

Supplement of

High-resolution land-cover dynamics reveal strong regional contrasts in China's biogenic isoprene emissions, 2000–2025

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10 Supporting Information

Text S1 land-cover evaluation

The Boston University Global Land Cover Estimation (GLanCE) Land Cover Training Dataset V1 provided independent reference labels for 2000–2020 (Stanimirova et al., 2023). We matched 2,815 high-confidence sites in China to the annual maps, yielding 54,695 site–year pairs that were not used to
15 train the classifier. The two legends were merged into eight classes: woody vegetation (IGBP 1–9), herbaceous vegetation (10), cropland (12 and 14), wetland (11), developed land (13), ice and snow (15), barren land (16), and water (17). Rows of the confusion matrix are reference classes and columns are predictions (Fig. S5).

Agreement was measured by overall accuracy (OA), balanced accuracy, macro-averaged F1, and
20 Cohen’s κ (Cohen, 1960; Sokolova and Lapalme, 2009; Brodersen et al., 2010):

$$\begin{aligned} OA &= \frac{\sum_{i=1}^{K^*} n_{ii}}{N} \\ \text{Balanced accuracy} &= \frac{1}{K^*} \sum_{i=1}^{K^*} \frac{n_{ii}}{n_{i+}} \\ \text{Macro-F1} &= \frac{1}{K^*} \sum_{i=1}^{K^*} \frac{2P_i R_i}{P_i + R_i} \\ \kappa &= \frac{p_o - p_e}{1 - p_e}, p_e = \frac{\sum_{i=1}^{K^*} n_{i+} n_{+i}}{N^2} \end{aligned} \tag{S1}$$

Here in Eq.(S1), N is the number of pairs; n_{ii} is the number correctly assigned to class i ; n_{i+} and n_{+i} are the reference and predicted totals; and P_i and R_i are precision and recall. Wetland had no reference record,
25 so $K^* = 7$ and $p_o = OA$. OA was 80.71%, balanced accuracy was 77.38%, Macro-F1 was 72.05%, and κ was 0.747. The ice-and-snow class had few reference records and is reported only as supporting information. These values describe agreement within the matched sample, not area-adjusted accuracy for all of China (Olofsson et al., 2014).

Text S2 Surrogate construction and blocked evaluation

30 Monthly emissions and drivers for 2000–2025 were aggregated with fixed area weights to 342 prefecture-level or equivalent units, giving 106,704 city–month records. The target was ISOP-China-100m dataset isoprene emission density ($\text{g m}^{-2} \text{month}^{-1}$). Predictors were grouped as standard emission potential, LAI, temperature, radiation, and other meteorology. The leaf area index (LAI) group included the monthly mean and change between adjacent composites. The temperature and radiation groups
35 included current conditions, 24 and 240 h histories, and monthly 90th percentiles. Other meteorology included wind speed, water-vapour mass ratio (QV), and pressure. Coordinates and sine and cosine terms for month were used as controls.

We fitted an area-weighted Extreme Gradient Boosting (XGBoost) surrogate with squared error loss (Chen and Guestrin, 2016). Fixed settings were a learning rate of 0.035, maximum depth of 5, minimum
40 child weight of 3, row and column subsampling of 0.85 and 0.90, L2 and L1 penalties of 2 and 0, 256 histogram bins, 700 boosting rounds, and random seed 44. Negative predictions were set to zero.

Generalization was tested with out-of-fold predictions from five contiguous-year blocks, five whole-province blocks, and 25 paired space time blocks (Roberts et al., 2017). Area-weighted coefficients of

determination (R^2) were 0.9887, 0.9792, and 0.9759, and national mass biases were -0.184% , -1.855% , and -2.219% . These scores show that the surrogate reproduced the source-model output within the test blocks. Wind speed, water vapour, and pressure were retained as diagnostic covariates. They are not direct terms in the configured source-model equation.

Text S3 Prescribed sensitivity tests

Sensitivity was evaluated with grouped one-at-a-time perturbations (Pianosi et al., 2016). Standard emission potential, LAI, radiation, wind speed, and QV were changed by $\pm 10\%$ and $\pm 20\%$; temperature variables by ± 1 and ± 2 K; and pressure by $\pm 1\%$ and $\pm 2\%$. Wind speed, QV, and pressure were also perturbed together as the other-meteorology group.

$$\begin{aligned}
 M_0 &= \sum A_j \hat{e}(X_j), M_k^\pm = \sum A_j \hat{e}(X_{j,k}^\pm) \\
 R_k^\pm &= 100 \left[\frac{M_k^\pm}{M_0} - 1 \right] \\
 S_k &= \frac{\frac{M_k^+}{M_0} - \frac{M_k^-}{M_0}}{2\delta_k} \\
 S_T &= 100 \frac{\frac{M_T^+}{M_0} - \frac{M_T^-}{M_0}}{2\Delta T}
 \end{aligned} \tag{S2}$$

In Eq.(S2), j indexes $J = 106,704$ records, A_j is valid area, and $\hat{e}$ is the surrogate prediction. $R_k^\pm$ is the percent response; δ_k is the relative perturbation; S_k is the central elasticity; and S_T is the temperature semi-elasticity in $\% K^{-1}$. We also recorded the share of perturbed records outside the training range. The results describe responses to prescribed changes and are not probability uncertainty intervals.

Text S4 Grouped Shapley decomposition and trend diagnostics

Temporal changes were allocated among the five driver groups with the same surrogate and an exact grouped Shapley decomposition (Shapley, 1953; Lundberg and Lee, 2017). All $2^5 = 32$ group combinations were evaluated. Coordinates and month controls remained at observed values. An absent group was replaced by its climatological mean for the same city and calendar month.

$$\varphi_{g,j} = \sum_{S \subseteq G \setminus \{g\}} \frac{|S|!(|G|-|S|-1)!}{|G|!} [f_j(S \cup \{g\}) - f_j(S)] \tag{S3}$$

In Eq.(S3), G contains the five driver groups, so $|G| = 5$, S is a subset that does not contain g , and $f_j(S)$ is the surrogate prediction for coalition S . Separate climatologies were used for 2000–2012 and 2013–2025 to limit the effect of the 2012–2013 source-product change. A common 2000–2025 climatology was used as a sensitivity test. The surrogate residual was retained so that the components closed to the ISOP-China-100m:

$$\begin{aligned}
 \eta_j &= E_j^{\text{GEE}} - \hat{E}_j \\
 E_j^{\text{GEE}} &= B_j + \sum_{g=1}^5 \varphi_{g,j} + \eta_j
 \end{aligned} \tag{S4}$$

Monthly components were multiplied by valid area and summed over all cities and months. Annual trends were fitted by ordinary least squares (OLS), and the Theil–Sen slope was used as a robustness check (Sen, 1968):

$$Z_{k,y} = \alpha_k + \beta_k y + \varepsilon_{k,y}$$

$$P_k = 100 \times \frac{\beta_k}{\beta_E} \quad (S5)$$

Here in Eq.(S5), β_E is the ISOP-China-100m emission trend. P_k was reported only when β_E was non-zero and $p < 0.05$. At city level, the Benjamini–Hochberg method controlled the false discovery rate, and contributions were reported only for $q < 0.05$ (Benjamini and Hochberg, 1995). The 2000–2012 and 2013–2025 trends were treated as the main results. A full-period slope, a 2013 level-shift model, and exclusion of 2013 were used only as robustness tests.

To separate interannual variation from long-term change, the source-minus-baseline series and each attribution component were detrended within each period. The signed covariance share was:

$$V_g = 100 \times \frac{\text{Cov}[\varphi_{g,y'}, E_y - B_y']}{\text{Var}[E_y - B_y']} \quad (S6)$$

Primes denote detrended annual series. The five driver shares and the surrogate-residual share sum to 100%. Confidence intervals were obtained by resampling complete years and checked with 2 and 3 years circular moving-block bootstrap tests (Künsch, 1989; Politis and Romano, 1992).

Text S5 Supporting spatial records

Figure S1 documents the spatial density of selected scenes from each optical sensor. Figures S2 and S3 show annual mean flux maps from the 100 m and 0.25° configurations. Figure S4 shows their annual differences. Figure S5 provides the independent land-cover reference distribution and confusion matrix.

Table S1 Multiyear mean plant functional type (PFT) areas used in ISOP-China-100m and MEGAN2.1-MODIS-0.25° dataset.

Plant functional type	MODIS	GEE-MEGAN
Needleleaf evergreen temperate tree	31.14 (3.28%)	45.32 (4.77%)
Needleleaf evergreen boreal tree	7.48 (0.79%)	23.63 (2.49%)
Needleleaf deciduous boreal tree	6.42 (0.68%)	18.95 (2.00%)
Broadleaf evergreen tropical tree	17.74 (1.87%)	23.53 (2.48%)
Broadleaf evergreen temperate tree	33.11 (3.49%)	40.43 (4.26%)
Broadleaf deciduous tropical tree	8.69 (0.92%)	8.35 (0.88%)
Broadleaf deciduous temperate tree	58.83 (6.19%)	47.51 (5.00%)
Broadleaf deciduous boreal tree	9.04 (0.95%)	14.99 (1.58%)
Broadleaf evergreen temperate shrub	0.69 (0.07%)	1.13 (0.12%)
Broadleaf deciduous temperate shrub	43.28 (4.56%)	44.94 (4.73%)
Broadleaf deciduous boreal shrub	5.45 (0.57%)	20.60 (2.17%)
Arctic C3 grass	107.03 (11.27%)	97.74 (10.29%)
Cool C3 grass	189.41 (19.94%)	90.89 (9.57%)
Warm C4 grass	37.78 (3.98%)	2.71 (0.29%)
Crop	138.19 (14.55%)	201.45 (21.21%)
Non-vegetated/ water	255.59 (26.91%)	267.69 (28.18%)

95 Table S2. Standard isoprene emission factors for the 16 plant functional types.

Plant functional type	Standard emission factor ($\mu\text{g m}^{-2} \text{h}^{-1}$)
Needleleaf evergreen temperate tree	600
Needleleaf evergreen boreal tree	3000
Needleleaf deciduous boreal tree	1
Broadleaf evergreen tropical tree	7000
Broadleaf evergreen temperate tree	10000
Broadleaf deciduous tropical tree	7000
Broadleaf deciduous temperate tree	10000
Broadleaf deciduous boreal tree	11000
Broadleaf evergreen temperate shrub	2000
Broadleaf deciduous temperate shrub	4000
Broadleaf deciduous boreal shrub	4000
Arctic C3 grass	1600
Cool C3 grass	800
Warm C4 grass	200
Crop	1
Non-vegetated	0

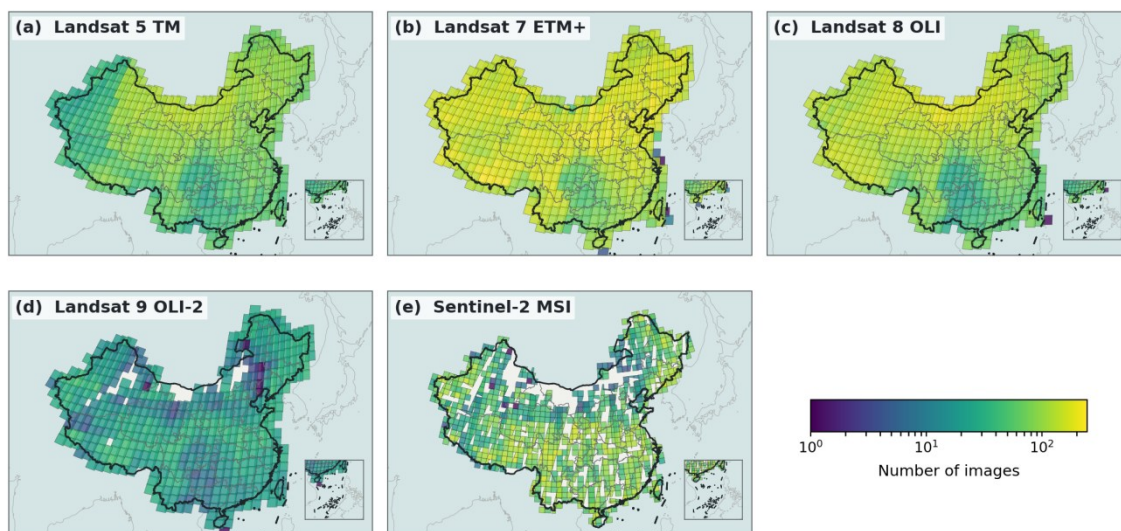


Figure S1 Spatial coverage of selected optical satellite scenes across China, 2000–2025: (a) Landsat 5 TM, (b) Landsat 7 ETM+, (c) Landsat 8 OLI, (d) Landsat 9 OLI-2, and (e) Sentinel-2 MSI. Colours show selected-scene counts on a logarithmic scale.

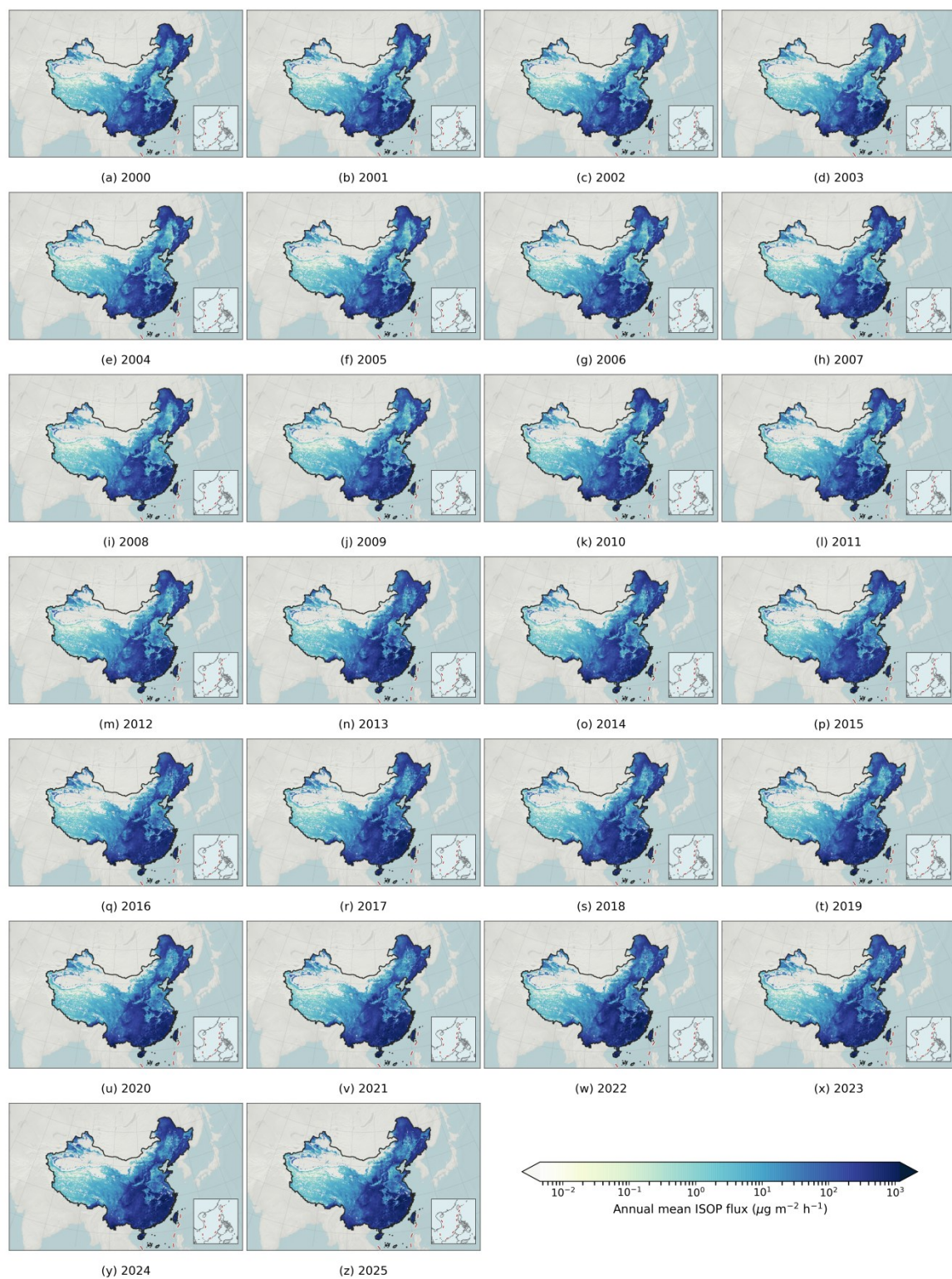


Figure S2 Annual mean ISOP-China-100m dataset isoprene emission fluxes across China, 2000–2025. Panels (a–z) show individual years on a logarithmic colour scale ($\mu\text{g m}^{-2} \text{h}^{-1}$).

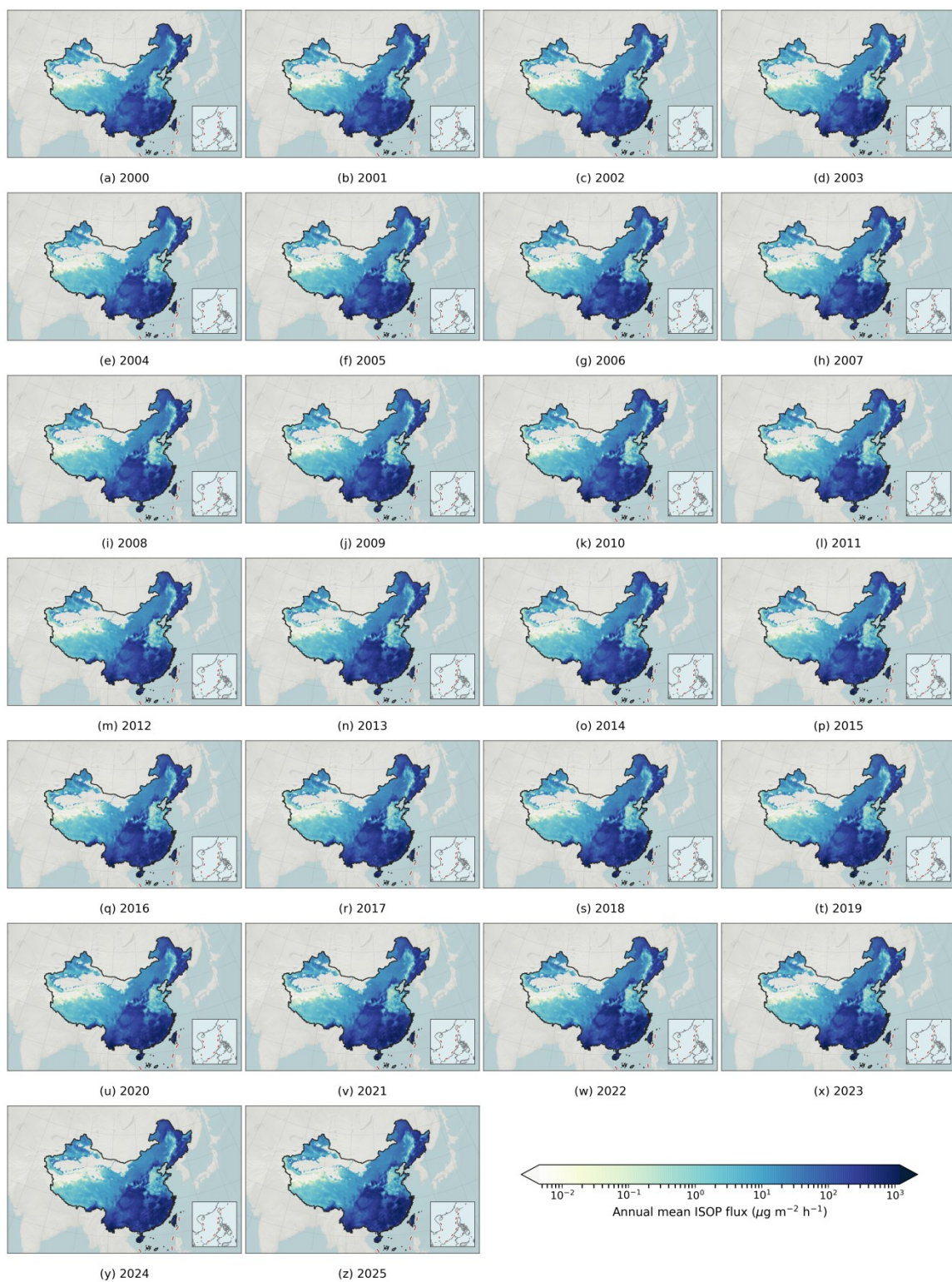


Figure S3 Annual mean MEGAN2.1-MODIS-0.25° dataset isoprene emission fluxes across China, 2000–2025. Panels (a–z) show individual years on a logarithmic colour scale ($\mu\text{g m}^{-2} \text{h}^{-1}$).

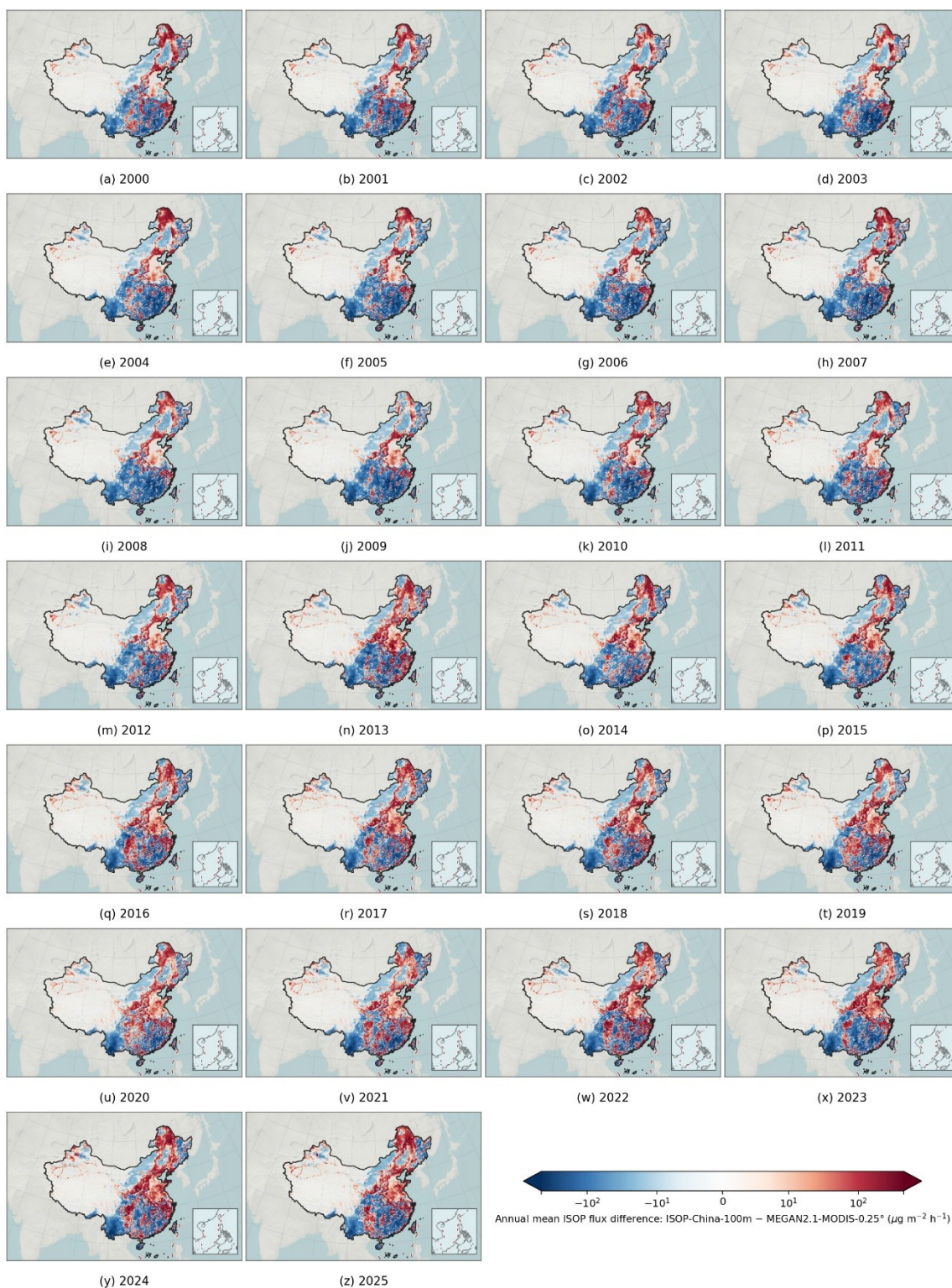


Figure S4 Annual mean differences in isoprene emission flux between ISOP-China-100m and MEGAN2.1-MODIS-0.25° dataset, 2000–2025. Panels (a–z) show ISOP-China-100m minus MEGAN2.1-MODIS-0.25° dataset for individual years. Differences are in $\mu\text{g m}^{-2} \text{h}^{-1}$.

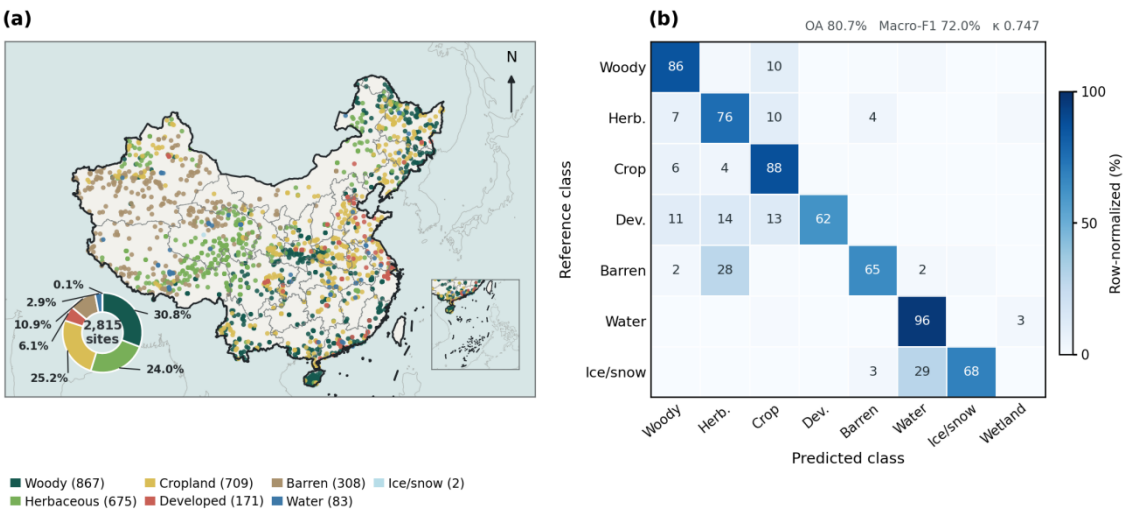


Figure S5 Independent evaluation of annual land cover used in ISOP-China-100m. (a) Locations of 2,815 high-confidence and temporally stable GLanCE reference sites. (b) Row-normalized confusion matrix for 54,695 matched site–year records in 2000–2020.

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