest, planted Masson pine forest, natural typical evergreen broad-leaved forest, natural Chinese fir forest, planted Chinese fir forest and planted typical evergreen broad-leaved forest—jointly contributed 70.43% of the national BAU–S1 difference, and the top 10 strata contributed 80.19%. These strata spanned natural and planted origins and included the dominant forest types of Masson pine, Chinese fir and typical evergreen broad-leaved forest, making them the main contributors to national BAU–S1 differences across management types, origins and regions (Fig. 3d).

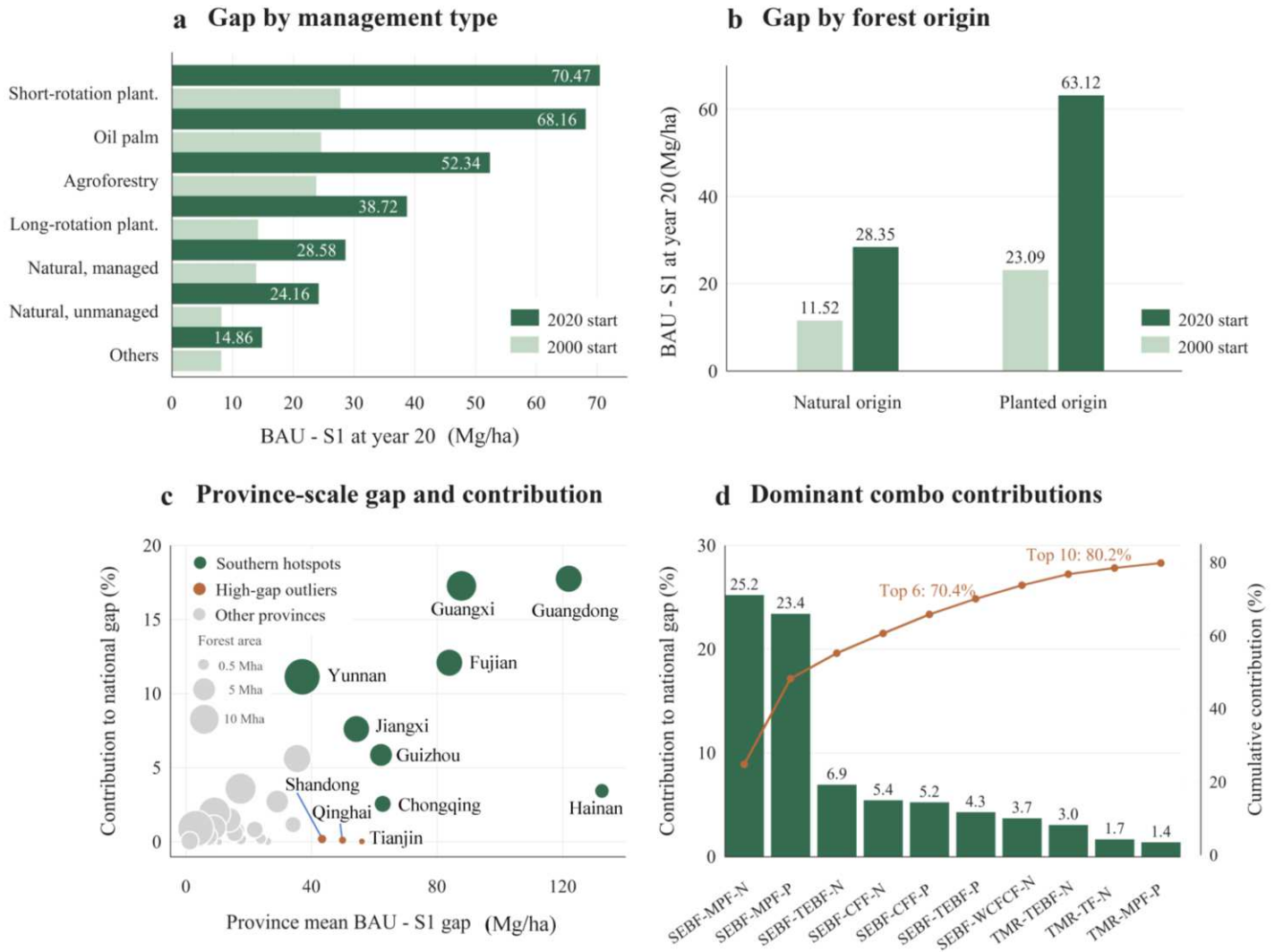


Figure 3. Decomposition of BAU versus S1 baseline differences across management type, origin, province and ecological stratum. a, Comparisons of the 20-year BAU–S1 gap across seven management types. b, Comparisons of natural and planted origins. c, Provincial mean gaps, area and national contribution for the 2020 start year. d, Ranks the leading ecological strata contributing to the national BAU–S1 difference. In panel d, SEBF denotes the subtropical evergreen broad-leaved forest region; TMR, the tropical monsoon and rain forest region; MPF, Masson pine forest; TEBF, typical evergreen broad-leaved forest; CFF, Chinese fir forest; WCFCF, other warm coniferous forest; and TF, tropical forest. N and P denote natural and planted forest origins, respectively.

At pixel scale, differences in starting age, current biomass and attainable biomass produced distinct trajectories even within the same vegetation zone, forest-type and origin stratum (Fig. 4). Three major recurring patterns emerged: near-overlap among BAU, S1 and S2; strong separation of both constrained scenarios from BAU; and a smaller local separation of S2 from S1. Natural Masson pine forest, for example, occurred across managed-natural, agroforestry, long-rotation, short-rotation and unmanaged-natural contexts. Effective annual loss-event probabilities were generally below 0.04% in unmanaged and managed natural forests, long-rotation plantations and agroforestry, but reached 0.07% in short-rotation plantations and 0.33% in oil-palm systems. After

detected events, retained biomass was typically 0.57–0.68 of the pre-event level (Supplementary Table 8). In 2000, pixels experiencing an event represented 0.156–0.272% of forest area, equivalent to 11.18–59.97 thousand ha (Fig. 2d,g). Results at both pixel and national scales showed that omitting management and disturbance constraints generally raises counterfactual baselines. Incorporating the management constraint yielded more consistent baseline representations across national and parcel-relevant scales

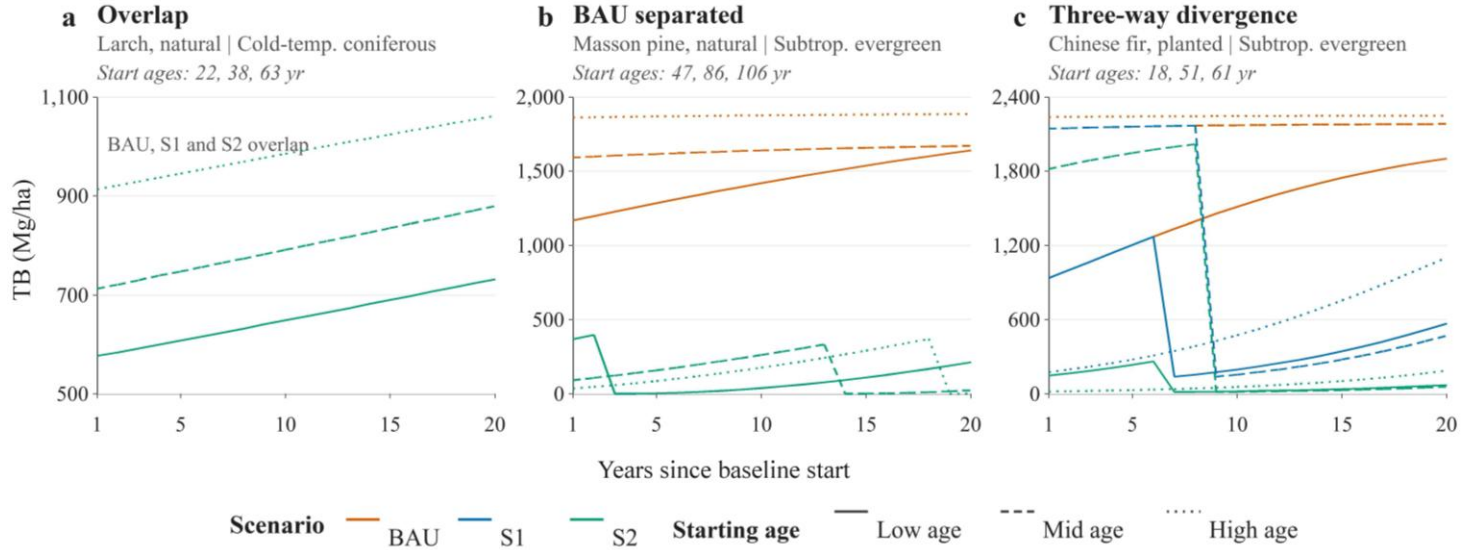


Figure 4. Representative pixel-scale counterfactual trajectory archetypes. The panels show representative pixel-scale baseline trajectories for the 2000 initialisation. a, An overlap case for larch forest of natural origin in the cold-temperate coniferous forest region. b, A BAU-separated case for Masson pine forest of natural origin in the subtropical evergreen broad-leaved forest region. c, A strict three-way divergence case for Chinese fir forest of planted origin in the same subtropical evergreen broad-leaved forest region. Solid, dashed and dotted lines denote low-, medium- and high-age starting pixels; orange, blue and green lines denote BAU, S1 and S2, respectively.

Uncertainty propagation in baseline projections

Uncertainty in the attainable biomass ceiling dominated the national projection. Refer to the national level, for the 2000 initialisation, the mean pixel-level 95% Random Forest ensemble half-width was 16.7 Mg ha^{-1} , or 8.0% of mean B_{eco} . After propagation through age structure and growth curves, the full national ensemble-interval width was $1.70\text{--}1.86 \text{ Mg ha}^{-1}$ at 10 years and $5.40\text{--}5.92 \text{ Mg ha}^{-1}$ at 20 years across the 2000–2020 initialisations (Fig. 5a).

Uncertainty was unevenly distributed at the pixel level. In the perspective of forest type, absolute uncertainty was concentrated in high-potential southern forests. Tropical forest and evergreen fast-growing forest with small areas had relative half-widths of 9.97% and 11.51%, respectively. While large-area Masson pine, Chinese fir,

other subtropical evergreen broad-leaved forest, evergreen broad-leaved and other warm coniferous forest strata combined moderately high relative uncertainty with substantial national coverage (Fig. 5b; Supplementary Tables 9–11). Combining vegetation zone and origin, the most important forest was natural and planted Masson pine forests covered 16.11% and 9.73% of the analysed area and had ensemble half-widths of 7.97% and 8.33%, respectively. Followed by natural typical evergreen broad-leaved forest covered 6.58% with a 7.43% half-width, and natural other warm-temperate coniferous forest in the subtropical evergreen region covered 6.18% with a 7.60% half-width. Across all the management classes, relative half-widths were narrower in range (7.28–8.65%), indicating that environmental and forest-type structure, rather than management labels alone, organised uncertainty in B_{eco} (Fig. 5b).

Uncertainty in observed loss-event parameters was much smaller than B_{eco} and concentrated in a few age-by-management groups. For 2000–2008 initialisations, the annual event probability for 31–40-year-old long-rotation plantations explained 32.17–43.23% of national 10-year variance by itself and 32.23–43.47% including interactions. For 2009–2020, the leading source shifted to the event probability for managed natural forests older than 60 years, which explained 51.87–72.15% alone and 59.43–79.62% including interactions. Other influential terms mainly represented event probability or post-event biomass retention in middle-aged and older natural forests (e.g. 31-40a and 40-60 a; Supplementary Table 12). Despite these rankings, the national 95% interval width attributable to loss-event parameters was only 0.0036–0.0049 Mg ha⁻¹ at 10 years and 0.0038–0.10 Mg ha⁻¹ at 20 years. Adding this component to the uncertainty from B_{eco} changed the combined national interval by less than 0.001%, and by at most 0.041% in locally sensitive strata (Fig. 5c,d). Group-level comparisons of biomass-potential, observed-loss and combined uncertainty at ecological-stratum, forest-type and management levels are reported in Supplementary Tables 13 – 15.

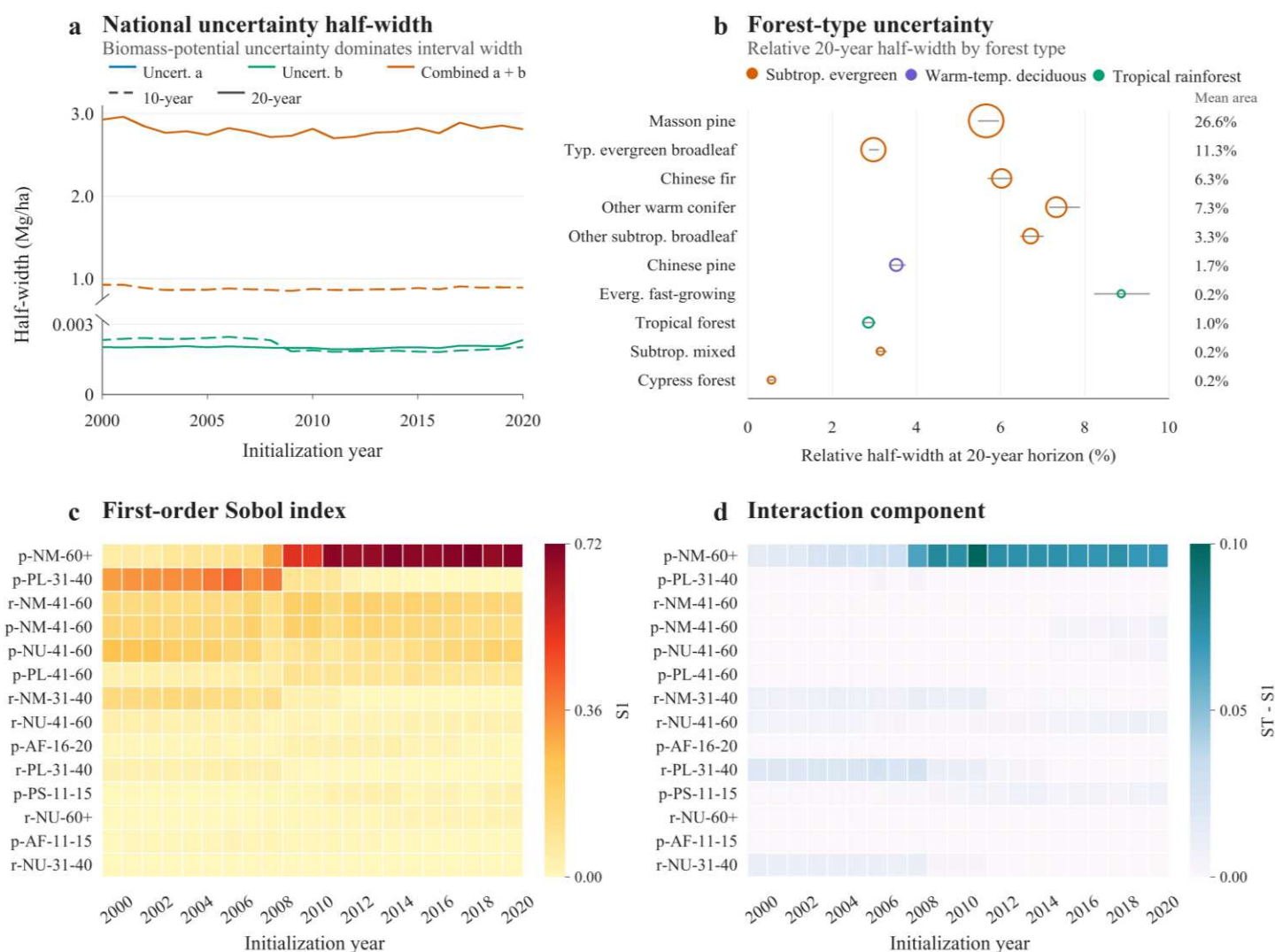


Figure 5. Sources of uncertainty in counterfactual biomass projections. a, National uncertainty half-width propagated from B_{eco} , observed loss-event parameters and their combination at 10- and 20-year horizons across 2000–2020 initialisation years. b, Forest types ranked by relative 20-year uncertainty half-width. The circle size represented the area proportion. c, First-order Sobol indices for the loss-event parameters retained in the main figure. d, Interaction contributions, calculated as the difference between total-effect and first-order Sobol indices, for the same parameter-by-year grid.

Discussion

Species-informed growth curves provide a suitable methodological backbone for counterfactual baseline prediction in IFM carbon projects. Compared with inventory conversion, allometric estimation, remote sensing estimation and process-based simulation, age–biomass curves provide a practical balance among dynamics, applicability and precision: they represent stand ageing, can be projected annually counterfactual trajectory and require fewer inputs than process-based ecosystem models.^{11,29–31} Their use as carbon-crediting baselines, however, depends on ecological ceilings, historical management and observed biomass-loss risk being

represented explicitly. Growth-curve modelling has evolved from early species-specific sigmoid functions to dynamic site-equation approaches that allow different sites to have different growth trajectories^{32–33}, and later to frameworks that couple climate, soil, water and management information to asymptotic or growth-rate terms^{34–35}. This evolution allows models to retain a common growth structure and preserve local heterogeneity.

Building on studies that use mature, protected or low-disturbance forests to estimate forest growth potential^{36–37}, we coupled stratified growth curves with spatially explicit Beco to represent both the age dimension of biomass accumulation and ecological constraints within a single framework³⁸. The stratified growth curves describe dominant age-biomass trajectories for different forest types. Beco captures pixel-level differences in attainable biomass determined by climate, soil and topography. Site quality and management background may also affect growth rates and curve shapes in some forest types^{39–40}, especially in young and old stands²².

Our comparison between the coupled M₁ model and the main M₀ model showed that non-asymptotic parameter changes mattered mainly in a small number of subtropical conifer-related forest types and one tropical planted-forest type. For crediting applications, this parsimony of M₀ model is useful because model fit is only one requirement; a baseline must also be stable, auditable and reproducible while representing age, management continuity and loss risk.^{5,41–42}

Bias in existing IFM project baselines often originates in bottom-up protocols designed around project implementation. Early CDM methodologies for afforestation on degraded land (e.g. AR-AM0001) became an important basis for early Chinese forest-management baseline construction⁵. These early baselines were often static and had low ex-ante trajectories, and together with zero-leakage assumptions, they could systematically inflate issued carbon-credit benefits^{1,5}.

Later, voluntary standards (e.g. VCS/Verra) and regional compliance markets (e.g. California Cap-and-Trade Program) introduced IFM and project-level REDD⁺ methodologies⁴³. These systems still relied heavily on reporting by project developers. Asymmetric monitoring created incentives to exaggerate deforestation risk or underestimate natural forest growth potential to obtain more credits⁴⁴. Common-practice baselines, fixed leakage rates and optimistic assumptions about harvested wood products can all systematically inflate credited benefits¹.

For example, California forest offset projects have been estimated to be over-credited by about 30 million tCO₂e because of coarse regional average baselines, corresponding to 29.4% of analysed credits⁸. Such problems have become increasingly visible as ex-post project monitoring has expanded.

To rebuild trust, baseline methodologies are moving toward more independent, top-down approaches⁴⁵. IFM projects increasingly use national or subnational permanent forest-inventory plots as baseline data, apply matching to construct treatment and control groups, and evaluate additionality using dynamic performance benchmarks⁴⁶. These reforms have substantially advanced dynamic, independent baseline setting²³. Their core function is to replace project-defined baselines with external empirical controls. They do not directly provide ex-ante, spatially explicit projections where continuous national inventory plots are unavailable or project areas are highly heterogeneous^{1,5}. For projects that avoid deforestation and REDD⁺, methods increasingly need data from the jurisdiction. Governments or other parties define aggregate deforestation-risk budgets that are then assigned to spatial pixels⁴⁷ and are often evaluated after implementation, greatly reducing the chances of manipulation⁴⁸.

The framework addresses three requirements for credible ex-ante baselines: limiting developer discretion, using external data that can be independently updated, and carrying historical constraints into the no-project trajectory. For IFM projects, a baseline that does not represent stand age structure or historical management continuity can misclassify natural recovery or ongoing carbon accumulation as project additionality. In the coupled growth-curve model, B_{eco} defines an environmentally informed biomass ceiling, S1 represents continuation of documented management rotations, and S2 adds the probability and severity of biomass-loss events observed in the historical time series. Because those events are identified from biomass change rather than attributed to a specific driver, S2 should be interpreted as an empirical loss regime rather than a map of natural disturbance. These components formed a baseline backbone that is verifiable, updateable and able to extend through time. Pixel-scale differences between S1 and S2 decreased after aggregation. Their convergence at the national scale supported stratification by management regime and showed that simplified management constraints can often produce results similar to those from more detailed dynamic disturbance accounting. Ignoring management and disturbance produced systematically higher baselines and reduced credited benefits. A credible

baseline should therefore carry historical management practices into the counterfactual trajectory of managed forests.

From an application perspective, our framework can be developed into a national baseline database for IFM carbon projects. Built from consistent rules, such a database would make projects comparable, retain pixel-level detail and account for regional differences in forest type and environmental context. It would therefore provide important support for developing IFM methodologies in China. Existing studies have noted that Chinese forest carbon projects still face fragmented rules, complex registration and verification procedures, and insufficient risk-prevention mechanisms^{3,4}. Accurate representation of historical management continuity and no-project growth trajectories is especially important for forest management projects. Such a database would not by itself resolve leakage, permanence, harvested-wood products or all carbon pools, but it would provide the counterfactual biomass module on which those safeguards can be built.^{1,49–51} Its principal policy value is therefore not the growth model alone, but a more transparent assessment of additionality and real mitigation.

Three issues require further development. First, B_{eco} is an attainable near-natural biomass ceiling under observed environmental conditions, not a theoretical biophysical maximum. It could be recalibrated as mature-forest plots and improved biomass products become available.^{37,52} Second, some forest types may require local rate-coupled or mixed-effects curves even though national projections were insensitive to that complexity.^{22,53} Third, the observed-loss layer inherits uncertainty from the 2000–2020 biomass time series and does not identify whether each event was caused by harvest, fire, weather, pests or other processes.^{54–55} Combining additional disturbance products, management records or project-level verification data would improve local baseline realism. Finally, credible crediting also requires leakage accounting, complete treatment of harvested products and soil carbon, and adequate protection against correlated reversals.^{1,49–51} Independent monitoring and periodic baseline updates will therefore remain necessary even when the ex-ante trajectory is spatially explicit.^{16–17}

Methods

Forest plot data

We compiled a national forest plot dataset from published studies, inventory-derived records and field surveys across China. Records were harmonised to whole-stand total tree biomass density (TB; the sum of above- and underground tree biomass; Mg ha^{-1}) and stand age (years). Location, dominant species or forest type, stand density, diameter at breast height, height and growing-stock volume were retained when available. Records missing essential variables, with unresolved classification or with biomass units that could not be reconciled were excluded according to documented rules. The final modelling dataset contained 24,237 plot records. Data sources, conversion equations, exclusion rules and quality control are detailed in Supplementary Methods section 2.

Stratified growth-curve framework

Forests were stratified by vegetation zone, forest type and origin to capture broad ecological differences in biomass accumulation with a tractable number of model groups. Vegetation zones represented large-scale climatic and biogeographic constraints; forest types were harmonised from the 1:1,000,000 vegetation map⁵⁶ using the forest-type classification⁵⁷; and origin distinguished natural and planted forests using the national forest-origin dataset⁵⁸. After harmonisation, the modelling framework used 155 standard ecological strata and 67 final growth-curve parameter sets.

For each supported ecological stratum, we evaluated Richards, Logistic and Weibull growth functions.⁵⁹ Candidate fits were assessed using fitting diagnostics, leave-one-out cross-validation when sample size permitted, monotonicity, biological plausibility and parameter consistency. Strata with insufficient or unreliable data inherited a curve from an ecologically similar donor stratum through a documented hierarchical matching procedure (Supplementary Methods sections 3.2–3.5). The final library contained 67 parameter sets assigned across 155 standard ecological strata.

Growth equations

The candidate growth functions were:

$$\text{Richards: } TB(t) = \alpha \times (1 - \exp(-kt))^{(1/\gamma)} \quad (1)$$

$$\text{Logistic: } TB(t) = \alpha / [1 + ((\alpha - y_0) / y_0) \exp(-kt)] \quad (2)$$

$$\text{Weibull: } TB(t) = \alpha \times (1 - \exp(-kt^\gamma)) \quad (3)$$

where α is the asymptotic biomass, k is the growth-rate parameter, γ controls curve shape, and y_0 is the initial biomass.

Ancillary datasets

Forest age was obtained from the China annual forest age dataset (CAFA; 30 m, 2000–2022),⁶⁰ and annual aboveground biomass from the China Forest Aboveground Biomass Dynamic dataset (CFATD; 30 m, 1985–2023).⁶¹ CFATD was used to identify biomass-loss events. Forest management classes were derived from the 2001–2020 gridded management dataset of He et al.⁶² and used to define rotation-based scenarios and age-by-management loss strata.

Climate predictors were derived from CHELSA-monthly v2.1 for 2000–2020.⁶³ Terrain originated from provincial HGT tiles of NASA SRTM Global 1 arc second V003,⁶⁴ reprojected to a 1-km China Albers grid; slope and aspect were calculated from this 1-km digital elevation model. Soil organic carbon, total nitrogen and pH were derived from SoilGrids 250-m layers and averaged over 0–30 cm using layer-thickness weights.⁶⁵ Terrain and soil were treated as static predictors.

Protected-area boundaries were compiled from the World Database on Protected Areas (WDPA)⁶⁶ and the List and Vector Boundaries of Nature Reserves in China.⁶⁷ We retained WDPA sites in IUCN categories Ia, Ib and II, and used the Chinese nature reserves dataset to supplement national or provincial forest ecological reserves established before 2000. Boundaries were rasterised to a 1-km China Albers binary grid, and Euclidean distance to the nearest protected-area pixel was calculated in metres with a distance transform and converted to kilometres. Annual tree cover was obtained from the 30-m China tree-cover dataset.⁶⁸

Environmental biomass potential was modelled on the 1-km China Albers grid, whereas age, origin and baseline trajectories were represented on the 30-m forest grid. Grid alignment and resampling procedures are described in Supplementary Methods section 1.

Experimental design

The central question was how total tree biomass would evolve without project intervention. Empirical growth curves describe age-dependent accumulation but, when fitted to broad ecological strata, mainly represent an average temporal shape. Environmental biomass-potential models resolve spatial variation in attainable biomass but do not provide an age-structured trajectory. We therefore coupled the two: curve shape remained specific to vegetation zone, forest type and origin, while the asymptotic biomass ceiling (B_{eco}) varied continuously across space.

This parameter-coupling strategy follows forest-growth and carbon-accounting studies that spatialise asymptotic or carrying-capacity terms while retaining stratum-level curve parameters.^{35,69} It is also consistent with using mature or low-disturbance forests to estimate carbon carrying capacity or maximum attainable biomass under observed site conditions.^{37,52,70} The objective was not to infer every growth parameter from the environmental model, but to use B_{eco} as an ecologically informed upper constraint on age-structured trajectories.

The analysis comprised two sequential modules. First, a Random Forest ensemble estimated pixel-level B_{eco} from mature, low-disturbance forests. Second, B_{eco} replaced the stratum-level asymptote in the growth equations, and annual counterfactual biomass was projected by combining the coupled curve with forest age, historical management and observed biomass-loss parameters. For each initialisation year from 2000 to 2020, we projected 20 years under three scenarios. We then tested the coupling assumption by allowing growth rate, as well as the asymptote, to vary with B_{eco} in 30 representative strata.

Pixel-level biomass potential model

We estimated pixel-level attainable near-natural biomass (B_{eco}) using a Random Forest ensemble trained on mature, low-disturbance forest pixels. Candidate samples came from two sources: WDPA pixels within the

retained high-protection categories, with no mapped biomass-loss event and valid age; and pixels in national or provincial forest ecological reserves established before 2000, subject to the same filters. Mature stands were selected using age-percentile thresholds within vegetation-zone $\times$ forest-type groups, yielding 19,110 training pixels. B_{eco} represented an attainable ceiling under observed site conditions rather than a theoretical biophysical maximum (Supplementary Methods section 4.1).

The model used 18 predictors: annual climate means and climate-variability metrics, elevation, slope, aspect, soil properties, tree cover and distance to protected areas. Protected-area membership was used to select low-disturbance training samples but was not included as a predictor. Management variables were excluded as well. Historical management entered the counterfactual scenarios S1 described below (Supplementary Methods section 4.2).

The ensemble comprised 50 independently seeded Random Forest models, each containing 100 regression trees. Performance was assessed with 33-km spatial blocks assigned to as many as 10 folds within the mature, low-disturbance training domain. The fitted ensemble was applied to the 1-km China Albers grid for each initialisation year from 2000 to 2020. Climate predictors varied by initialisation year; terrain and soil remained fixed. The resulting B_{eco} for an initialisation year was held constant over its 20-year projection (Supplementary Methods sections 4.3).

Counterfactual baseline scenarios

For every initialisation year from 2000 to 2020, we simulated a 20-year annual no-project trajectory under three scenarios. BAU allowed uninterrupted age progression without harvest or biomass reset and therefore represents an unconstrained upper-envelope trajectory rather than a lower bound. S1 continued stylised rotations for production-oriented management classes: 60 years for long-rotation plantations, 15 years for short-rotation plantations, and 25 years for oil palm and agroforestry. Unmanaged natural forest, managed natural forest and remaining classes were not assigned a fixed rotation reset in S1.

S2 added empirically observed biomass-loss events to BAU. Annual event probability and post-event biomass retention were estimated from age resets and declines in the CFATD aboveground-biomass time series during 2000–2020, stratified by management class and age group. A minimum detectable-change threshold based on CFATD uncertainty was used to reduce the influence of interannual remote-sensing noise. Since the time series identifies loss but not cause, S2 is an observed-loss scenario and should not be interpreted as attribution to natural disturbance (Supplementary Methods sections 4.4 and 5).

Observed-loss update equation

The expected baseline under the observed-loss scenario was updated as:

$$TB_{loss}(t) = p(m, a_t) \times TB_{loss}(t-1) \times r(m, a_t) + [1 - p(m, a_t)] \times TB_{curve}(a_t, B_{eco}) \quad (4)$$

where $p(m, a_t)$ is the annual probability of an observed biomass-loss event and $r(m, a_t)$ is the proportion of biomass retained after an event, for management class m and age class a_t .

Uncertainty propagation and structural sensitivity

We evaluated two statistical and two structural uncertainty components. Statistical components were uncertainty in B_{eco} and uncertainty in the S2 event-probability and retention parameters. B_{eco} uncertainty was propagated by rerunning trajectories with the pixel-level ensemble mean and percentile bounds from the 50-model Random Forest ensemble. Event probability and post-event retention were represented by beta and triangular distributions, respectively, propagated with Saltelli sampling and summarised by first-order and total-effect Sobol indices. Under an approximate independence assumption, variances from the two modules were combined by the root-sum-of-squares rule (Supplementary Methods section 4.4).

Structural uncertainty comprised parameter uncertainty in the original fitted growth curves and uncertainty in the coupling assumption. A 1,000-resample Monte Carlo analysis propagated forest-age and original curve-parameter errors as a historical diagnostic. It was not added again as an independent layer in the coupled model because the fitted asymptotic term was replaced by pixel-level B_{eco} (Supplementary Methods section 4.4). The coupling assumption was tested by comparing the main ceiling-only model (M_0) with a rate-coupled alternative

(M₁), in which the growth-rate parameter also varied with standardised B_{eco} within each stratum. The comparison used 30 representative strata; those with more than 5% relative-RMSE improvement under M₁ were classed as structurally sensitive, and national effects were evaluated by substituting M₁ only in those strata (Supplementary Methods section 4.4 and Supplementary Results section 6).

Data availability

Public input datasets are available from their original repositories: the Chinese Forest Ecosystem Biomass Dataset (CForBioData; <https://doi.org/10.6084/m9.figshare.c.3306930.v1>),⁵⁷ CAFA (<https://doi.org/10.5194/essd-17-3219-2025>),⁶⁰ CFATD (<https://doi.org/10.5194/essd-17-6993-2025>),⁶¹ the gridded forest-management dataset (<https://doi.org/10.11888/Terre.tpd.c.300975>),⁶² CHELSA-monthly v2.1 (<https://doi.org/10.16904/envdat.686>),⁶³ NASA SRTMGL1.003 (<https://doi.org/10.5067/MEaSURES/SRTM/SRTMGL1.003>),⁶⁴ SoilGrids,⁶⁵ WDPA (<https://www.protectedplanet.net>),⁶⁶ the List and Vector Boundaries of Nature Reserves in China (<https://doi.org/10.5281/zenodo.14875797>),⁶⁷ and the China annual tree-cover dataset.⁶⁸ B_{eco} distribution of China from 2000–2020 is available from https://drive.google.com/drive/folders/1bH0hQQR1GjuGV0bfYaJPWEg5tXw4SEyT?usp=drive_link.

References

1. Haya, B. K. et al. Comprehensive review of carbon quantification by improved forest management offset protocols. *Front. For. Glob. Change* **6**, 958879 (2023).
2. Liang, Z. et al. China certified emission reduction projects: historical and current status, development, and future prospects—taking forestry projects as an example. *Sustainability* **17**, 3284 (2025).
3. Xu, S. Forestry offsets under China’s certificated emission reduction (CCER) for carbon neutrality: regulatory gaps and the ways forward. *Int. J. Clim. Change Strateg. Manag.* **16**, 140–156 (2024).
4. Pan, C. et al. Key challenges and approaches to addressing barriers in forest carbon offset projects. *J. For. Res.* **33**, 1109–1122 (2022).
5. Yu, R., Zhu, Z., Qin, S. & Zhang, D. Dynamic ex-post baselines for enhancing the credibility of improved forest management carbon offsets. *Environ. Sci. Technol.* **60**, 6885–6898 (2026).
6. Grassi, G., Pilli, R., House, J., Federici, S. & Kurz, W. A. Science-based approach for credible accounting of mitigation in managed forests. *Carbon Balance Manag.* **13**, 8 (2018).
7. Bento, A., Kanbur, R. & Leard, B. On the importance of baseline setting in carbon offsets markets. *Clim. Change* **137**, 625–637 (2016).

8. Badgley, G. et al. Systematic over-crediting in California's forest carbon offsets program. *Glob. Change Biol.* **28**, 1433–1445 (2022).
9. Neeff, T. What is the risk of overestimating emission reductions from forests – and what can be done about it? *Clim. Change* **166**, 26 (2021).
10. Yu, Z. et al. Maximizing carbon sequestration potential in Chinese forests through optimal management. *Nat. Commun.* **15**, 3154 (2024).
11. Repo, A. et al. Age-dependence of stand biomass in managed boreal forests based on the Finnish National Forest Inventory data. *For. Ecol. Manag.* **498**, 119507 (2021).
12. Nolan, C., Van Paasschen, C. A. & Field, C. B. Additionality, baselines, and the proper accounting for land-based climate change mitigation efforts. *Oxf. Open Clim. Change* **4**, kgae012 (2024).
13. Coffield, S. R. et al. Using remote sensing to quantify the additional climate benefits of California forest carbon offset projects. *Glob. Change Biol.* **28**, 6789–6806 (2022).
14. Stapp, J. et al. Little evidence of management change in California's forest offset program. *Commun. Earth Environ.* **4**, 331 (2023).
15. West, T. A. P. et al. Action needed to make carbon offsets from forest conservation work for climate change mitigation. *Science* **381**, 873–877 (2023).
16. Badgley, G. et al. California's forest carbon offsets buffer pool is severely undercapitalized. *Front. For. Glob. Change* **5**, 930426 (2022).
17. Wu, C. et al. Forest carbon protocols underestimate climate-driven carbon loss risks. *Nature* **654**, 107–113 (2026).
18. Takahata, K., Suetsugu, H., Fukaya, K. & Shiota, S. Bayesian state-space synthetic control method for deforestation baseline estimation for forest carbon credits. *Environ. Data Sci.* **3**, e6 (2024).
19. Cheng, K. et al. Carbon storage through China's planted forest expansion. *Nat. Commun.* **15**, 4106 (2024).
20. Tang, X. et al. Carbon pools in China's terrestrial ecosystems: new estimates based on an intensive field survey. *Proc. Natl Acad. Sci. USA* **115**, 4021–4026 (2018).
21. Chen, Y. et al. Maps with 1 km resolution reveal increases in above- and belowground forest biomass carbon pools in China over the past 20 years. *Earth Syst. Sci. Data* **15**, 897–910 (2023).
22. Li, P. et al. Species-specific relationships between net primary productivity and forest age for subtropical China. *Biogeosciences* **22**, 5705–5721 (2025).
23. Delacote, P. et al. Restoring credibility in carbon offsets through systematic ex post evaluation. *Nat. Sustain.* **8**, 733–740 (2025).

24. Rau, E.-P. et al. Strengthening the integrity of REDD+ credits: objectively assessing counterfactual methods using placebos. *Environ. Res. Lett.* **20**, 114051 (2025).
25. Shang, R. et al. China's current forest age structure will lead to weakened carbon sinks in the near future. *Innovation* **4**, 100515 (2023).
26. Yu, Z., You, W., Agathokleous, E., Zhou, G. & Liu, S. Forest management required for consistent carbon sink in China's forest plantations. *For. Ecosyst.* **8**, 54 (2021).
27. Tong, X. et al. Forest management in southern China generates short term extensive carbon sequestration. *Nat. Commun.* **11**, 129 (2020).
28. Leng, Y. et al. Forest aging limits future carbon sink in China. *One Earth* **7**, 822–834 (2024).
29. Forsell, N. et al. Impact of modelling choices on setting the reference levels for the EU forest carbon sinks: how do different assumptions affect the country-specific forest reference levels? *Carbon Balance Manag.* **14**, 10 (2019).
30. Paine, C. E. T. et al. How to fit nonlinear plant growth models and calculate growth rates: an update for ecologists. *Methods Ecol. Evol.* **3**, 245–256 (2012).
31. Austin, S. H., Robinson, T. R., Robinson, W. D. & Ricklefs, R. E. Potential biases in estimating the rate parameter of sigmoid growth functions. *Methods Ecol. Evol.* **2**, 43–51 (2011).
32. Biging, G. S. Improved estimates of site index curves using a varying-parameter model. *For. Sci.* **31**, 248–259 (1985).
33. Cieszewski, C. J. & Bailey, R. L. Generalized algebraic difference approach: theory-based derivation of dynamic site equations with polymorphism and variable asymptotes. *For. Sci.* **46**, 116–126 (2000).
34. Nothdurft, A., Wolf, T., Ringeler, A., Böhner, J. & Saborowski, J. Spatio-temporal prediction of site index based on forest inventories and climate change scenarios. *For. Ecol. Manag.* **279**, 97–111 (2012).
35. Scolforo, H. F. et al. Site index estimation for clonal eucalypt plantations in Brazil: a modelling approach refined by environmental variables. *For. Ecol. Manag.* **466**, 118079 (2020).
36. Mo, L. et al. Integrated global assessment of the natural forest carbon potential. *Nature* **624**, 92–101 (2023).
37. Keith, H. et al. Carbon carrying capacity in primary forests shows potential for mitigation achieving the European Green Deal 2030 target. *Commun. Earth Environ.* **5**, 256 (2024).
38. Dean, C., Roxburgh, S. & Mackey, B. G. Forecasting landscape-level carbon sequestration using gridded, spatially adjusted tree growth. *For. Ecol. Manag.* **194**, 109–129 (2004).
39. Chisholm, P. J. & Gray, A. N. Forest carbon sequestration on the west coast, USA: role of species, productivity and stockability. *PLoS ONE* **19**, e0302823 (2024).

40. Yu, Y. et al. Influence of site index on the relationship between forest net primary productivity and stand age. *PLoS ONE* **12**, e0177084 (2017).
41. Simpson, M. J., Browning, A. P., Warne, D. J., Maclaren, O. J. & Baker, R. E. Parameter identifiability and model selection for sigmoid population growth models. *J. Theor. Biol.* **535**, 110998 (2022).
42. Probst, B. S. et al. Systematic assessment of the achieved emission reductions of carbon crediting projects. *Nat. Commun.* **15**, 9562 (2024).
43. Richards, K. R. & Huebner, G. E. Evaluating protocols and standards for forest carbon-offset programs, part A: additionality, baselines and permanence. *Carbon Manag.* **3**, 393–410 (2012).
44. Liu, X. & Cui, Q. Baseline manipulation in voluntary carbon offset programs. *Energy Policy* **111**, 9–17 (2017).
45. Haya, B. et al. Managing uncertainty in carbon offsets: insights from California’s standardized approach. *Clim. Policy* **20**, 1112–1126 (2020).
46. Randazzo, N. A., Gordon, D. R. & Hamburg, S. P. Improved assessment of baseline and additionality for forest carbon crediting. *Ecol. Appl.* **33**, e2817 (2023).
47. Meena, D. P., Bhandari, K. & Ghosh, S. M. Implication of the new VCS jurisdictional and nested REDD methodology on baselines of existing avoided deforestation projects. *J. Environ. Manag.* **351**, 119857 (2024).
48. Teo, H. C. et al. Uncertainties in deforestation emission baseline methodologies and implications for carbon markets. *Nat. Commun.* **14**, 8277 (2023).
49. Henders, S. & Ostwald, M. Forest carbon leakage quantification methods and their suitability for assessing leakage in REDD. *Forests* **3**, 33–58 (2012).
50. Schwarze, R., Niles, J. O. & Olander, J. Understanding and managing leakage in forest-based greenhouse-gas-mitigation projects. *Philos. Trans. R. Soc. A* **360**, 1685–1703 (2002).
51. Mayer, M. et al. Tamm review: influence of forest management activities on soil organic carbon stocks: a knowledge synthesis. *For. Ecol. Manag.* **466**, 118127 (2020).
52. Liu, Y., Yu, G., Wang, Q., Zhang, Y. & Xu, Z. Carbon carry capacity and carbon sequestration potential in China based on an integrated analysis of mature forest biomass. *Sci. China Life Sci.* **57**, 1218–1229 (2014).
53. Zhu, G., Hu, S., Chhin, S., Zhang, X. & He, P. Modelling site index of Chinese fir plantations using a random effects model across regional site types in Hunan province, China. *For. Ecol. Manag.* **446**, 143–150 (2019).
54. Araza, A. et al. A comprehensive framework for assessing the accuracy and uncertainty of global above-ground biomass maps. *Remote Sens. Environ.* **272**, 112917 (2022).

55. Duncanson, L. et al. The importance of consistent global forest aboveground biomass product validation. *Surv. Geophys.* **40**, 979–999 (2019).
56. Hou, X. 1:1 million vegetation map of China. National Tibetan Plateau Data Center <https://data.tpdac.cn/en/data/eac4f2cf-d527-4140-a35d-79992957f043/> (2019).
57. Luo, Y., Wang, X., Zhang, X. & Lu, F. *Biomass and Its Allocation of Forest Ecosystems in China* (China Forestry Publishing House, Beijing, 2013) (in Chinese).
58. Cheng, K. et al. Unveiling China's natural and planted forest spatial–temporal dynamics from 1990 to 2020. *ISPRS J. Photogramm. Remote Sens.* **209**, 37–50 (2024).
59. Tjørve, E. & Tjørve, K. M. C. A unified approach to the Richards-model family for use in growth analyses: why we need only two model forms. *J. Theor. Biol.* **267**, 417–425 (2010).
60. Shang, R. et al. China's annual forest age dataset at a 30 m spatial resolution from 1986 to 2022. *Earth Syst. Sci. Data* **17**, 3219–3241 (2025).
61. Cai, Y. et al. Dynamics of China's forest carbon storage: the first 30 m annual aboveground biomass mapping from 1985 to 2023. *Earth Syst. Sci. Data* **17**, 6993–7018 (2025).
62. He, B. et al. Global annual forest management type spatial data (2001–2020). National Tibetan Plateau Data Center <https://doi.org/10.11888/TERRE.tpdac.300975> (2024).
63. Karger, D. N., Brun, P. & Zilker, F. CHELSA-monthly climate data at high resolution, version 2.1. EnviDat <https://doi.org/10.16904/envidat.686> (2025).
64. NASA JPL. NASA Shuttle Radar Topography Mission Global 1 arc second V003. NASA Land Processes Distributed Active Archive Center <https://doi.org/10.5067/MEaSUREs/SRTM/SRTMGL1.003> (2013).
65. Poggio, L. et al. SoilGrids 2.0: producing soil information for the globe with quantified spatial uncertainty. *SOIL* **7**, 217–240 (2021).
66. UNEP-WCMC & IUCN. Protected Planet: The World Database on Protected Areas (WDPA), July 2026 release. UNEP-WCMC and IUCN, Cambridge, UK <https://www.protectedplanet.net> (2026).
67. China Nature Reserve Specimen Resource Sharing Platform. List and Vector Boundaries of Nature Reserves in China, version 1. Zenodo <https://doi.org/10.5281/zenodo.14875797> (2024).
68. Cai, Y. et al. Unveiling spatiotemporal tree cover patterns in China: the first 30 m annual tree cover mapping from 1985 to 2023. *ISPRS J. Photogramm. Remote Sens.* **216**, 240–258 (2024).
69. Roxburgh, S. H. et al. A revised above-ground maximum biomass layer for the Australian continent. *For. Ecol. Manag.* **432**, 264–275 (2019).
70. Peng, B. et al. Maximum potential of vegetation carbon sink in Chinese forests. *Sci. Total Environ.* **905**, 167325 (2023).

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Author contributions

S.D.Z. conceived and designed the research and conducted the Random Forest modelling, growth-curve coupling, counterfactual scenario analysis and uncertainty analysis. X.J.W. compiled the plot data, designed and fitted the growth curves and prepared the figures. S.D.Z., X.J.W., X.Y.W. and J.X.G. wrote the original draft and revised the manuscript. Y.F.H compiled the plot data and revised the manuscript. F.C. and Y.R. critically revised the manuscript and contributed to interpretations. All authors reviewed and contributed to the revised manuscript.

Competing interests

The authors declare no competing interests.

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