

Climate and plant traits drive a cross-continental imbalance in atmospheric Hg uptake

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This Supplementary Information provides the data, modeling framework and validation analyses supporting the quantification of global forest foliar Hg⁰ uptake. The approach integrates leaf lifespan, foliar Hg accumulation and biomass constraints within a trait-driven modeling architecture. The following sections describe data compilation, model development, evaluation and uncertainty analyses underlying the main results. Together, these components establish a process-resolved basis for interpreting spatial patterns of atmospheric Hg⁰ uptake by forests.

SUPPLEMENTARY INFORMATION STRUCTURE

Texts S1–S12: Model framework, data, and methodological details

Figures S1–S54: Model evaluation, spatial patterns, and sensitivity analyses

Tables S1–S4: Data sources, model inputs, and parameterization

I. SUPPLEMENTARY TEXT

Text S1: Structural equation modeling (SEM).

To identify the key drivers of foliar Hg concentrations, we developed a structural equation model (SEM) comprising four latent variables: climate (precipitation, temperature, radiation), spatial factors (longitude, latitude, elevation), tree traits (leaf area index, tree height, leaf age), and direct anthropogenic effects (anthropogenic Hg emissions and atmospheric Hg concentrations), with foliar Hg concentration as the response variables. Model fitting was performed using partial least-squares path modeling (PLS-PM; R v4.4.0, *pls* package), which is suitable for handling non-normally distributed data and multicollinearity. Path coefficients were expressed as standardized regression coefficients (β), and both direct and indirect effects were estimated to quantify the overall influence of different factors on foliar Hg. Model performance was assessed using the coefficient of determination (R^2), goodness-of-fit (GOF), and outer model loadings.

Text S2: Modeling Global pattern of leaf lifespan.

Leaf Lifespan Data Compilation. The leaf lifespan dataset was constructed by integrating multiple sources. Primary data were obtained from the TRY Plant Trait Database (Kattge et al., 2020) and the GLOPNET database (Wright et al., 2004), which together provide the most comprehensive global compilation of plant functional traits. These were supplemented with additional records retrieved from CNKI and Google Scholar using the keywords "leaf lifespan" and "leaf longevity." After rigorous quality screening, a total of 2,415 observational records were retained for model development.

Input Features for Modeling. Input Features for Modeling. To predict the spatial distribution of leaf lifespan, we assembled a set of predictor variables known to influence leaf longevity based on plant ecological theory. These include: (1) climatic factors—mean annual precipitation, temperature, and solar radiation; (2) spatial factors—longitude, latitude, and elevation; and (3) plant functional traits—specific leaf area (SLA), leaf nitrogen (N) and phosphorus (P) content, and leaf area index (LAI). SLA, leaf N, and leaf P were included because they are closely linked to plant resource acquisition strategies, photosynthetic capacity, and metabolic rates, which co-vary with leaf lifespan along the global leaf economics spectrum (Wright et al., 2004). Leaf N and P are key plant functional traits associated with photosynthetic capacity and metabolic activity, and are widely recognized predictors of leaf lifespan^{1,2}. Previous research has established a fundamental trade-off in plant resource economics: leaves with high N and P contents typically exhibit high photosynthetic rates and rapid tissue turnover, resulting in shorter leaf lifespans², whereas leaves with low N and P contents are associated with slower metabolic rates, greater resource conservation, and extended leaf longevity³. Incorporating foliar N and P into the modeling framework

therefore constrains the spatial prediction of leaf lifespan, which in turn determines the residence time of Hg in foliage and the magnitude of foliar Hg⁰ uptake.

Model Implementation and Validation. A machine learning framework was developed to predict leaf lifespan at 0.1° × 0.1° spatial resolution. Model performance was evaluated using 5-fold cross-validation to ensure robustness and minimize overfitting. The models achieved coefficient of determination (R²) values of 0.55 for evergreen broadleaf forests, 0.67 for deciduous broadleaf forests, and 0.64 for evergreen needleleaf forests, indicating satisfactory predictive performance given the inherent variability in leaf lifespan observations.

Integration into Hg Uptake Modeling. The predicted leaf lifespan maps were then used to parameterize the foliar Hg uptake model. Specifically, foliar Hg concentrations in senesced foliage (i.e., litterfall Hg concentrations) were estimated by integrating the leaf lifespan predictions with the foliar Hg accumulation rate model. Annual foliar Hg accumulation rates were derived by dividing the Hg concentration in senesced foliage by the corresponding leaf lifespan, consistent with the approximately linear accumulation relationship observed in Figs. 1c and 1d.

Text S3: Global pattern of leaf lifespan.

The results revealed distinct spatial patterns among different forest types (Fig. S5). For evergreen needleleaf forests, leaf lifespan increased progressively from low to high latitudes and elevations. This pattern reflects an adaptive strategy in cold and nutrient-limited environments, where prolonged lifespan helps offset the high cost of leaf construction (Figs. S5a, b) ^{4,5}. In contrast, deciduous broadleaf forests exhibited the longest lifespans in tropical regions (6–8 months), which gradually shortened with increasing latitude, suggesting that under high solar radiation, extended leaf longevity supports sustained carbon gain over longer periods (Figs. S5c, d) ⁶. Evergreen broadleaf forests generally displayed lifespans ranging from 6 to 15 months, but exceptionally high values (18–24 months) were observed in Australia, likely due to arid and nutrient-poor conditions, where prolonged leaf retention enhances nutrient-use efficiency (Figs. S5e, f) ⁷. These patterns reflect fundamental vegetation adaptation strategies, whereby extended leaf lifespan under cold, high-light, or nutrient-limited conditions maximizes resource investment and improves nutrient-use efficiency ^{4,5}.

We further compared our modeled leaf lifespan with previous estimates. Our results are broadly consistent with global plant trait syntheses, such as the "worldwide leaf economics spectrum" (Wright et al., 2004) ². However, a remote-sensing-based study for tropical regions reported longer leaf lifespans (21–48 months) ⁸, compared with our modeled range of 12–21 months. Estimating leaf lifespan in tropical forests from satellite-derived leaf area index (LAI) remains challenging, as persistent cloud cover and the complex, multi-layered structure of dense tropical canopies can obscure signals of leaf demography and introduce substantial uncertainty⁹. Our machine

learning approach, while leveraging extensive global trait databases, is constrained by the limited availability of direct, ground-based leaf lifespan observations in tropical regions. This geographical bias in the training data may increase predictive uncertainty, as reflected in the model performance ($R^2 = 0.55$) for these regions.

Text S4: Modeling global foliar biomass

Following the derivation of global foliar Hg accumulation rates, estimation of forest foliar Hg⁰ uptake requires incorporation of foliar biomass. However, currently available global aboveground biomass (AGB) products show considerable discrepancies. As a result, foliar biomass estimates based on leaf-to-AGB ratios carry substantial uncertainties (Fig. S7), with regional differences of up to a factor of 2–3 (Fig. S8). To reduce these uncertainties arising from inconsistencies among data sources, we harmonized multiple AGB products to produce a consistent global dataset of foliar biomass distribution (Fig. S9).

Global leaf biomass data. Data on the proportion of leaf biomass relative to aboveground biomass (AGB) were primarily obtained from the Chinese Forest Biomass Database ¹⁰ and the Eurasian regional AGB dataset ¹¹. These were supplemented with additional records retrieved from CNKI and Google Scholar using the keywords “forest aboveground biomass” and “forest leaf biomass.” In total, 7,510 records of leaf biomass fraction were compiled (Fig. S29), covering four major forest functional types: 4,701 from evergreen needleleaf forests, 524 from deciduous needleleaf forests, 464 from evergreen broadleaf forests, and 1,821 from deciduous broadleaf forests.

Harmonization and conversion of global aboveground biomass datasets. In global forest biomass datasets, some products report aboveground carbon density (AGCD) rather than biomass. To ensure consistency and comparability across data sources, we converted AGCD to dry biomass using woody density data ¹². Additionally, for AGB products that exclude the foliar component, we incorporated the simulated leaf fraction (i.e., the ratio of leaf biomass to total AGB) and reconstructed total AGB including foliage by dividing by (1 – leaf fraction).

Leaf biomass ratio LightGBM model. To predict the proportion of leaf biomass relative to AGB, we employed a LightGBM regression model (LGBMRegressor) and developed independent models for four major forest functional types: evergreen broadleaf, evergreen coniferous, deciduous broadleaf, and deciduous coniferous forests. Prior to model training, key hyperparameters (e.g., `n_estimators`, `learning_rate`, `max_depth`, and `num_leaves`) were tuned using grid search combined with cross-validation to determine suitable parameter ranges, followed by fine-tuning to identify the optimal configuration for each forest type. The final optimized hyperparameters are listed in Table S4. To ensure reproducibility, all models were trained using a fixed random seed.

Regional integration and dataset harmonization. We divided the major forested regions of the world into eight zones: China, Europe, the United States, Russia, Canada, South America, Africa, and Southeast Asia. Biomass data were extracted from multiple global AGB products based on these regional boundaries, and additional regional datasets were compiled for each zone (Table S1). These regional AGB datasets were then combined with simulated leaf-to-AGB ratios to derive foliar biomass.

To ensure internal consistency, we used the mean value of each regional dataset as a reference and calculated its standard deviation (SD). A filtering threshold of mean ± 2 SD was applied, and only AGB products within this range were retained for integration (Table S2). Based on this approach, screened global AGB products and regional datasets were first integrated to obtain robust regional biomass estimates. The resulting estimates for the eight major forest zones were subsequently combined with biomass estimates for other forested regions derived from seven global AGB products to produce a spatially continuous global AGB map. Finally, by coupling this harmonized AGB dataset with the simulated leaf-to-AGB ratios, we generated the global spatial distribution of forest foliar biomass.

Text S5: Estimation of foliar Hg uptake from regions near Hg emission sources

Data compilation. We searched the literature using Google Scholar with keywords such as “foliar mercury” and “contaminated area,” and compiled foliar Hg concentration data from regions near Hg emission sources, particularly mining sites (Fig. S10, $n = 143$). These data were used to construct a dataset representing foliar Hg concentrations in emission-impacted areas. The field-measured leaf Hg data from contaminated environments mainly fall into two categories: artisanal and small-scale gold mining (ASGM) areas, and mercury or gold mining areas. Given that ASGM is currently the significant anthropogenic source of global Hg emissions, we thus focused specifically on ASGM (small-scale gold mining) and Au (industrial-scale gold mining) and Hg mining areas—both of which are typical sources of Hg pollution—while other mining types are not considered at this stage due to insufficient observational data. The leaf Hg uptake in these forests was estimated using two approaches: a machine learning model built on all collected field observations and empirical estimates based on literature-reported leaf Hg concentrations combined with foliage biomass.

Feature selection and model tuning. Based on this dataset, we first developed an XGBoost model to simulate foliar Hg concentrations in emission-impacted areas. Predictor variables included climatic factors (precipitation, temperature, and radiation), spatial variables (longitude, latitude, and elevation), vegetation variables (leaf area index, tree height, and leaf age), and anthropogenic Hg emissions and atmospheric Hg concentrations. Model parameters were initially optimized through hyperparameter tuning and subsequently refined based on model performance. Model performance

was evaluated using five-fold cross-validation. The final model achieved an R^2 of 0.84 on the training set and 0.67 on the test set (Fig. S52), with optimized hyperparameters of $n_estimators = 20$, $max_depth = 3$, $reg_alpha = 8.6$, $reg_lambda = 9$, $subsample = 0.6$, $colsample_bytree = 0.8$, and $random_state = 42$.

Estimation of foliar Hg uptake in emission-impacted regions. We first identified source-proximal grid cells using two spatial data sources: ASGM site locations obtained from the UNEP/MapX platform ([https://app.mapx.org/static.html?views=MX-DYYKK-FAWSZ-NXSIO&theme=color light&zoomToViews=true](https://app.mapx.org/static.html?views=MX-DYYKK-FAWSZ-NXSIO&theme=color%20light&zoomToViews=true)), which compiles ASGM locations extracted from National Action Plan documents, and mercury- and gold-mining areas obtained from the ICMG Global Mining Dataset website (<https://www.icmg.com/en-gb/research/data/2025/global-mining-dataset>). From the global prediction outputs, we then extracted the model-predicted foliar Hg concentrations for these grid cells and combined them with simulated leaf biomass and leaf lifespan to estimate foliar Hg uptake in these regions. The leaf Hg uptake was estimated using two approaches: (1) a machine learning model built on all collected field observations, which yields a total leaf Hg uptake of $24.7 \pm 28.8 \text{ Mg yr}^{-1}$ for forests adjacent to ASGM and mercury/gold mining areas, with $19.6 \pm 23.2 \text{ Mg yr}^{-1}$ attributed to ASGM-proximal forests and $5.1 \pm 5.6 \text{ Mg yr}^{-1}$ to mercury/gold-mining-proximal forests; (2) empirical estimates based on literature-reported leaf Hg concentrations combined with foliage biomass. Using the mean of the measured leaf Hg concentrations, the estimated uptake is $19.6 \pm 23.1 \text{ Mg yr}^{-1}$ for ASGM-adjacent forests and $14.9 \pm 18.5 \text{ Mg yr}^{-1}$ for mercury/gold-mining-adjacent forests, while using the median yields $10.4 \pm 9.6 \text{ Mg yr}^{-1}$ and $5.2 \pm 4.5 \text{ Mg yr}^{-1}$, respectively.

We note that the current estimate of foliar Hg uptake in source-proximal forests remains subject to high uncertainty. This uncertainty arises primarily from (1) the large inter-site variability in observed leaf Hg concentrations (ranging from 20 to 6654 ng g^{-1}), which makes extrapolation from limited observations challenging, and (2) the still-insufficient spatial coverage of measured leaf Hg data in ASGM and mercury/gold mining regions, particularly in areas with intense ASGM activity such as Africa and Indonesia, as well as in certain mercury/gold mining hotspots. Future field campaigns targeting leaf Hg in these source-proximal forests are needed to further constrain the estimate.

Text S6. Estimation of woody Hg sink.

In this study, we compiled more than 1,500 records of Hg concentrations in woody tissues, encompassing two structural components: twigs and stems. According to Equation (2), the woody Hg sink can be estimated as the product of net primary productivity (NPP), corresponding Hg concentration, and the proportion of Hg derived from atmospheric sources. This atmospheric contribution was constrained by isotopic

studies¹⁴, which reported that atmospheric inputs account for $84 \pm 25\%$ of total Hg in woody tissues. Therefore, estimation of the woody Hg sink requires two key parameters: Hg concentrations in woody tissues and woody NPP.

For Hg concentrations, we first calculated site-level averages for twigs and stems, resulting in 72 stem sampling sites ($n = 1,239$) and 48 twig sampling sites ($n = 431$). To avoid bias caused by unequal sample sizes, weighted means were applied, with sample counts used as weights. Using this approach, the weighted mean concentrations and standard deviations were obtained for twigs and stems. The results showed mean Hg concentrations of $11.85 \pm 4.65 \text{ ng g}^{-1}$ for twigs and $2.19 \pm 0.84 \text{ ng g}^{-1}$ for stems.

To estimate woody NPP, we first obtained MODIS-derived total NPP data for 2010-2024 and calculated the 14-year mean to represent the long-term average¹⁵. The proportion of woody NPP within total NPP was determined using partitioning coefficients assigned to four major forest types: 0.34 for evergreen needleleaf, 0.33 for deciduous conifer, 0.22 for evergreen broadleaf, and 0.33 for deciduous broadleaf forests¹⁶. Woody NPP was then further partitioned into stem and twig components, with twigs accounting for $0.13 \pm 0.09\%$ of aboveground woody NPP¹⁷.

Text S7 Data Collection and cleaning for foliar Hg and litterfall Hg

Global Hg concentration data. This study compiled global datasets of Hg concentrations in forest foliage and woody tissues. Literature searches were conducted in Google Scholar and CNKI using the keywords “forest mercury” and “mercury concentration.” Studies were included if they met the following criteria: (1) sampling sites were located in non-contaminated regions or sufficiently distant from point sources; (2) sampling strategies and analytical methods for Hg determination were explicitly described; and (3) quality assurance and quality control procedures were documented. In total, 2,263 records of foliar Hg concentrations and 1,670 records of woody tissue Hg concentrations were assembled (Fig. 1a). Litterfall Hg concentrations were considered to represent cumulative Hg accumulation at the end of the leaf lifespan. Accordingly, 112 litterfall records were compiled. In total, 2,375 records of foliar Hg concentrations were assembled, comprising 1,225 from coniferous forests and 1,242 from broadleaf forests.

Method for assigning leaf age to Hg data. Leaf age is a key factor determining the estimation of the foliar Hg sink; therefore, age information was assigned to the collected foliar Hg concentration data (Fig. S53). In total, 88% of samples had leaf age directly reported in the literature, while the remaining samples were supplemented using three approaches:

(1) **Deciduous species.** For deciduous trees with known sampling dates, leaf age was estimated by subtracting the local leaf-flushing month (i.e., onset of the growing season) from the sampling month.

(2) **Evergreen species.** For the remaining evergreen species (approximately 4% of the dataset), we modeled the relationship between foliar Hg concentration and leaf age. Using datasets with age information (389 broadleaf and 605 conifer records), linear regressions were established between Hg concentration and leaf age for sites with three or more age groups, ensuring sufficient data for reliable fitting. Leaf age was then inferred from the regression slope, which represents the Hg accumulation rate. On average, Hg accumulated at $5.71 \text{ ng g}^{-1} \text{ month}^{-1}$ in broadleaf species and $9.40 \text{ ng g}^{-1} \text{ yr}^{-1}$ in coniferous species (Fig. S54).

(3) **Litterfall.** Hg concentrations in litterfall reflect the end-of-life stage of leaves and thus correspond to their final age. Therefore, the age of litterfall leaves was assigned according to the simulated distribution of leaf lifespan (Fig. S5).

Data cleaning. During data cleaning, some sites contained multiple tree species within the same forest type. Since model fitting and prediction were not performed at the species level, these data were aggregated by functional forest type (evergreen broadleaf, deciduous broadleaf, evergreen needleleaf, and deciduous needleleaf) to minimize biases arising from interspecific variation. Outliers were identified using the interquartile range (IQR) method, and extreme values exceeding the upper bound ($Q3 + 4 \times \text{IQR}$) were removed. For variables with a small number of missing values, median imputation was applied. To improve model stability and eliminate scale differences, all predictor variables were standardized using Z-score normalization prior to modeling. The final foliar Hg concentration model was trained using 1,266 samples, including 652 records for coniferous forests and 614 records for broadleaf forests.

Text S8: Foliar Hg concentration deep learning model (DNN).

To predict global forest foliar Hg concentrations, we developed separate regression models for broadleaf and coniferous species using a deep neural network (DNN) framework. The network architecture consisted of two fully connected hidden layers, each containing 32 neurons and employing the ReLU activation function. To enhance training stability and mitigate overfitting, batch normalization and a dropout rate of 0.1 were applied after the first hidden layer, and an additional dropout rate of 0.1 was applied after the second hidden layer. The output layer comprised a single linear neuron that generated continuous prediction values. Both models were trained using the Adam optimizer (learning rate = 0.01) with the mean squared error (MSE) as the loss function.

To evaluate model generalization performance, we employed five-fold cross-validation ($K = 5$). For each fold, the coefficient of determination (R^2) and root mean square error (RMSE) were calculated for both training and testing sets, and the mean values and ranges were summarized to assess the robustness and stability of model performance.

Text S9: Modeling foliar Hg uptake

The estimation framework developed in this study consists of three interrelated modules: foliar Hg concentration, leaf lifespan, and leaf-to-aboveground biomass ratios. These components form a trait-constrained modeling architecture in which Hg uptake is resolved as a canopy accumulation process. The modules are jointly driven by topographic, climatic, and plant trait factors, with the foliar Hg concentration model additionally incorporating anthropogenic influences. In this framework, topographic factors (latitude, longitude, elevation) and climatic factors (temperature, precipitation, solar radiation) are consistently included across all models, whereas plant trait variables differ depending on the specific modeling objectives.

Specifically, the foliar Hg concentration model incorporates leaf age, leaf area index (LAI), and tree height as key plant traits, together with anthropogenic Hg emissions and atmospheric Hg concentrations. The leaf lifespan model primarily relies on physiological traits, including specific leaf area (SLA), leaf nitrogen (N) and phosphorus (P) contents, and LAI. For the leaf-to-aboveground biomass ratio model, structural attributes such as forest age, normalized difference vegetation index (NDVI), LAI, and tree density were used as predictors.

These modules were coupled in a hierarchical manner. The predicted leaf lifespan was first used to constrain Hg accumulation time in foliage, enabling the estimation of Hg concentrations in senesced leaves (i.e., litterfall Hg concentrations). Annual foliar Hg accumulation rates were then derived by dividing these concentrations by the corresponding leaf lifespan, and subsequently combined with outputs from the foliar biomass model to quantify global forest foliar Hg⁰ uptake (Fig. S29). All modules were implemented at a spatial resolution of 0.1° × 0.1°, with predictor variables extracted on this grid to ensure consistency across models. The data sources of all variables are summarized in Table S3.

Model performance was evaluated using 5-fold cross-validation rather than a single independent test set. In this approach, the full dataset was randomly partitioned into five equal-sized subsets. For each fold, 80% of the data (four subsets) was used for model training, while the remaining 20% (one subset) was reserved for performance evaluation. This process was repeated five times, with each subset serving as the test set exactly once. The performance metrics reported in Figs. S30–S50 represent the aggregated results across all test predictions—i.e., each data point was evaluated when it was part of the held-out test set in its respective fold. This procedure ensures full use of the dataset for both training and evaluation while maintaining independence between them. Model performance was assessed using the coefficient of determination (R^2) and root mean square error (RMSE) derived from the aggregated predictions, together with residual diagnostics to evaluate error distribution and variance structure.

Text S10: Canopies function as a near steady-state sink for atmospheric Hg⁰

Our modelling further highlights the strong agreement between simulated foliar Hg⁰ uptake and observed litterfall deposition¹⁸, providing robust evidence that forest canopies function as a near steady-state sink for atmospheric Hg⁰. This balance can be expressed as:

$$H_A = L + \Delta P_{\text{annual}},$$

where H_A represents foliar Hg uptake, L denotes litterfall deposition, and ΔP_{annual} is the net annual change in the canopy Hg pool.

The near-zero value of ΔP_{annual} indicates steady-state behaviour of global forest canopies. In mature forests, Hg concentrations in woody tissues remain low (1–5 ng g⁻¹) and annual biomass increments are typically small (1–10%)^{19,20}, rendering long-term storage in wood negligible. For deciduous species, Hg assimilated during the growing season is largely returned to the soil via litterfall, whereas evergreen foliage exhibits similarly limited interannual variation (<10%) due to relatively stable leaf biomass and modest climatic variability (temperature and radiation <5%; precipitation 10–20%)^{21,22}. Together, these constraints maintain a close balance between canopy uptake and litterfall transfer, supporting the interpretation of forests as a dynamically regulated interface rather than a progressively accumulating Hg pool.

We acknowledge that the identification of tropical rainforests as major sinks for atmospheric Hg⁰ is consistent with previous studies, including the litterfall-based assessment by Wang et al. (2016)¹⁸. However, the methodological approach and conceptual basis of the present study differ in several important respects. First, the two studies resolve different components of the forest Hg cycle. Wang et al. (2016) estimated Hg deposition through litterfall, which indirectly reflects foliar Hg⁰ uptake under the assumption of annual steady state (i.e., canopy uptake approximately equals litterfall export). Here, we resolve this flux explicitly by linking foliar Hg accumulation rates with independently constrained leaf biomass and leaf lifespan, allowing uptake to be quantified as a time-integrated canopy process.

Second, the frameworks differ in their ability to identify mechanistic drivers. Wang et al. (2016) relied on statistical extrapolation within biome classes, where spatial variability in litterfall Hg deposition was primarily attributed to differences in forest structure. By contrast, our study develops a trait-constrained, mechanistically interpretable modelling framework that explicitly links climatic gradients and plant functional traits to foliar Hg accumulation rates and uptake fluxes. This structure enables attribution of spatial variability to process-level controls rather than statistical co-variation.

Third, although the global patterns are broadly consistent between the two approaches (compare Fig. 5 in Wang et al. (2016) with Fig. 3 in this study), our framework substantially reduces uncertainty in global forest Hg⁰ uptake. The previous

estimate of $1180 \pm 710 \text{ Mg yr}^{-1}$ corresponds to a relative uncertainty of $\sim 60\%$, whereas our estimate of $1188 \pm 438 \text{ Mg yr}^{-1}$ reduces this to $\sim 30\%$, representing an approximate twofold improvement in precision. This reduction arises from explicitly constraining Hg residence time in foliage and canopy storage capacity, thereby limiting key sources of variability in previous extrapolation-based approaches.

Text S11: Artificial overestimation of tropical uptake in earlier studies.

We use the term “artificial overestimation of tropical uptake” to describe specific methodological choices in previous studies that systematically inflate uptake estimates in tropical regions, rather than reflecting true uncertainty in the underlying observations.

In particular, Zhou and Obrist (2021)²³ estimated foliar Hg uptake by multiplying foliar Hg concentrations by leaf net primary production (NPP), with leaf NPP derived from total aboveground NPP using fixed leaf allocation coefficients. While computationally efficient, this approach introduces systematic bias in tropical regions for two primary reasons. First, fixed allocation coefficients do not capture the structural and functional characteristics of tropical forests. Temperate and boreal forests typically allocate a smaller fraction of total NPP to foliage (15–40%) compared to tropical forests (25–55%), reflecting differences in canopy structure, turnover rates, and resource allocation strategies^{24,25}. Applying fixed coefficients therefore leads to biased estimates of leaf biomass, particularly in high-productivity tropical systems.

Second, the use of foliar Hg concentrations measured in mature leaves introduces a temporal mismatch. These concentrations represent cumulative Hg uptake over the full leaf lifespan. In tropical evergreen forests, where leaf lifespans typically range from 1–3 years, multiplying cumulative concentrations by annual NPP effectively attributes multi-year Hg accumulation to a single year, resulting in overestimation factors of approximately 2–3 $\times$.

When leaf biomass estimates are compared directly, the magnitude of this bias becomes evident. Our harmonized leaf biomass product, which integrates multiple observational datasets (Text S3), yields tropical forest leaf biomass values of 6–10 t ha⁻¹. In contrast, the NPP-based approach with fixed allocation coefficients effectively implies leaf biomass values approximately 3–8 t ha⁻¹ higher than our observation-constrained estimates (Fig. S18), corresponding to a 30–80% overestimation of the leaf pool available for Hg accumulation.

The combined effect of biased biomass estimation and temporal misinterpretation of foliar Hg concentrations explains the systematically elevated uptake estimates reported in previous studies. Zhou and Obrist (2021) reported global foliar Hg uptake of $1466 \pm 490 \text{ Mg yr}^{-1}$, substantially higher than our estimate of $1119 \pm 334 \text{ Mg yr}^{-1}$. This discrepancy is not uniform, but is concentrated in tropical regions where longer leaf lifespans amplify the cumulative concentration bias.

Text S12: Scenario analyses for futural climate changes

Simulating the future forest Hg^0 sink under climate change is inherently complex, as it is influenced by multiple interacting factors, including atmospheric Hg^0 concentrations, anthropogenic emissions, climatic conditions, and vegetation traits²⁶⁻²⁹. As an initial exploration, we conducted a simplified scenario analysis using the IPSL climate model under the SSP1-2.6 scenario (a low greenhouse gas emissions pathway), with future temperature and precipitation projections downscaled from WorldClim, to examine the isolated effects of projected climatic changes on the global forest Hg^0 sink for the period 2081–2100^{30,31}.

Our results show that when only precipitation was altered, future changes in the global forest Hg^0 sink relative to the present were minimal (<0.2%, Fig. S25). Correspondingly, the ratios of future-to-present leaf lifespan and leaf biomass remained within 0.98–1.02 across regions (Figs. S25b, S25c), resulting in negligible changes in the global forest Hg^0 sink (Fig. S25d).

When only temperature was modified, the overall response likewise remained limited (~1%, Fig. S26), but exhibited clear regional variability. In high-latitude boreal regions (60–70°N), projected temperature increases of 10–50% (Fig. S26a) led to a reduction in the forest Hg sink of approximately 3 Mg yr^{-1} (Fig. S26d). This decline was primarily driven by shortened leaf lifespan (Fig. S26b), which reduced the duration of Hg accumulation in foliage. In contrast, temperate regions of the Northern Hemisphere showed an increase of approximately 15 Mg yr^{-1} , where the stimulatory effect of warming on foliar Hg uptake rates—likely mediated by enhanced stomatal conductance and photosynthetic activity^{29,32}—outweighed the negative impacts of reduced leaf lifespan and biomass (Figs. S26b, S26c). In low-latitude Northern Hemisphere and Southern Hemisphere forests, projected temperature changes were modest (<10%, Fig. S26a), with no substantial changes in leaf lifespan or biomass, resulting in limited impacts on the forest Hg^0 sink.

These scenario analyses, while simplified, highlight the complex and regionally variable responses of forest Hg cycling to future climate change. They also indicate that climate-driven changes in vegetation traits may either reinforce or offset changes in atmospheric Hg inputs, complicating predictions of the future forest Hg sink. We acknowledge that this represents only a first step, and that a comprehensive assessment would require fully coupled simulations integrating dynamic vegetation, evolving atmospheric Hg concentrations, and land-use change. Nonetheless, these findings underscore the need to consider climate-driven vegetation feedbacks when evaluating the long-term effectiveness of the Minamata Convention.

Future increases in atmospheric CO_2 concentrations may further influence forest Hg^0 uptake by modulating stomatal conductance. On one hand, elevated CO_2 can induce partial stomatal closure, thereby reducing gas exchange rates³³ and potentially suppressing foliar Hg^0 uptake. Previous studies have suggested that future CO_2

increases could reduce forest Hg^0 uptake by up to 50% ³⁴. However, this estimate remains highly uncertain, as existing observations are primarily derived from short-term controlled experiments on individual plants or young leaves ^{35,36}, and it remains unclear how these responses scale to mature forest canopies and whole ecosystems. On the other hand, stomatal conductance is not regulated by CO_2 alone, but is co-regulated by multiple environmental factors, including water availability, temperature, and light ^{37,38}. Future changes in temperature and precipitation may therefore partially offset CO_2 -induced stomatal closure, moderating or even counteracting the expected suppression of Hg^0 uptake.

Given these uncertainties, and the current lack of coordinated observations linking CO_2 , stomatal conductance, and foliar Hg dynamics across global forests, we do not explicitly incorporate CO_2 effects into the present modelling framework. Addressing this gap will require long-term field observations integrating gas exchange measurements, vegetation trait dynamics, and process-based modelling approaches to constrain CO_2 –Hg interactions under future climate scenarios.

II. SUPPLEMENTARY FIGURES

- A. Data constraints and observational relationships (S1–S4)
- B. Trait controls and model drivers (S5–S6)
- C. Biomass and structural constraints (S7–S9)
- D. Contaminated regions and validation (S10–S17)
- E. Model comparison and uncertainty (S18–S20)
- F. Tropical validation and cross-flux consistency (S21–S24)
- G. Climate sensitivity analyses (S25–S26)
- H. Model architecture and performance (S27–S53)

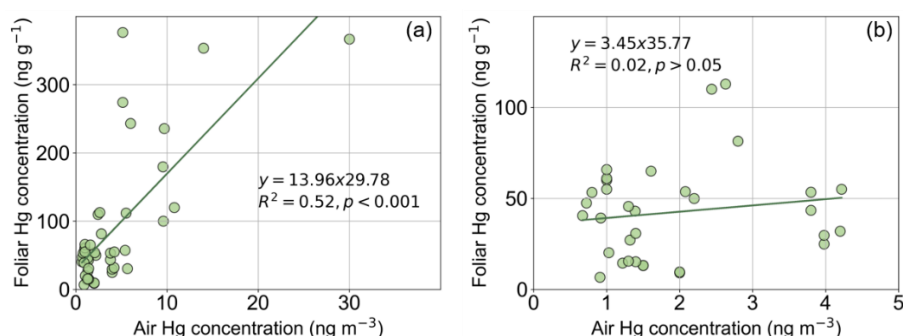


Figure S1. Relationship between atmospheric Hg concentration and foliar Hg concentration derived from co-located field measurements. (a) Relationship across the full atmospheric Hg concentration range. (b) Relationship restricted to background atmospheric Hg conditions (0 – 5 ng m⁻³). These results indicate that atmospheric Hg⁰ constrains foliar Hg only above a threshold, while below it other controls dominate.

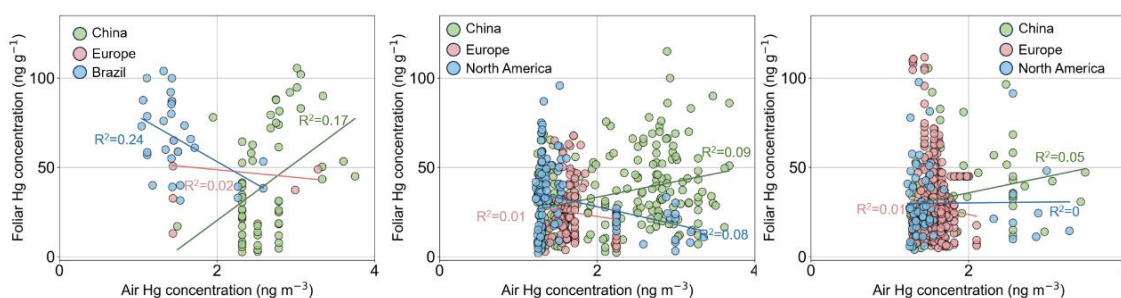


Figure S2. Relationships between foliar Hg concentrations and modeled atmospheric Hg⁰ concentrations across different regions and forest types. Panel (a) shows evergreen broadleaf forests, panel (b) shows deciduous broadleaf forests and panel (c) shows evergreen needleleaf forests. These relationships show weak or absent correlations under background conditions, indicating limited regional control by atmospheric Hg⁰.

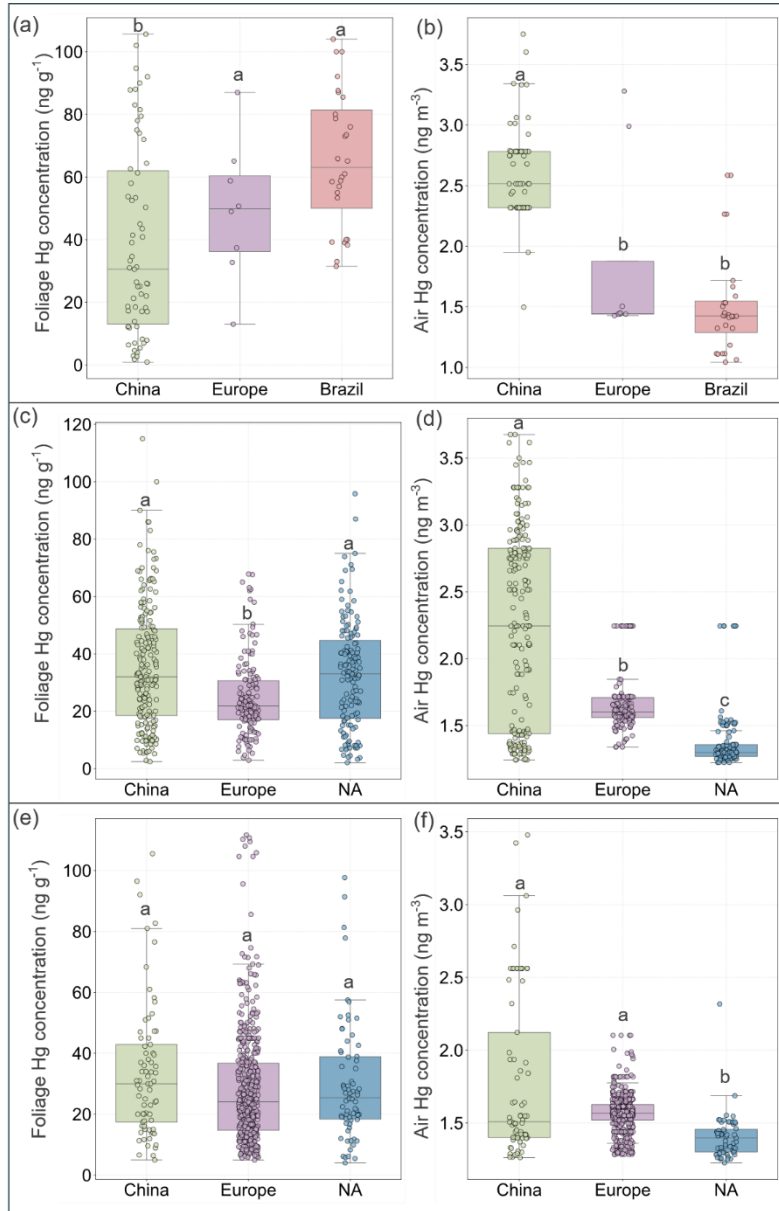


Figure S3. Foliar Hg concentrations and corresponding atmospheric Hg⁰ concentrations across regions. (a) Foliar Hg concentrations in evergreen broadleaf species across regions; (b) corresponding atmospheric Hg⁰ concentrations at the same sites; (c) foliar Hg concentrations in deciduous broadleaf species across regions; (d) corresponding atmospheric Hg⁰ concentrations at the same sites; (e) foliar Hg concentrations in evergreen needleleaf species across regions; (f) corresponding atmospheric Hg⁰ concentrations at the same sites. Abbreviation: NAE, North America. The spatial mismatch between foliar Hg and atmospheric Hg⁰ further indicates that regional atmospheric levels do not govern foliar Hg patterns. The center line indicates the median, box limits indicate the lower and upper quartiles, whiskers represent $1.5 \times$ the interquartile range, and points show individual observations.

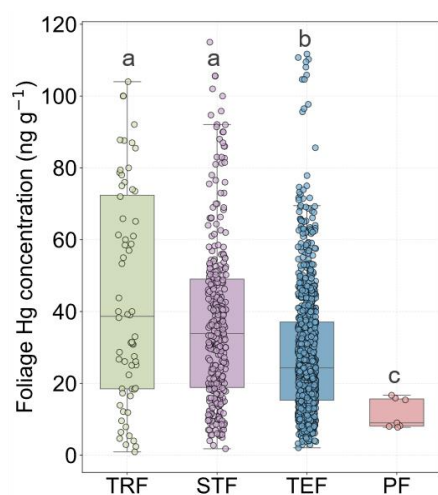


Figure S4. Foliar Hg concentrations across major latitudinal forest zones. TRF: Tropical forest; STF: Subtropical forest; TEF: Temperate forest; PF: Boreal (polar) forest. The center line indicates the median, box limits indicate the lower and upper quartiles, whiskers represent 1.5 × the interquartile range, and points show individual observations.

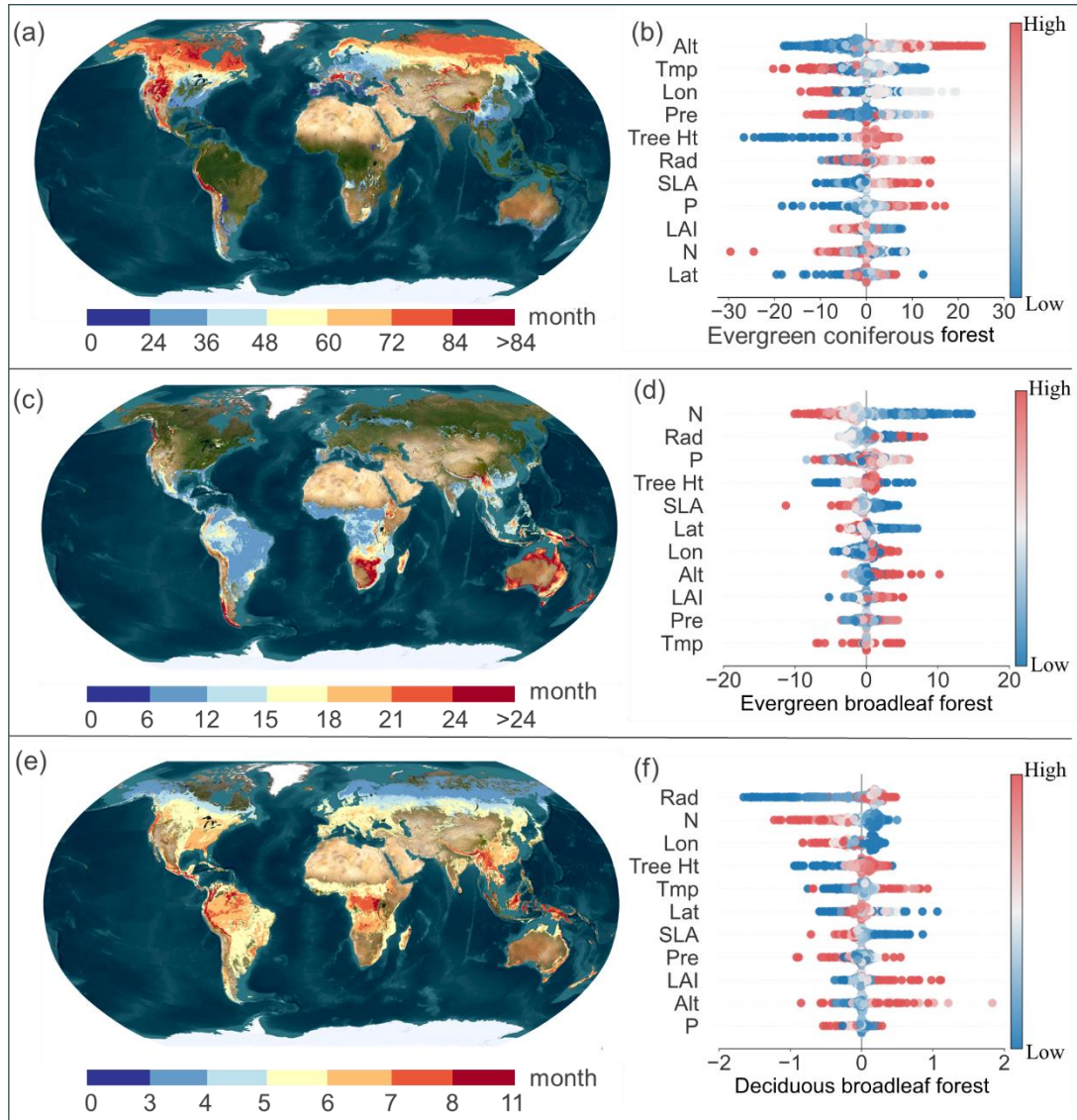


Figure S5. Global spatial distribution of leaf lifespan and its key controlling factors. (a) Spatial distribution of leaf lifespan in evergreen needleleaf forests; (b) SHAP analysis of factors influencing leaf lifespan in evergreen needleleaf forests; (c) Spatial distribution of leaf lifespan in evergreen broadleaves; (d) SHAP analysis of factors influencing leaf lifespan in evergreen broadleaves; (e) Spatial distribution of leaf lifespan in deciduous broadleaves; (f) SHAP analysis of factors influencing leaf lifespan in deciduous broadleaves. Abbreviations: Pre, precipitation; Tmp, temperature; Rad, solar radiation; Lon, longitude; Lat, latitude; Alt, altitude; N, leaf nitrogen content; P, leaf phosphorus content; SLA, specific leaf area; LAI, leaf area index; Tree Ht, tree height. These patterns show that leaf lifespan is systematically regulated by climate and plant traits, constraining Hg residence time in foliage. The satellite basemap was obtained from the World Imagery basemap in ArcGIS Pro.

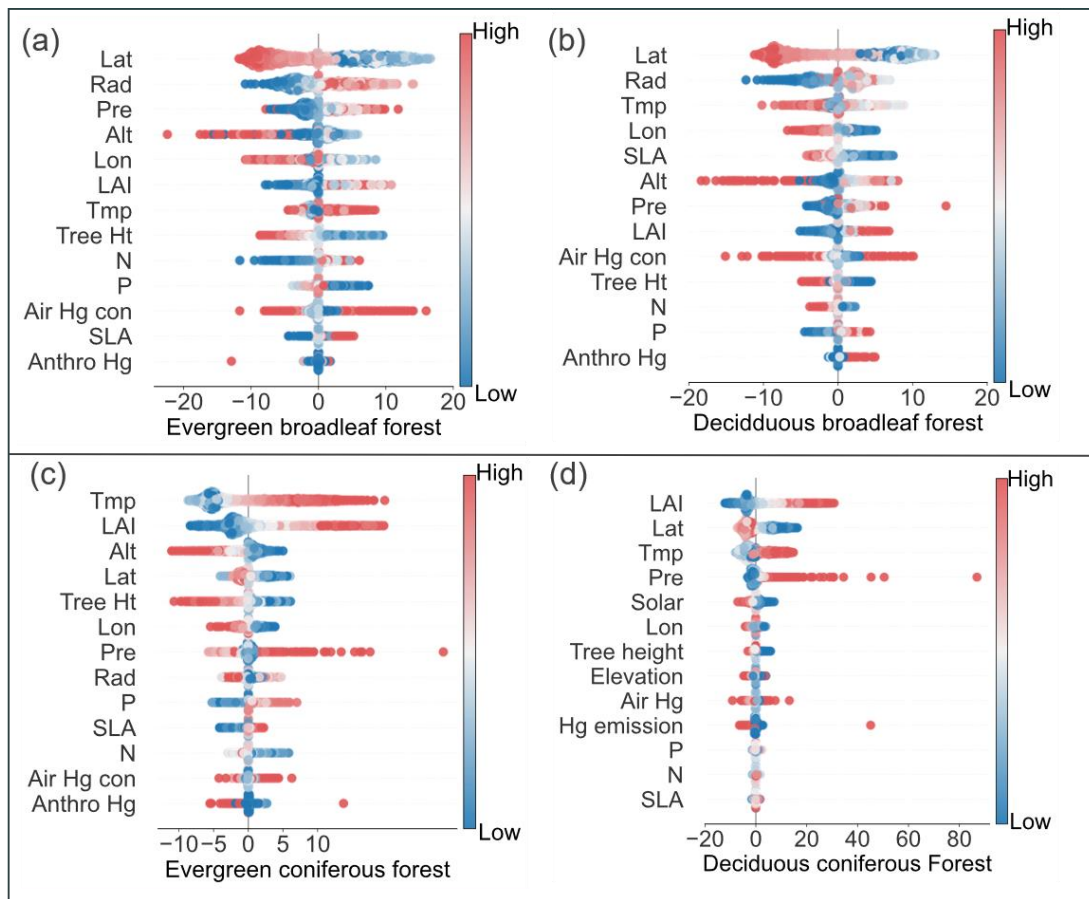


Figure S6. Key factors controlling foliar Hg accumulation. SHAP analysis of factors influencing foliar Hg concentration in (a) evergreen broadleaf forests, (b) deciduous broadleaf forests, (c) evergreen needleleaf forests, and (d) deciduous needleleaf forests. These results show that foliar Hg accumulation is primarily governed by leaf age and trait-related factors rather than atmospheric Hg⁰ concentration.

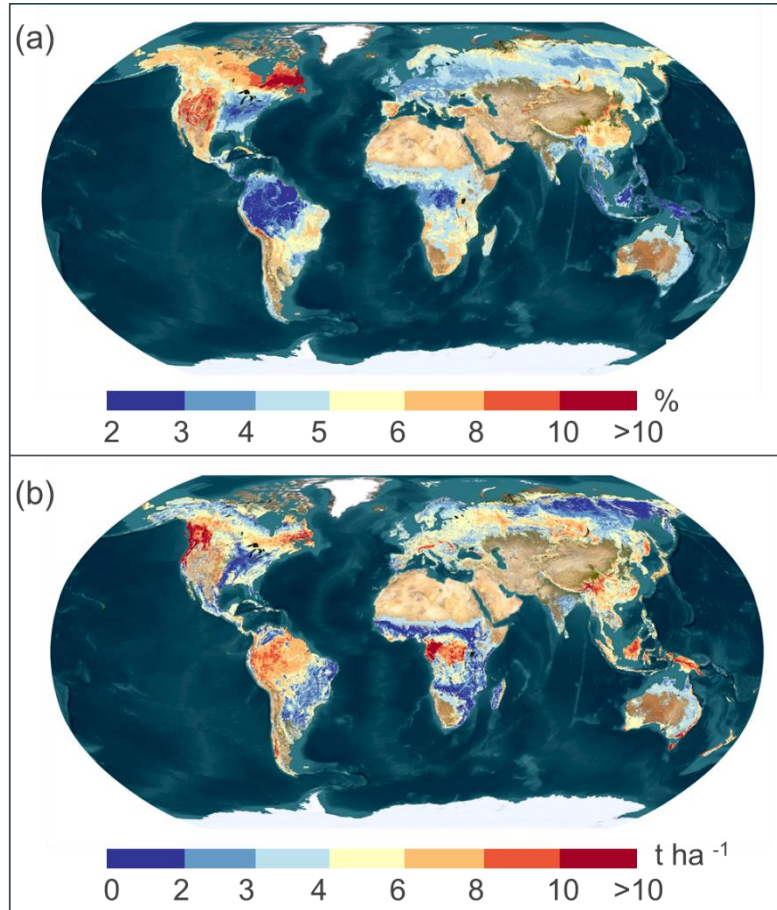


Figure S7. Spatial patterns of modeled leaf-to-aboveground biomass ratio and leaf biomass. (a) Global distribution of the leaf-to-aboveground biomass ratio; (b) global distribution of leaf biomass. The satellite basemap was obtained from the World Imagery basemap in ArcGIS Pro.

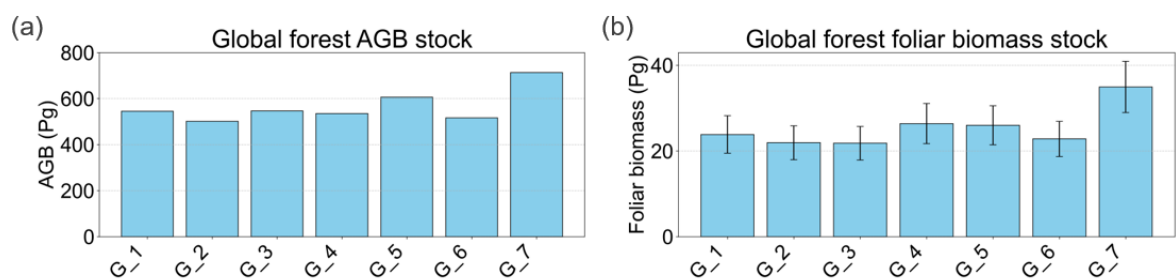


Figure S8. Global forest AGB stock and foliar biomass stock estimated using different aboveground biomass datasets. (a) Global forest aboveground biomass (AGB) stock; (b) global forest foliar biomass stock. G1–G7 refer to seven global aboveground biomass datasets (see Table S1 for details). Error bars indicate ± 1 standard deviation (SD).

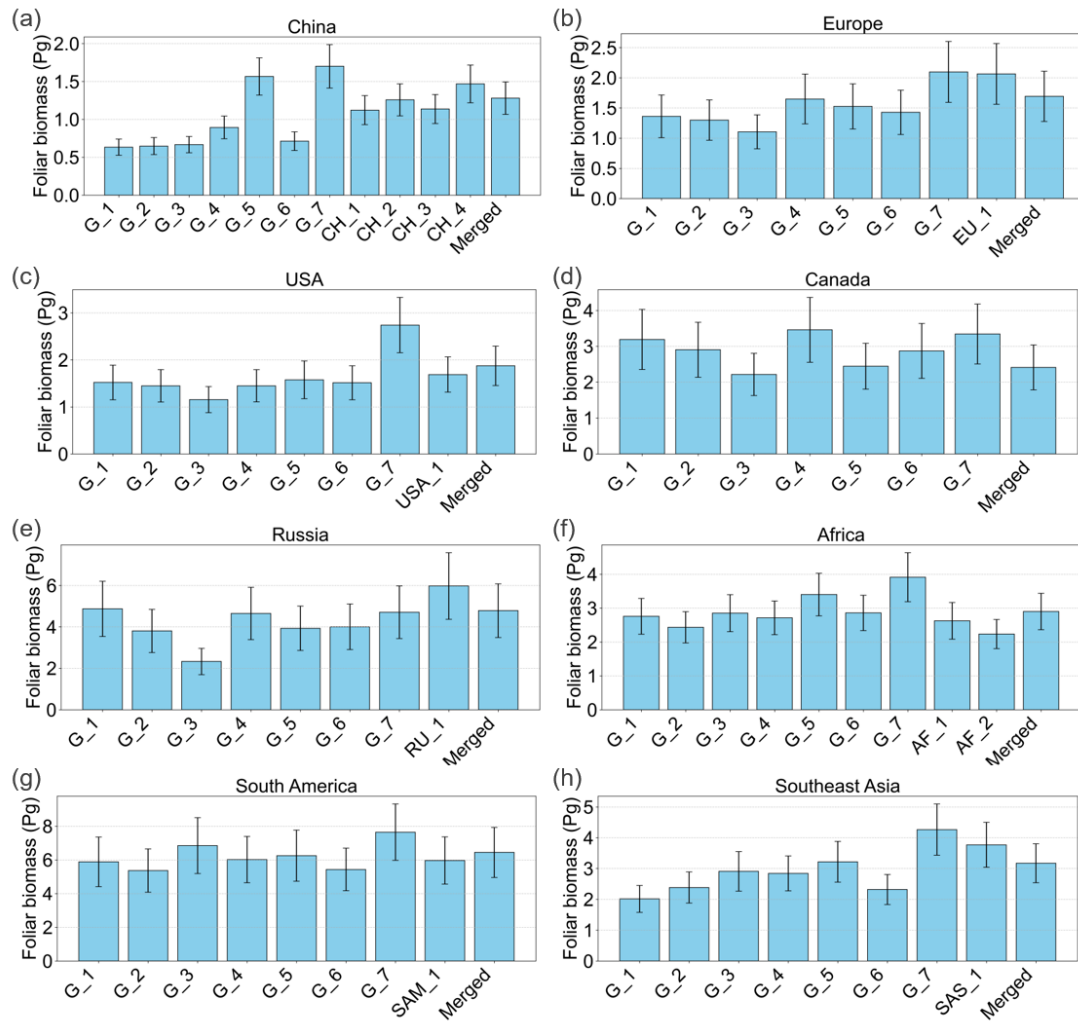


Figure S9. Regional comparisons of foliar biomass based on different biomass datasets. Panels (a – h) represent results for China, Europe, USA, Canada, Russia, Africa, South America, and Southeast Asia, respectively. G1 – G7 denote global aboveground biomass datasets; CH1 – CH4 represent datasets for China; EU1 refers to the European dataset; USA1 refers to the U.S. dataset; RU1 refers to the Russian dataset; AF1 and AF2 represent African datasets; SAM1 refers to the South American dataset; SAS refers to the Southeast Asian dataset. “Merged” denotes the integrated estimate obtained by combining all available global and regional AGB datasets to derive a unified foliar biomass. Bars indicate the mean regional foliar biomass (or corresponding Hg assimilation), and error bars indicate ± 1 standard deviation (SD) across datasets.

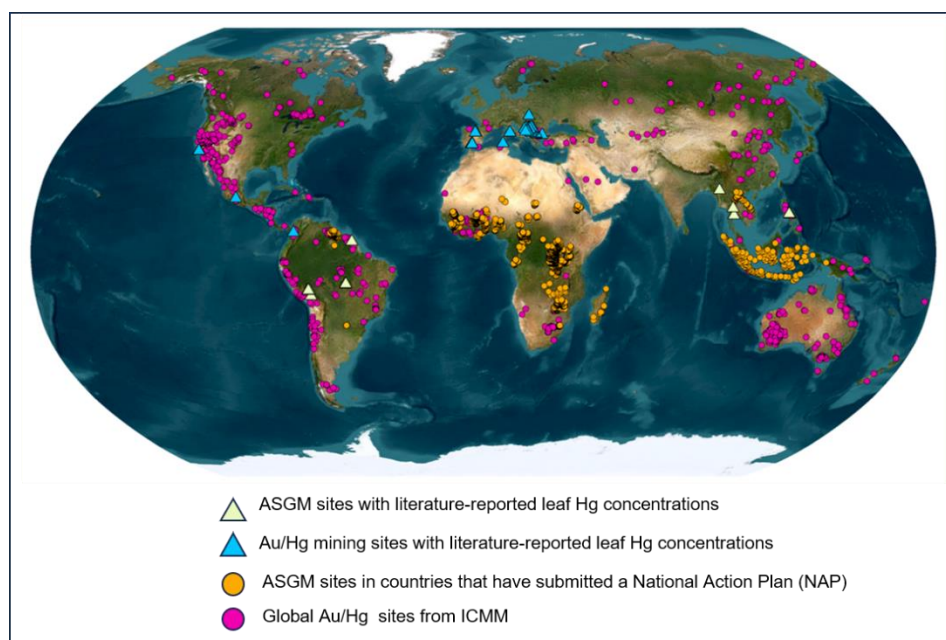


Fig. S10. Global distribution of ASGM sites, Au/Hg mines, and corresponding literature-reported leaf Hg concentration sites. The satellite basemap was obtained from the World Imagery basemap in ArcGIS Pro.

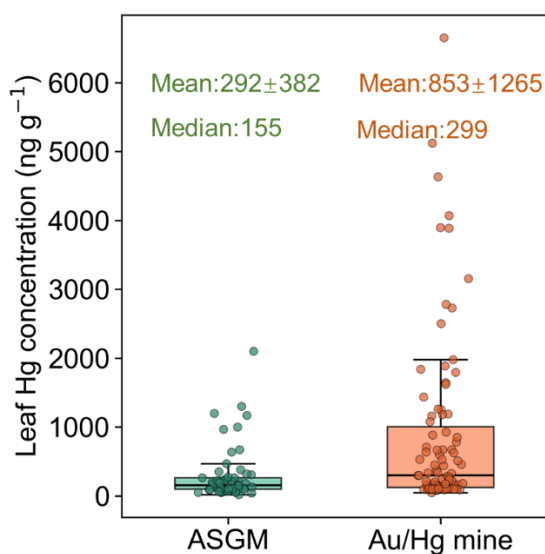


Fig. S11. Literature-reported leaf Hg concentrations at ASGM and Au/Hg mining sites. The center line indicates the median, box limits indicate the lower and upper quartiles, whiskers represent $1.5 \times$ the interquartile range, and points show individual observations.

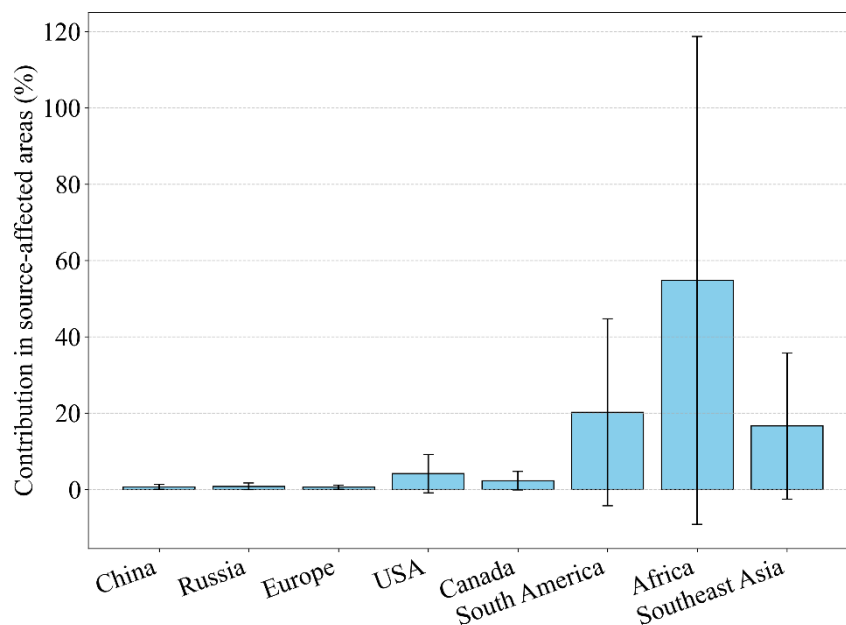


Figure S12. Regional statistics of foliar Hg^0 uptake in source-affected (contaminated) areas. Error bars indicate ± 1 standard deviation (SD).

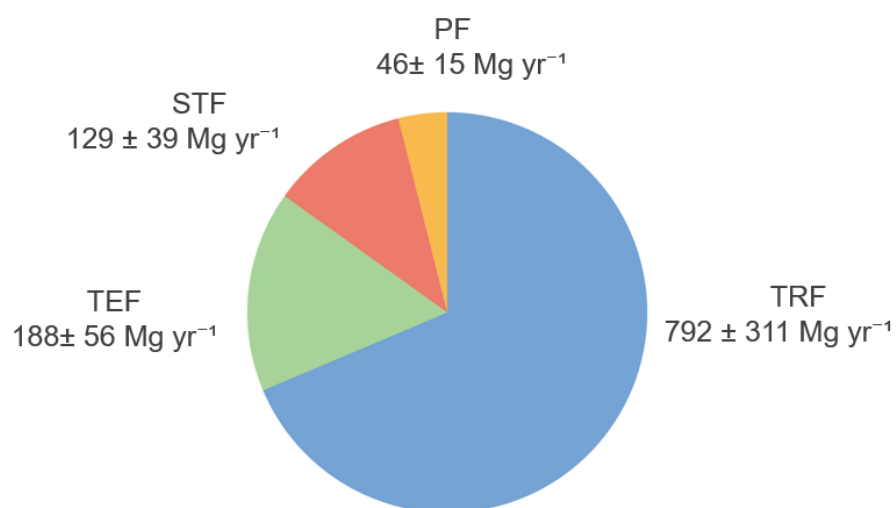


Figure S13. Mean global foliar Hg^0 uptake and standard deviation (SD) across major latitudinal forest zones. TRF: Tropical forest; STF: Subtropical forest; TEF: Temperate forest; PF: Boreal (polar) forest.

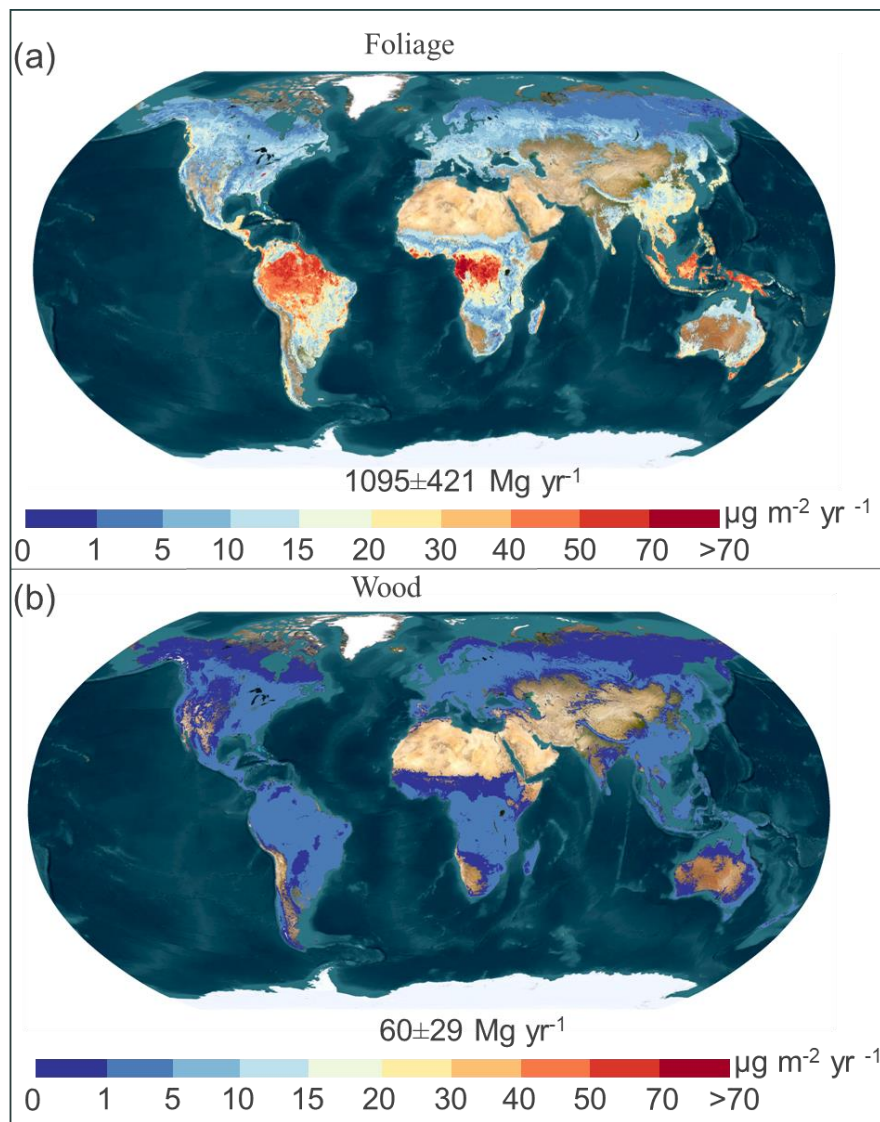


Figure S14. Spatial patterns of modeled global foliar Hg^0 uptake (a) and woody Hg uptake (b). The satellite basemap was obtained from the World Imagery basemap in ArcGIS Pro.

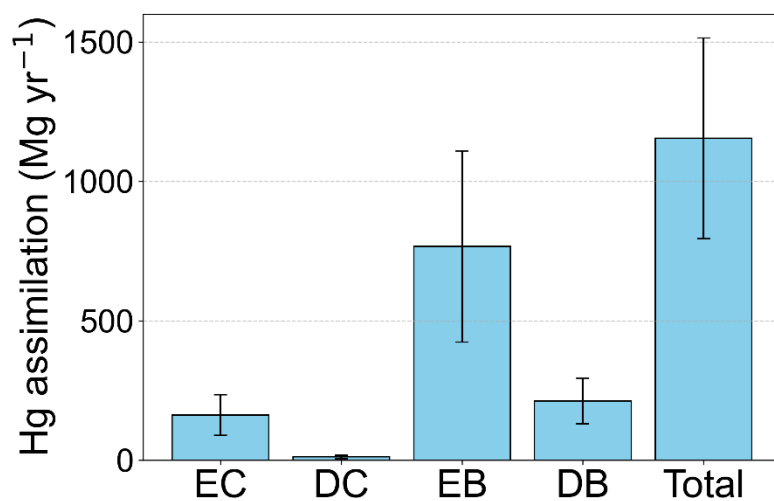


Figure S15. Global mean values and standard deviations (SD) of foliar Hg⁰ uptake (Mg yr⁻¹) across major forest types under different estimation approaches. Forest types: EC – evergreen needleleaf forests; DC – deciduous needleleaf forests; EB – evergreen broadleaf forests; DB – deciduous broadleaf forests; Total – EC + DC + EB + DB. Error bars indicate ± 1 standard deviation (SD).

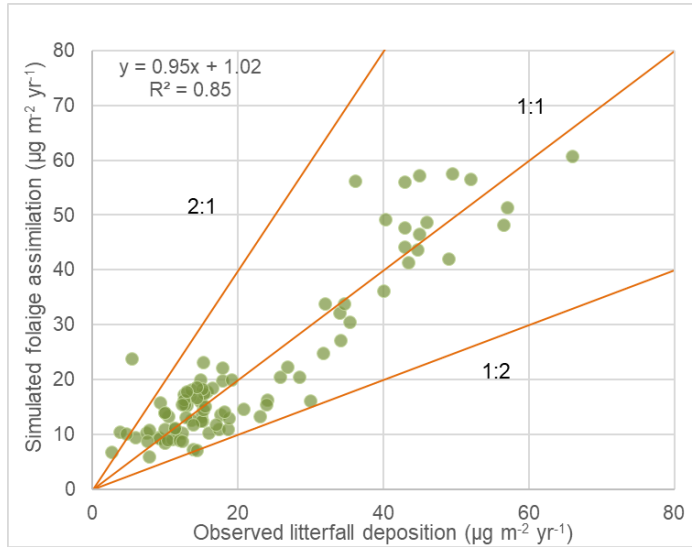


Figure S16. Comparison of modeled foliar Hg^0 uptake with observed litterfall Hg deposition. The close agreement supports a near balance between canopy Hg uptake and litterfall export at annual timescales.

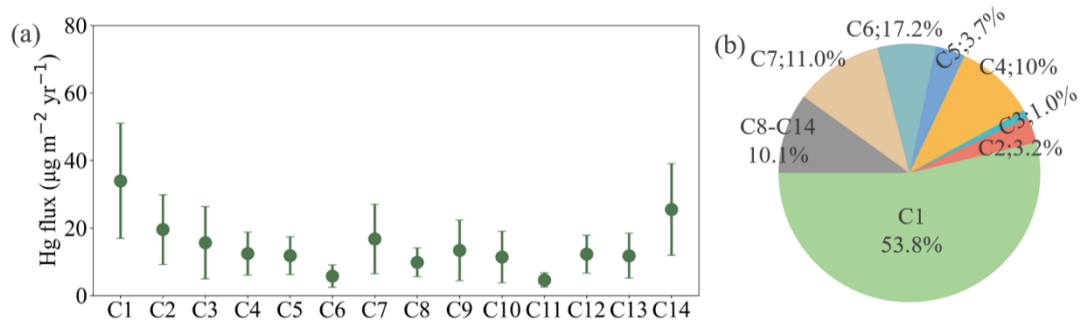


Figure S17. Foliar Hg^0 uptake across different biomes. (a) Mean foliar Hg^0 uptake in different biomes with standard deviations (SD); (b) proportional contribution of foliar Hg^0 uptake across biomes. Error bars indicate ± 1 standard deviation (SD).

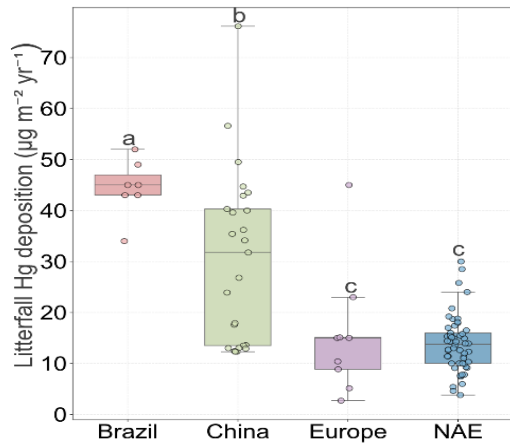


Figure S18. Litterfall Hg deposition at monitoring sites across major regions. The center line indicates the median, box limits indicate the lower and upper quartiles, whiskers represent $1.5 \times$ the interquartile range, and points show individual observations.

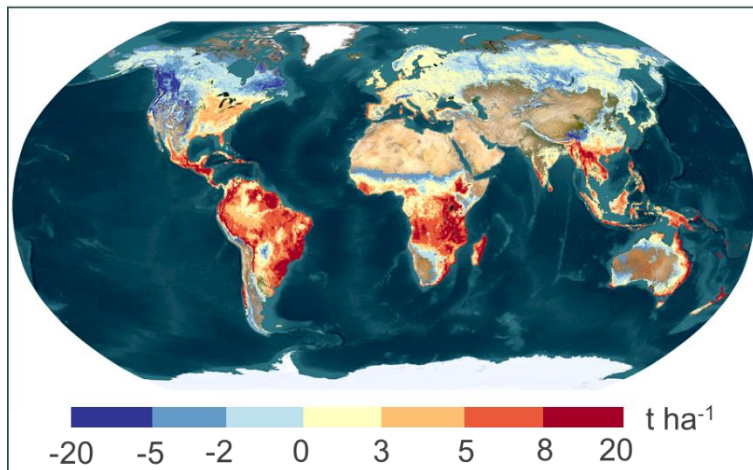


Figure S19. Difference between global foliar NPP (2010–2024) and modeled foliar biomass in this study. Foliar NPP was derived from aboveground NPP using leaf allocation fractions for four forest types (evergreen needleleaf: 0.46; deciduous needleleaf: 0.56; evergreen broadleaf: 0.58; and deciduous broadleaf: 0.64; Cleveland et al., 2013¹⁶) and weighted by forest-type-specific tree density³⁹. The resulting foliar NPP was then converted to foliar biomass using a fixed carbon fraction of 0.5. The satellite basemap was obtained from the World Imagery basemap in ArcGIS Pro.

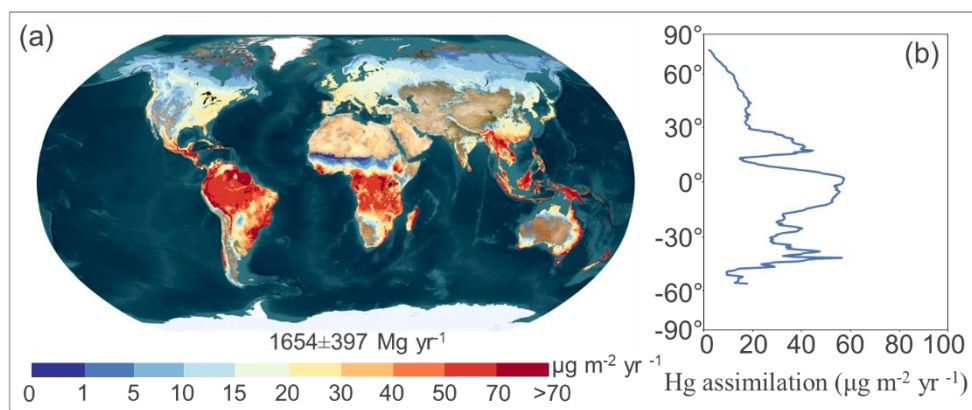


Figure S20. Spatial patterns and latitudinal gradients of modeled global foliar Hg⁰ uptake. (a–b) Foliar Hg⁰ uptake estimated using an NPP-based approach by multiplying leaf NPP with mean foliar Hg concentrations for different forest types: (a) global distribution and (b) latitudinal gradient. The satellite basemap was obtained from the World Imagery basemap in ArcGIS Pro.

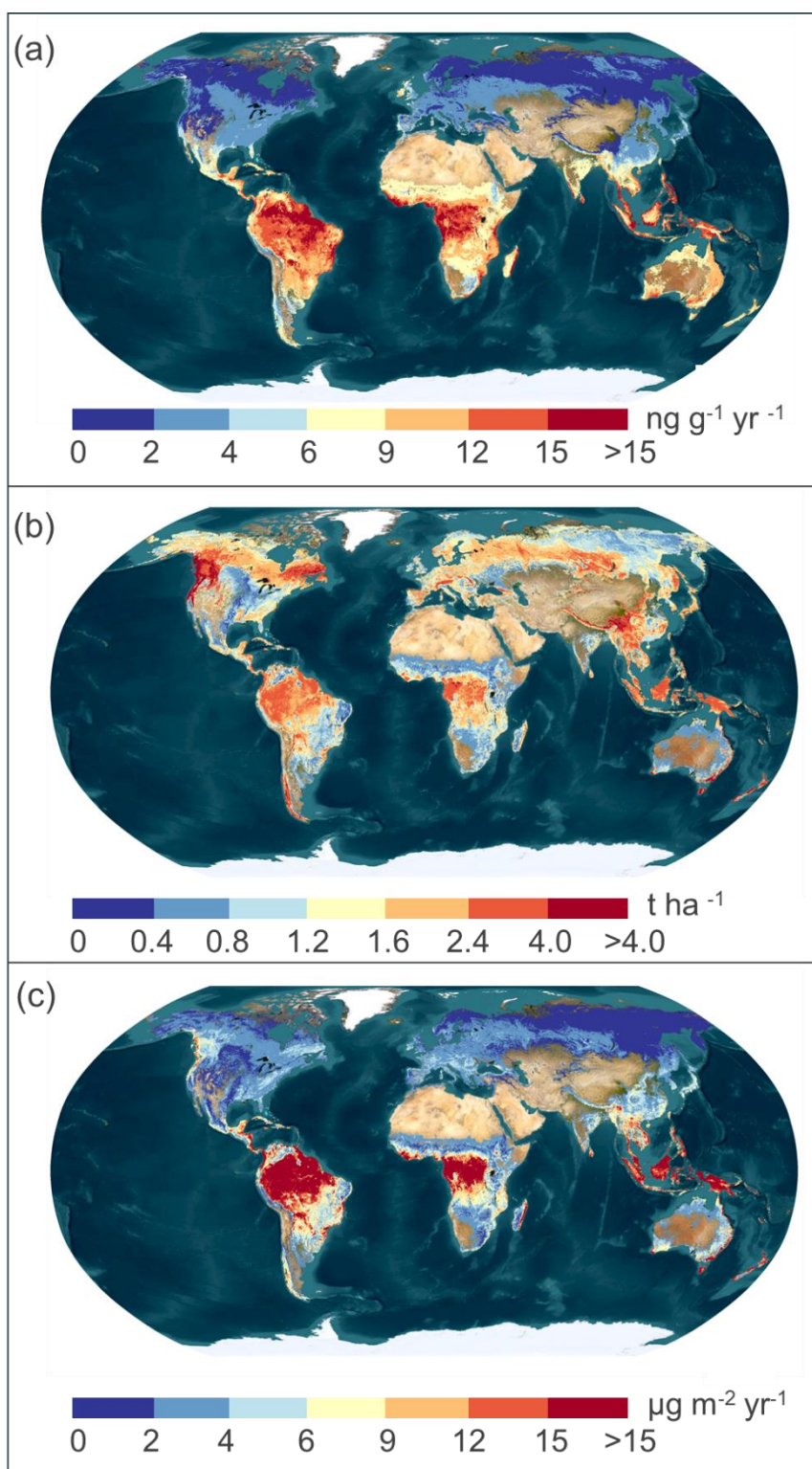


Figure S21. Global distribution of model uncertainty, represented by standard deviations (SD), for each module. (a) Foliar Hg accumulation rate model; (b) foliar biomass model; (c) foliar Hg^0 uptake model. The satellite basemap was obtained from the World Imagery basemap in ArcGIS Pro.

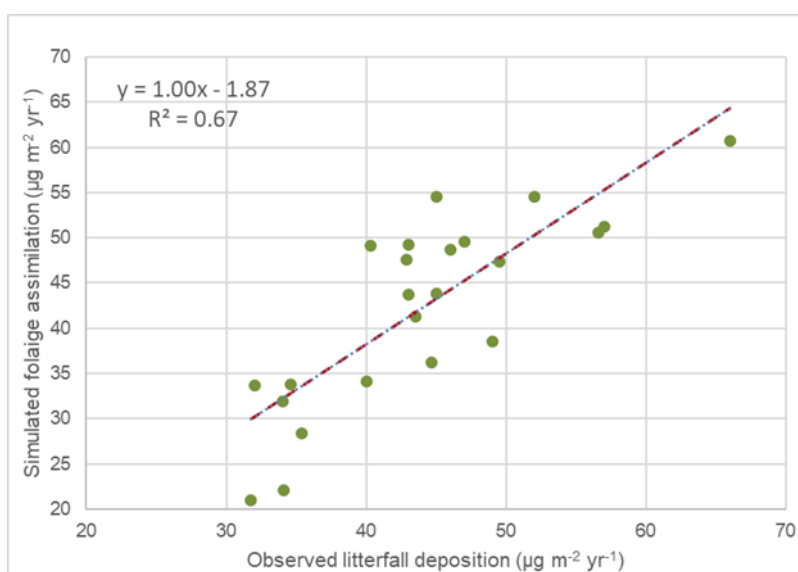


Figure S22. Comparison of modeled foliar Hg^0 uptake in tropical evergreen broadleaf forests (Africa and the Amazon) with observed litterfall Hg deposition. The strong agreement indicates that the model captures Hg uptake in tropical forests despite limited observational coverage.

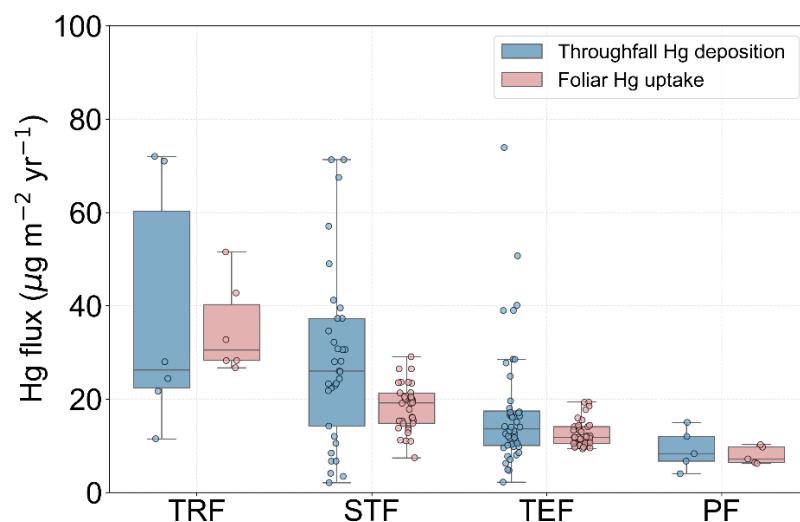


Figure S23. Measured throughfall Hg deposition and modeled foliar Hg^0 uptake in this study across major latitudinal forest zones. TRF: Tropical forest; STF: Subtropical forest; TEF: Temperate forest; PF: Boreal (polar) forest. The consistent latitudinal gradients indicate that canopy uptake and throughfall reflect coherent patterns of atmospheric Hg inputs. The center line indicates the median, box limits indicate the lower and upper quartiles, whiskers represent $1.5 \times$ the interquartile range, and points show individual observations.

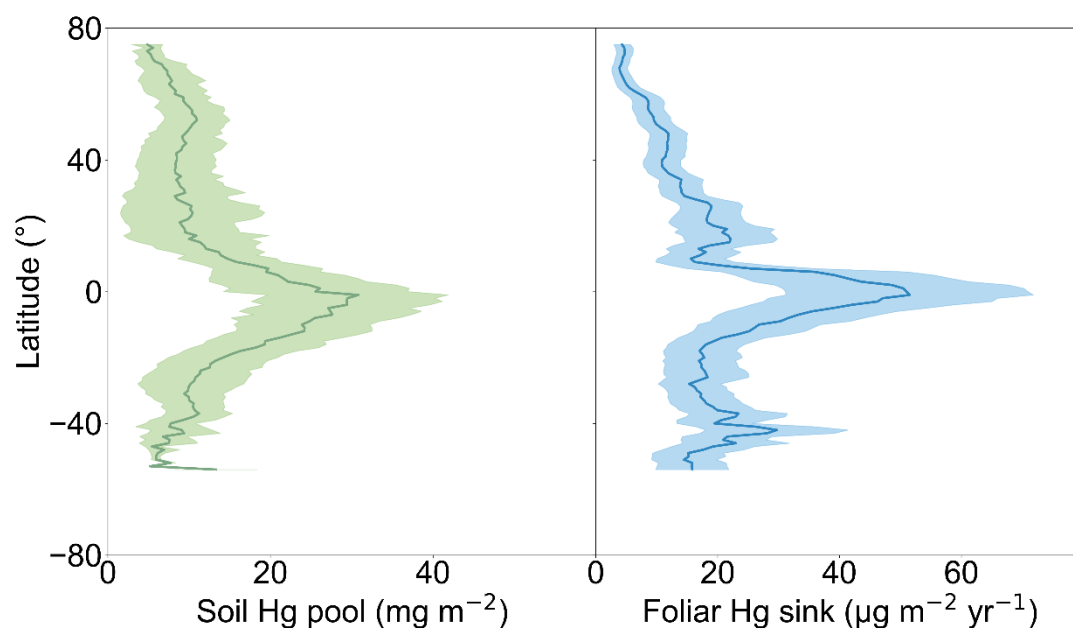


Figure S24. Latitudinal distribution of soil Hg pools⁴⁰ and modeled foliar Hg⁰ uptake. The aligned latitudinal patterns suggest that foliar uptake followed by litterfall transfer governs surface soil Hg accumulation.

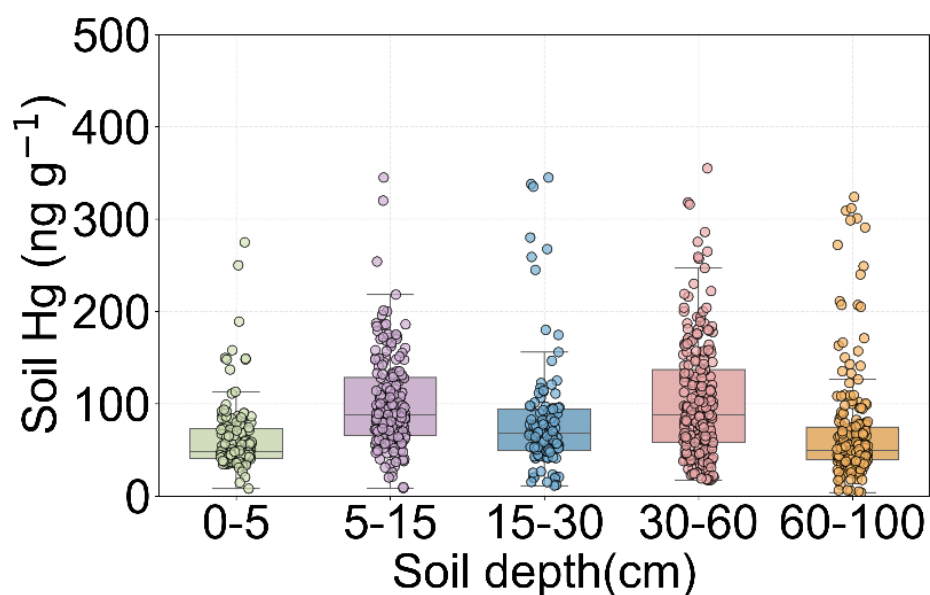


Figure S25. Soil Hg concentrations at different depth intervals. The vertical distribution indicates downward transport and retention of Hg from surface inputs into deeper soil layers. The center line indicates the median, box limits indicate the lower and upper quartiles, whiskers represent $1.5 \times$ the interquartile range, and points show individual observations.

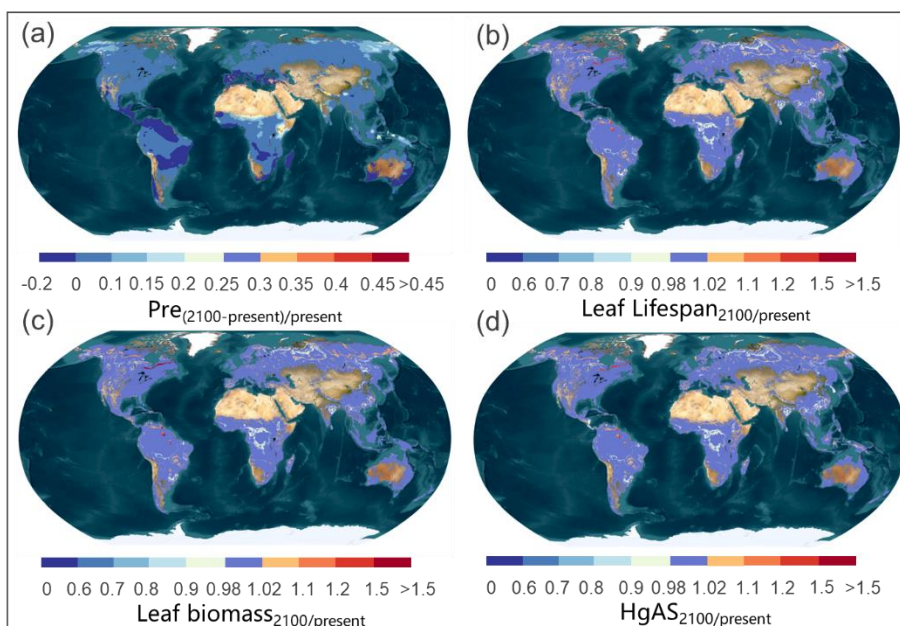


Figure S26. Projected changes in forest Hg^0 uptake under SSP1-2.6 driven by precipitation only (2081–2100): (a) relative change in precipitation ((future – present)/present); (b) leaf lifespan; (c) leaf biomass; (d) foliar Hg^0 uptake. Minimal changes indicate that precipitation alone exerts limited control on future forest Hg^0 uptake. The satellite basemap was obtained from the World Imagery basemap in ArcGIS Pro.

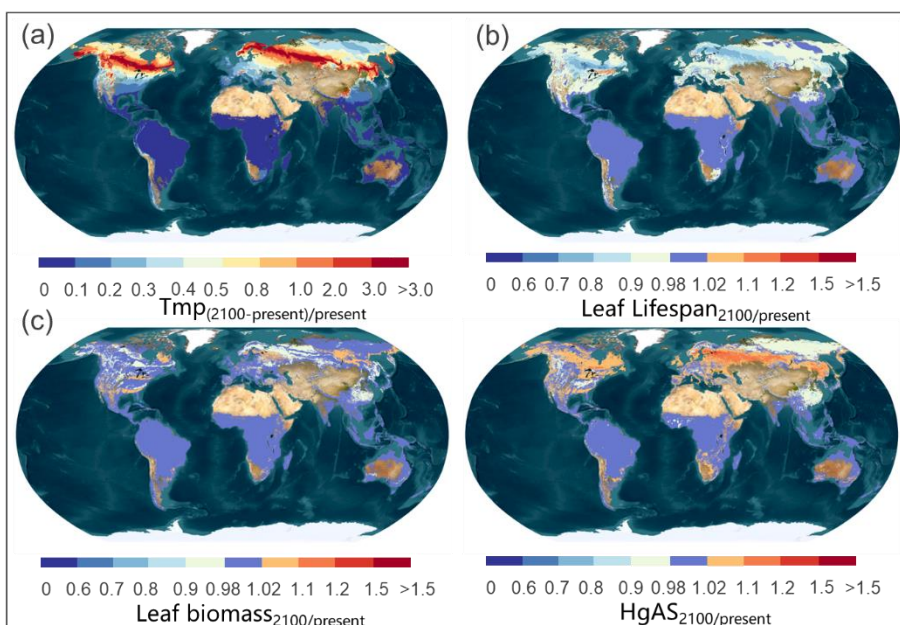


Figure S27. Projected changes in forest Hg^0 uptake under SSP1-2.6 driven by temperature only (2081–2100): (a) relative change in temperature ((future – present)/present); (b) leaf

lifespan; (c) leaf biomass; (d) foliar Hg^0 uptake. Temperature effects are modest overall but drive contrasting regional responses in forest Hg^0 uptake. The satellite basemap was obtained from the World Imagery basemap in ArcGIS Pro.

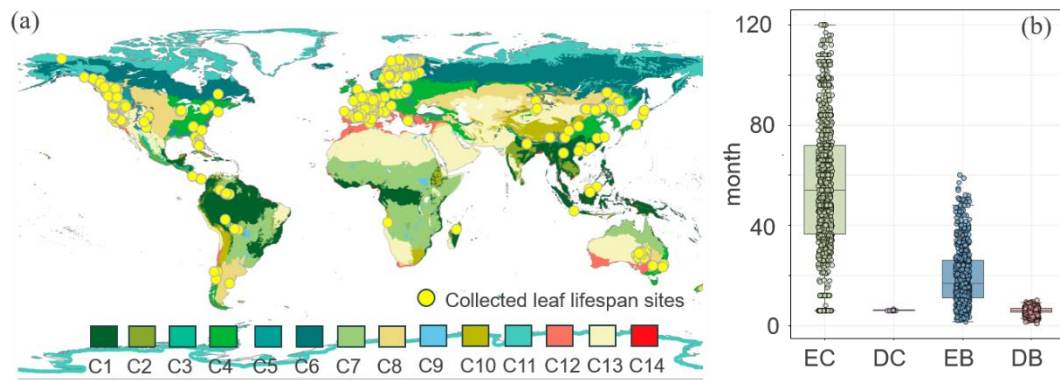


Figure S28. Spatial patterns of leaf lifespan across global forest types and ecoregions. (a) Global distribution of leaf lifespan; (b) boxplots of leaf lifespan across four forest types. The center line indicates the median, box limits indicate the lower and upper quartiles, whiskers represent $1.5 \times$ the interquartile range, and points show individual observations.

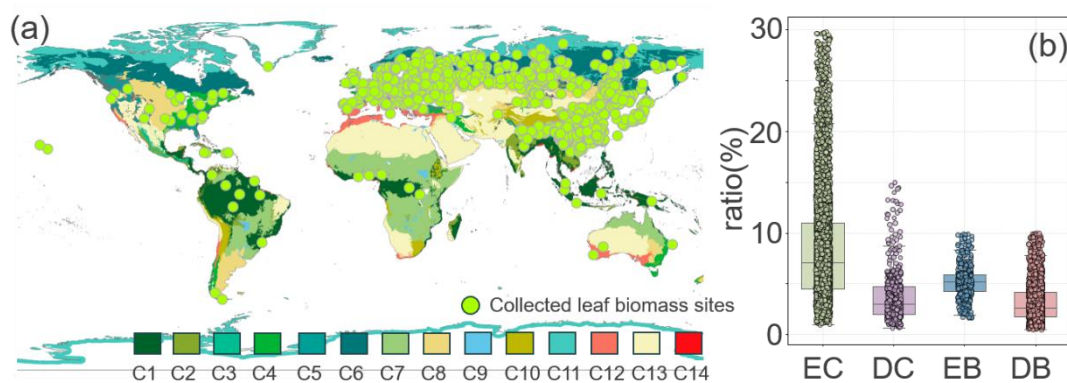


Figure S29. Spatial patterns of the proportion of leaf biomass relative to aboveground biomass (AGB) across global forest types and ecoregions. (a) Global distribution of the leaf-to-aboveground biomass (AGB) ratio; (b) boxplots of this ratio across four forest types. The center line indicates the median, box limits indicate the lower and upper quartiles, whiskers represent $1.5 \times$ the interquartile range, and points show individual observations.

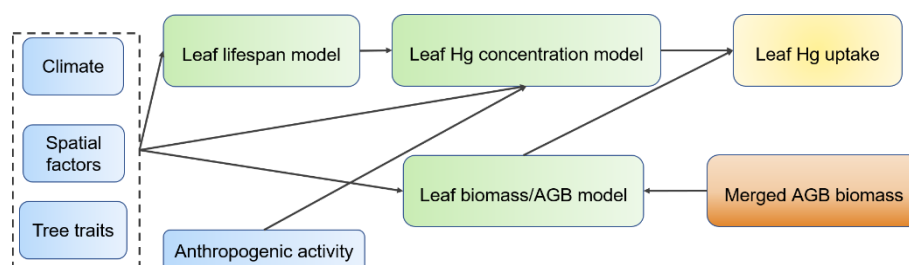


Figure S30. Schematic structure of the machine learning (ML)-coupled modelling framework. The framework consists of three core modules: the leaf lifespan model, the foliar Hg concentration model, and the foliar biomass (leaf-to-AGB) model. These modules are driven by climatic, spatial, and plant trait factors, with direct anthropogenic effects additionally

incorporated into the foliar Hg concentration model. Outputs from the three modules are integrated to estimate foliar Hg⁰ uptake at the canopy scale, yielding a global estimate of forest foliar Hg⁰ uptake.

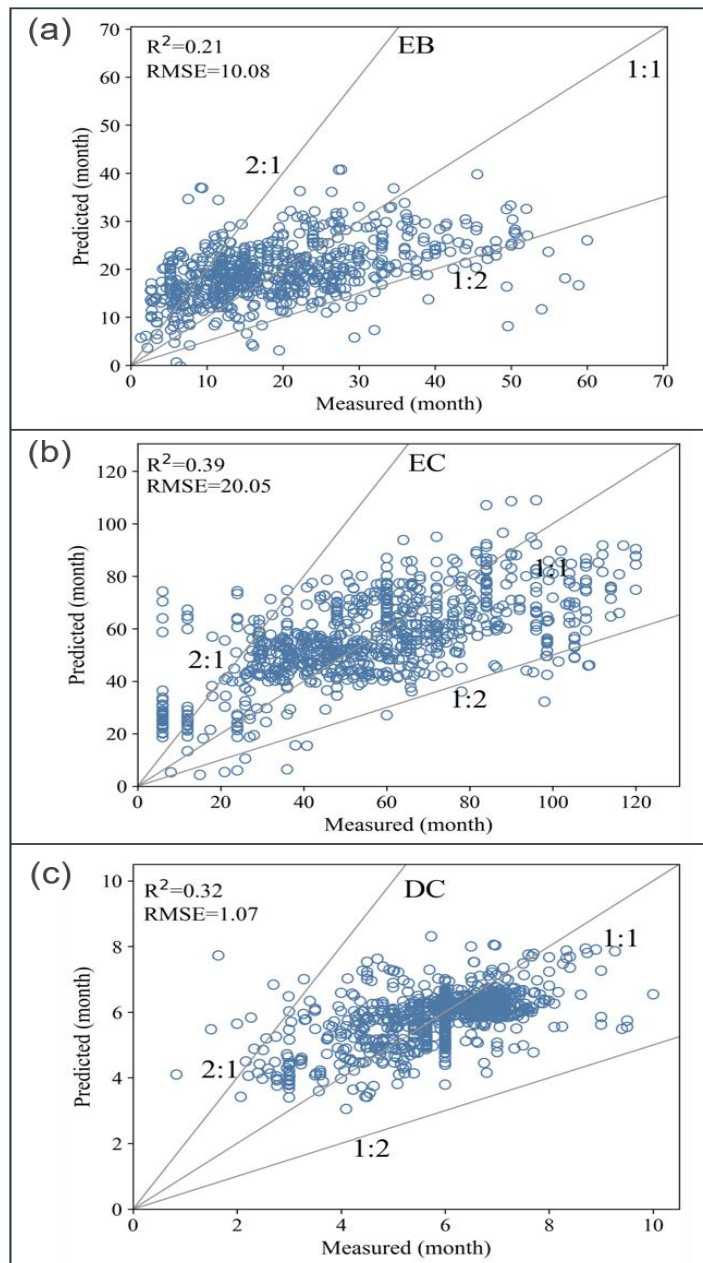


Figure S31. Linear regression performance of modeled leaf lifespan for (a) evergreen broadleaf forests (EB), (b) evergreen needleleaf forests (EN), and (c) deciduous needleleaf forests (DN). Model performance was evaluated using the test set.

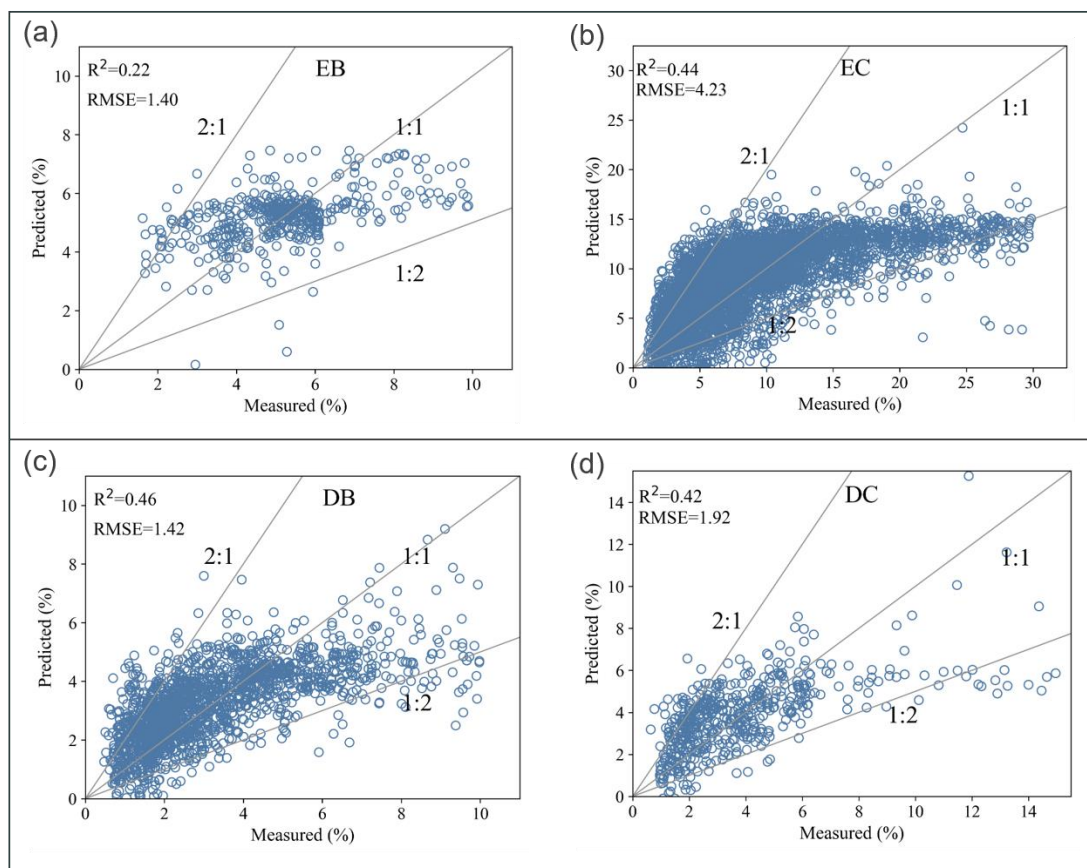


Figure S32. Linear regression performance of the modeled leaf-to-AGB ratio for (a) evergreen broadleaf forests (EB), (b) evergreen needleleaf forests (EN), (c) deciduous broadleaf forests (DB), and (d) deciduous needleleaf forests (DN). Model performance was evaluated using the test set.

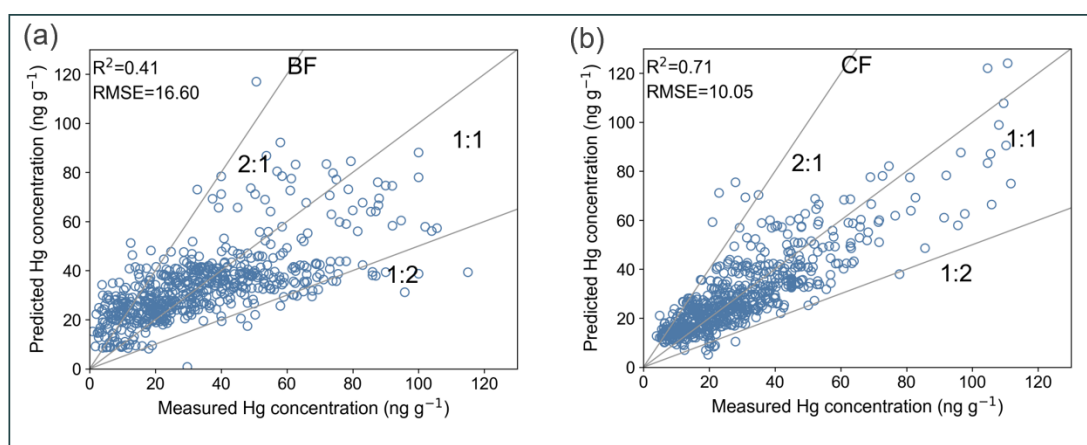


Figure S33. Linear regression performance of modeled foliar Hg concentrations for (a) broadleaf forests (BF) and (b) needleleaf forests (NF). Model performance was evaluated using the test set.

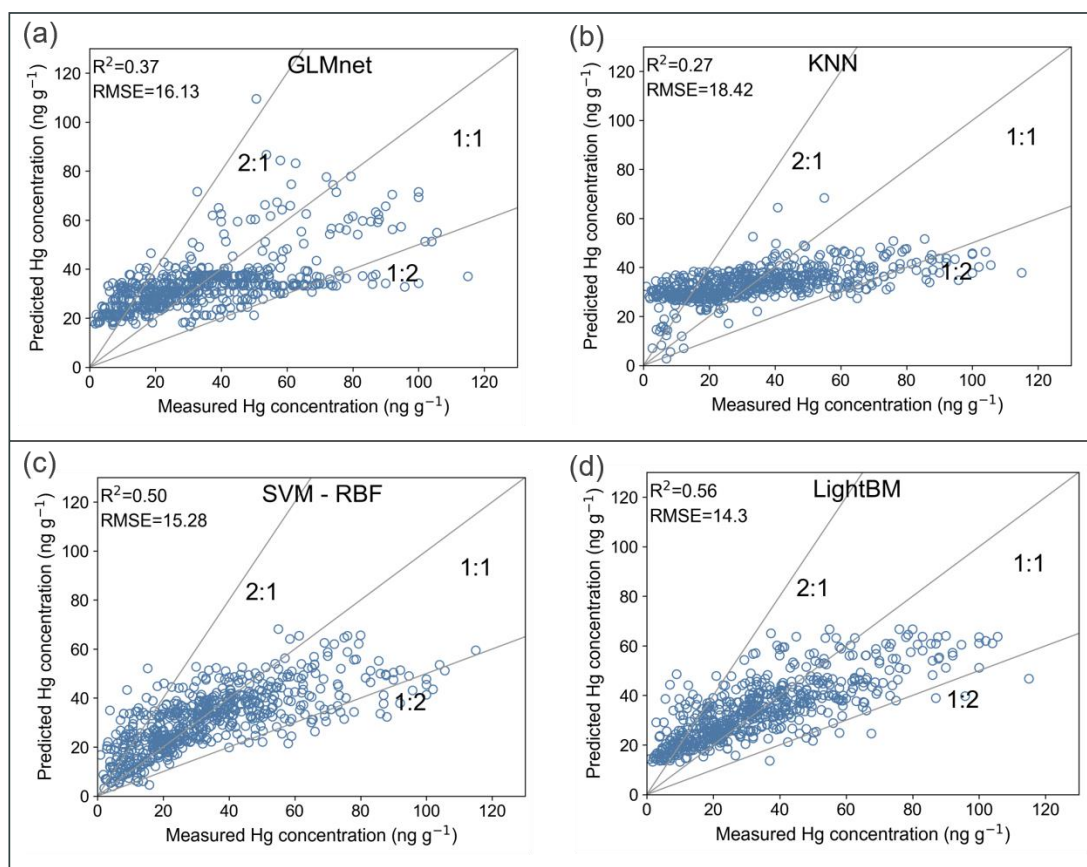


Figure S34. Performance of four machine learning models in predicting foliar Hg concentrations for broadleaf forests: (a) GLMnet, (b) KNN, (c) SVM-RBF, and (d) LightGBM. Model performance was evaluated using the test set.

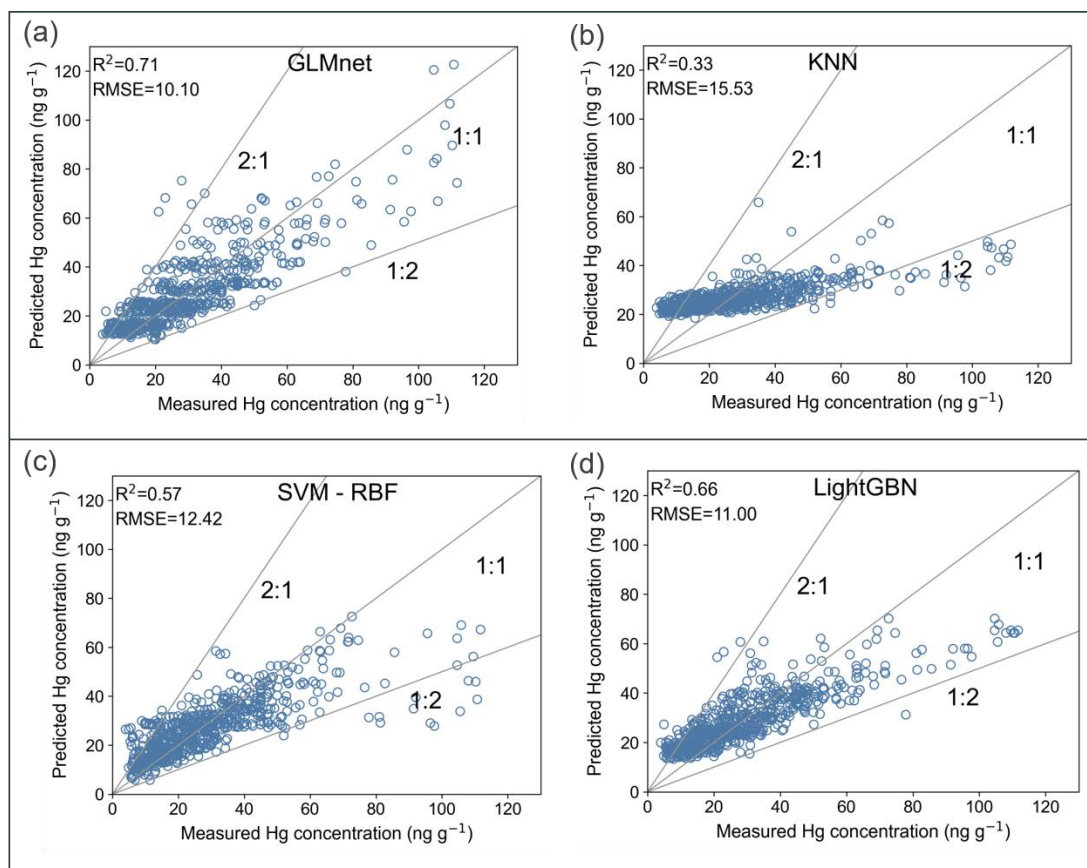


Figure S35. Performance of machine learning models in predicting foliar Hg concentrations for needleleaf forests: (a) GLMnet, (b) KNN, (c) SVM–RBF, and (d) LightGBM. Model performance was evaluated using the test set.

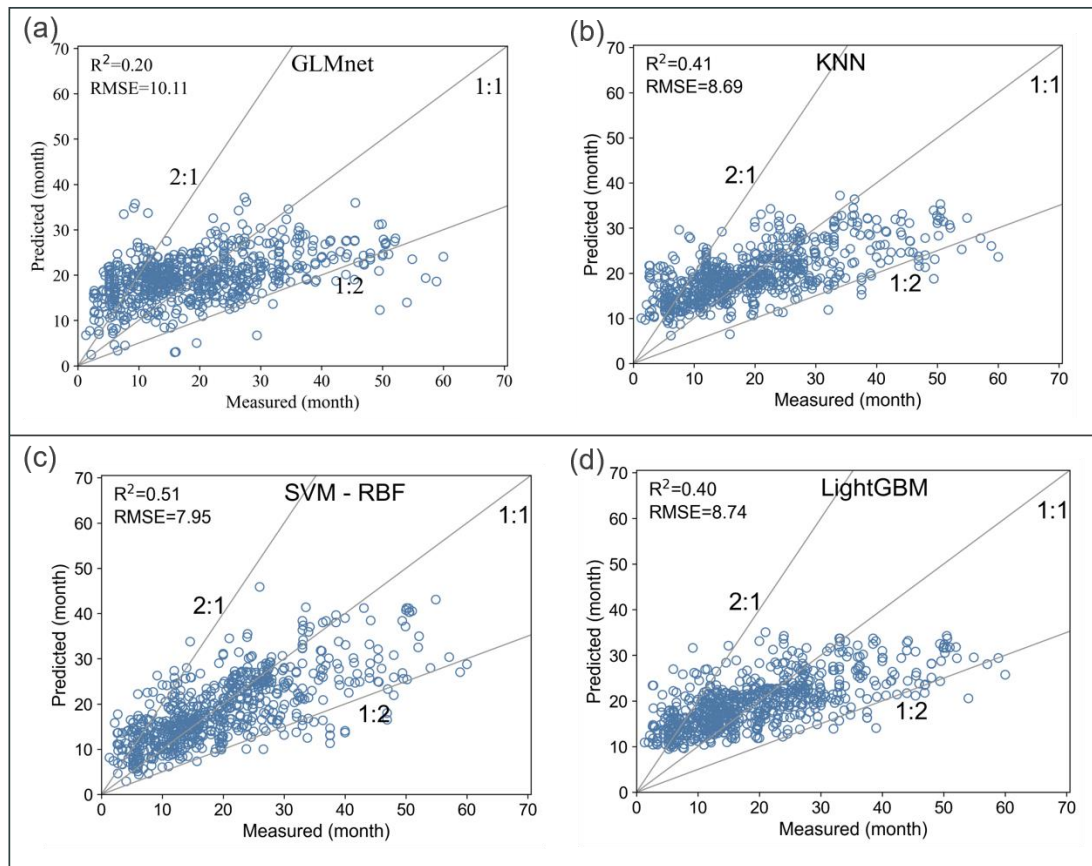


Figure S36. Performance of machine learning models in predicting leaf lifespan for evergreen broadleaf forests: (a) GLMnet, (b) KNN, (c) SVM–RBF, and (d) LightGBM. Model performance was evaluated using the test set.

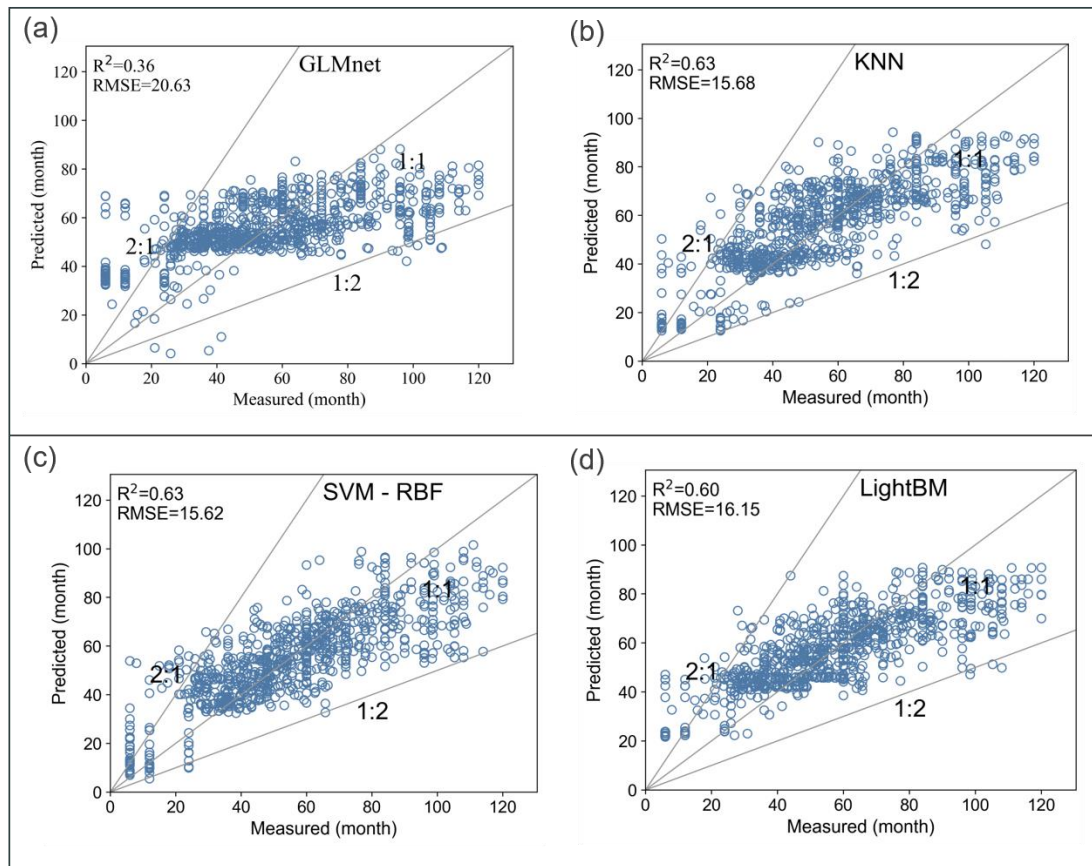


Figure S37. Performance of machine learning models in predicting leaf lifespan for evergreen needleleaf forests: (a) GLMnet, (b) KNN, (c) SVM–RBF, and (d) LightGBM. Model performance was evaluated using the test set.

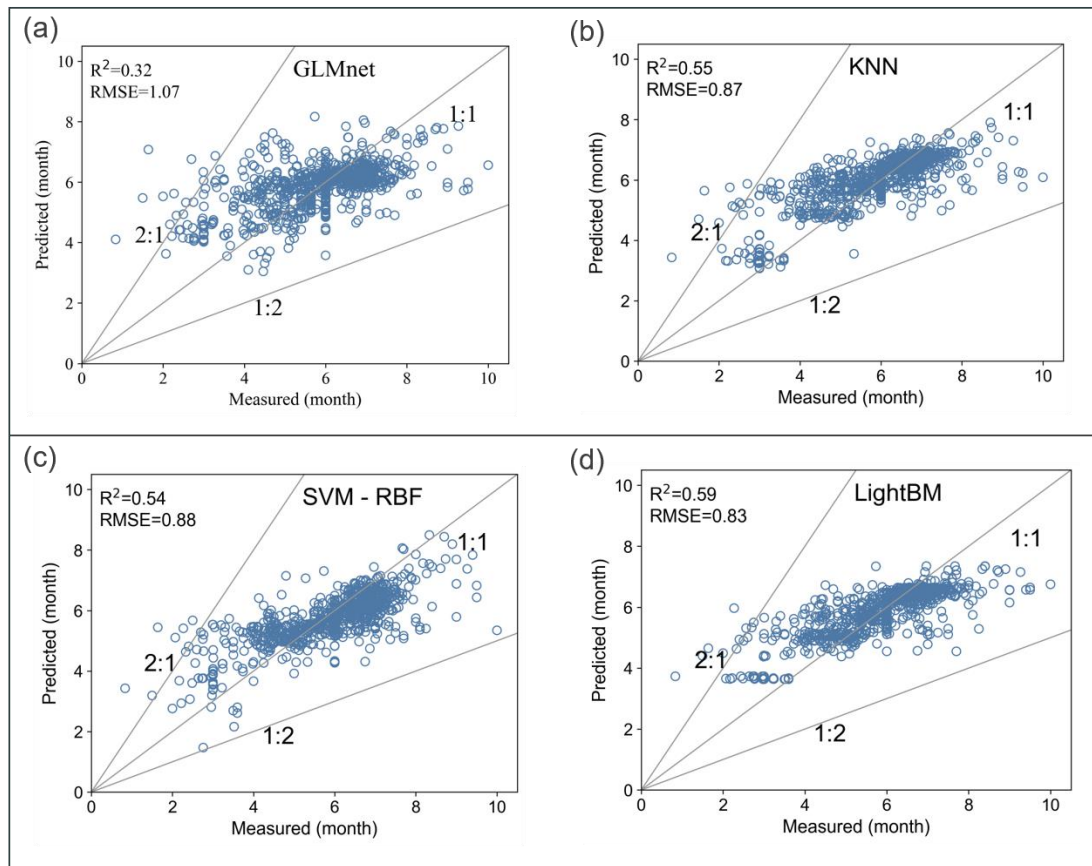


Figure S38. Performance of machine learning models in predicting leaf lifespan for deciduous broadleaf forests: (a) GLMnet, (b) KNN, (c) SVM–RBF, and (d) LightGBM. Model performance was evaluated using the test set.

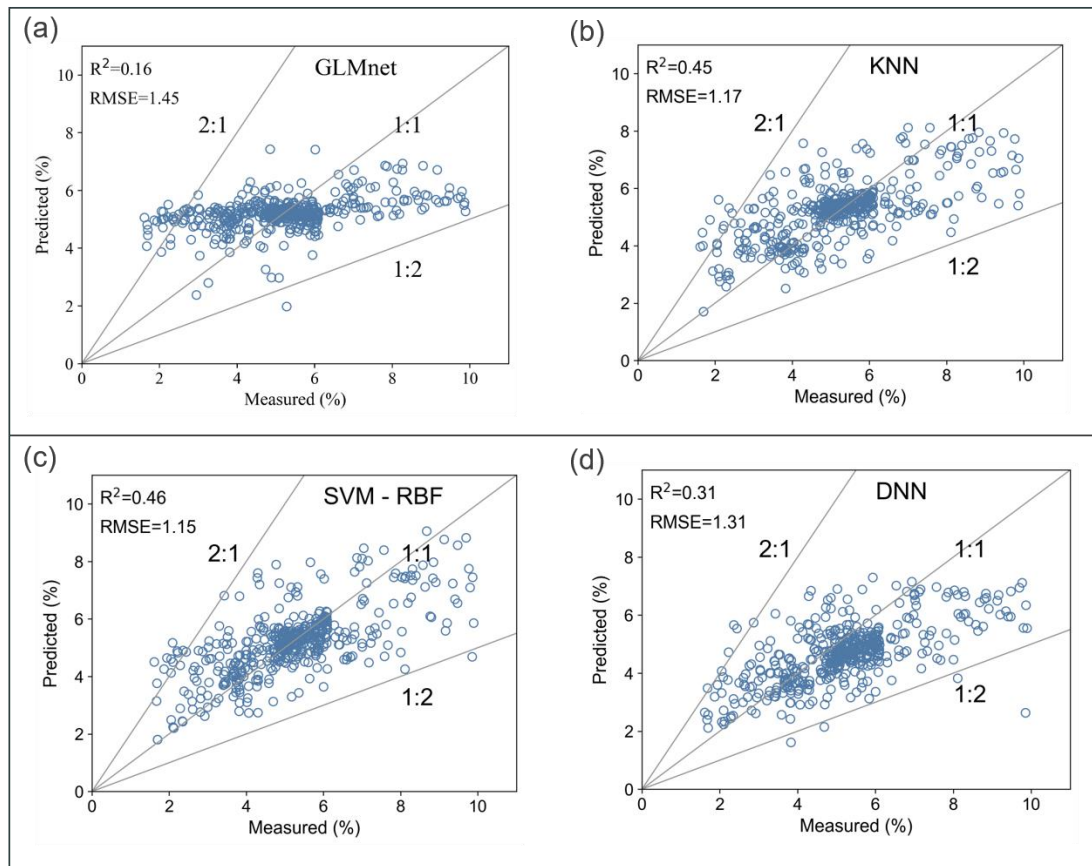


Figure S39. Performance of four machine learning models in predicting the leaf-to-AGB ratio for evergreen broadleaf forests: (a) GLMnet, (b) KNN, (c) SVM–RBF, and (d) LightGBM. Model performance was evaluated using the test set.

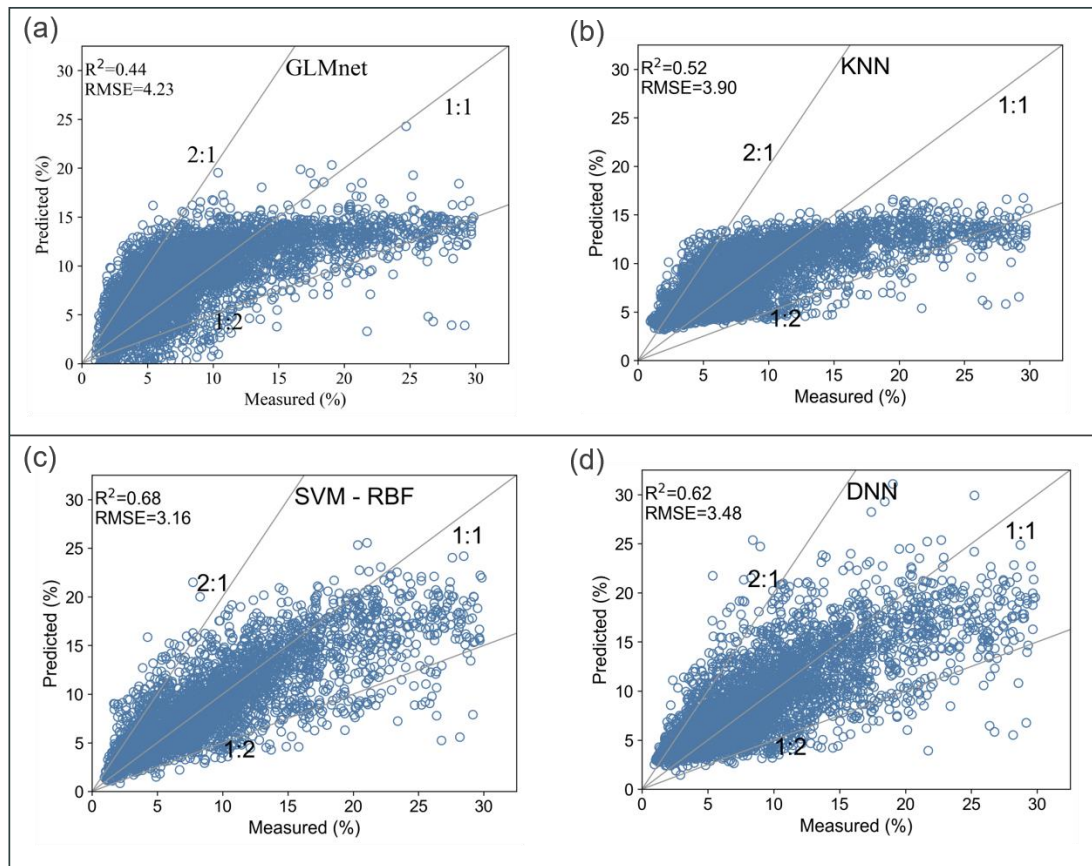


Figure S40. Performance of four machine learning models in predicting the leaf-to-AGB ratio for evergreen needleleaf forests: (a) GLMnet, (b) KNN, (c) SVM-RBF, and (d) LightGBM. Model performance was evaluated using the test set.

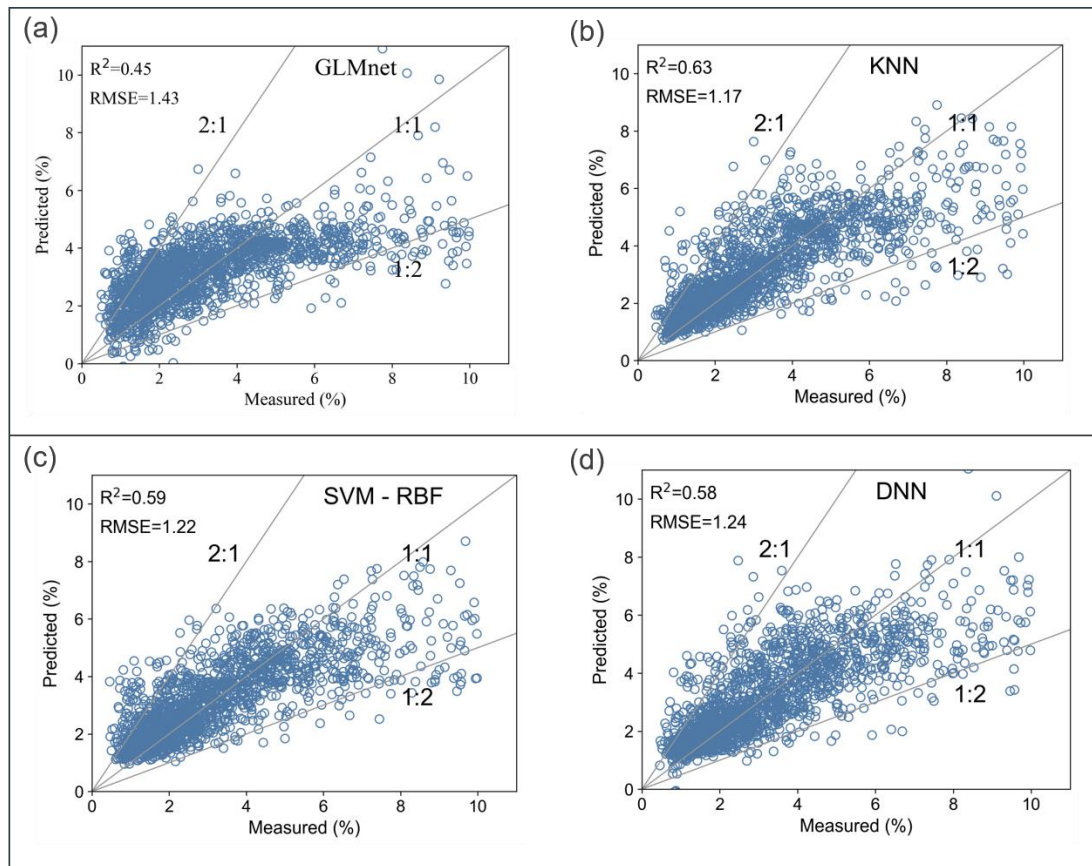


Figure S41. Performance of four machine learning models in predicting the leaf-to-AGB ratio for deciduous broadleaf forests: (a) GLMnet, (b) KNN, (c) SVM-RBF, and (d) LightGBM. Model performance was evaluated using the test set.

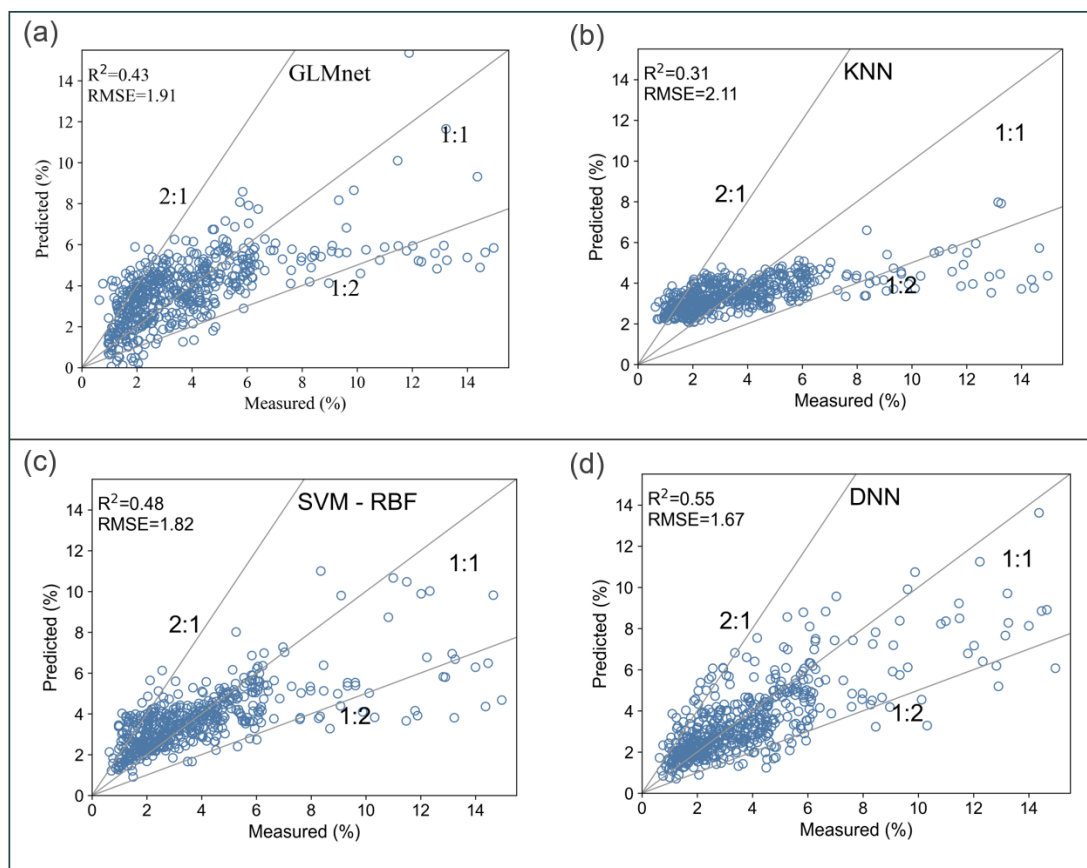


Figure S42. Performance of machine learning models in predicting the leaf-to-AGB ratio for deciduous needleleaf forests: (a) GLMnet, (b) KNN, (c) SVM–RBF, and (d) LightGBM. Model performance was evaluated using the test set.

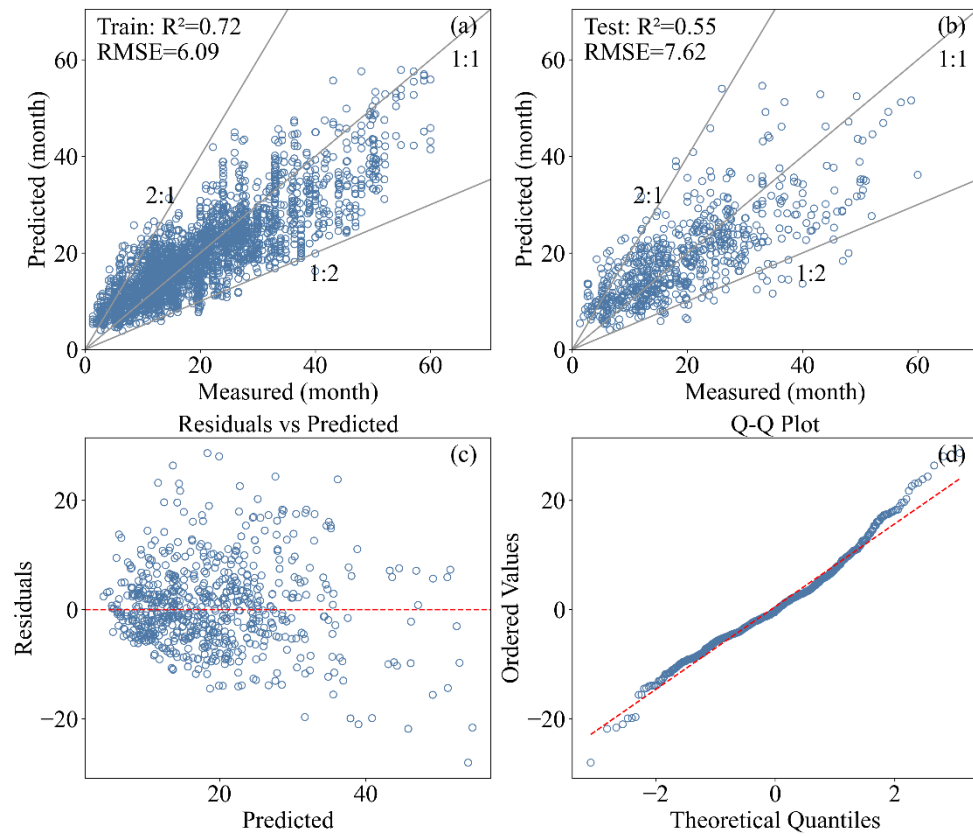


Figure S43. Model performance of leaf lifespan for evergreen broadleaf forests. (a) Training dataset; (b) testing dataset; (c) scale–location plot; (d) Q–Q plot.

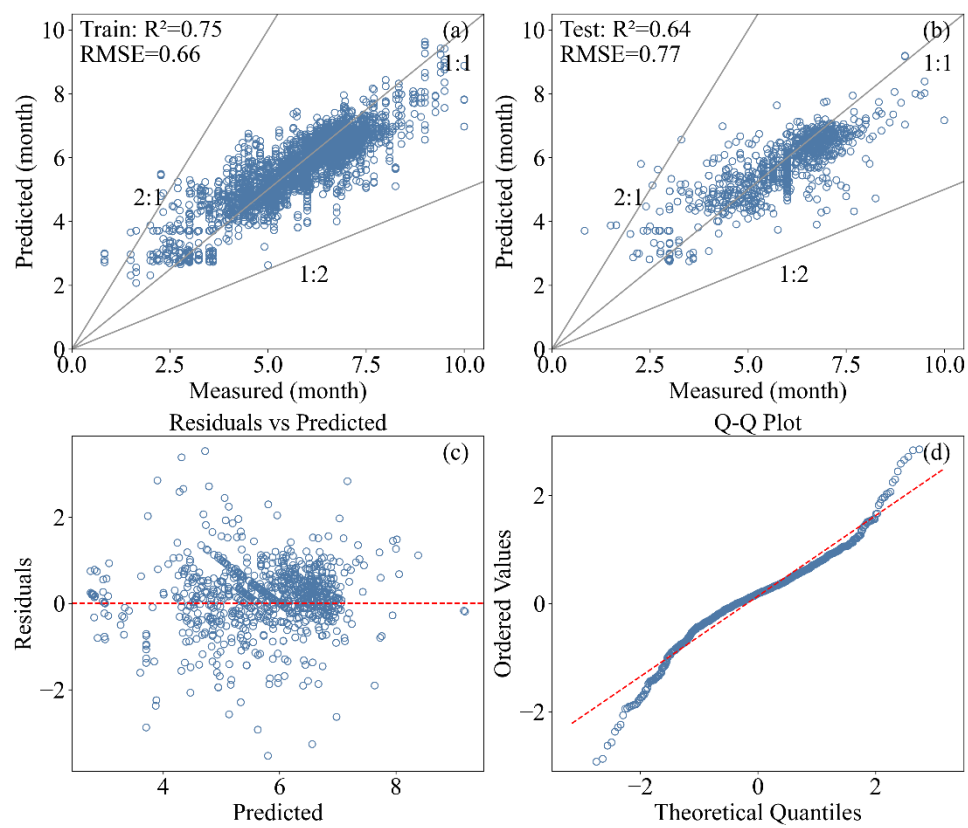


Figure S44. Model performance of leaf lifespan for deciduous broadleaf forests. (a) Training dataset; (b) testing dataset; (c) scale–location plot; (d) Q–Q plot.

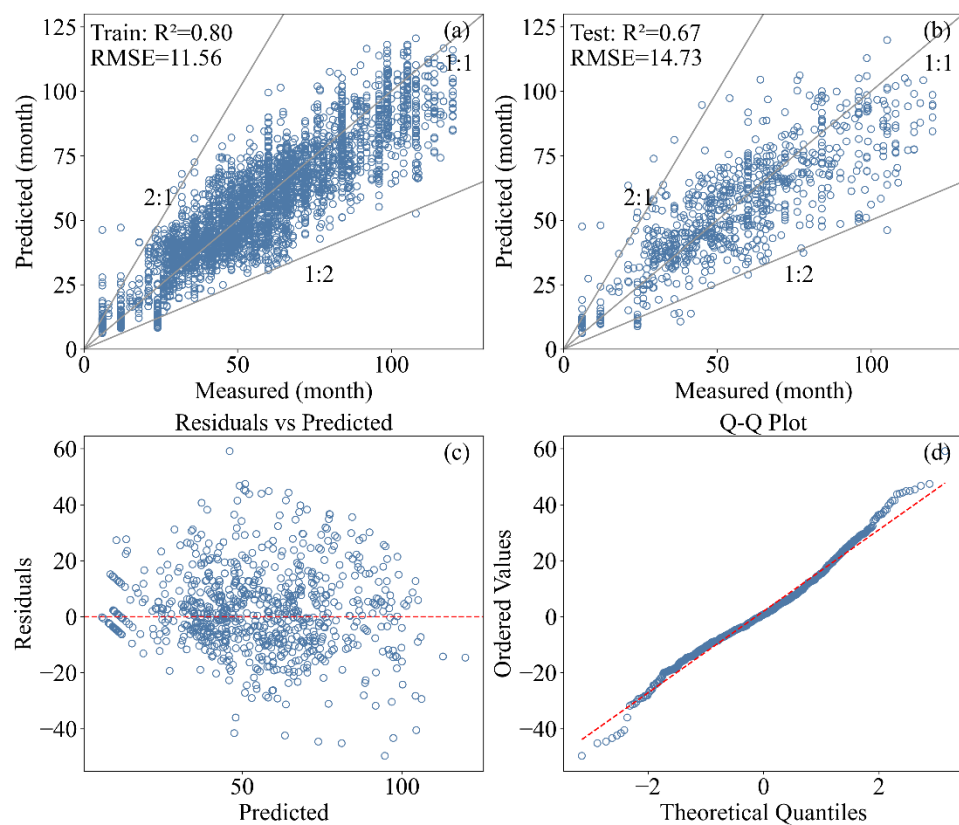


Figure S45. Model performance of leaf lifespan for evergreen needleleaf forests. (a) Training dataset; (b) testing dataset; (c) scale–location plot; (d) Q–Q plot.

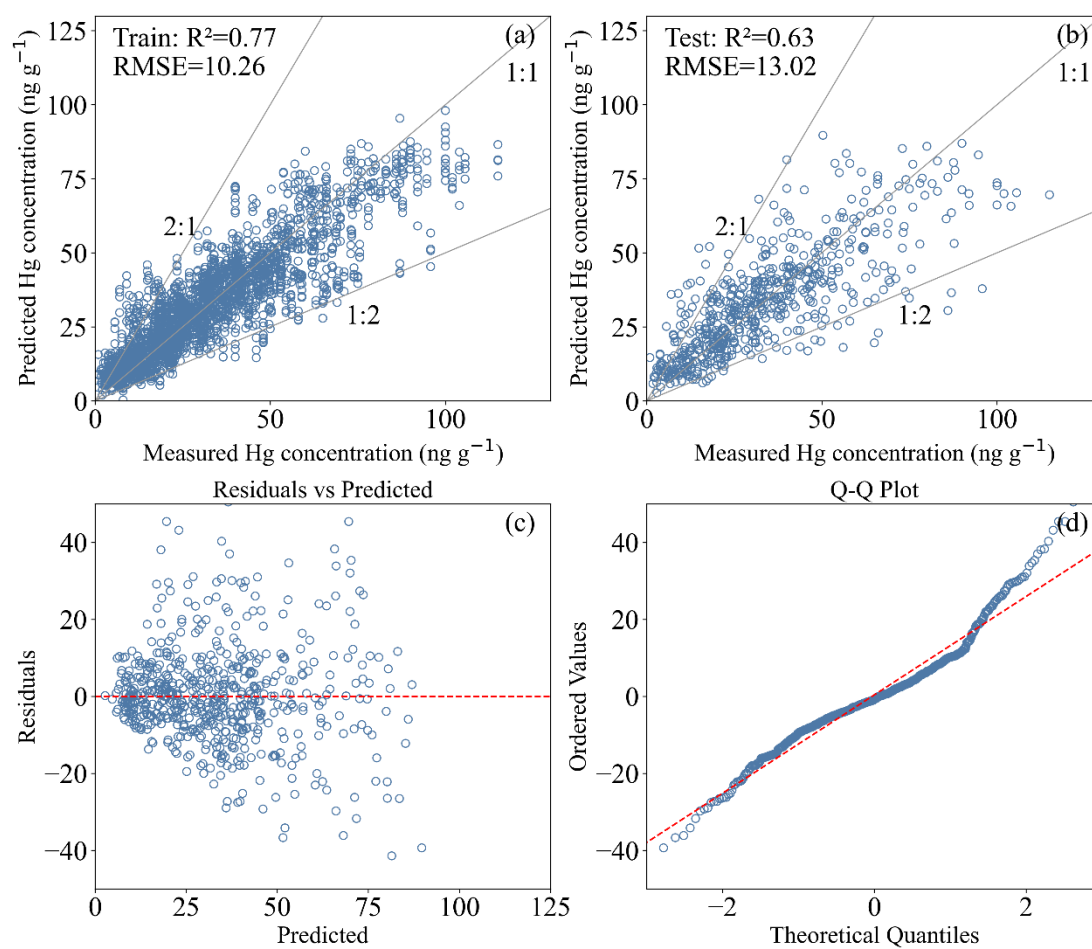


Figure S46. Model performance of foliar Hg concentrations for broadleaf forests. (a) Training dataset; (b) testing dataset; (c) scale–location plot; (d) Q–Q plot.

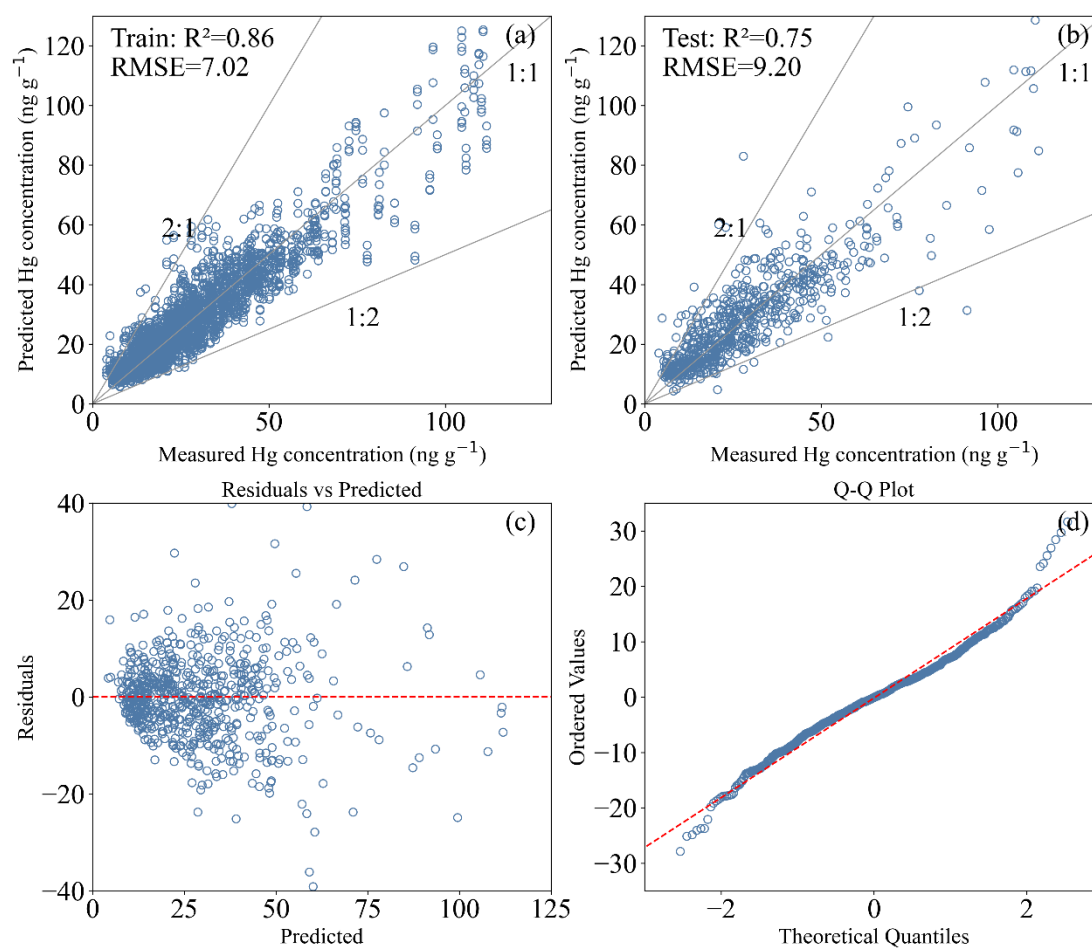


Figure S47. Model performance of foliar Hg concentrations for coniferous forests. (a) Training dataset; (b) testing dataset; (c) scale–location plot; (d) Q–Q plot.

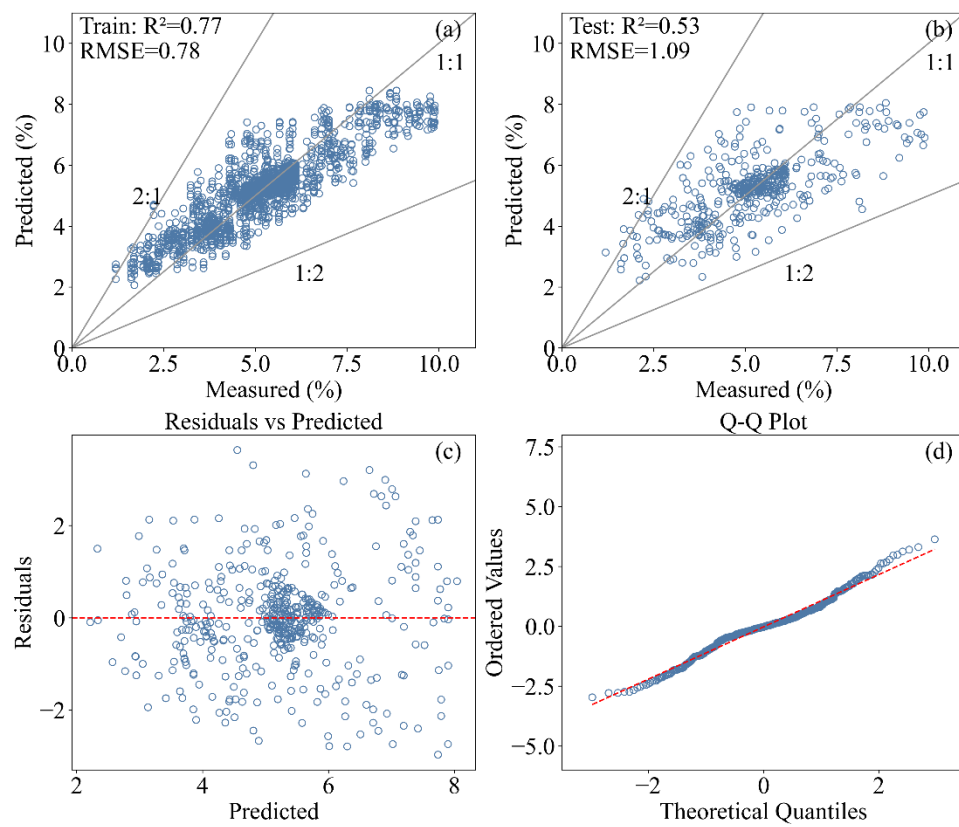


Figure S48. Model performance of the leaf-to-AGB ratio for evergreen broadleaf forests. (a) Training dataset; (b) testing dataset; (c) scale–location plot; (d) Q–Q plot.

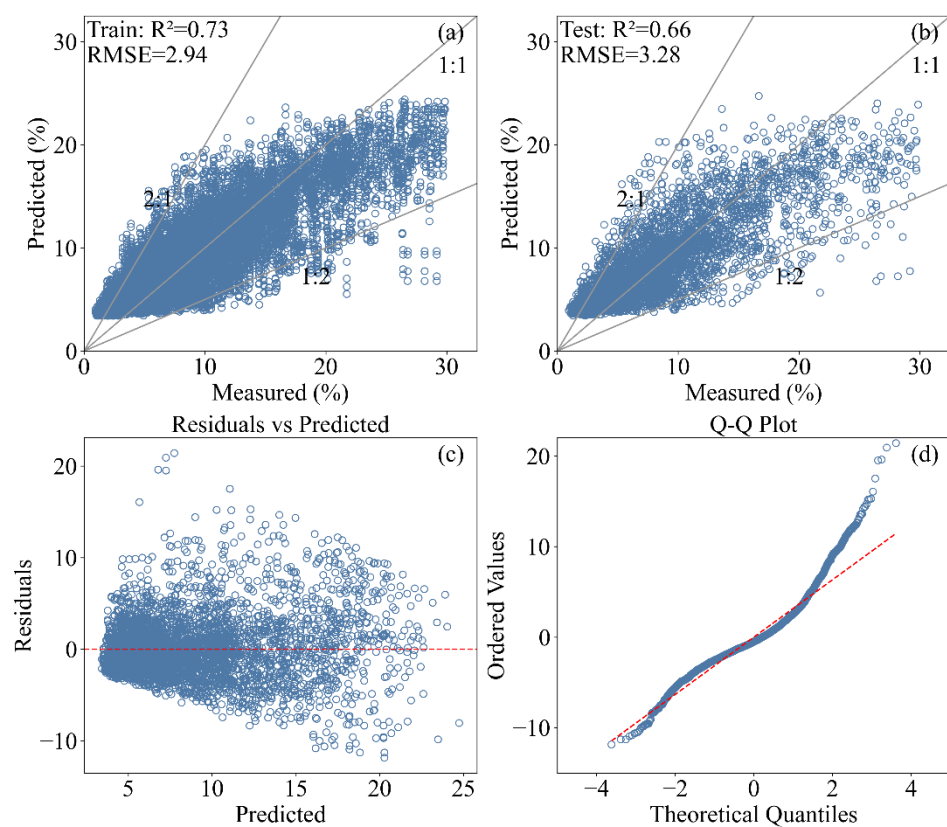


Figure S49. Model performance of the leaf-to-AGB ratio for evergreen needleleaf forests. (a) Training dataset; (b) testing dataset; (c) scale-location plot; (d) Q-Q plot.

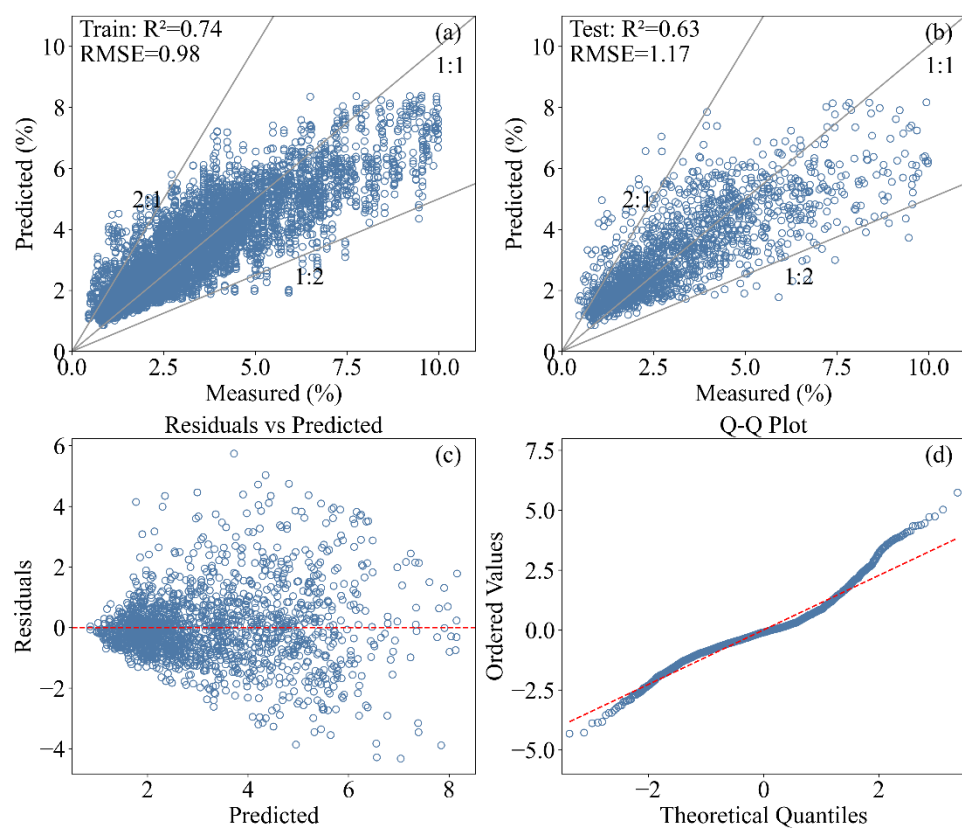


Figure S50. Model performance of the leaf-to-AGB ratio for deciduous broadleaf forests. (a) Training dataset; (b) testing dataset; (c) scale–location plot; (d) Q–Q plot.

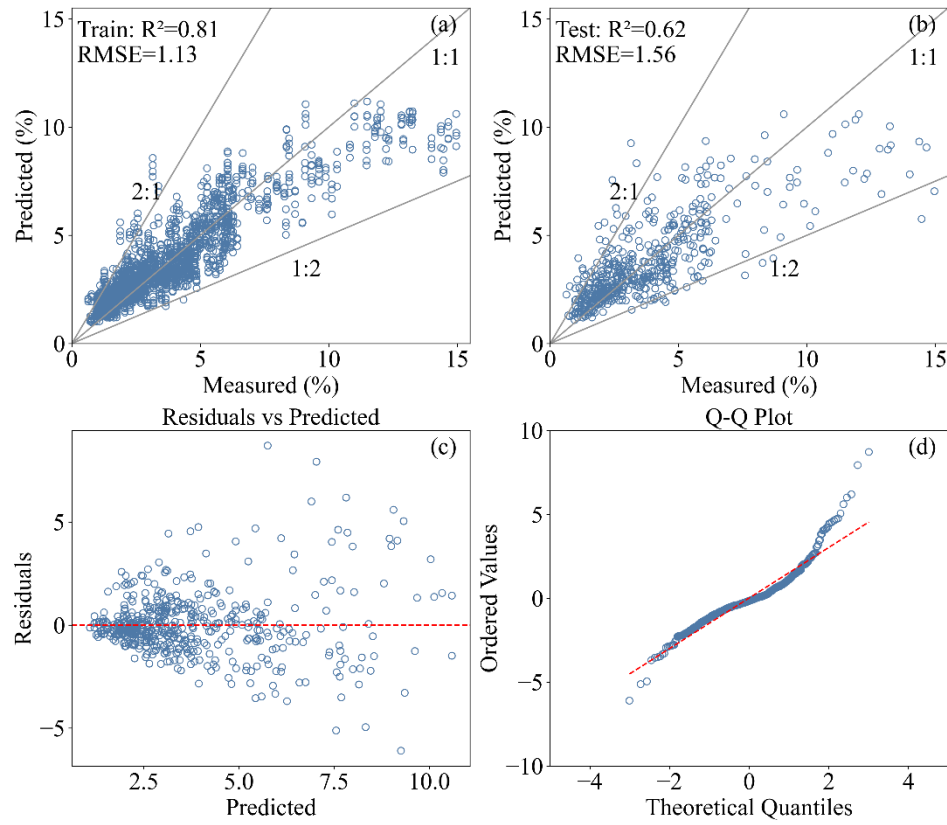


Figure S51. Model performance of the leaf-to-AGB ratio for deciduous needleleaf forests. (a) Training dataset; (b) testing dataset; (c) scale–location plot; (d) Q–Q plot.

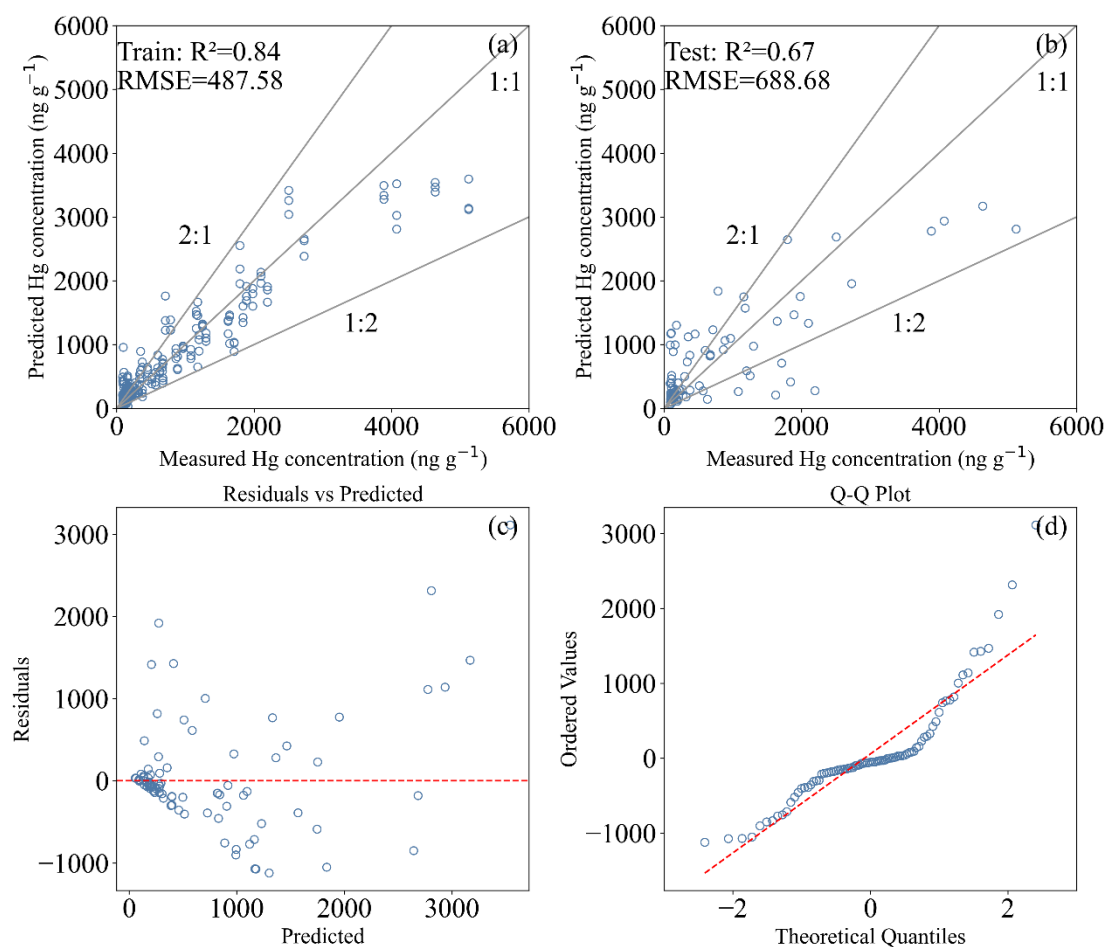


Figure S52. Performance of the contaminated-area foliar Hg concentration model. (a) Training dataset; (b) testing dataset; (c) scale–location plot; (d) Q–Q plot.

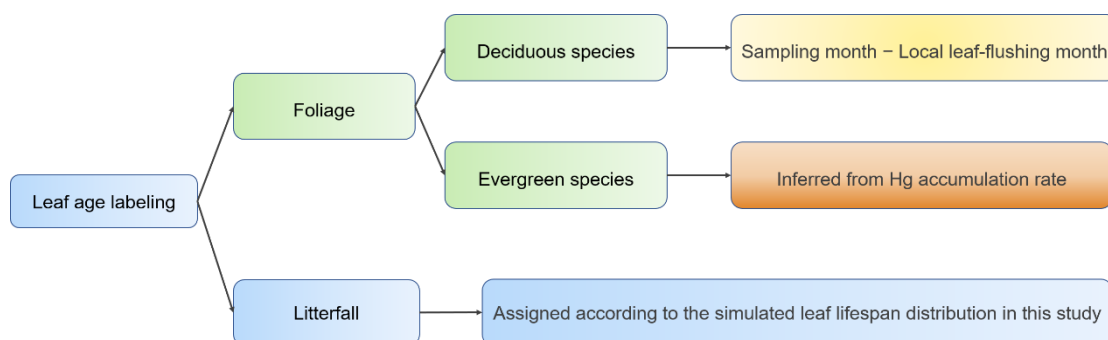


Figure S53. Workflow for assigning leaf age labels to foliar Hg observations.

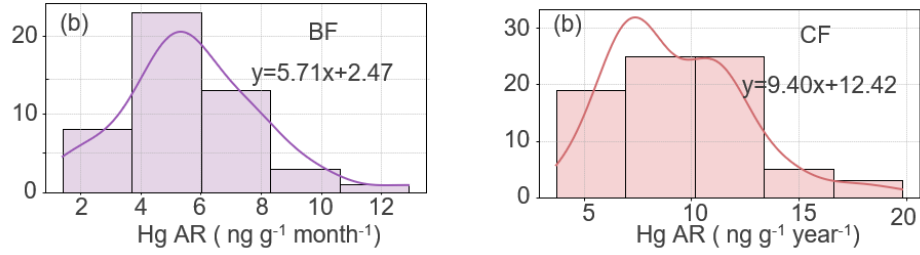


Figure S54. Frequency distributions of foliar Hg accumulation rates (Hg AR) in broadleaf (BF) and coniferous (CF) forests. Panels show the distributions of foliar Hg accumulation rates for (a) broadleaf forests and (b) coniferous forests. The fitted linear relationships (shown in each panel) were derived from datasets containing three or more leaf-age groups, representing global mean accumulation trends (BF: $y = 5.71x + 2.47$, $\text{ng g}^{-1} \text{ month}^{-1}$; CF: $y = 9.40x + 12.42$, $\text{ng g}^{-1} \text{ yr}^{-1}$).

III. SUPPLEMENTARY TABLE

Table S1. Datasets of aboveground biomass (AGB) and aboveground carbon density (AGCD) used in foliar Hg sink simulations.

Global	Dataset ID	Includes_Leaf_Biomas	Categories	Reference
Global	G_1	True	AGB	Santoro and Cartus 2024 ⁴¹
Global	G_2	True	AGB	Santoro et al. 2021 ⁴²
Global	G_3	True	AGB	Ma et al. 2021 ⁴³
Global	G_4	False	AGCD	Spawn et al. 2024 ⁴⁴
Global	G_5	True	AGCD	Walker et al. 2022 ⁴⁵
Global	G_6	True	AGCD	Mo et al. 2024 ¹²
Global	G_7	False	AGB	Zhang et al. 2020 ⁴⁶
China	CH_1	True	AGB	Yang et al.2024 ⁴⁷
China	CH_2	True	AGB	Su et al.2024 ⁴⁸
China	CH_3	True	AGB	Liao et al.2024 ⁴⁹
China	CH_4	True	AGB	Cai et al.2024 ⁵⁰
Europe	EU_1	False	AGB	Avitabile et al.2024 ⁵¹
USA	USA_1	False	AGB	KelIndorfer et al.2013 ⁵²
Rusia	RU_1	True	AGCD	Filipchuk et al. ,2023 ⁵³
South America	SAM_1	False	AGB	Avitabile et al., 2016 ⁵⁴
Southeast Asia	SAS_1	False	AGB	Avitabile et al., 2016 ⁵⁴
Africa	AF_1	False	AGB	Avitabile et al., 2016 ⁵⁴
Africa	AF_2	False	AGB	Hanan et al.2020 ⁵⁵

Notes: True indicates datasets that include leaf biomass. False indicates datasets that do not include leaf biomass.

Table S2. Aboveground biomass (AGB) datasets used for regional data fusion after quality screening.

Region	AGB Datasets							
China	CH_1	CH_2	CH_3	CH_4				
Europe	G_1	G_2	G_3	G_4	G_5	G_6	G_7	
USA	G_1	G_2	G_3	G_4	G_5	G_6	USA_1	
Rusia	G_1	G_2	G_4	G_5	G_6	G_7	RU_1	
Canada	G_1	G_2	G_3	G_4	G_5	G_6	G_7	
SAM	G_1	G_2	G_3	G_4	G_5	G_6	G_7	SAM_1
Africa	G_1	G_2	G_3	G_4	G_5	G_6	AF_1	AF_2
SAS	G_1	G_2	G_3	G_4	G_5	G_6	G_7	SAS_1

Table S3. Summary of predictor variables used in the machine learning–coupled model for foliar Hg uptake estimation, grouped by model components and their functional roles in constraining Hg accumulation and fluxes.

Variable	Includes_Leaf_Biomas	Reference
Tmp	1km	World Climate ⁵⁶
Pre	1km	World Climate ⁵⁶
Rad	1km	World Climate ⁵⁶
Elevation	15"×15"	GEBCO ⁵⁷
Leaf lifespan	0.1°×0.1°	This study predicted
LAI	0.05°×0.05°	NESSDC ⁵⁸
Tree Height	30m	Potapov et al., 2021 ⁵⁹
Anthropogenic emission	Hg 0.25°×0.25°	Steenhuisen and Wilson 2019 ⁶⁰
Atmosphere concentration	Hg 0.25°×0.25°	Dastoor et al. (2025) ⁶¹
SLA	1km	TRY Plant Trait DataBase ⁶²
N	1km	TRY Plant Trait DataBase ⁶²
P	1km	TRY Plant Trait DataBase ⁶²
Forest age	15"×15"	Besnard ⁶³
NDVI	0.1°×0.1°	Modis ⁶⁴
Tree density	30"×30"	Ma et al. 2023 ³⁹

Abbreviations: NESD, National Earth System Science Data Center.

Table S4. Optimal hyperparameter settings of LightGBM models for predicting leaf biomass fractions across forest functional types.

Forest type	n_estimators	learning_rate	max_depth	num_leaves
EC	20	0.2	5	20
DC	20	0.2	5	20
EB	16	0.2	6	15
DB	20	0.2	4	20

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