



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

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Abstract. Isoprene is a reactive biogenic volatile organic compound whose atmospheric impacts depend strongly on spatio-temporal emission patterns. Because Chinese inventories often rely on coarse or static land-cover information, we quantified how annual land-cover dynamics altered isoprene emissions across China during 2000–2025. Using a Google Earth Engine implementation of the Model of Emissions of Gases and Aerosols from Nature (MEGAN), driven by Landsat and Sentinel-2 land cover, satellite leaf area index, and 0.1° ERA5-Land meteorology, emissions were calculated on native 10–30 m grids. These were aggregated to an hourly 100 m output and compared with a 0.25° coarse simulation. National emissions averaged 9.87 ± 1.53 Tg yr⁻¹, increasing from 8.49 in 2000 to 12.35 Tg yr⁻¹ in 2025. Following a non-significant trend (2000–2012), emissions increased by 0.23 Tg yr⁻¹ during 2013–2025 ($p < 0.05$), driven by temperature (40.4%) and land-cover change (39.6%). Crucially, fine land-cover data yielded a national mean only 6.2% lower than the coarse simulation, yet exposed massive regional contrasts: +101.2% in Beijing–Tianjin–Hebei and –20.2% in the Pearl River Delta. Regional seasonality also varied, with summer contributing 49.4% of emissions in Southwest China versus 78.8% in the Northeast. Therefore, national-level agreement between inventories can mask substantial regional redistributions, with major implications for biogenic volatile organic compound inputs to atmospheric chemistry models. Estimates remain sensitive to satellite product transitions, default MEGAN emission factors, land-cover-to-plant-functional-type conversion, and meteorological forcing.

1 Introduction

Biogenic volatile organic compounds (BVOCs) constitute a major fraction of terrestrial non-methane volatile organic compound emissions, and isoprene is typically the largest individual component (Guenther et al., 1995, 2006; Arneth et al., 2011; Guenther et al., 2012). Isoprene reacts rapidly with atmospheric oxidants and therefore influences both the oxidation capacity and the chemical lifetimes of the atmosphere (Atkinson and Arey, 2003; Lelieveld et al., 2008; Wells et al., 2020). Its oxidation can promote ozone (O₃) production in the presence of NO_x, while oxidation products can contribute to secondary organic aerosol (SOA) formation (Sillman, 1999; Claeys et al., 2004; Paulot et al., 2009; Lin et al., 2013). Consequently, the



30 atmospheric relevance of an isoprene inventory depends not only on its total annual mass, but also on the location and timing
 of emissions (Wells et al., 2020; W. Wang et al., 2024).

The spatial and temporal structure of isoprene emissions is governed by the interaction between vegetation properties and
 canopy conditions. In MEGAN (Model of Emissions of Gases and Aerosols from Nature)-type formulations, plant functional
 type (PFT), vegetation composition and emission factor determine the standard emission potential, whereas leaf area index
 35 (LAI), leaf age, radiation, and temperature regulate the activity factor (Guenther et al., 2006, 2012). This factorization provides
 a physically interpretable framework, but it also makes the inventory sensitive to how vegetation is represented. Field
 measurements in China show substantial variability among plant species and ecosystems, and do not always agree with
 emission factors transferred from global databases (Klinger et al., 2002; Geron et al., 2006; Han et al., 2026). Land cover
 classification and the subsequent conversion to PFT can therefore change both the amount and the type of emitting vegetation
 40 assigned to a grid cell. For example, land cover and PFT choices produced larger differences in estimated emissions than
 alternative LAI products in Beijing (Mo et al., 2018; Wang et al., 2018). Thus, uncertainty and differences among inventories
 arise not only from the spatial resolution of land-cover inputs but also from classification errors that alter the composition of
 emitting vegetation and the resulting standard emission potential.

Fine spatial representation is particularly important in heterogeneous landscapes. Coarse or static land cover inputs can mix
 45 forests, cropland, urban green space and forest edges within the same cell, smoothing emission gradients and redistributing
 source strength among neighbouring regions (Pfister et al., 2008; Wang et al., 2018; Li et al., 2019; Ma et al., 2022; Zhang et
 al., 2020; Zhang et al., 2025). Such redistribution matters for air-quality applications because the response of O₃ to BVOCs
 depends nonlinearly on the local chemical regime, including the balance between VOC and NO_x reactivity (Sillman, 1999;
 Jin and Holloway, 2015). China-wide sensitivity studies have consequently reported appreciable changes in simulated BVOC
 50 emissions and in the resulting O₃ and SOA fields when land-cover and vegetation inputs are changed (Fu and Liao, 2014; Ma
 et al., 2023). These results do not imply that every difference between inventories is caused by nominal grid size alone. They
 do show that the spatial allocation of vegetation, especially in fragmented forests and urban landscapes, is a scientifically
 relevant part of the emission estimate.

Under common meteorological forcing, it remains unclear whether finer, dynamically updated land-cover information
 55 produces only modest changes in national isoprene emissions or also redistributes emissions among regions and alters their
 long-term trends. This question is particularly relevant to China, which has undergone pronounced greening and land-system
 change, while warming, heat waves, ecological restoration, agricultural intensification and urban expansion have modified
 both vegetation distribution and the meteorological controls on emissions (Bryan et al., 2018; Chen et al., 2019; Ma et al.,
 2019, 2022). Meteorology can dominate short-term variability, whereas persistent changes in land cover, LAI and vegetation
 60 composition can shift the longer-term emission baseline (Fu and Liao, 2012; Wang et al., 2021; Cao et al., 2024; H. Wang et
 al., 2024). Existing inventories have progressively improved their temporal coverage and vegetation representation, but they
 necessarily make different trade-offs. China-focused studies have used reconstructed biomass, periodic land-cover products or
 kilometer-scale vegetation fields, while global MEGAN-based products provide consistent long-term records at approximately



0.25–0.5° and commonly report monthly means or daily profiles rather than an hourly, vegetation-resolved field (Fu and Liao, 2012; Wang et al., 2021; Cao et al., 2022; Sindelarova et al., 2014, 2022). Satellite inversions provide an additional observational constraint, but their available periods and retrieved quantities do not substitute for a continuous bottom-up emission field for regional modelling (Li et al., 2025). Cross-study comparisons therefore cannot readily isolate how vegetation representation shapes regional emission patterns and long-term trends. Regional changes of opposite sign may cancel in the national total, yet still alter the emission inputs relevant to regional atmospheric chemistry.

To address this question, we used the Google Earth Engine-based Model of Emissions of Gases and Aerosols from Nature (GEE-MEGAN) to construct ISOP-China-100m, an hourly record of isoprene emissions across China from 2000 to 2025. The dataset was generated with the GEE-MEGAN, which retains the MEGAN version 2.1 (MEGAN2.1) emission response functions while integrating dynamic satellite observations within Google Earth Engine (Guenther et al., 2012; Gorelick et al., 2017; Zhang et al., 2025). Annual Landsat and, where available, Sentinel-2 observations describe land cover on native 10–30 m grids; these data are combined with satellite LAI and hourly ERA5-Land meteorology, and the resulting emissions are area-aggregated to a 100 m output grid (Muñoz-Sabater et al., 2021; Zhang et al., 2025). The resulting product combines three characteristics not jointly represented by the existing datasets considered here: 100 m vegetation-resolved output, hourly temporal resolution, and continuous 26-year coverage. We evaluate the underlying annual land-cover record against independent reference data, characterize spatial and temporal variability from national to prefecture scales, compare ISOP-China-100m, generated using the default MEGAN2.1 emission factors, with a companion 0.25° MEGAN2.1-MODIS configuration, and use statistical decomposition to examine the factors associated with long-term changes. Together, these analyses clarify how dynamic vegetation representation shapes the spatial and temporal distribution of isoprene emissions relevant to regional atmospheric chemistry.

2 Data and methods

2.1 Dataset design

We estimated hourly isoprene emissions using the Google Earth Engine-based Model of Emissions of Gases and Aerosols from Nature (GEE-MEGAN), a novel computational framework we developed as an extension of MEGAN2.1 (Guenther et al., 2012; Zhang et al., 2025). The core innovation of GEE-MEGAN is its ability to leverage the established MEGAN2.1 emission algorithms while dynamically integrating annual, high-resolution (10–30 m) satellite-derived land cover and vegetation data. This advancement enabled an unprecedented 26-year (2000–2025) simulation of hourly emissions across China, including Taiwan, at a 100-m output resolution. Computationally, the domain was processed in 1°×1° tiles. Within each tile, key parameters like Plant Functional Type (PFT) fractions and standard emission potentials were resolved at the native 10–30 m resolution of the satellite inputs before being aggregated to the final 100 m emission grid. It is important to note that while this captures fine-scale heterogeneity in vegetation, the meteorological forcing was resampled without adding sub-grid scale information.



To benchmark our high-resolution product and compare vegetation input configurations, we developed a companion simulation, termed MEGAN2.1-MODIS-0.25°. This simulation represents a more conventional approach, generating emissions at a coarser 0.25° resolution (~27 km). It used the same core emission equations and ERA5-Land meteorology but different land cover and LAI inputs. PFT fractions were derived from the standard MODIS land cover product (MCD12Q1.061; Friedl and Sulla-Menashe, 2022). For clarity, our high-resolution (100 m) isoprene product is formally named ISOP-China-100m used the GEE-MEGAN satellite LAI workflow with MODIS supplementation (Table 1). The coarse-resolution companion dataset is denoted as MEGAN2.1-MODIS-0.25°. Table 1 summarizes the configurations of these two datasets.

Table 1. Input datasets and output grids of ISOP-China-100m and the companion MEGAN2.1-MODIS-0.25° simulation.

Dataset	Model	Meteorology	Leaf Area Index	Land Cover	Output Grid
ISOP-China-100m	GEE-MEGAN	ERA5-Land, hourly, 0.1°	LAI retrieved from Landsat observations and with MOD15A2H.061, MCD15A3H.061, MYD15A2H.061	Annual Landsat/Sentinel classification	100 m
MEGAN2.1-MODIS-0.25°	MEGAN2.1	ERA5-Land, hourly, 0.1°	MOD15A2H.061, MCD15A3H.061, MYD15A2H.061	MCD12Q1.061	0.25°

2.2 GEE-MEGAN emission formulation

The GEE-MEGAN framework calculates the hourly isoprene flux, $E(x, t)$, for each grid cell (x) as the sum of emissions from all constituent Plant Functional Types (PFTs):

$$E(x, t) = \sum_{i=1}^n \gamma_i(x, t) \times EF_i \times F_i(x, y) \quad (1)$$

In Eq.(1), where EF_i is the standard-condition isoprene emission factor for PFT_{*i*} (in $\mu\text{g m}^{-2} \text{h}^{-1}$), $F_i(x, y)$ is its fractional cover in a given year y , and γ_i is the dimensionless emission activity factor that modulates the base emission. Critically, this formulation ensures that the total grid-cell emission is a dynamically weighted sum based on the high-resolution PFT distribution, with non-vegetated fractions assigned zero emission potential.

The activity factor, γ , encapsulates the environmental controls on emissions and is defined in Eq.(2):

$$\gamma_i(x, t) = C_{CE} \times LAI(x, t) \times \gamma_{P,i}(x, t) \times \gamma_{T,i}(x, t) \times \gamma_{A,i}(x, t) \times \gamma_{SM}(x, t) \times \gamma_{CO_2}(x, t) \quad (2)$$

Here, C_{CE} is the canopy-environment coefficient, while γ_P , γ_T , and γ_A represent the response functions for light, temperature, and leaf age, respectively. This study utilized the full multilayer canopy energy balance option within MEGAN2.1 to derive these terms. As a deliberate choice to isolate the primary biophysical drivers, the soil-moisture (γ_{SM}) and CO_2 inhibition (γ_{CO_2}) terms were disabled by setting them to 1. A key component of our high-resolution approach is the dynamic LAI, generated via



the GEE-MEGAN satellite workflow (Zhang et al., 2025). Landsat observations with scene cloud cover below 20% were selected between the MODIS LAI dates bracketing each calculation time and used to retrieve LAI. To create a temporally complete and robust LAI time series, gaps from cloud contamination or infrequent satellite revisits in our primary data were systematically filled using a hierarchy of MODIS products (MOD15A2H.061, MCD15A3H.061, MYD15A2H.061; Myneni et al., 2021a,b,c). The light and temperature algorithms were driven by current-hour meteorology as well as the 24-hour and 240-hour historical conditions, consistent with the original MEGAN2.1 formulation (Guenther et al., 2012).

2.3 Meteorology

To drive the emission model, we used hourly meteorological data from the ERA5-Land reanalysis for the period 2000–2025. This dataset was selected for its high spatial resolution (0.1°) and its consistent, state-of-the-art data assimilation system (Muñoz Sabater, 2019; Muñoz-Sabater et al., 2021). The required variables included 2 m air temperature, 2 m dew-point temperature, surface pressure, 10 m zonal and meridional wind components, and downward surface solar radiation. Water-vapour variable (QV; kg kg⁻¹) was derived from dew-point temperature and surface pressure.

A crucial preprocessing step involved converting the accumulated surface solar radiation (J m⁻²) from ERA5-Land into the Photosynthetic Photon Flux Density (PPFD, μmol m⁻² s⁻¹) required by MEGAN. First, hourly mean downward solar radiation (SRR; W m⁻²) was calculated by differencing consecutive accumulations. PPFD was then estimated using the established relationship: PPFD ≈ 2.25 × SRR. This coefficient approximates the conversion from total irradiance to photosynthetically active photon flux (McCree, 1972; Jacovides et al., 2004). The ERA5-Land SRR input includes direct and diffuse radiation and already represents cloud effects on radiation (Muñoz-Sabater et al., 2021). All meteorological fields, including their 24-hour and 240-hour histories, were computed on an hourly time axis before being ingested by the emission model.

2.4 Satellite observations and vegetation cover

The foundation of our high-resolution emissions inventory is a set of annual land cover maps produced at 10–30 m resolution. To achieve unprecedented spatiotemporal consistency from 2000 to 2025, we developed a data fusion methodology within Google Earth Engine (Gorelick et al., 2017) that leverages the entire Landsat Collection 2 (Tier 1) and Sentinel-2 archives (Drusch et al., 2012; EROS Center, 2020a, b, c). This multi-sensor approach (Landsat 5/7/8/9 and Sentinel-2) maximized data availability, resulting in a dense collection of 370,929 quality-filtered optical scenes (Fig. S1).

Rigorous pre-processing was applied to ensure the quality of the input data. Scenes with >20% cloud cover were excluded, and pixels contaminated by clouds, shadows, snow, or sensor saturation were masked using a combination of sensor-specific quality assurance (QA) layers. We elected six corresponding reflectance bands from each sensor (blue, green, red, NIR, SWIR1 and SWIR2) and expressed them on a common numerical scale before constructing annual composites. For each year, these quality-controlled observations were aggregated into an annual median composite. To enhance the classifier's performance,



we derived a suite of five well-established spectral indices (e.g., NDVI, EVI) as additional predictor variables (Tucker, 1979; Huete et al., 2002; Rikimaru et al., 2002; Zha et al., 2003; Xu, 2006).

150 Our land cover classification employed a random forest classifier (Breiman, 2001) trained using a novel data-fusion approach that synthesized training labels from multiple authoritative sources, including GLC_FCS30D, Copernicus land cover, MCD12Q1.061, and ESA WorldCover 2020 (Copernicus Climate Change Service, 2019; Zanaga et al., 2021; Friedl and Sulla-Menashe, 2022; Liu et al., 2023; Zhang et al., 2024). This strategy overcomes the limitations of any single product. The training was further constrained using ancillary datasets on global canopy height, forest change, and impervious surfaces to improve
 155 the distinction between woody vegetation, built-up land, and areas of change (Hansen et al., 2013; Huang et al., 2021; Lang et al., 2023). All labels were cross-walked to the 17-class IGBP scheme. To ensure a complete time series, data from years outside the native range of these auxiliary products were carefully extrapolated. The final annual IGBP maps were then translated into 16 PFT classes by integrating information on canopy height and Köppen–Geiger climate zonation (Beck et al., 2018), linking the mapped landscape to the biophysical parameters of the emission model.

160 2.5 Standard isoprene emission potential

From the annual PFT maps, we calculated the standard-condition isoprene emission potential, $EP(x, y)$ in Eq.(3), which represents the baseline emission capacity of the landscape before environmental modulation. It was computed for each grid cell (x) and year (y) by weighting the PFT-specific standard emission factors (EF_i , from Table S2) by their corresponding fractional area (F_i), following the methodology of MEGAN2.1 and GEE-MEGAN (Guenther et al., 2012; Zhang et al., 2025):

$$165 \quad EP(x,y) = \sum_{i=1}^n EF_i \times F_i(x,y) \quad (3)$$

This key variable (in $\mu\text{g m}^{-2} \text{h}^{-1}$) represents land cover changes in emission potential under fixed MEGAN2.1 emission factors, as it only varies annually with the PFT fractions. The final hourly emissions were then obtained by applying the environmental activity factor (γ , from Eq. (2)) to this baseline potential.

2.6 Evaluation and statistical analysis

170 We employed a multi-faceted strategy to rigorously evaluate our model and the resulting emission inventory. This involved (1) independent land cover accuracy assessment, (2) model sensitivity analysis using a machine learning surrogate, (3) robust statistical trend attribution, and (4) compared GEOS-Chem HCHO columns with satellite observations.

First, to independently validate our annual land cover maps, we used the GLanCE training dataset (Stanimirova et al., 2023), a source explicitly not used during classifier training. We assessed the accuracy of our maps against 2,815 high-confidence
 175 reference sites (54,695 site–year records) across China from 2000–2020 using a confusion matrix approach (Olofsson et al., 2014; Fig. S5). Performance was quantified using standard metrics including overall accuracy, balanced accuracy, macro-averaged F1 score, and Cohen's κ to provide a comprehensive view of classification quality (Cohen, 1960; see Text S1).



Second, to probe the behavior of the computationally intensive GEE-MEGAN model and attribute emission drivers, we developed an Extreme Gradient Boosting (XGBoost) surrogate model (Chen and Guestrin, 2016). The surrogate's ability to faithfully reproduce monthly ISOP-China-100m outputs was confirmed using robust, spatially and temporally blocked cross-validation, which prevents data leakage (Roberts et al., 2017). This validated surrogate then enabled both a one-at-a-time sensitivity analysis and a formal driver attribution using grouped Shapley values, which precisely quantifies the contribution of each input variable to the final emission estimate (Shapley, 1953; Lundberg and Lee, 2017; see Texts S2–S4).

Finally, we analyzed spatiotemporal trends in the 26-year emission product using ordinary least squares, with the Theil–Sen estimator employed as a robust non-parametric check (Theil, 1950; Sen, 1968). To control for false positives in spatially explicit trend analysis, significance at the prefecture level was adjusted using the Benjamini–Hochberg false-discovery-rate correction (Benjamini and Hochberg, 1995). The stability of inter-annual variability was further confirmed using circular moving-block bootstrap resampling.

As an additional large-scale evaluation, we conducted paired GEOS-Chem Classic v14.7.1 (Bey et al., 2001) full-chemistry simulations for each July from 2005 to 2025 at $4^{\circ} \times 5^{\circ}$ resolution. Within China, the default biogenic isoprene emissions were replaced separately by hourly ISOP-China-100m (GEE-MEGAN) and MEGAN2.1-MODIS emissions, while emissions outside China and all other model inputs were kept identical. Model tropospheric HCHO columns sampled at 13:00–14:00 local solar time were compared with the corresponding NASA OMI OMHCHOd V003 daily product on a 0.1° grid (Chance, 2019). Satellite pixels were area-weighted to the model grid, and monthly cells required at least five matched days. Performance was evaluated using normalized mean bias (NMB), root-mean-square error (RMSE), the spatial Pearson correlation coefficient, and the interannual Pearson correlation coefficient.

3 Data characteristics and discussion

3.1 National spatial and temporal characteristics

Our high-resolution ISOP-China-100m inventory reveals a profoundly heterogeneous isoprene emission landscape across China, with major source regions concentrated in the forested parts of the south, southeast, and northeast, contrasting sharply with the arid northwest and the Tibetan Plateau (Fig. 1a). At its 100 m resolution, the model output shows distinct emission features corresponding to mountain forests, fragmented vegetation, cropland boundaries, and urban green space. When these data are aggregated to a 0.25° grid, these fine-scale details are averaged into a single value. This within-grid heterogeneity is not resolved in inventories based on coarser-resolution data (Wang et al., 2018, 2021; Ma et al., 2022; Zhang et al., 2025). The underlying vegetation record was constructed from 370,929 optical satellite scenes, with Landsat 7 (29.3%) and Sentinel-2 (28.0%) being the primary contributors by scene count (Fig. 1b and c; Fig. S1).

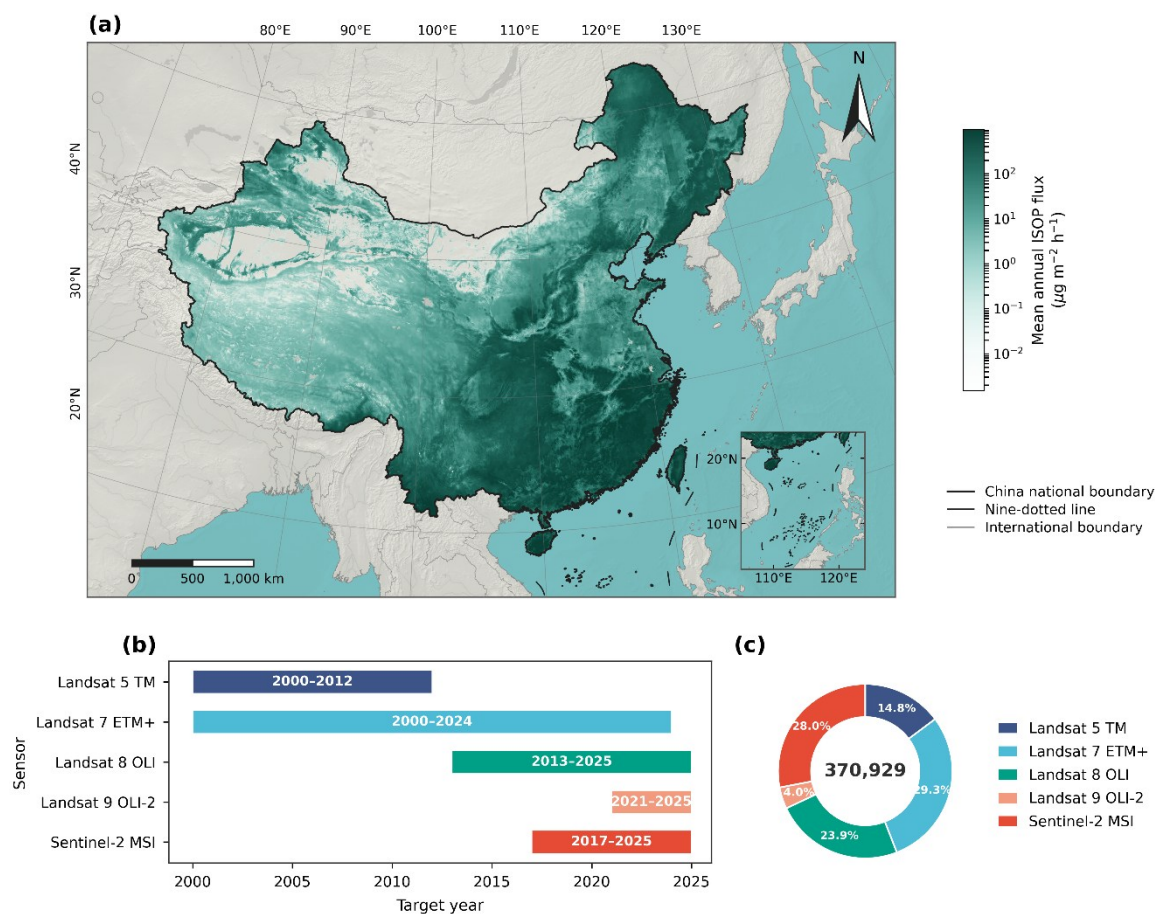


Figure 1 Multiyear mean isoprene emissions and remote-sensing data coverage over China. (a) Spatial distribution of the 2000–2025 mean annual ISOP-China-100m dataset isoprene emission flux. (b) Temporal coverage of the Landsat and Sentinel-2 sensors. (c) Relative scene contributions of the five selected satellite sensors to the total used dataset ($n = 370,929$ scenes).

At the national scale, total annual emissions from ISOP-China-100m increased from 8.49 Tg in 2000 to 12.35 Tg in 2025, with a 26-year average of $9.87 \pm 1.53 \text{ Tg yr}^{-1}$ (Fig. 2a). For comparison, a parallel simulation using MEGAN2.1 with MODIS (MEGAN2.1-MODIS-0.25°) vegetation data yielded an average of 10.51 Tg, making the ISOP-China-100m dataset estimate lower by 0.65 Tg (~6.2%). The difference between the two model outputs was not constant over the study period. For 2000–2012, the ISOP-China-100m estimate was 1.13 Tg lower than the MEGAN2.1-MODIS-0.25° dataset estimate; for 2013–2025, this difference narrowed to 0.16 Tg. A discontinuity in the national emission time series was observed between 2012 and 2013, which coincided with the transition of the primary Landsat sensor from Landsat 5 to Landsat 8. For this reason, a segmented trend analysis was performed. The analysis yielded a slope of $+0.022 \text{ Tg yr}^{-1}$ for the 2000–2012 period ($p > 0.05$) and $+0.23 \text{ Tg yr}^{-1}$ for the 2013–2025 period ($p < 0.05$). The MODIS-driven comparison also showed an increasing similar trend during 2013–2025 (Fig. 2a). Annual maps from both simulations and their differences are provided in Figs. S2–S4.

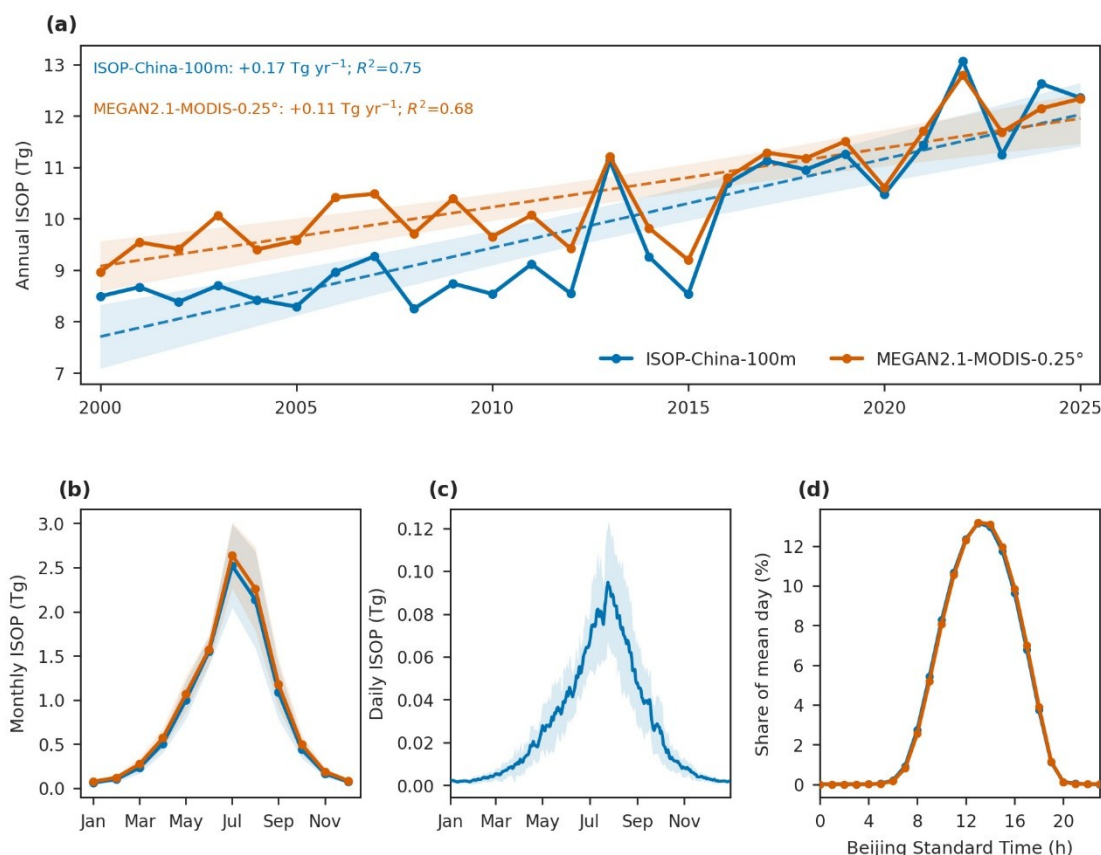


Figure 2 Temporal variability of isoprene emissions over China from 2000 to 2025. (a) Annual total emissions simulated by ISOP-China-100m and MEGAN2.1-MODIS-0.25° dataset. Dashed lines indicate fitted linear trends, and shaded areas represent pointwise 95% confidence intervals. (b) Mean monthly variation for both simulation frameworks, with shading representing ± 1 standard deviation. (c) Mean daily annual cycle from ISOP-China-100m dataset, with shading representing ± 1 standard deviation. (d) Mean hourly contributions to daily total emissions from ISOP-China-100m and MEGAN2.1-MODIS-0.25° dataset.

In contrast to the complex interannual variability, the seasonal and diurnal emission cycles exhibit a robust and predictable pattern. Monthly emissions increased during spring, peaked in July at approximately 2.6 Tg month⁻¹, and declined after August (Fig. 2b). On a daily basis, emissions were close to zero at night and peaked near 13:00 China Standard Time, when one hour contributed about 13% of the daily total (Fig. 2d). The timing of these cycles aligns with the light and temperature response functions within the MEGAN2.1 model. Since both ISOP-China-100m and the comparative MEGAN2.1-MODIS-0.25° dataset used the same meteorological forcing data, the differences in emission magnitudes between them are attributable to the differences in the vegetation inputs and their respective spatial representations.

3.2 Regional Heterogeneity in Emission Budgets and Phenology

The national isoprene emission budget was unevenly distributed among the seven study regions. South China (SC), East China (EC), and Southwest China (SWC) were the dominant source areas, collectively accounting for approximately 69% of the total

China. SC contributed the largest share (2.89 ± 0.52 Tg), followed by EC (2.24 ± 0.40 Tg) and SWC (1.62 ± 0.31 Tg). In contrast, emissions from Northwest China (NWC) and the Tibetan Plateau (TP) were substantially lower, at 0.25 ± 0.05 and 0.13 ± 0.02 Tg, respectively (Table 2; Fig. 3a–c). This spatial distribution aligns with the known influence of vegetation composition and the prevalence of high-emitting species on regional isoprene source strength in China (Klinger et al., 2002; Bai et al., 2006; Geron et al., 2006).

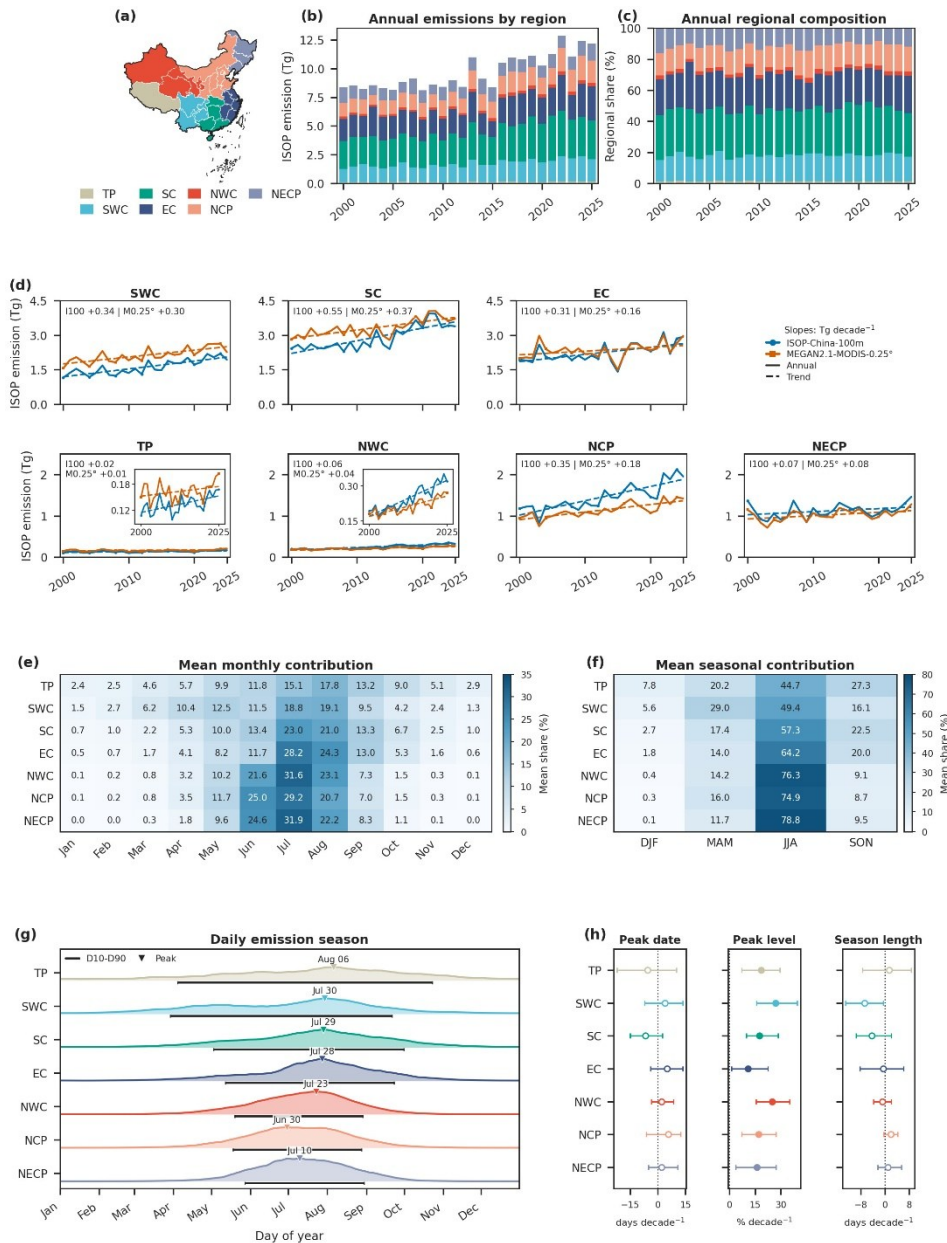


Figure 3 Regional and seasonal variations in isoprene emissions across China (2000–2025). (a) Geographical definitions of the seven regional divisions. (b) Annual ISOP-China-100m dataset categorized by region. (c) Annual percentage contributions of each region



245 to the combined emissions from the seven regions. (d) Regional annual emission totals and long-term trends comparing ISOP-China-100m and MEGAN2.1-MODIS-0.25° dataset. Mean (e) monthly and (f) seasonal emission contributions by region. (g) Mean daily emission patterns. D10 and D90 denote the dates when cumulative annual emissions reach 10% and 90%, respectively; the interval D10 - D90 defines the main emission season. (h) Trends in peak emission dates, peak magnitudes, and the length of the emission season. Points and error bars represent Theil–Sen estimator slopes and their 95% confidence intervals.

250 A key finding is that the ISOP-China-100m and MEGAN2.1-MODIS-0.25° datasets yielded divergent regional estimates, with the direction and magnitude of the difference varying by region (Fig. 3d). ISOP-China-100m estimates were lower than MEGAN2.1-MODIS-0.25° datasets in SWC (−23.9%), SC (−13.0%), and EC (−4.7%), but higher in NWC (+19.0%), the North China Plain (NCP; +27.2%), and the Northeast China Plain (NECP; +9.8%). These inter-model discrepancies correspond to systematic differences in land cover characterization between the ISOP-China-100m and MEGAN2.1-MODIS-0.25° dataset
 255 (Table S1). Specifically, the vegetation map used to produce ISOP-China-100m identified a greater fraction of tree cover (23.46% vs. 18.17%) and shrub (7.02% vs. 5.20%) cover, while reducing the grass fraction (20.15% vs. 35.19%). The net effect on emissions is determined by the balance between two competing mechanisms: 1) the explicit mapping of high-emitting woody vegetation previously unclassified in coarse pixels, and 2) the separation of lower- or non-emitting surfaces (e.g., cropland, non-vegetated land) from pixels formerly classified as mixed forest. The regional differences reflect the combined
 260 effects of fine-scale vegetation representation, LAI and spatial aggregation.

Beyond magnitude, the regions exhibited distinct emission patterns (Fig. 3e, f). Northern regions such as NWC, NCP, and NECP were characterized by sharply peaked summer cycles, with over 74% of annual emissions occurring in June–August. In contrast, SWC displayed a broader spring-to-autumn season, with comparable contributions from July (18.8%) and August (19.1%), while the TP showed the broadest and latest seasonal distribution, peaking in August. These differences in seasonal
 265 breadth are mirrored in the timing of peak emissions (Fig. 3g, h). The mean peak date occurred earliest in the NCP (30 June) and latest on the TP (6 August). Correspondingly, the 10%–90% emission window was shorter in NWC, NCP, and NECP compared to SWC and the TP.

Over the 26-year period, positive descriptive trends were observed across all regions, with the largest absolute increases occurring in SC (+0.055 Tg yr^{−1}), SWC (+0.034 Tg yr^{−1}), and NCP (+0.035 Tg yr^{−1}). Theil–Sen analysis of the seasonal cycle
 270 indicates that this long-term increase was primarily expressed as an amplification of the seasonal peak magnitude, rather than a systematic shift in the timing or duration of the emission season. This suggests that regional changes were driven more by factors influencing emission intensity than by those altering phenological timing.

3.3 Heterogeneity of High-Resolution Effects at Regional and Sub-Regional Scales

The discrepancies between ISOP-China-100m and MEGAN2.1-MODIS-0.25° dataset were more pronounced at the scale of
 275 key economic regions than at the national level (Fig. 4). The regional percentage differences below were calculated from the mean of annual emission ratios over 2000–2025, using MEGAN2.1-MODIS-0.25° emissions as the denominator. Estimates from ISOP-China-100m dataset were higher in the Beijing–Tianjin–Hebei region (BTH; +101.2%), the Yangtze River Delta (YRD; +13.1%), the Shandong Peninsula (SP; +446.4%), and the Central Plains (CP; +35.4%). Conversely, estimates were

lower in the Pearl River Delta (PRD; -20.2%), the Chengdu–Chongqing Economic Circle (CCEC; -15.3%), and the Middle
 Reaches of the Yangtze River (MRYS; -16.2%). The opposing signs of these regional differences indicate that the modest 6.2%
 national-level difference results from the cancellation of larger, countervailing effects at sub-national scales, rather than from
 uniformly small differences at the grid level.

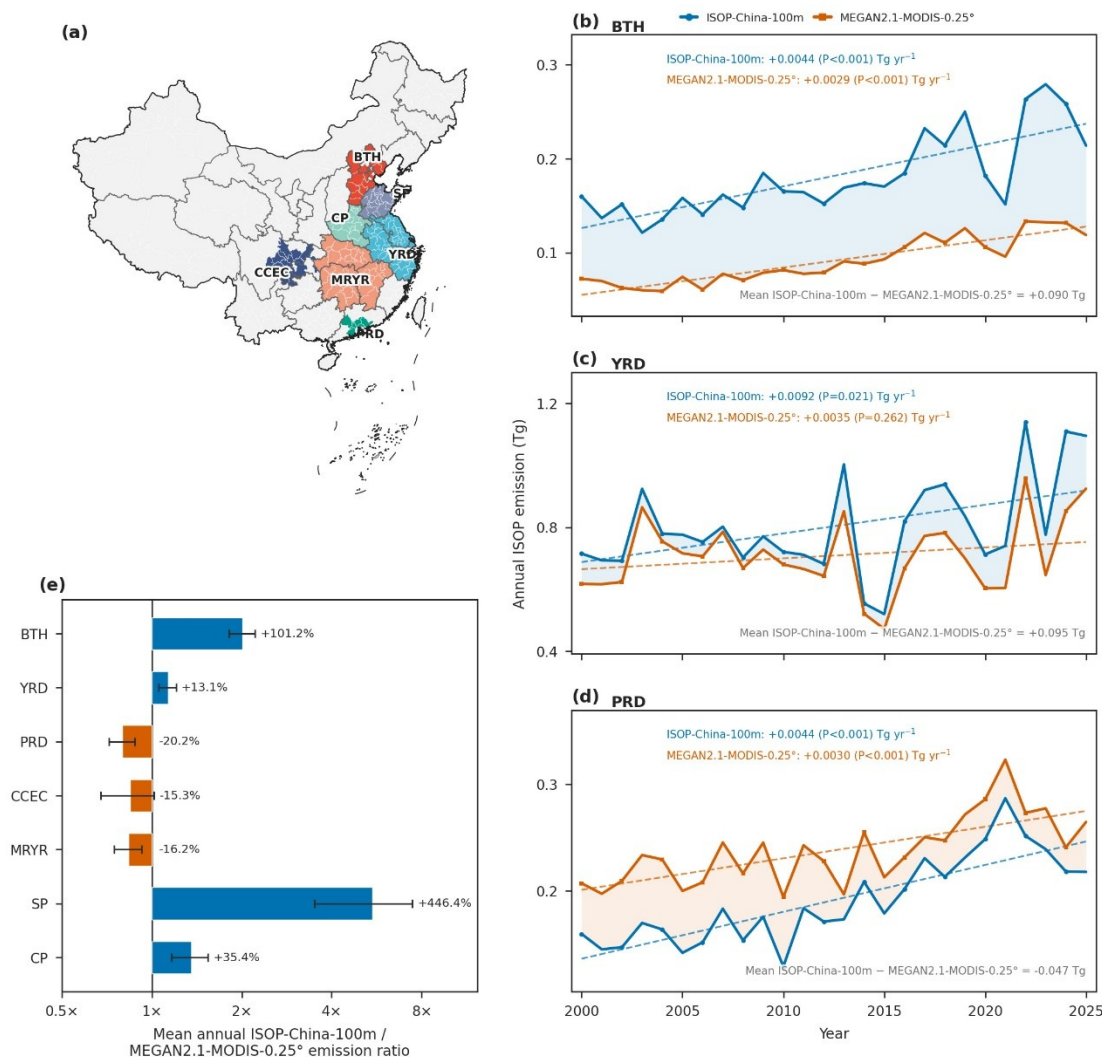


Figure 4 Spatial distribution and long-term differences in isoprene emissions across seven key regions. (a) Locations of the seven
 defined regions in China. (b–d) Annual emissions and linear trends for three distinct focus areas: the Beijing–Tianjin–Hebei (BTH)
 region, the Yangtze River Delta (YRD), and the Pearl River Delta (PRD). (e) Mean annual spatial emission ratios between ISOP-
 China-100m and MEGAN2.1-MODIS-0.25° dataset across the domains.

For BTH, the mean emission estimate from ISOP-China-100m was 0.182 ± 0.043 Tg , double the MEGAN2.1-MODIS-0.25°
 dataset of 0.091 ± 0.024 Tg (Table 2; Fig. 4b). The derived long-term trend was also larger in the high-resolution simulation
 ($+0.0044$ Tg yr^{-1} vs. $+0.0029$ Tg yr^{-1}). In the YRD, while the difference in a mean emission was smaller, the ISOP-China-



100m trend was $+0.0092 \text{ Tg yr}^{-1}$ ($p = 0.021$), whereas the trend from the coarse simulation was not statistically significant ($+0.0035 \text{ Tg yr}^{-1}$, $p = 0.262$) (Fig. 4c). This demonstrates that the choice of land cover and vegetation changes can influence not only the absolute emission magnitude but also the magnitude and statistical significance of derived long-term trends.

Table 2 Annual mean isoprene emissions and descriptive full-period trends in typical regions, 2000–2025.

Regions	ISOP-China-100m	ISOP-China-100m	MEGAN2.1-MODIS-0.25°	MEGAN2.1-MODIS-0.25°
	mean $\pm$ SD (Tg yr^{-1})	Trends (Gg yr^{-1})	mean $\pm$ SD (Tg yr^{-1})	Trends (Gg yr^{-1})
TP	0.13 ± 0.02	1.5	0.16 ± 0.02	0.9
SWC	1.62 ± 0.31	34.3	2.13 ± 0.30	29.9
SC	2.89 ± 0.52	55.1	3.32 ± 0.38	36.5
EC	2.24 ± 0.40	31.2	2.35 ± 0.34	16.2
NWC	0.25 ± 0.05	6.1	0.21 ± 0.03	3.5
NCP	1.45 ± 0.31	34.6	1.14 ± 0.17	18.2
NECP	1.12 ± 0.16	7.4	1.02 ± 0.13	8.1
BTH	0.182 ± 0.043	4.4	0.091 ± 0.024	2.9
YRD	0.803 ± 0.157	9.2	0.709 ± 0.117	3.5
PRD	0.191 ± 0.040	4.4	0.238 ± 0.032	3
CCEC	0.281 ± 0.103	10.3	0.326 ± 0.071	4
MRYR	1.853 ± 0.384	34.4	2.199 ± 0.299	18
SP	0.050 ± 0.037	4.2	0.008 ± 0.004	0.4
CP	0.215 ± 0.059	6.3	0.157 ± 0.029	2.6

SD is the sample standard deviation of annual emissions and represents interannual variability. SWC includes Sichuan, Chongqing, Guizhou and Yunnan; SC includes Guangdong, Guangxi, Hainan, Hubei, Hunan, Hong Kong and Macao; EC includes Shanghai, Jiangsu, Zhejiang, Anhui, Fujian and Jiangxi; NWC includes Xinjiang, Qinghai, Gansu and Ningxia; NCP includes Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Shandong, Henan and Shaanxi; and NECP includes Liaoning, Jilin and Heilongjiang. TP represents Tibet and is excluded from South and North; Taiwan is included in the national totals but excluded from the seven-region summaries in this table. Hong Kong and Macao are included in SC. BTH covers Beijing, Tianjin and Hebei; YRD covers Shanghai, Jiangsu, Zhejiang and Anhui; PRD represents the nine-city Pearl River Delta core; CCEC (Chengdu–Chongqing Economic Circle) comprises Chongqing and 15 designated prefecture-level units in Sichuan; MRYP (Middle Reaches of the Yangtze River) covers Hubei, Hunan and Jiangxi; SP (Shandong Peninsula) covers the whole of Shandong; and CP (Central Plains) covers the whole of Henan.

The largest relative difference was observed in SP (ratio of 5.46), though its absolute emissions were minor (0.050 Tg vs. 0.008 Tg). The high ratio is arithmetically influenced by the small denominator in the coarse-resolution estimate (Fig. 4c). At the prefecture level, positive and negative differences were frequently juxtaposed in neighboring areas (Fig. 5), with ISOP-China-100m dataset generally higher in northern and northeastern China and lower in parts of the southwest and south. This spatially heterogeneous pattern may reflect differences in LAI as well as the dual effect of high-resolution mapping, which can either increase local estimates by resolving small patches of woody vegetation or decrease them by separating non-emitting



surfaces (e.g., cropland, built-up land) from coarse mixed-vegetation pixels (Wang et al., 2018; Ma et al., 2022; Zhang et al., 2025).

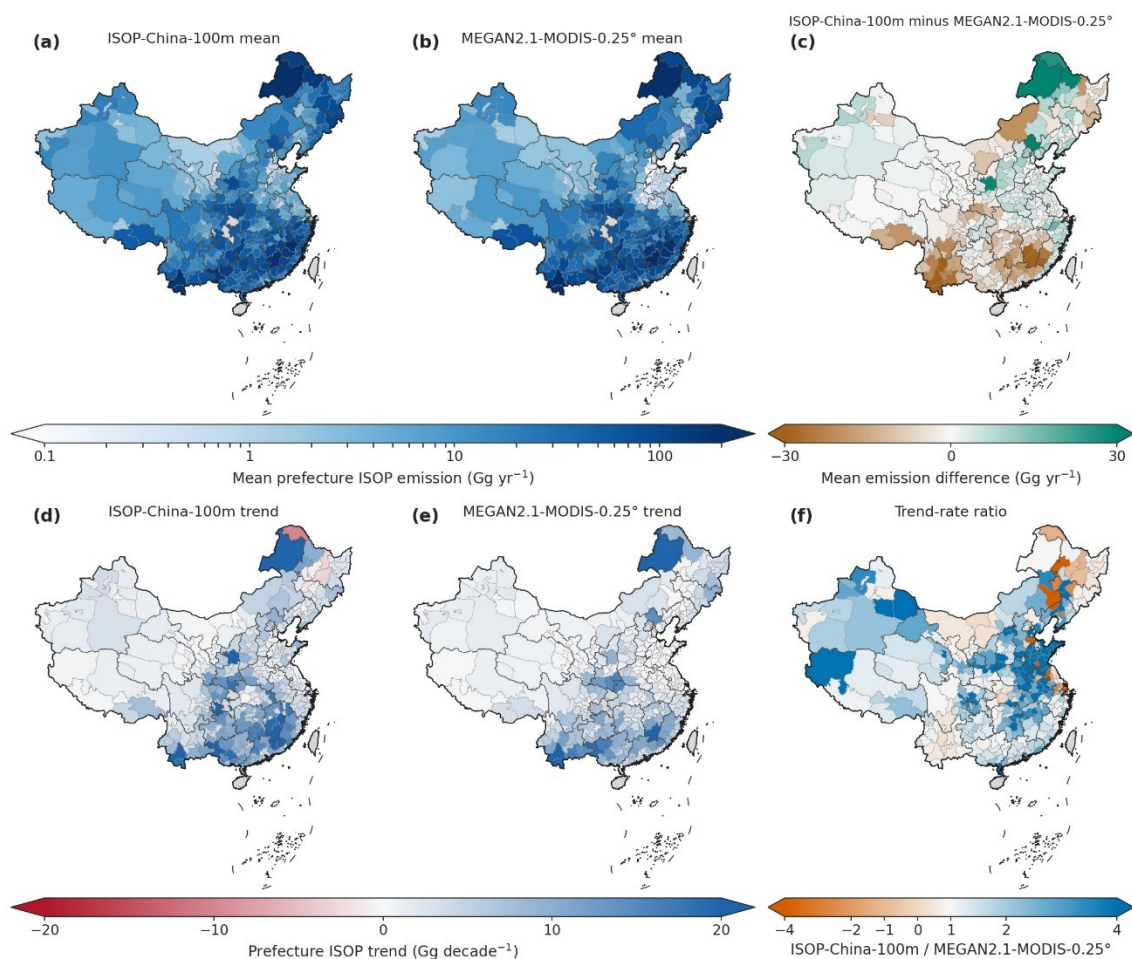


Figure 5 Prefecture-level isoprene emissions and multi-decadal trends (2000–2025). (a, b) Mean annual emissions derived from ISOP-China-100m and MEGAN2.1-MODIS-0.25° dataset (Gg yr^{-1} ; common logarithmic colour scale). (c) Absolute differences in mean annual emissions between the two datasets. (d, e) Decadal changes in annual emissions based on linear trends (Gg decade^{-1}). (f) Spatial ratio of the trends between the two datasets.

3.4 Attribution of Temporal Emission Changes

To attribute the sources of temporal variation, a factorial decomposition was performed on the national emission time series. Consistent with the analysis in Section 3.1, the trend was analyzed in two segments. The trend for 2000–2012 was $+0.022 \text{ Tg yr}^{-1}$ ($p > 0.05$) and was not statistically significant. For the 2013–2025 period, the national trend accelerated to $+0.23 \text{ Tg yr}^{-1}$ ($p < 0.05$) (Fig. 6a).

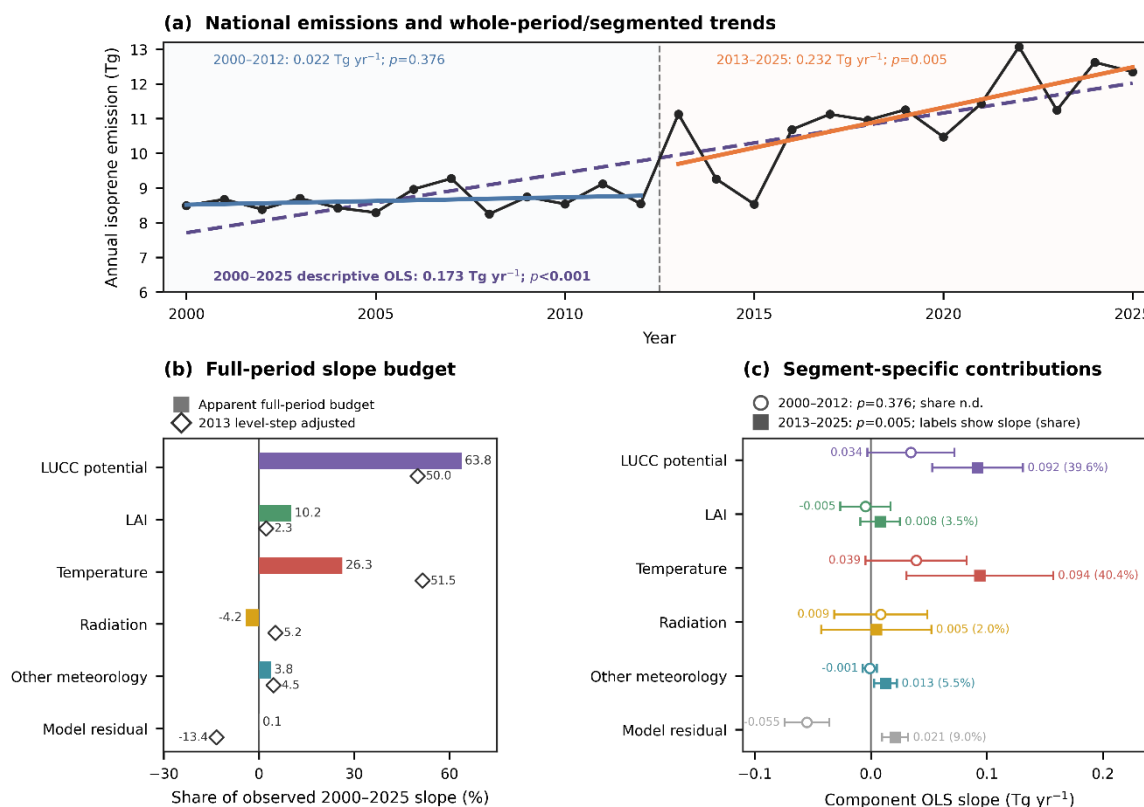


Figure 6 Multiyear trends and exploratory statistical attribution of ISOP-China-100m dataset. (a) Annual national total emissions. (b) Robustness diagnostic checks for the overall 2000–2025 slope. (c) Segment-specific ordinary least-squares (OLS) slopes of the decomposed statistical components. Open circles and filled squares indicate the separate trend phases for 2000–2012 and 2013–2025, respectively.

Decomposition analysis of the statistically significant 2013–2025 period identified changes in land-cover-related emission potential and temperature as the principal contributors to the trend (Fig. 6c). Their respective fitted slopes were $+0.092$ and $+0.094 \text{ Tg yr}^{-1}$, which correspond to 39.6% and 40.4% of the total trend, collectively accounting for 80% of the simulated increase. Contributions from LAI ($+0.008 \text{ Tg yr}^{-1}$), radiation ($+0.005 \text{ Tg yr}^{-1}$), and other meteorological variables ($+0.013 \text{ Tg yr}^{-1}$) were smaller. These findings align with previous studies that have linked long-term emission changes in Asia to vegetation dynamics, afforestation policies, and meteorological forcing (Fu and Liao, 2012; Stavrakou et al., 2014; Zhang et al., 2016; Wang et al., 2021; Gai et al., 2024). We assessed the sensitivity of the full-period attribution using a model accounting for a level shift in 2013 and a separate analysis excluding 2013 (Text S4). The contribution of standard emission potential associated with land cover to the 2000–2025 trend decreased from 63.8% to 50.0% after the level shift adjustment (Fig. 6b), whereas excluding 2013 yielded a contribution of 63.8%. This component remained a major positive contribution in both robustness tests.

It is noted that this decomposition represents a statistical attribution within the model's framework. The input variables (land cover, LAI, meteorology) can covary, and any effects associated with the 2012–2013 input data transition may be distributed



among correlated components or the residual term. Furthermore, the simulation did not account for soil-moisture stress or CO₂ inhibition. The reported contributions should therefore be interpreted as a closed statistical description of the simulated change, not as a complete attribution of all underlying physical drivers.

3.5 Comparison with Existing Inventory and Evaluation of Model Limits

The ISOP-China-100m dataset is distinguished by its synthesis of high spatial resolution (100 m), continuous annual coverage (2000–2025), and hourly temporal frequency. Existing China-specific inventories are typically constructed at coarser spatial resolutions (approx. 1–250 km) or for non-continuous years (Tie et al., 2006; Fu and Liao, 2012; Li et al., 2020; Wu et al., 2020; Wang et al., 2021; Cao et al., 2022; Ma et al., 2022; Gai et al., 2024). Global and regional inventories that cover China generally use grids of approximately 11.1–277.5 km (Fig. 7) (Guenther et al., 1995; Arneth et al., 2007; Sindelarova et al., 2014, 2022; Stavrakou et al., 2014; Woo et al., 2020; Opacka et al., 2021; Opacka and Stavrakou, 2026a; Opacka et al., 2026b; H. Wang et al., 2024; Müller et al., 2024; Li et al., 2025, Sfindla et al., 2026).

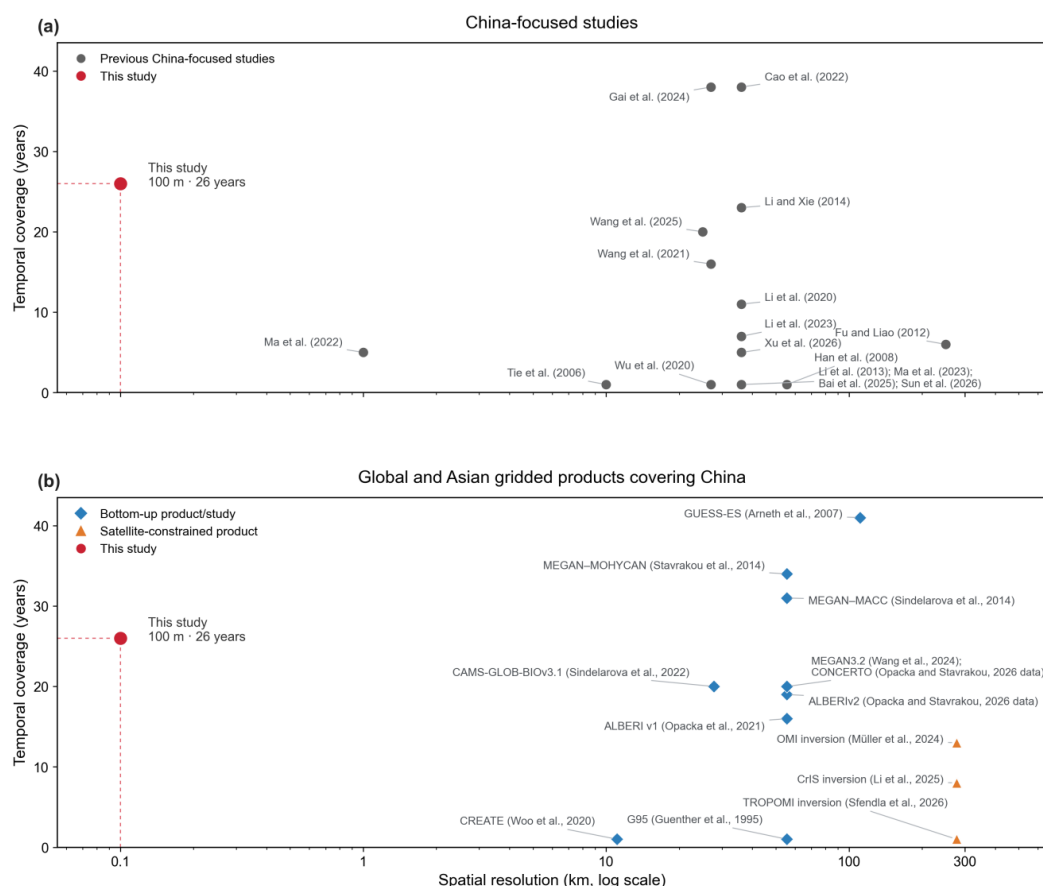


Figure 7 Spatial resolution and calendar coverage of existing isoprene emission inventories covering China. Comparison across (a) China-focused regional studies and (b) Global and Asian gridded products.



The ISOP-China-100m dataset multiyear mean estimate of 9.87 Tg yr^{-1} falls within the lower spectrum of published national totals for China, which range from approximately 7.5 to 37.5 Tg yr^{-1} (Fig. 8). The estimate is comparable to the 10.87 Tg yr^{-1} mean for 2001–2006 from Fu and Liao (2012) but is lower than the $15.94 \pm 1.12 \text{ Tg yr}^{-1}$ for 2001–2016 reported by Wang et al. (2021) and substantially lower than estimates for 2018 from Gai et al. (2024; 26.94 Tg) and Li et al. (2020; 37.45 Tg). This wide range in published values is a known consequence of methodological differences in emission factors, PFT maps, meteorological drivers, canopy models, and the inclusion of biophysical responses (e.g., soil moisture, CO_2). The position of any single estimate within this range is therefore not a direct measure of its accuracy.

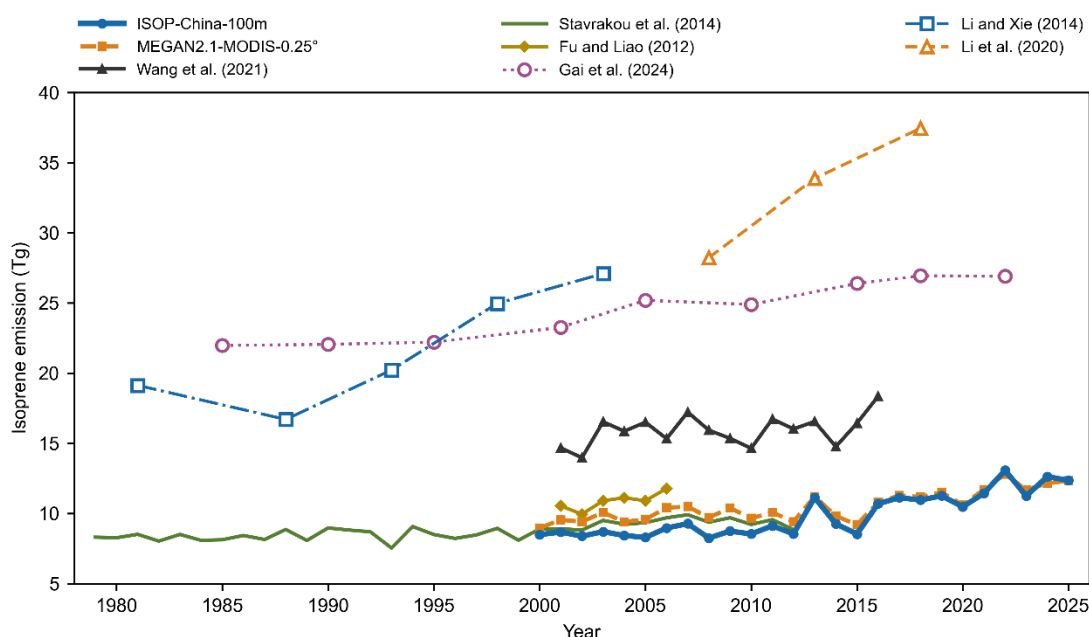


Figure 8 Comparison of annual isoprene emission estimates for China across different studies.

To characterize the uncertainty of the simulated emissions and evaluate the spatial validity of ISOP-China-100m, we combined internal model-component evaluation, sensitivity experiments, and an atmospheric-chemistry comparison against satellite HCHO columns. First, the dynamic land cover maps, when compared against the independent Global Land Cover Estimation (GLanCE) validation dataset, achieved an overall accuracy of 80.71%, a balanced accuracy of 77.38%, and a Cohen's κ of 0.747 (Fig. S5). These results support the reliability of the land-cover classification used to derive vegetation composition and standard emission potential.

Second, the XGBoost surrogate model, which emulates the full MEGAN2.1 model, demonstrated high fidelity in blocked tests, yielding area-weighted R^2 values between 0.98 and 0.99 and national mass biases between -2.22% and -0.18% . These tests indicate that the surrogate model can reproduce the full-model response sufficiently well for the prescribed sensitivity experiments. Based on this surrogate-model evaluation, we conducted grouped one-at-a-time sensitivity experiments, with detailed perturbation settings provided in Text S3. National isoprene emissions were most sensitive to temperature, radiation,



and standard emission potential. A ± 1 K temperature perturbation changed national emissions by -12.03% and $+14.0\%$, while
 375 a ± 2 K perturbation changed them by -22.14% and $+29.72\%$. Radiation perturbations of $\pm 10\%$ and $\pm 20\%$ changed emissions
 by -12.88% to $+14.49\%$ and -23.43% to $+28.10\%$, respectively. Standard emission potential showed an almost proportional
 response, with $\pm 10\%$ and $\pm 20\%$ perturbations producing -9.96% to $+9.94\%$ and -19.83% to $+19.70\%$ changes. These
 perturbations assess sensitivity to standard emission potential, not the effects of alternative PFT or local species emission factor.
 LAI had a moderate effect, with $\pm 10\%$ and $\pm 20\%$ perturbations causing -3.72% to $+3.35\%$ and -7.97% to $+6.47\%$ changes.
 380 Water vapour had a weaker effect, with $\pm 10\%$ and $\pm 20\%$ perturbations causing -2.91% to $+2.68\%$ and -5.78% to $+4.99\%$
 changes. Wind speed and pressure had limited individual effects, changing national emissions by less than 0.5% even under
 the larger perturbations. These results indicate that temperature, radiation, and standard emission potential are the dominant
 uncertainty-sensitive drivers, while LAI and water vapour play secondary roles and wind speed and pressure contribute little
 individually.
 385 Finally, the large-scale atmospheric consistency was evaluated by propagating ISOP-China-100m and MEGAN2.1-MODIS
 emissions through GEOS-Chem and comparing the simulated July HCHO columns with OMI observations for 2005–2025.
 ISOP-China-100m achieved a pooled spatial correlation of 0.904, a mean annual spatial correlation of 0.913, and an RMSE of
 0.402×10^{16} molec cm^{-2} , compared with 0.890, 0.899, and 0.417×10^{16} molec cm^{-2} , respectively, for MEGAN2.1-MODIS.
 ISOP-China-100m also produced the higher spatial correlation in all 21 years. These results provide indirect atmospheric
 390 evidence supporting the large-scale consistency and relative spatial validity of the ISOP-China-100m emission allocation
 across the July simulations for 2005–2025.

4 Conclusions

We developed ISOP-China-100m, a model-derived hourly isoprene emission dataset for China covering 2000–2025. Using
 the 2000–2025 ISOP-China-100m record and its companion MEGAN2.1-MODIS-0.25° simulation, we compared isoprene
 395 emissions estimated with finer and coarser vegetation representations. The difference in the national total was modest, whereas
 regional estimates differed substantially and in opposite directions. National emissions from ISOP-China-100m averaged 9.87 ± 1.53 Tg yr^{-1} (mean $\pm$ sample SD), with annual values ranging from 8.25 Tg yr^{-1} in 2008 to 13.07 Tg yr^{-1} in 2022. No
 significant trend was detected for 2000–2012, whereas emissions increased by 0.23 Tg yr^{-1} during 2013–2025. In the latter
 period, land-cover-related standard emission potential and temperature accounted for 39.6 % and 40.4 %, respectively, of the
 400 fitted trend. These percentages are contributions within the fitted statistical decomposition, not independent causal effects.
 Relative to the companion MEGAN2.1-MODIS-0.25° configuration, the national mean was 6.2 % lower, but regional
 differences were larger and could have opposite signs, including a 101.2% higher estimate in the Beijing–Tianjin–Hebei region
 and a 20.2 % lower estimate in the Pearl River Delta. These contrasting regional responses indicate that finer vegetation
 representation primarily reshapes the spatial allocation of isoprene emissions, even when its influence on the national total is
 405 limited.



The robustness of these results was assessed using independent land-cover validation, blocked surrogate-model tests, prescribed sensitivity experiments, and an atmospheric-chemistry comparison. The dynamic land-cover maps achieved an overall accuracy of 80.71% and a Cohen's κ of 0.747 against the independent GLanCE reference data. The XGBoost surrogate reproduced the full-model response with area-weighted R^2 values of 0.98–0.99 and national mass biases between –2.22% and –0.18%. The sensitivity experiments identified temperature, radiation, and standard emission potential as the dominant uncertainty-sensitive drivers, with LAI and water vapour exerting secondary effects. In the 2005–2025 OMI HCHO evaluation, the GEOS-Chem simulation driven by ISOP-China-100m achieved a pooled spatial correlation of 0.904, compared with 0.890 for MEGAN2.1-MODIS. It also produced the higher spatial correlation in all 21 years. These complementary evaluations support the internal consistency of the modelling framework and the relative large-scale spatial validity of the ISOP-China-100m emission allocation, with the HCHO comparison providing indirect atmospheric support at the $4^\circ \times 5^\circ$ scale.

The improved representation of regional emission patterns has implications for atmospheric-chemistry applications because ozone and secondary organic aerosol formation depend on the spatial co-location of BVOCs emissions with anthropogenic emissions, oxidants, radiation, and boundary-layer conditions. The nominal 100 m resolution should also be interpreted as the spatial resolution of vegetation and emission allocation rather than that of environmental forcing, which remains constrained by the 0.1° ERA5-Land hourly data. The emission estimates, regional contrasts, temporal trends and attribution fractions are conditional on the default MEGAN2.1 emission factors. Additional uncertainties arise from conversion from land cover classes to PFTs, satellite LAI gap filling, the 2012–2013 satellite data input transition, and the omission of soil-moisture stress and CO_2 inhibition. Future integration with direct flux and concentration measurements, higher-resolution satellite retrievals, and atmospheric inverse modelling will be important for further constraining emission magnitudes and evaluating their effects on atmospheric composition.

Code and data availability

The ISOP-China-100m product was generated using the GEE-MEGAN framework described by Zhang et al. (2025), with source code and documentation available at <https://doi.org/10.5281/zenodo.15714886>. The MEGAN2.1-MODIS- 0.25° comparison product was generated using the MEGAN2.1 source code described by Guenther et al. (2012), available at <https://bai.ess.uci.edu/megan/data-and-code/megan21>. Source data are available at <https://doi.org/10.5281/zenodo.22090178> (Ran et al., 2026). GEOS-Chem 14.7.1 code available at <https://doi.org/10.5281/zenodo.19632222>. OMI/Aura Formaldehyde Total Column Daily L3 available at <https://doi.org/10.5067/AURA/OMI/DATA3010>.

Supplement link

The link to the supplement related to this article will be included by Copernicus.



435 **Author contributions**

HR, YZ, and XW conceived the study. HR designed and implemented the data-production workflow, performed the simulations and formal analysis, curated the dataset, and prepared the figures. HR and YL produced and prepared the data for different periods of the 2000–2025 record. HR prepared the original draft. YZ and XW reviewed and edited the manuscript. All authors contributed to the interpretation of the results, revised the manuscript, and approved the final version.

440 **Competing interests**

The authors declare that they have no conflict of interest.

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References

- Arneth, A., Niinemets, Ü., Pressley, S., Bäck, J., Hari, P., Karl, T., Noe, S., Prentice, I. C., Serça, D., Hickler, T., Wolf, A., and Smith, B.: Process-based estimates of terrestrial ecosystem isoprene emissions: incorporating the effects of a direct CO₂–
 460 isoprene interaction, *Atmos. Chem. Phys.*, 7, 31–53, <https://doi.org/10.5194/acp-7-31-2007>, 2007.
- Arneth, A., Schurgers, G., Lathiere, J., Duhl, T., Beerling, D. J., Hewitt, C. N., Martin, M., and Guenther, A.: Global terrestrial isoprene emission models: sensitivity to variability in climate and vegetation, *Atmos. Chem. Phys.*, 11, 8037–8052, <https://doi.org/10.5194/acp-11-8037-2011>, 2011.
- Atkinson, R. and Arey, J.: Atmospheric degradation of volatile organic compounds, *Chem. Rev.*, 103, 4605–4638,
 465 <https://doi.org/10.1021/cr0206420>, 2003.
- Bai, G., Kong, F., Li, Z., and Li, L.: Characteristic of biogenic volatile organic compound (BVOC) emissions and their impacts on the formation of atmospheric secondary pollutants in China, *Chin. J. Ecol.*, 44, 3694–3703, <https://doi.org/10.13292/j.1000-4890.202511.035>, 2025.
- Bai, J., Baker, B., Liang, B., Greenberg, J., and Guenther, A.: Isoprene and monoterpene emissions from an Inner Mongolia
 470 grassland, *Atmos. Environ.*, 40, 5753–5758, <https://doi.org/10.1016/j.atmosenv.2006.05.019>, 2006.
- Beck, H. E., Zimmermann, N. E., McVicar, T. R., Vergopolan, N., Berg, A., and Wood, E. F.: Present and future Köppen–Geiger climate classification maps at 1-km resolution, *Sci. Data*, 5, 180214, <https://doi.org/10.1038/sdata.2018.214>, 2018.
- Benjamini, Y. and Hochberg, Y.: Controlling the false discovery rate: a practical and powerful approach to multiple testing, *J. R. Stat. Soc. B*, 57, 289–300, <https://doi.org/10.1111/j.2517-6161.1995.tb02031.x>, 1995.
- 475 Bey, I., Jacob, D. J., Yantosca, R. M., Logan, J. A., Field, B. D., Fiore, A. M., Li, Q., Liu, H. Y., Mickley, L. J., and Schultz, M. G.: Global modeling of tropospheric chemistry with assimilated meteorology: Model description and evaluation, *J. Geophys. Res.-Atmos.*, 106, 23073–23095, <https://doi.org/10.1029/2001JD000807>, 2001.
- Breiman, L.: Random Forests, *Mach. Learn.*, 45, 5–32, <https://doi.org/10.1023/A:1010933404324>, 2001.
- Brodersen, K. H., Ong, C. S., Stephan, K. E., and Buhmann, J. M.: The balanced accuracy and its posterior distribution, in:
 480 *Proceedings of the 20th International Conference on Pattern Recognition*, 3121–3124, <https://doi.org/10.1109/ICPR.2010.764>, 2010.
- Bryan, B. A., Gao, L., Ye, Y., Sun, X., Connor, J. D., Crossman, N. D., Stafford-Smith, M., Wu, J., He, C., Yu, D., Liu, Z., Li, A., Huang, Q., Ren, H., Deng, X., Zheng, H., Niu, J., Han, G., and Hou, X.: China’s response to a national land-system sustainability emergency, *Nature*, 559, 193–204, <https://doi.org/10.1038/s41586-018-0280-2>, 2018.
- 485 Cao, J., Situ, S., Hao, Y., Xie, S., and Li, L.: Enhanced summertime ozone and SOA from biogenic volatile organic compound (BVOC) emissions due to vegetation biomass variability during 1981–2018 in China, *Atmos. Chem. Phys.*, 22, 2351–2364, <https://doi.org/10.5194/acp-22-2351-2022>, 2022.



- Cao, J., Han, H., Qiao, L., and Li, L.: Biogenic volatile organic compound emission and its response to land cover changes in China during 2001–2020 using an improved high-precision vegetation data set, *J. Geophys. Res.-Atmos.*, 129, e2023JD040421,
 490 <https://doi.org/10.1029/2023JD040421>, 2024.
- Chance, K.: OMI/Aura Formaldehyde (HCHO) Total Column Daily L3 Weighted Mean Global 0.1deg Lat/Lon Grid V003, NASA Goddard Earth Sciences Data and Information Services Center [data set],
<https://doi.org/10.5067/AURA/OMI/DATA3010>, 2019.
- Chen, C., Park, T., Wang, X., Piao, S., Xu, B., Chaturvedi, R. K., Fuchs, R., Brovkin, V., Ciais, P., Fensholt, R., Tømmervik,
 495 H., Bala, G., Zhu, Z., Nemani, R. R., and Myneni, R. B.: China and India lead in greening of the world through land-use management, *Nat. Sustain.*, 2, 122–129, <https://doi.org/10.1038/s41893-019-0220-7>, 2019.
- Chen, T. and Guestrin, C.: XGBoost: a scalable tree boosting system, in: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 785–794, <https://doi.org/10.1145/2939672.2939785>, 2016.
- Claeys, M., Graham, B., Vas, G., Wang, W., Vermeylen, R., Pashynska, V., Cafmeyer, J., Guyon, P., Andreae, M. O., Artaxo,
 500 P., and Maenhaut, W.: Formation of secondary organic aerosols through photooxidation of isoprene, *Science*, 303, 1173–1176, <https://doi.org/10.1126/science.1092805>, 2004.
- Cohen, J.: A coefficient of agreement for nominal scales, *Educ. Psychol. Meas.*, 20, 37–46, <https://doi.org/10.1177/001316446002000104>, 1960.
- Copernicus Climate Change Service: Land cover classification gridded maps from 1992 to present derived from satellite
 505 observations, Climate Data Store [data set], <https://doi.org/10.24381/cds.006f2c9a>, 2019 (last access: 3 August 2026).
- Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gascon, F., Hoersch, B., Isola, C., Laberinti, P., Martimort, P., Meygret, A., Spoto, F., Sy, O., Marchese, F., and Bargellini, P.: Sentinel-2: ESA's optical high-resolution mission for GMES operational services, *Remote Sens. Environ.*, 120, 25–36, <https://doi.org/10.1016/j.rse.2011.11.026>, 2012.
- EROS Center: Landsat 4–5 TM Level-2, Collection 2, U.S. Geological Survey [data set], <https://doi.org/10.5066/P9IAXOVV>,
 510 2020a.
- EROS Center: Landsat 7 ETM+ Level-2, Collection 2, U.S. Geological Survey [data set], <https://doi.org/10.5066/P9C7I13B>, 2020b.
- EROS Center: Landsat 8–9 OLI/TIRS Level-2, Collection 2, U.S. Geological Survey [data set], <https://doi.org/10.5066/P9OGBGM6>, 2020c.
- 515 Friedl, M. and Sulla-Menashe, D.: MCD12Q1 MODIS/Terra+Aqua Land Cover Type Yearly L3 Global 500 m SIN Grid V061, NASA EOSDIS Land Processes DAAC [data set], <https://doi.org/10.5067/MODIS/MCD12Q1.061>, 2022.
- Fu, Y. and Liao, H.: Simulation of the interannual variations of biogenic emissions of volatile organic compounds in China: impacts on tropospheric ozone and secondary organic aerosol, *Atmos. Environ.*, 59, 170–185, <https://doi.org/10.1016/j.atmosenv.2012.05.053>, 2012.



- 520 Fu, Y. and Liao, H.: Impacts of land use and land cover changes on biogenic emissions of volatile organic compounds in China from the late 1980s to the mid-2000s: implications for tropospheric ozone and secondary organic aerosol, *Tellus B*, 66, 24987, <https://doi.org/10.3402/tellusb.v66.24987>, 2014.
- Gai, Y., Sun, L., Fu, S., Zhu, C., Zhu, C., Li, R., Liu, Z., Wang, B., Wang, C., Yang, N., Li, J., Xu, C., and Yan, G.: Impact of greening trends on biogenic volatile organic compound emissions in China from 1985 to 2022: contributions of afforestation projects, *Sci. Total Environ.*, 929, 172551, <https://doi.org/10.1016/j.scitotenv.2024.172551>, 2024.
- 525 Geron, C., Owen, S., Guenther, A., Greenberg, J., Rasmussen, R., Bai, J.-H., Li, Q.-J., and Baker, B.: Volatile organic compounds from vegetation in southern Yunnan Province, China: emission rates and some potential regional implications, *Atmos. Environ.*, 40, 1759–1773, <https://doi.org/10.1016/j.atmosenv.2005.11.022>, 2006.
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., and Moore, R.: Google Earth Engine: planetary-scale geospatial analysis for everyone, *Remote Sens. Environ.*, 202, 18–27, <https://doi.org/10.1016/j.rse.2017.06.031>, 2017.
- 530 Guenther, A., Hewitt, C. N., Erickson, D., Fall, R., Geron, C., Graedel, T., Harley, P., Klinger, L., Lerdau, M., McKay, W. A., Pierce, T., Scholes, B., Steinbrecher, R., Tallamraju, R., Taylor, J., and Zimmerman, P.: A global model of natural volatile organic compound emissions, *J. Geophys. Res.-Atmos.*, 100, 8873–8892, <https://doi.org/10.1029/94JD02950>, 1995.
- Guenther, A., Karl, T., Harley, P., Wiedinmyer, C., Palmer, P. I., and Geron, C.: Estimates of global terrestrial isoprene emissions using MEGAN (Model of Emissions of Gases and Aerosols from Nature), *Atmos. Chem. Phys.*, 6, 3181–3210, <https://doi.org/10.5194/acp-6-3181-2006>, 2006.
- 535 Guenther, A. B., Jiang, X., Heald, C. L., Sakulyanontvittaya, T., Duhl, T., Emmons, L. K., and Wang, X.: The Model of Emissions of Gases and Aerosols from Nature version 2.1 (MEGAN2.1): an extended and updated framework for modeling biogenic emissions, *Geosci. Model Dev.*, 5, 1471–1492, <https://doi.org/10.5194/gmd-5-1471-2012>, 2012.
- 540 Han, H., Jia, Y., Shi, R., Nie, C., Kajii, Y., Wu, Y., and Li, L.: A localized plant species-specific BVOC emission rate library of China established using a developed statistical approach based on field measurements, *Atmos. Chem. Phys.*, 26, 1587–1604, <https://doi.org/10.5194/acp-26-1587-2026>, 2026.
- Han, Z., Zhang, R., Wang, Q., Wang, W., Cao, J., and Xu, J.: Regional modeling of organic aerosols over China in summertime, *J. Geophys. Res.-Atmos.*, 113, D11202, <https://doi.org/10.1029/2007JD009436>, 2008.
- 545 Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O., and Townshend, J. R. G.: High-resolution global maps of 21st-century forest cover change, *Science*, 342, 850–853, <https://doi.org/10.1126/science.1244693>, 2013.
- Huang, X., Li, J., Yang, J., Zhang, Z., Li, D., and Liu, X.: 30 m global impervious surface area dynamics and urban expansion pattern observed by Landsat satellites: from 1972 to 2019, *Sci. China Earth Sci.*, 64, 1922–1933, <https://doi.org/10.1007/s11430-020-9797-9>, 2021.
- 550 Huete, A., Didan, K., Miura, T., Rodriguez, E. P., Gao, X., and Ferreira, L. G.: Overview of the radiometric and biophysical performance of the MODIS vegetation indices, *Remote Sens. Environ.*, 83, 195–213, [https://doi.org/10.1016/S0034-4257\(02\)00096-2](https://doi.org/10.1016/S0034-4257(02)00096-2), 2002.



- Jacovides, C. P., Tymvios, F. S., Papaioannou, G., Asimakopoulos, D. N., and Theofilou, C. M.: Ratio of PAR to broadband solar radiation measured in Cyprus, *Agric. For. Meteorol.*, 121, 135–140, <https://doi.org/10.1016/j.agrformet.2003.10.001>, 2004.
- Jin, X. and Holloway, T.: Spatial and temporal variability of ozone sensitivity over China observed from the Ozone Monitoring Instrument, *J. Geophys. Res.-Atmos.*, 120, 7229–7246, <https://doi.org/10.1002/2015JD023250>, 2015.
- Klinger, L. F., Li, Q.-J., Guenther, A. B., Greenberg, J. P., Baker, B., and Bai, J.-H.: Assessment of volatile organic compound emissions from ecosystems of China, *J. Geophys. Res.-Atmos.*, 107, 4603, <https://doi.org/10.1029/2001JD001076>, 2002.
- Künsch, H. R.: The jackknife and the bootstrap for general stationary observations, *Ann. Stat.*, 17, 1217–1241, <https://doi.org/10.1214/aos/1176347265>, 1989.
- Lang, N., Jetz, W., Schindler, K., and Wegner, J. D.: A high-resolution canopy height model of the Earth, *Nat. Ecol. Evol.*, 7, 1778–1789, <https://doi.org/10.1038/s41559-023-02206-6>, 2023.
- Lelieveld, J., Butler, T. M., Crowley, J. N., Dillon, T. J., Fischer, H., Ganzeveld, L., Harder, H., Lawrence, M. G., Martinez, M., Taraborrelli, D., and Williams, J.: Atmospheric oxidation capacity sustained by a tropical forest, *Nature*, 452, 737–740, <https://doi.org/10.1038/nature06870>, 2008.
- Li, H., Ciais, P., Kumar, P., Hauglustaine, D. A., Chevallier, F., Broquet, G., Millet, D. B., Wells, K. C., Lian, J., and Zheng, B.: Global biogenic isoprene emissions 2013–2020 inferred from satellite isoprene observations, *Earth Syst. Sci. Data*, 17, 7035–7054, <https://doi.org/10.5194/essd-17-7035-2025>, 2025.
- Li, K., Jacob, D. J., Liao, H., Shen, L., Zhang, Q., and Bates, K. H.: Anthropogenic drivers of 2013–2017 trends in summer surface ozone in China, *Proc. Natl. Acad. Sci. USA*, 116, 422–427, <https://doi.org/10.1073/pnas.1812168116>, 2019.
- Li, L., Yang, W., Xie, S., and Wu, Y.: Estimations and uncertainty of biogenic volatile organic compound emission inventory in China for 2008–2018, *Sci. Total Environ.*, 733, 139301, <https://doi.org/10.1016/j.scitotenv.2020.139301>, 2020.
- Li, L., Cao, J., and Hao, Y.: Spatial and species-specific responses of biogenic volatile organic compound (BVOC) emissions to elevated ozone from 2014–2020 in China, *Sci. Total Environ.*, 868, 161636, <https://doi.org/10.1016/j.scitotenv.2023.161636>, 2023.
- Li, L. Y. and Xie, S. D.: Historical variations of biogenic volatile organic compound emission inventories in China, 1981–2003, *Atmos. Environ.*, 95, 185–196, <https://doi.org/10.1016/j.atmosenv.2014.06.033>, 2014.
- Li, L. Y., Chen, Y., and Xie, S. D.: Spatio-temporal variation of biogenic volatile organic compounds emissions in China, *Environ. Pollut.*, 182, 157–168, <https://doi.org/10.1016/j.envpol.2013.06.042>, 2013.
- Lin, Y.-H., Zhang, H., Pye, H. O. T., Zhang, Z., Marth, W. J., Park, S., Arashiro, M., Cui, T., Budisulistiorini, S. H., Sexton, K. G., Vizuete, W., Xie, Y., Luecken, D. J., Piletic, I. R., Edney, E. O., Bartolotti, L. J., Gold, A., and Surratt, J. D.: Epoxide as a precursor to secondary organic aerosol formation from isoprene photooxidation in the presence of nitrogen oxides, *Proc. Natl. Acad. Sci. USA*, 110, 6718–6723, <https://doi.org/10.1073/pnas.1221150110>, 2013.
- Liu, L., Zhang, X., and Zhao, T.: GLC_FCS30D: global land-cover dynamics with a fine classification system at 30 m in 1985–2022, Zenodo [data set], <https://doi.org/10.5281/zenodo.8239305>, 2023.



- Lundberg, S. M. and Lee, S.-I.: A unified approach to interpreting model predictions, *Adv. Neural Inf. Process. Syst.*, 30, 4765–4774, <https://proceedings.neurips.cc/paper/2017/hash/8a20a8621978632d76c43dfd28b67767-Abstract.html>, 2017.
- 590 Ma, J., Zhu, S., Wang, S., Wang, P., Chen, J., and Zhang, H.: Impacts of land cover changes on biogenic emission and its contribution to ozone and secondary organic aerosol in China, *Atmos. Chem. Phys.*, 23, 4311–4325, <https://doi.org/10.5194/acp-23-4311-2023>, 2023.
- Ma, M., Gao, Y., Wang, Y., Zhang, S., Leung, L. R., Liu, C., Wang, S., Zhao, B., Chang, X., Su, H., Zhang, T., Sheng, L., Yao, X., and Gao, H.: Substantial ozone enhancement over the North China Plain from increased biogenic emissions due to
- 595 heat waves and land cover in summer 2017, *Atmos. Chem. Phys.*, 19, 12195–12207, <https://doi.org/10.5194/acp-19-12195-2019>, 2019.
- Ma, M., Gao, Y., Ding, A., Su, H., Liao, H., Wang, S., Wang, X., Zhao, B., Zhang, S., Fu, P., Guenther, A. B., Wang, M., Li, S., Chu, B., Yao, X., and Gao, H.: Development and assessment of a high-resolution biogenic emission inventory from urban green spaces in China, *Environ. Sci. Technol.*, 56, 175–184, <https://doi.org/10.1021/acs.est.1c06170>, 2022.
- 600 McCree, K. J.: Test of current definitions of photosynthetically active radiation against leaf photosynthesis data, *Agric. Meteorol.*, 10, 443–453, [https://doi.org/10.1016/0002-1571\(72\)90045-3](https://doi.org/10.1016/0002-1571(72)90045-3), 1972.
- Mo, Z., Shao, M., Wang, W., Liu, Y., Wang, M., and Lu, S.: Evaluation of biogenic isoprene emissions and their contribution to ozone formation by ground-based measurements in Beijing, China, *Sci. Total Environ.*, 627, 1485–1494, <https://doi.org/10.1016/j.scitotenv.2018.01.336>, 2018.
- 605 Müller, J.-F., Stavrou, T., Oomen, G.-M., Opacka, B., De Smedt, I., Guenther, A., Vigouroux, C., Langerock, B., Aquino, C. A. B., Grutter, M., Hannigan, J., Hase, F., Kivi, R., Lutsch, E., Mahieu, E., Makarova, M., Metzger, J.-M., Morino, I., Murata, I., Nagahama, T., Notholt, J., Ortega, I., Palm, M., Röhlhng, A., Stremme, W., Strong, K., Sussmann, R., Té, Y., and Fried, A.: Bias correction of OMI HCHO columns based on FTIR and aircraft measurements and impact on top-down emission estimates, *Atmos. Chem. Phys.*, 24, 2207–2237, <https://doi.org/10.5194/acp-24-2207-2024>, 2024.
- 610 Muñoz Sabater, J.: ERA5-Land hourly data from 1950 to present, Copernicus Climate Change Service Climate Data Store [data set], <https://doi.org/10.24381/cds.e2161bac>, 2019 (last access: 3 August 2026).
- Muñoz-Sabater, J., Dutra, E., Agustí-Panareda, A., Albergel, C., Arduini, G., Balsamo, G., Boussetta, S., Choulga, M., Harrigan, S., Hersbach, H., Martens, B., Miralles, D. G., Piles, M., Rodríguez-Fernández, N. J., Zsoter, E., Buontempo, C., and Thépaut, J.-N.: ERA5-Land: a state-of-the-art global reanalysis dataset for land applications, *Earth Syst. Sci. Data*, 13,
- 615 4349–4383, <https://doi.org/10.5194/essd-13-4349-2021>, 2021.
- Myneni, R., Knyazikhin, Y., and Park, T.: MCD15A3H MODIS/Terra+Aqua Leaf Area Index/FPAR 4-Day L4 Global 500 m SIN Grid V061, NASA EOSDIS Land Processes DAAC [data set], <https://doi.org/10.5067/MODIS/MCD15A3H.061>, 2021a.
- Myneni, R., Knyazikhin, Y., and Park, T.: MOD15A2H MODIS/Terra Leaf Area Index/FPAR 8-Day L4 Global 500 m SIN Grid V061, NASA EOSDIS Land Processes DAAC [data set], <https://doi.org/10.5067/MODIS/MOD15A2H.061>, 2021b.
- 620 Myneni, R., Knyazikhin, Y., and Park, T.: MYD15A2H MODIS/Aqua Leaf Area Index/FPAR 8-Day L4 Global 500 m SIN Grid V061, NASA EOSDIS Land Processes DAAC [data set], <https://doi.org/10.5067/MODIS/MYD15A2H.061>, 2021c.



- Olofsson, P., Foody, G. M., Herold, M., Stehman, S. V., Woodcock, C. E., and Wulder, M. A.: Good practices for estimating area and assessing accuracy of land change, *Remote Sens. Environ.*, 148, 42–57, <https://doi.org/10.1016/j.rse.2014.02.015>, 2014.
- 625 Opacka, B. and Stavrakou, T.: MEGAN-MOHYCAN global isoprene emissions accounting for space-based land cover changes (ALBERIV2), Royal Belgian Institute for Space Aeronomy [data set], <https://doi.org/10.18758/B1PO4YRB>, 2026a.
- Opacka, B., Müller, J.-F., Stavrakou, T., Bauwens, M., Sindelarova, K., Markova, J., and Guenther, A. B.: Global and regional impacts of land cover changes on isoprene emissions derived from spaceborne data and the MEGAN model, *Atmos. Chem. Phys.*, 21, 8413–8436, <https://doi.org/10.5194/acp-21-8413-2021>, 2021.
- 630 Opacka, B., Stavrakou, T., and Müller, J.-F.: MEGAN-MOHYCAN isoprene emissions accounting for drought effects (CONCERTO bottom-up dataset), Royal Belgian Institute for Space Aeronomy [data set], <https://doi.org/10.18758/wsa1oabs>, 2026b.
- Paulot, F., Crounse, J. D., Kjaergaard, H. G., Kürten, A., St. Clair, J. M., Seinfeld, J. H., and Wennberg, P. O.: Unexpected epoxide formation in the gas-phase photooxidation of isoprene, *Science*, 325, 730–733, <https://doi.org/10.1126/science.1172910>, 2009.
- 635 Pfister, G. G., Emmons, L. K., Hess, P. G., Lamarque, J.-F., Orlando, J. J., Walters, S., Guenther, A., Palmer, P. I., and Lawrence, P. J.: Contribution of isoprene to chemical budgets: a model tracer study with the NCAR CTM MOZART-4, *J. Geophys. Res.-Atmos.*, 113, D05308, <https://doi.org/10.1029/2007JD008948>, 2008.
- Pianosi, F., Beven, K., Freer, J., Hall, J. W., Rougier, J., Stephenson, D. B., and Wagener, T.: Sensitivity analysis of environmental models: a systematic review with practical workflow, *Environ. Model. Softw.*, 79, 214–232, <https://doi.org/10.1016/j.envsoft.2016.02.008>, 2016.
- Politis, D. N. and Romano, J. P.: A circular block-resampling procedure for stationary data, in: *Exploring the Limits of Bootstrap*, edited by LePage, R. and Billard, L., Wiley, New York, 263–270, 1992.
- Ran, H., Lu, Y., Zhang, Y., and Wang, X.: Source data for: High-resolution land-cover dynamics reveal strong regional contrasts in China's biogenic isoprene emissions, 2000–2025, Zenodo [data set], <https://doi.org/10.5281/zenodo.22090178>, 2026.
- 645 Rikimaru, A., Roy, P. S., and Miyatake, S.: Tropical forest cover density mapping, *Trop. Ecol.*, 43, 39–47, 2002.
- Roberts, D. R., Bahn, V., Ciuti, S., Boyce, M. S., Elith, J., Guillera-Arroita, G., Hauenstein, S., Lahoz-Monfort, J. J., Schröder, B., Thuiller, W., Warton, D. I., Wintle, B. A., Hartig, F., and Dormann, C. F.: Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure, *Ecography*, 40, 913–929, <https://doi.org/10.1111/ecog.02881>, 2017.
- 650 Sen, P. K.: Estimates of the regression coefficient based on Kendall's tau, *J. Am. Stat. Assoc.*, 63, 1379–1389, <https://doi.org/10.1080/01621459.1968.10480934>, 1968.
- Sfendla, Y., Stavrakou, T., Müller, J.-F., Oomen, G.-M., Opacka, B., Danckaert, T., De Smedt, I., and Lerot, C.: Global VOC emissions quantified from inversion of TROPOMI spaceborne formaldehyde and glyoxal data, *Atmos. Chem. Phys.*, 26, 733–767, <https://doi.org/10.5194/acp-26-733-2026>, 2026.



- Shapley, L. S.: A value for n -person games, in: Contributions to the Theory of Games II, edited by Kuhn, H. W. and Tucker, A. W., Princeton University Press, Princeton, 307–317, 1953.
- Sillman, S.: The relation between ozone, NO_x and hydrocarbons in urban and polluted rural environments, *Atmos. Environ.*, 33, 1821–1845, [https://doi.org/10.1016/S1352-2310\(98\)00345-8](https://doi.org/10.1016/S1352-2310(98)00345-8), 1999.
- 660 Sindelarova, K., Granier, C., Bouarar, I., Guenther, A., Tilmes, S., Stavrakou, T., Müller, J.-F., Kuhn, U., Stefani, P., and Knorr, W.: Global data set of biogenic VOC emissions calculated by MEGAN over the last 30 years, *Atmos. Chem. Phys.*, 14, 9317–9341, <https://doi.org/10.5194/acp-14-9317-2014>, 2014.
- Sindelarova, K., Markova, J., Simpson, D., Huszar, P., Karlicky, J., Darras, S., and Granier, C.: High-resolution biogenic global emission inventory for the time period 2000–2019 for air quality modelling, *Earth Syst. Sci. Data*, 14, 251–270, <https://doi.org/10.5194/essd-14-251-2022>, 2022.
- 665 Sokolova, M. and Lapalme, G.: A systematic analysis of performance measures for classification tasks, *Inf. Process. Manage.*, 45, 427–437, <https://doi.org/10.1016/j.ipm.2009.03.002>, 2009.
- Stanimirova, R., Tarrio, K., Turlej, K., McAvoy, K., Stonebrook, S., Hu, K.-T., Arévalo, P., Bullock, E. L., Zhang, Y., Woodcock, C. E., Olofsson, P., Zhu, Z., Barber, C. P., Souza, C. M., Chen, S., Wang, J. A., Mensah, F., Calderón-Loor, M.,
- 670 Hadjikakou, M., Bryan, B. A., Graesser, J., Beyene, D. L., Mutasha, B., Siame, S., Siampale, A., and Friedl, M. A.: A global land cover training dataset from 1984 to 2020, *Sci. Data*, 10, 879, <https://doi.org/10.1038/s41597-023-02798-5>, 2023.
- Stavrakou, T., Müller, J.-F., Bauwens, M., De Smedt, I., Van Roozendaal, M., Guenther, A., Wild, M., and Xia, X.: Isoprene emissions over Asia 1979–2012: impact of climate and land-use changes, *Atmos. Chem. Phys.*, 14, 4587–4605, <https://doi.org/10.5194/acp-14-4587-2014>, 2014.
- 675 Sun, C., Zhou, T., Han, H., Wang, X., Jiang, Y., and Li, L.: Summertime biogenic volatile organic compounds in China: emissions and their modulation on O_3 and $\text{PM}_{2.5}$ pollution, *Atmosphere*, 17, 473, <https://doi.org/10.3390/atmos17050473>, 2026.
- Theil, H.: A rank-invariant method of linear and polynomial regression analysis, I, II, III, *Nederl. Akad. Wetensch. Proc.*, 53, 386–392, 521–525, and 1397–1412, 1950.
- Tie, X., Li, G., Ying, Z., Guenther, A., and Madronich, S.: Biogenic emissions of isoprenoids and NO in China and comparison
- 680 to anthropogenic emissions, *Sci. Total Environ.*, 371, 238–251, <https://doi.org/10.1016/j.scitotenv.2006.06.025>, 2006.
- Tucker, C. J.: Red and photographic infrared linear combinations for monitoring vegetation, *Remote Sens. Environ.*, 8, 127–150, [https://doi.org/10.1016/0034-4257\(79\)90013-0](https://doi.org/10.1016/0034-4257(79)90013-0), 1979.
- Wang, H., Wu, Q., Liu, H., Wang, Y., Cheng, H., Wang, R., Wang, L., Xiao, H., and Yang, X.: Sensitivity of biogenic volatile organic compound emissions to leaf area index and land cover in Beijing, *Atmos. Chem. Phys.*, 18, 9583–9596, <https://doi.org/10.5194/acp-18-9583-2018>, 2018.
- 685 Wang, H., Wu, Q., Guenther, A. B., Yang, X., Wang, L., Xiao, T., Li, J., Feng, J., Xu, Q., and Cheng, H.: A long-term estimation of biogenic volatile organic compound (BVOC) emission in China from 2001–2016: the roles of land cover change and climate variability, *Atmos. Chem. Phys.*, 21, 4825–4848, <https://doi.org/10.5194/acp-21-4825-2021>, 2021.



- Wang, H., Liu, X., Wu, C., and Lin, G.: Regional to global distributions, trends, and drivers of biogenic volatile organic
690 compound emission from 2001 to 2020, *Atmos. Chem. Phys.*, 24, 3309–3328, <https://doi.org/10.5194/acp-24-3309-2024>, 2024.
- Wang, N., Liu, S., Xu, J., Wang, Y., Li, C., Xie, Y., Lu, H., and Yang, F.: Climate-driven biogenic emissions alleviate the
impact of human-made emission reductions on O₃ control in the Pearl River Delta region, southern China, *Atmos. Chem. Phys.*,
25, 8859–8870, <https://doi.org/10.5194/acp-25-8859-2025>, 2025.
- Wang, W., Li, X., Cheng, Y., Parrish, D. D., Ni, R., Tan, Z., Liu, Y., Lu, S., Wu, Y., Chen, S., Lu, K., Hu, M., Zeng, L., Shao,
695 M., Huang, C., Tian, X., Leung, K. M., Chen, L., Fan, M., Zhang, Q., Rohrer, F., Wahner, A., Pöschl, U., Su, H., and Zhang,
Y.: Ozone pollution mitigation strategy informed by long-term trends of atmospheric oxidation capacity, *Nat. Geosci.*, 17, 20–
25, <https://doi.org/10.1038/s41561-023-01334-9>, 2024.
- Wells, K. C., Millet, D. B., Payne, V. H., Deventer, M. J., Bates, K. H., de Gouw, J. A., Graus, M., Warneke, C., Wisthaler,
A., and Fuentes, J. D.: Satellite isoprene retrievals constrain emissions and atmospheric oxidation, *Nature*, 585, 225–233,
700 <https://doi.org/10.1038/s41586-020-2664-3>, 2020.
- Woo, J.-H., Kim, Y., Kim, H.-K., Choi, K.-C., Eum, J.-H., Lee, J.-B., Lim, J.-H., Kim, J., and Seong, M.: Development of the
CREATE inventory in support of integrated climate and air quality modeling for Asia, *Sustainability*, 12, 7930,
<https://doi.org/10.3390/su12197930>, 2020.
- Wu, K., Yang, X., Chen, D., Gu, S., Lu, Y., Jiang, Q., Wang, K., Ou, Y., Qian, Y., Shao, P., and Lu, S.: Estimation of biogenic
705 VOC emissions and their corresponding impact on ozone and secondary organic aerosol formation in China, *Atmos. Res.*, 231,
104656, <https://doi.org/10.1016/j.atmosres.2019.104656>, 2020.
- Xu, H.: Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery,
Int. J. Remote Sens., 27, 3025–3033, <https://doi.org/10.1080/01431160600589179>, 2006.
- Xu, H., Zhang, J., Chen, Y., Zhou, Y., Qiao, F., Huang, H., Fan, L., and Ye, D.: A BVOC emission inventory for China in
710 2023 and its impacts on ozone and secondary organic aerosol formation, *Atmosphere*, 17, 386,
<https://doi.org/10.3390/atmos17040386>, 2026.
- Zanaga, D., Van De Kerchove, R., De Keersmaecker, W., Souverijns, N., Brockmann, C., Quast, R., Wevers, J., Grosu, A.,
Paccini, A., Vergnaud, S., Cartus, O., Santoro, M., Fritz, S., Georgieva, I., Lesiv, M., Carter, S., Herold, M., Li, L., Tsendbazar,
N.-E., Ramoino, F., and Arino, O.: ESA WorldCover 10 m 2020 v100, Zenodo [data set],
715 <https://doi.org/10.5281/zenodo.5571936>, 2021.
- Zha, Y., Gao, J., and Ni, S.: Use of normalized difference built-up index in automatically mapping urban areas from TM
imagery, *Int. J. Remote Sens.*, 24, 583–594, <https://doi.org/10.1080/01431160304987>, 2003.
- Zhang, X., Huang, T., Zhang, L., Shen, Y., Zhao, Y., Gao, H., Mao, X., Jia, C., and Ma, J.: Three-North Shelter Forest Program
contribution to long-term increasing trends of biogenic isoprene emissions in northern China, *Atmos. Chem. Phys.*, 16, 6949–
720 6960, <https://doi.org/10.5194/acp-16-6949-2016>, 2016.
- Zhang, X., Zhao, T., Xu, H., Liu, W., Wang, J., Chen, X., and Liu, L.: GLC_FCS30D: the first global 30 m land-cover dynamics
monitoring product with a fine classification system for the period from 1985 to 2022 generated using dense-time-series



- Landsat imagery and the continuous change-detection method, *Earth Syst. Sci. Data*, 16, 1353–1381, <https://doi.org/10.5194/essd-16-1353-2024>, 2024.
- 725 Zhang, Y., Zhang, R., Yu, J., Zhang, Z., Yang, W., Zhang, H., Lyu, S., Wang, Y., Dai, W., Wang, Y., and Wang, X.: Isoprene mixing ratios measured at twenty sites in China during 2012–2014: comparison with model simulation, *J. Geophys. Res.-Atmos.*, 125, e2020JD033523, <https://doi.org/10.1029/2020JD033523>, 2020.
- Zhang, Y., Ran, H., Guenther, A., Zhang, Q., George, C., Mellouki, W., Sheng, G., Peng, P., and Wang, X.: Improved modelling of biogenic emissions in human-disturbed forest edges and urban areas, *Nat. Commun.*, 16, 8064, 730 <https://doi.org/10.1038/s41467-025-63437-8>, 2025.