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Abstract

Long-term, spatially detailed land surface temperature (LST) records are needed to compare thermal environments across heterogeneous landscapes, but combining fine spatial detail with nationwide coverage over decades remains challenging. We present ChinaTherm30, annual 30 m leaf-on daytime LST composites across China for 2000–2024. Quality-screened Terra MODIS thermal targets were combined with annual Landsat optical indices, topography and geographic coordinates in a cross-year random forest, followed by low-frequency residual adjustment. Spatial-block validation of the random forest yielded a correlation of 0.904 and an RMSE of 3.967 °C. The median annual nationwide correlation with Landsat 8 LST during 2013–2024 was 0.864. Ground evaluation across 23 sites and 131 site-years, predominantly in the Heihe basin, yielded a correlation of 0.840 and an RMSE of 5.397 °C. Independent unmanned aerial vehicle thermal imagery further evaluated local spatial patterns. The record supports long-term comparisons of leaf-on daytime thermal environments in urban, agricultural and vegetated landscapes.

Keywords: ChinaTherm30; land surface temperature; statistical downscaling; random forest; MODIS; Landsat; China; data record

1 Background & Summary

Land surface temperature (LST) describes the radiative thermal state of the land surface and is a key variable for understanding surface energy exchange and the water cycle^{1–3}. Solar radiation, water availability and land cover jointly influence the partitioning of sensible and latent heat, producing thermal contrasts among landscapes⁴. Leaf emergence, growth and senescence further alter canopy structure and its exchanges of heat and water with the atmosphere, giving surface thermal conditions a pronounced seasonal character⁵. Long-term satellite observations capture these contrasts from regional to continental scales and provide a spatial basis for studying the relationship between land cover and surface thermal environments.

During the leaf-on season, canopy development and water availability jointly influence evaporative cooling, linking LST to vegetation growth and water status⁴. Temperature contrasts between cropland and

surrounding surfaces therefore provide useful information on irrigation and crop-growing environments⁶, while contrasts between urban vegetation and built-up areas have also attracted substantial attention^{7,8}. Annual LST records focused on this season can support studies of cropland and oasis thermal environments, temperature differences around urban green spaces, and the relationship between vegetation cover and regional thermal patterns. The timing of vegetation growth varies among climatic regions⁵; a fixed seasonal window provides a common date range for comparing spatial thermal patterns across years.

Existing LST products provide extensive observations, but long-term coverage, temporal sampling and spatial detail remain difficult to achieve together. Kilometre-scale MODIS products frequently observe the regional thermal background^{9,10}, yet individual pixels often contain cropland, buildings, vegetation and bare ground. The Landsat archive spans several decades of finer-resolution thermal infrared observations, with native thermal-band resolutions of 120 m for Landsat 5, 60 m for Landsat 7 and 100 m for Landsat 8/9¹¹. Collection 2 surface temperature and 30 m gridded products for mainland China have advanced fine-scale thermal mapping over large areas^{12–14}. However, cloud cover, limited revisit frequency and intersensor differences lead to uneven annual distributions of valid observations, requiring reconstruction and compositing for long-term records¹⁵. Thermal sharpening and spatiotemporal fusion use finer-resolution auxiliary imagery to supplement spatial information^{16,17}. Applying these approaches to a long-term national annual record also requires continuous fine-scale inputs and clearly defined seasonal selection and compositing procedures.

This study combines long-term Terra MODIS thermal observations with 30 m annual leaf-on Landsat surface reflectance composites from the China Earth Observation Data Cube¹⁸. The latter provide six bands—blue, green, red, near-infrared and two shortwave-infrared bands—from which we calculate optical indices. These indices, together with topographic and geographic variables, describe annual spatial differences in surface conditions. Annual thermal targets are constructed as the pixelwise median of quality-screened MODIS eight-day daytime composites whose nominal start dates fall within day of year (DOY) 150–300. The optical inputs are leaf-on composites, whereas the LST temporal window is explicitly defined by these dates. Random forest regression relates the annual thermal targets to surface predictors matched to the target spatial support^{19,20}. A single cross-year model produces a 30 m temperature baseline, and smoothed kilometre-scale residuals then adjust the regional thermal background, combining annual thermal observations with local surface information.

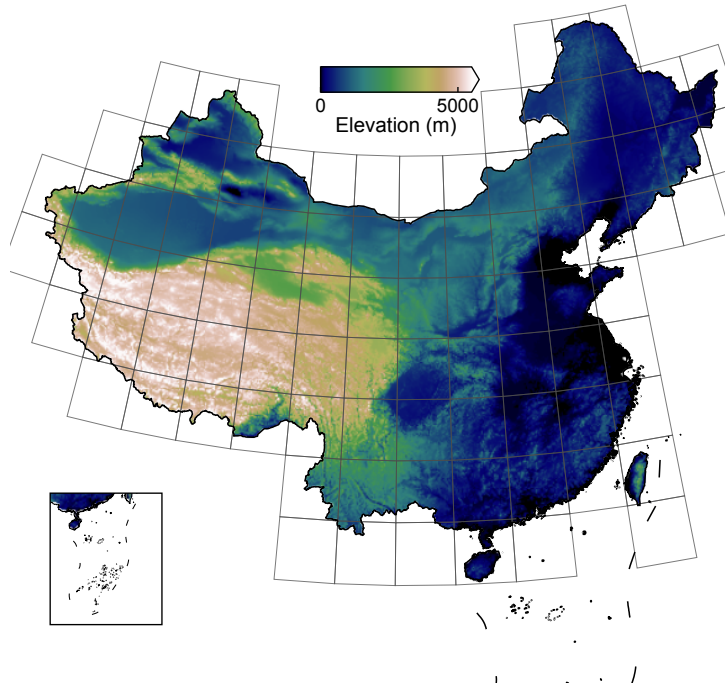
We release ChinaTherm30, a record of annual 30 m leaf-on daytime LST composites across China for 2000–2024, comprising 25 annual products with 91 tiles of 4° by 4° per year. A common model and compositing procedure provide a long-term spatial record for studying the seasonal thermal environments of vegetation, cropland and urban landscapes. Blocked validation, cross-scale consistency analysis, and comparisons with Landsat 8, unmanned aerial vehicle (UAV) imagery and ground observations predominantly from the Heihe basin evaluate model generalization, national temperature patterns and local thermal conditions. Cases from the new urban districts of Yan’an and Lanzhou illustrate long-term thermal changes accompanying landscape development.

2 Methods

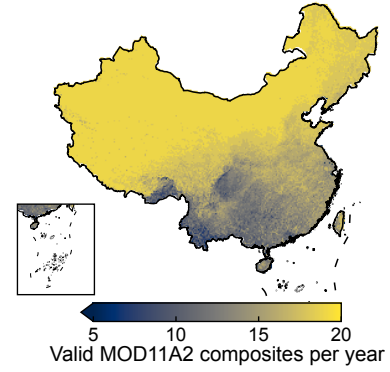
2.1 Study domain and target definition

The record covers land areas across China from 2000 to 2024. Outputs follow the 4° latitude–longitude tiling scheme of the China Earth Observation Data Cube, with 91 tiles per year (Fig. 1a). Annual thermal targets were derived from the LST_Day_1km and QC_Day bands of the Earth Engine collection MODIS/061/MOD11A2. MOD11A2 V061 provides the simple average of the corresponding daily MOD11A1 LST values within each eight-day period on an approximately 1 km grid^{9,21,22}.

a Study area and 4° product tiles



b Median valid 8-day composites



c Annual MOD11A2 data support

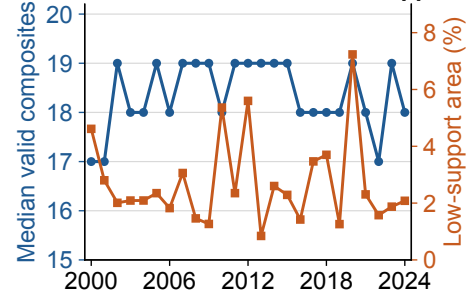


Figure 1: Study area, tiling scheme and observational support for the thermal target. a, Topography of China and the 91 output tiles of 4° by 4°. b, Multiyear median of the annual number of valid daytime eight-day thermal composites at each pixel during 2000–2024. c, Annual numbers of valid eight-day thermal composites and the proportion of land area with low observational support across China.

For each year, images were selected by nominal start dates within DOY 150–300. Pixels were retained when the two least significant bits of QC_Day were 00 or 01, indicating that LST was produced with good or other quality, respectively. In the standard eight-day sequence, this selection corresponds to 19 composites starting on DOY 153, 161, ..., 297; the last eight-day window may extend to DOY 304. Values in LST_Day_1km were multiplied by 0.02 to obtain kelvin and then converted to degrees Celsius by subtracting 273.15. The annual target was the pixelwise median of the retained eight-day mean LST values. Each annual value therefore summarizes the median thermal state represented by up to 19 candidate eight-day periods; hereafter, it is termed the kilometre-scale annual thermal target.

National statistics were restricted to land within China. The 30 m non-water pixels from JRC Global Surface Water were aggregated to the 0.01° grid, and cells with a land fraction of at least 50% were defined as land for that year. Cells meeting this threshold in every year during 2000–2021 formed the common stable-land domain. Annual land status for 2022–2024 followed the 2021 result. Cross-year statistics and independent satellite comparisons used this common stable-land domain.

For regional statistics, the China eco-geographical regionalization was aggregated into six macroregions: the Tibetan Plateau (TP), Northeast China (NEC), North China–Loess Plateau (NCLP), Arid Northwest (ANW), Humid Southeast (HSE) and Southwest Mountains (SWM). Their boundaries are shown in Supplementary Fig. S1. These abbreviations are used throughout the text and figures.

2.2 Input data

The annual seamless leaf-on Landsat composites from the China Earth Observation Data Cube provide 30 m surface reflectance in six bands: blue, green, red, near-infrared and two shortwave-infrared bands¹⁸. Let the cross-sensor-harmonized, TM-equivalent reflectances be ρ_B , ρ_G , ρ_R , ρ_{NIR} , ρ_{SWIR1} and ρ_{SWIR2} . The normalized difference vegetation index (NDVI) and tasseled-cap wetness (WET) were calculated as follows^{23–26}:

$$NDVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R}, \quad (1)$$

$$WET = 0.0315\rho_B + 0.2021\rho_G + 0.3102\rho_R + 0.1594\rho_{NIR} - 0.6806\rho_{SWIR1} - 0.6109\rho_{SWIR2}. \quad (2)$$

The normalized difference built-up and soil index (NDBSI) was the arithmetic mean of the soil index (SI) and the index-based built-up index (IBI):

$$SI = \frac{(\rho_{SWIR1} + \rho_R) - (\rho_{NIR} + \rho_B)}{(\rho_{SWIR1} + \rho_R) + (\rho_{NIR} + \rho_B)}, \quad (3)$$

$$D = \frac{2\rho_{SWIR1}}{\rho_{SWIR1} + \rho_{NIR}}, \quad V = \frac{\rho_{NIR}}{\rho_{NIR} + \rho_R} + \frac{\rho_G}{\rho_G + \rho_{SWIR1}}, \quad (4)$$

$$IBI = \frac{D - V}{D + V}, \quad NDBSI = \frac{SI + IBI}{2}. \quad (5)$$

Static topographic predictors were obtained from the Copernicus DEM GLO-30 collection in Earth Engine, a global digital surface model with approximately 30 m spacing. Elevation was mosaicked, aligned to the output grid and stored in 4° tiles; slope was derived from the same elevation surface²⁷. Longitude and latitude were taken at the centres of the 30 m pixels to describe large-scale geographic variation. Terra eight-day daytime LST supplied the annual thermal targets and residual-adjustment fields. JRC Global Surface Water provided annual water status and the common stable-land domain²⁸. The principal inputs and their uses are summarized in Table 1.

2.3 Predictors and training samples

To match the spatial support of the thermal target, NDVI, WET, NDBSI, elevation and slope were first aggregated by area averaging to the 0.01° target grid for each year and tile. Longitude and latitude were evaluated at grid-cell centres. Candidate samples required complete values for all seven predictors and a valid annual thermal target. Stratified random sampling was then performed by year and 4° tile. A fully covered tile had a baseline quota of 500 samples; this quota was reduced in proportion to the fraction of valid target pixels in the tile, rounded to an integer and capped by the number of eligible pixels. This procedure yielded 1,026,617 training records. The response variable was the annual thermal target at the same 0.01° grid cell as the predictors. Training samples were drawn from all 91 rectangular tiles without an additional water mask. Statistics and independent evaluations over Chinese land used the annual or common stable-land domains defined in Section 2.1.

2.4 Random forest spatial downscaling

Samples from all 25 years were combined to train a single random forest regressor²⁹, providing a shared predictor–temperature relationship for the annual products. The model contained 100 regression trees with a maximum depth of 25 and a minimum of one sample per leaf. All predictors were available at each split, bootstrap sampling was enabled, and the random seed was fixed at 42. This configuration balanced model capacity against the computational cost of national 30 m inference; sensitivity to tree number and depth was evaluated using the same spatial test folds. The trained model was applied pixel by pixel to the

Table 1: Principal input datasets for production and evaluation.

Dataset	Nominal resolution	Period	Use
Annual seamless leaf-on Landsat six-band surface reflectance composites	30 m	2000–2024	Calculation of NDVI, WET and NDBSI predictors
MODIS Terra MOD11A2 V061 eight-day daytime LST	1 km; 8 days	2000–2024	Annual median targets and low-frequency residual reference
Copernicus DEM GLO-30 elevation and derived slope	30 m	Static	Topographic predictors
Longitude and latitude	30 m grid	Static	Geographic predictors
JRC Global Surface Water	30 m	2000–2021	Annual water status, land domains and quality control
Landsat 8 Collection 2 Level-2 surface temperature	30 m grid	2013–2024	Nationwide spatially stratified independent evaluation
Landsat 5/7/8 Collection 2 surface reflectance	30 m	2000–2024	Optical imagery and NDVI series for the case studies
Heihe UAV thermal infrared brightness temperature	0.4 m	2020	Local spatial-structure evaluation
Automatic-station surface infrared radiometric temperature from the National Cryosphere Desert Data Center	Point	2008–2024	Independent annual ground evaluation across sites

seven predictors from each year’s original 30 m optical and topographic tiles to generate the random forest baseline, RF-LST.

Model evaluation began with a random 70% training and 30% test split using seed 42. To assess spatial and temporal generalization, the 91 tiles were grouped into five spatial folds by k -means clustering of their centre coordinates, while 2000–2024 was divided into five consecutive five-year temporal folds. Spatial and temporal blocked tests each held out one complete fold. In the joint spatiotemporal tests, the intersection of spatial and temporal folds with the same index formed the test set; both the corresponding spatial fold and temporal fold were excluded from training. This design follows structured cross-validation principles for spatially and temporally correlated data^{30–32}. Evaluation metrics were R^2 , Pearson correlation, root mean square error (RMSE), mean absolute error (MAE) and bias. Models without longitude and latitude, and configurations with different tree numbers and depths, were compared on the same spatial folds. Feature importance in the complete model was calculated from normalized decreases in impurity.

2.5 Low-frequency residual adjustment

To calibrate the regional thermal background, RF-LST was first aggregated to the 0.01° grid by averaging valid pixels. The kilometre-scale residual for year y was

$$r_y = M_y - A(T_y^{\text{RF}}), \quad (6)$$

where M_y is the annual thermal target and $A(\cdot)$ denotes aggregation from the 30 m grid to the 0.01° grid. Let I_y indicate valid residual cells within China. The smoothed adjustment field was calculated by normalized Gaussian convolution:

$$c_y = \frac{G_{\sigma=10} * (I_y r_y)}{G_{\sigma=10} * I_y}. \quad (7)$$

The Gaussian kernel had a standard deviation of ten 0.01° grid cells and a truncation radius of 2.5σ . Weight normalization allowed neighbouring valid residuals to determine the adjustment near missing-data boundaries. The smoothed field was bilinearly resampled to 30 m and added to the baseline:

$$T_y^{\text{CT30}} = T_y^{\text{RF}} + U(c_y), \quad (8)$$

where $U(\cdot)$ denotes resampling. Residuals were added wherever the adjustment field was available; elsewhere, the original RF-LST values were retained, preserving the valid-pixel domain. The adjusted result forms the core LST layer of ChinaTherm30. The smooth field corrects broad-scale temperature offsets, while local 30 m differences remain determined by the random forest baseline and its fine-resolution predictors.

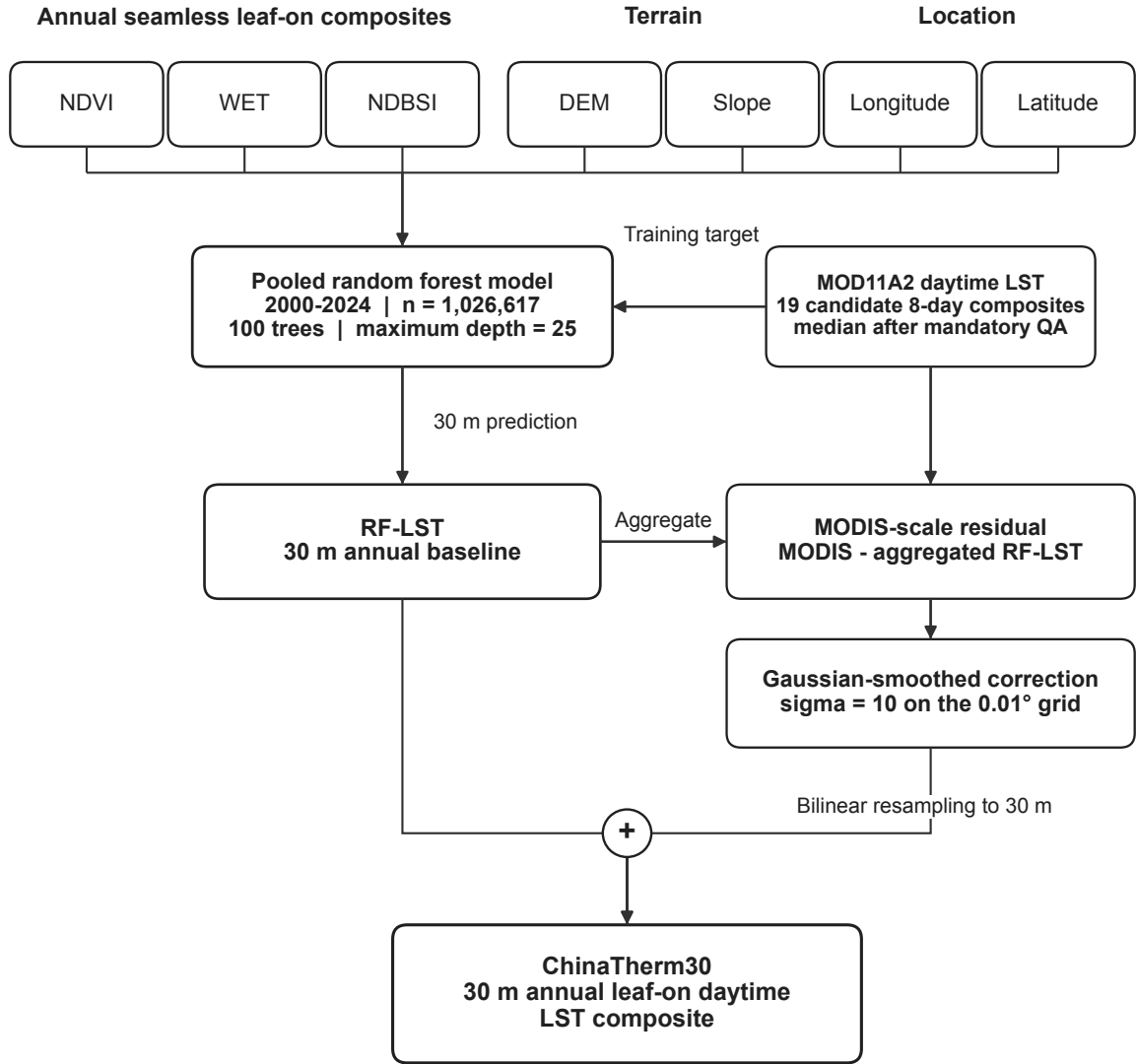


Figure 2: Production workflow for ChinaTherm30. Leaf-on NDVI, WET and NDBSI calculated from six-band surface reflectance composites enter the cross-year random forest together with Copernicus DEM GLO-30 elevation, slope, longitude and latitude. The pixelwise median of quality-screened observations from 19 candidate eight-day daytime composites provides the kilometre-scale annual training target. The random forest generates RF-LST. Residuals between the annual thermal target and aggregated RF-LST are Gaussian-smoothed, resampled to 30 m and added to RF-LST to produce the core ChinaTherm30 LST layer.

2.6 Independent observation-based evaluation

2.6.1 Spatial consistency with Landsat 8 surface temperature

The nationwide satellite comparison used Landsat 8 OLI/TIRS Collection 2 Tier 1 Level-2 surface temperature for 2013–2024^{12,13,33}. Observations of ST_B10 within DOY 150–300 were converted to degrees Celsius using $T = DN \times 0.00341802 + 149.0 - 273.15$. The QA_PIXEL band excluded fill, dilated cloud, cirrus, cloud, cloud shadow, snow and water pixels, and QA_RADSAT excluded radiometric saturation. Strict screening additionally required $ST_QA \leq 5$ K and $ST_CDIST \geq 1$ km. Scene temperatures were bilinearly re-sampled to a common 120 m grid, with nearest-neighbour resampling for quality masks. Annual reference values were the median of valid scene temperatures at each grid cell.

A fixed set of 20,000 candidate points was selected from the common stable-land domain, stratified by 4° tile, macroregion and elevation band. Comparisons used the mean of valid ChinaTherm30 pixels within a 3×3 neighbourhood. Each annual pair required at least three strictly quality-screened Landsat 8 observations and a neighbourhood water fraction no greater than 10%. Eligible paired samples were selected separately for each year. Area weights restored each stratum's represented area within the common stable-land domain. Confidence intervals were estimated with 2,000 bootstrap replicates over 2° spatial blocks for each year. Supplementary Figs. S2 and S3 describe the sample distribution and annual support of an additional multisensor Landsat 5/7/8/9 comparison for 2000–2024. That comparison used the same date window and quality thresholds, combining valid observations from the different sensors before calculating annual medians.

2.6.2 UAV thermal spatial-structure evaluation

The UAV evaluation used 0.4 m thermal infrared brightness-temperature orthomosaics acquired in the middle Heihe basin in 2020 from the MUSOES-UAV dataset^{34,35}. Three scenes over Daman cropland were acquired on 13 July, 20 August and 19 September; four over Huazhaizi desert were acquired on 14 July, 20 August, 19 September and 20 October; and four over the wetland were acquired on 14 July, 21 August, 20 September and 21 October.

Each scene was aggregated by area averaging to the ChinaTherm30 grid, with additional aggregation to 90 and 300 m. Individual scenes were compared using spatial Pearson correlation and centred RMSE. UAV imagery records conditions during a single flight, whereas ChinaTherm30 represents an annual leaf-on composite. To compare spatial patterns, each UAV scene was standardized spatially, and a pixelwise median across dates was calculated for each site and compared with spatially standardized ChinaTherm30. High-frequency components were obtained by subtracting a Gaussian low-pass field with a standard deviation of four 30 m pixels from the original image.

2.6.3 Ground infrared radiometric temperature evaluation

Ground evaluation used station-year datasets from automatic stations in the Heihe and Haihe basins released by the [National Cryosphere Desert Data Center \(NCDC\)](#). Entries were grouped by station and observation year; temporal coverage is given in Supplementary Table S1. Heihe station metadata follow the 23-station hydrometeorological network described by Liu et al.³⁶, spanning the upper, middle and lower reaches and including alpine meadows, forests, cropland, wetlands and deserts. The evaluation design was informed by established error sources and reporting practices for ground validation of satellite LST^{37,38}.

Station timestamps were interpreted as China Standard Time and converted to local mean solar time using station longitude. The primary protocol selected observations within ±30 min of Terra's nominal 10:30 overpass. When both infrared radiometric temperature (IRT) sensors were valid, their readings were

averaged; paired observations differing by more than 5 °C were rejected, while a single valid sensor was retained when the other was unavailable. Daily medians were calculated within the time window and assigned to MOD11A2 eight-day bins with nominal start dates within DOY 150–300. Valid daily values were averaged within each bin, and the annual ground composite was the median of the eight-day means. A clear-sky index derived from downward shortwave radiation was required to satisfy $K \geq 0.65$, and each site-year required at least eight valid eight-day bins. All-sky conditions, $K \geq 0.60$, and ± 60 and ± 90 min windows were examined in sensitivity tests.

The temporal, clear-sky and eight-day coverage filters yielded 145 candidate site-years. Ground-reference consistency screening further required the site-year median of daily absolute paired-IRT differences to be no greater than 5 °C. Site-years lacking a dual-sensor diagnostic were retained if they met the other observation criteria. The resulting evaluation included 23 sites and 131 site-years; site-year diagnostics are provided in Supplementary Figs. S5–S6 and Table S3.

Colocated ChinaTherm30 values were extracted for the centre pixel and as medians over 3×3 , 5×5 , 9×9 and 33×33 neighbourhoods. Centre pixels provided direct comparisons, while the neighbourhood sequence assessed spatial-support differences associated with point IRT measurements, pixel geolocation and surface heterogeneity^{39–42}. The predefined 3×3 neighbourhood was used for overall statistics; the remaining scales supported sensitivity analysis. Metrics included Pearson correlation, RMSE, MAE and bias. Overall uncertainty was estimated using 2,000 bootstrap replicates clustered by site, with additional site-level and sub-basin results. Station metadata, coverage and processing definitions are provided in Supplementary Fig. S4 and Tables S1–S2.

2.7 Case studies of landscape change

The case studies cover Yan'an New District and its surrounding loess hills (109.435–109.570°E, 36.605–36.705°N) and part of Lanzhou New Area (103.600–103.730°E, 36.480–36.600°N). Analysis zones were delineated from construction extents and contiguous landscape patches in historical optical imagery. Yan'an includes the main construction zone Y1 and surrounding hills Y2, the latter comprising three polygons. Lanzhou includes the main built-up zone L1, western cropland L2 and airport window L3.

Temperature statistics used a fixed set of pixels with valid ChinaTherm30 observations in all 25 years and non-water status in every available annual water mask during 2000–2021. Annual zonal means were weighted by actual pixel area. NDVI additionally required valid observations covering at least 80% of each zone. Equal-weight averages across years were calculated for 2000–2004, 2010–2014 and 2020–2024. Temperature-difference maps compared the early and middle periods, the middle and recent periods, and the early and recent periods, alongside the complete annual series for 2000–2024.

3 Data Records

ChinaTherm30 contains 25 annual LST products for 2000–2024, each comprising 91 tiles of 4° by 4°. The record consists of 2,275 single-band GeoTIFF files with a total size of approximately 611.03 GiB. The GeoTIFFs use Deflate compression. ScienceDB provides 25 annual TAR archives, together with an English README and data dictionary⁴³.

The GeoTIFFs use the EPSG:4326 coordinate reference system and an angular pixel spacing of approximately 0.0002695°. Values are stored as Int16, with a scale factor of 0.01 °C and a NoData value of –32768. Filenames identify the product year and the integer longitude and latitude of the tile's western and southern edges. Field definitions are provided in the accompanying data dictionary.

The scientific domain is land within China. The core files retain rectangular tiles for mosaicking, so water areas and portions of boundary tiles outside China may contain model outputs; land statistics require

the corresponding national and land boundaries. Figure 3 shows the national distributions for 2000 and 2024 and progressively finer views of western Sichuan and Beijing, from 4° tiles to local 30 m patterns.

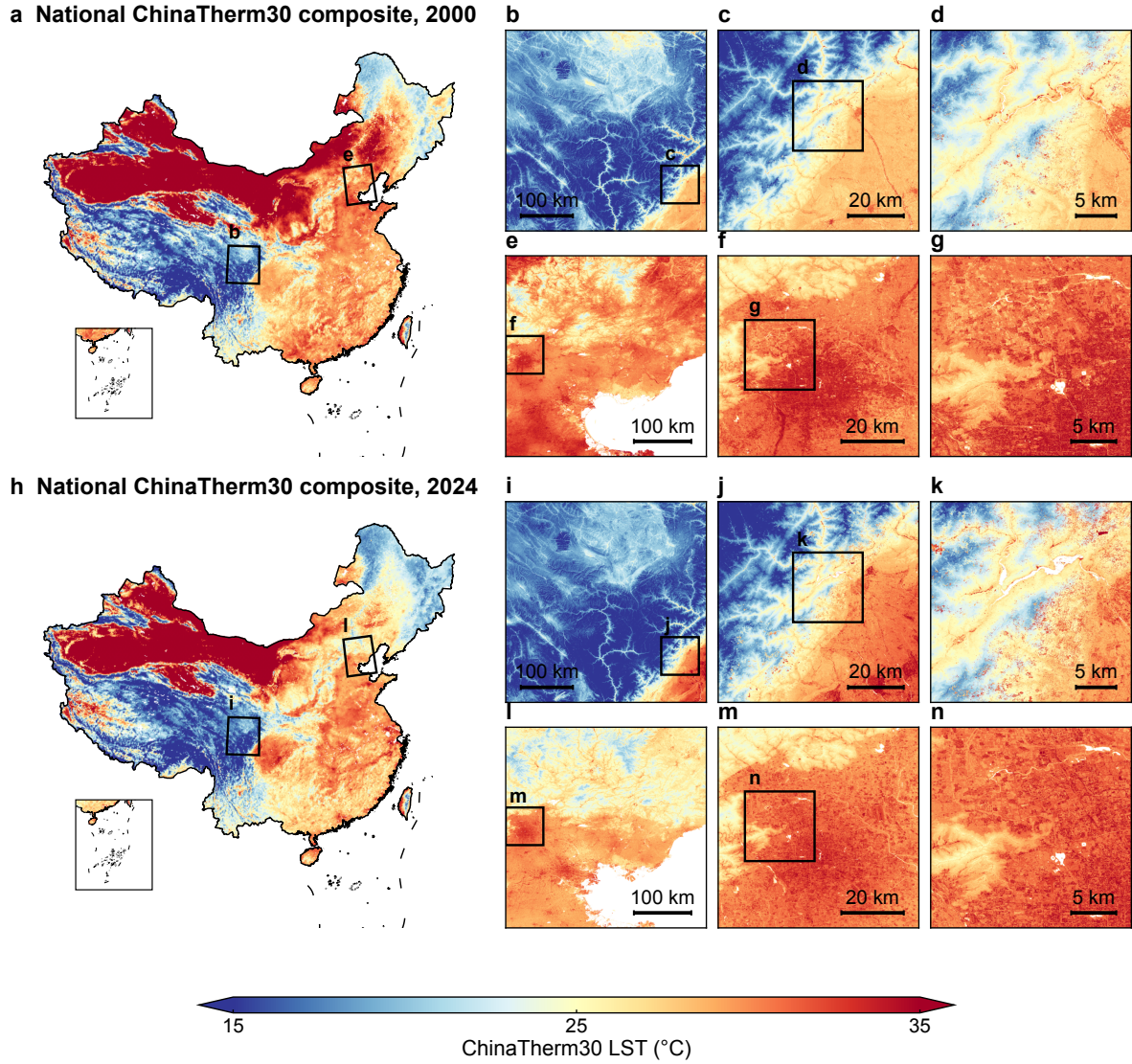


Figure 3: National coverage and multiscale spatial views of ChinaTherm30 in 2000 and 2024. a, h, National overviews at 0.01° for 2000 and 2024, respectively. b–d and e–g, The 4° tiles, 0.75° local windows and 0.26° close-up windows for western Sichuan (X100_Y30) and Beijing–Yanshan (X116_Y38) in 2000. i–k and l–n, Corresponding views at the same locations and scales in 2024.

4 Technical Validation

4.1 Random forest generalization and parameter sensitivity

In the random 70/30 test set, model predictions agreed closely with the kilometre-scale annual thermal targets (Fig. 4a), with $R^2 = 0.945$, Pearson $r = 0.972$, RMSE of 2.140 °C and MAE of 1.559 °C. In the complete model, feature importances for elevation, NDBSI and NDVI were 0.414, 0.290 and 0.126, respectively, summing to 0.830; the remaining four predictors together accounted for 0.170 (Fig. 4b).

The blocked tests showed a larger increase in error when predicting new regions than when withholding consecutive years (Fig. 4c). Five-fold spatial-block validation yielded overall $R^2 = 0.809$, Pearson $r = 0.904$, RMSE of 3.967 °C and MAE of 2.922 °C. Temporal-block validation yielded $R^2 = 0.940$ and RMSE of 2.218 °C, close to the random-split results. Joint spatial and temporal holdouts yielded $R^2 = 0.806$ and RMSE of 3.983 °C, similar to spatial-block validation. Tile-level spatial-block RMSE had a median of 3.448 °C and ranged from 1.294 to 7.802 °C, with higher values mainly at the margins of NEC and in parts of ANW (Fig. 4d). Removing longitude and latitude increased spatial-block RMSE to 4.409 °C, indicating that geographic coordinates helped represent temperature differences among regions.

Parameter sensitivity was evaluated for five configurations using the same five spatial folds. With maximum depth fixed at 25, tree numbers were increased from 100 to 300 and 500; with 300 trees, maximum depths of 15, 25 and unrestricted growth were compared. Overall RMSE differed by only approximately 0.015 °C among these configurations (Fig. 4e). The configuration with 100 trees and a maximum depth of 25 had the lowest RMSE (3.9666 °C), whereas the total fitting times of the other four configurations were 1.99–4.75 times greater (Fig. 4f). Increasing tree number or allowing deeper trees did not reduce spatial-block error but substantially increased computation time; the 100-tree, depth-25 configuration was therefore used for production.

4.2 Cross-scale consistency and preservation of 30 m detail

After RF-LST and ChinaTherm30 were aggregated to a common 0.01° grid, the adjusted temperatures were closer to the kilometre-scale annual targets (Fig. 5a–b). Across annual grid-cell values for 2000–2024, RMSE decreased from 2.101 to 1.414 °C, a reduction of 32.7%; Pearson correlation increased from 0.973 to 0.988, and mean bias decreased from 0.034 to 0.003 °C. RMSE decreased in every year, with improvements in all six macroregions (Fig. 5c–d).

The smoothing scale influenced both local variation in the adjustment field and agreement with the kilometre-scale target. Comparisons among $\sigma = 5, 10, 20$ and 40 showed that smaller values produced more localized fields with steeper gradients. Larger values produced smoother fields but smaller reductions in kilometre-scale RMSE (Fig. 5e). At $\sigma = 10$, RMSE was 1.414 °C and the mean absolute adjustment gradient was 0.0377, intermediate among the four smoothing scales. Figure 5f illustrates the regional temperature background, raw residuals and smoothed adjustment over the eastern TP and Sichuan Basin in 2024.

At 30 m, the 2024 views of Chengdu, Wuhan, the western Sichuan mountains and the Urumqi–Tianshan piedmont illustrate adjustment effects across urban, agricultural, riverine, mountainous and arid piedmont landscapes (Fig. 6a). Mean adjustments in the four windows were +1.029, +1.320, −0.919 and −1.191 °C, respectively, with spatial standard deviations of 0.273–0.613 °C. RMSE relative to the bilinearly resampled kilometre-scale target decreased by 0.267–0.522 °C, with the direction and magnitude of adjustment varying with the regional thermal background.

Local profiles showed nearly identical short-distance fluctuations in the two 30 m products, with adjustment acting mainly as a spatially gradual temperature shift (Fig. 6b). Across the four windows, Pearson correlations between the high-frequency components of RF-LST and ChinaTherm30 were 0.999995–0.999999, and their standard-deviation ratios were 0.999998–1.000006. Urban boundaries, cropland, watercourses, valleys and terrain-related patterns were therefore almost unchanged. Low-frequency calibration improved kilometre-scale consistency while preserving the spatial structure represented by the random forest baseline.

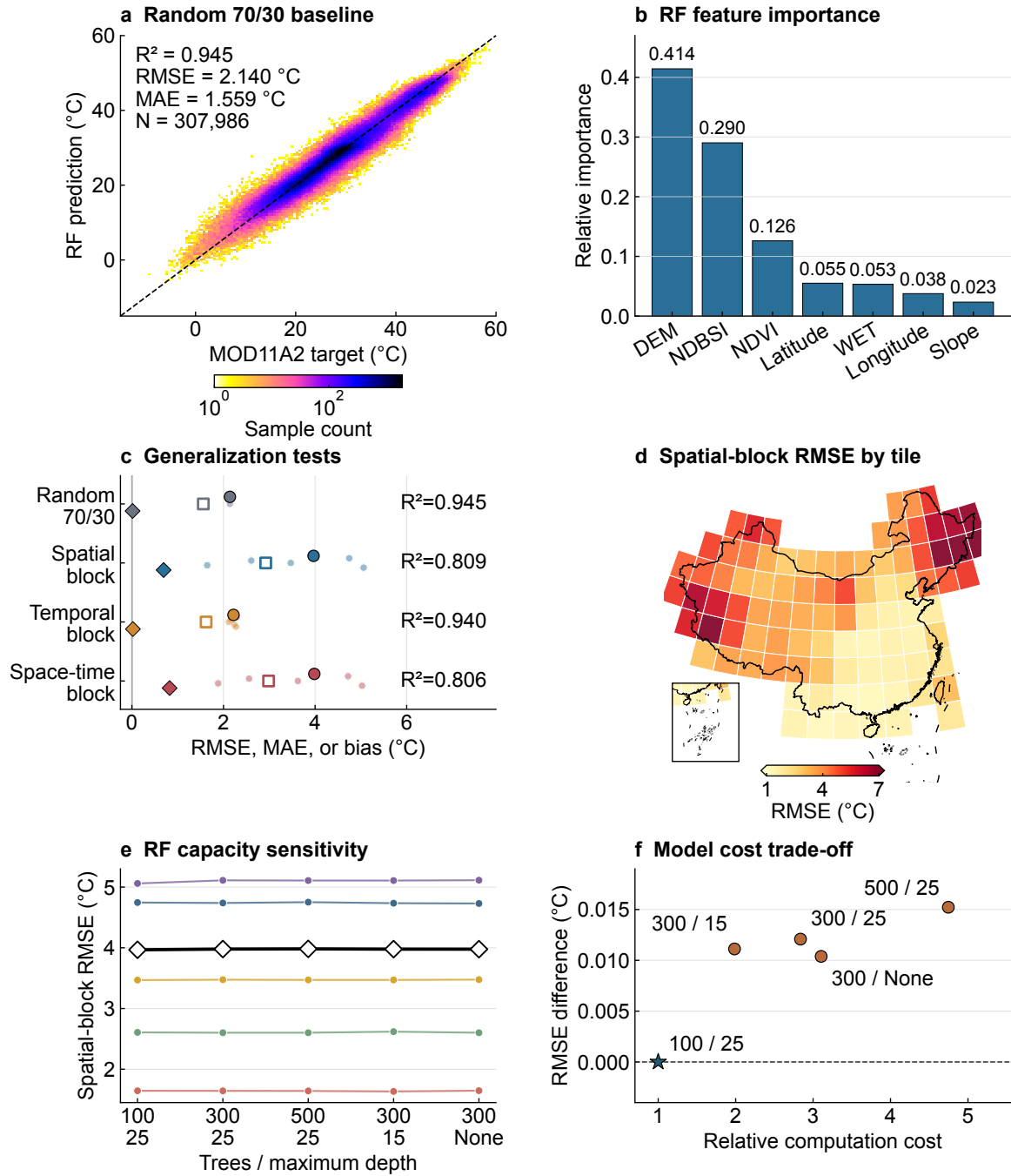


Figure 4: Generalization and configuration sensitivity of the random forest baseline. a, Density of predictions against kilometre-scale annual thermal targets in the random 70/30 test set, with the 1:1 line. b, Feature importance of the seven predictors in the complete model, based on normalized impurity reduction. c, RMSE, MAE, bias and R^2 for random, spatial-block, temporal-block and joint spatiotemporal tests. Filled circles, open squares and diamonds represent overall RMSE, MAE and bias, respectively; small circles show fold-level RMSE. d, Five-fold spatial-block RMSE across the 91 tiles of 4° by 4° . e, RMSE for five tree-number and maximum-depth configurations on the same spatial test folds; black diamonds show overall results. f, Relative computation cost and overall RMSE differences from the configuration with 100 trees and a maximum depth of 25. Cost is the ratio of total model fitting times.

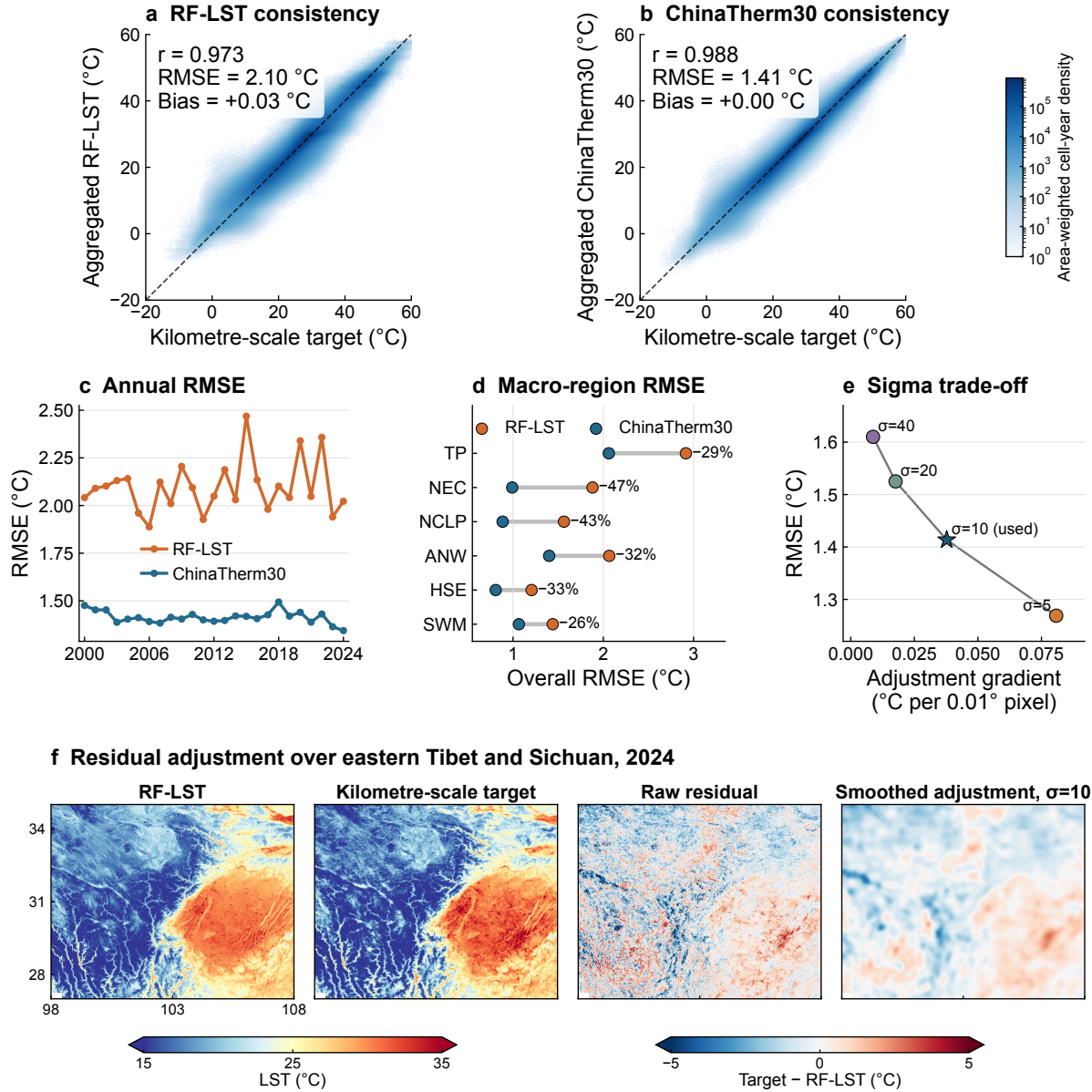


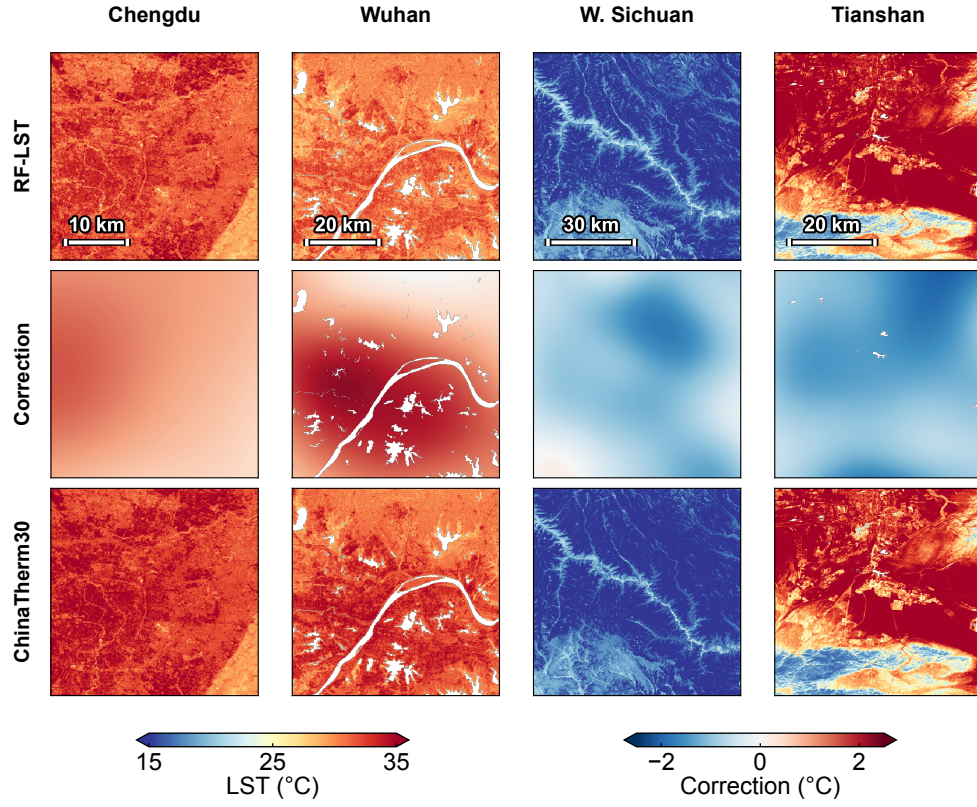
Figure 5: Low-frequency residual adjustment and kilometre-scale consistency. a–b, Area-weighted density of annual grid-cell values for RF-LST and ChinaTherm30 against the kilometre-scale thermal target over the common stable-land domain during 2000–2024; dashed lines indicate 1:1 agreement. c, Annual national RMSE for both products. d, Overall RMSE and percentage reductions after adjustment in TP, NEC, NCLP, ANW, HSE and SWM. e, National mean kilometre-scale RMSE and mean absolute gradient of the adjustment field for $\sigma = 5, 10, 20$ and 40 ; the star marks $\sigma = 10$. f, RF-LST, kilometre-scale target, raw residual and smoothed adjustment at $\sigma = 10$ over the eastern TP and Sichuan Basin in 2024.

4.3 Spatial consistency with Landsat 8 surface temperature

ChinaTherm30 and Landsat 8 annual composites showed consistent national spatial temperature patterns during 2013–2024. Each year contained 12,531–13,625 valid paired samples, representing approximately 5.70–6.38 million km^2 of land. Annual area-weighted spatial Pearson correlations ranged from 0.812 to 0.887, with a median of 0.8635 (Fig. 7a).

The two sets of annual composites also differed in their overall temperature levels. Median annual RMSE and centred RMSE were 5.856 and 4.867 $^{\circ}\text{C}$, respectively, and the median annual mean bias, defined

a Low-frequency adjustment across four 30 m windows



b Local profiles

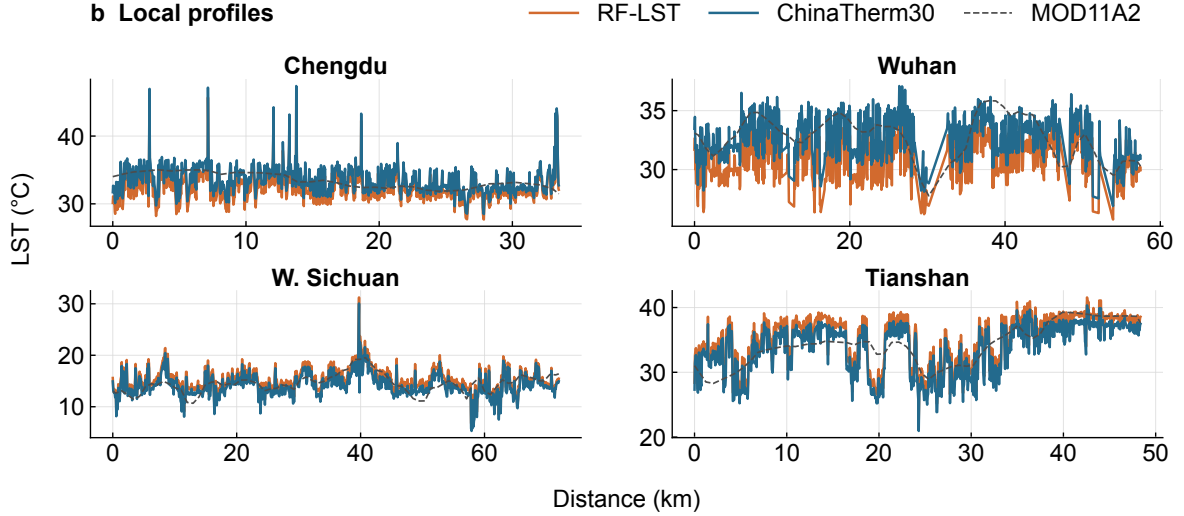


Figure 6: Spatial structure at 30 m before and after low-frequency residual adjustment. a, RF-LST, smoothed adjustment and ChinaTherm30 for Chengdu, Wuhan, the western Sichuan mountains and the Tianshan piedmont in 2024. b, Central profiles through the four windows, comparing RF-LST, ChinaTherm30 and the bilinearly resampled kilometre-scale annual target. Across the four windows, Pearson correlations between high-frequency components of RF-LST and ChinaTherm30 are 0.999995–0.999999, with standard-deviation ratios of 0.999998–1.000006.

as ChinaTherm30 minus Landsat 8, was -3.206°C (Fig. 7b). Macroregional comparisons comprised 72 region–year combinations. Median centred RMSE was 3.509°C in SWM, 3.818°C in HSE and 5.202°C in TP; median spatial correlations were 0.820 in ANW and 0.796 in NEC (Fig. 7c–d).

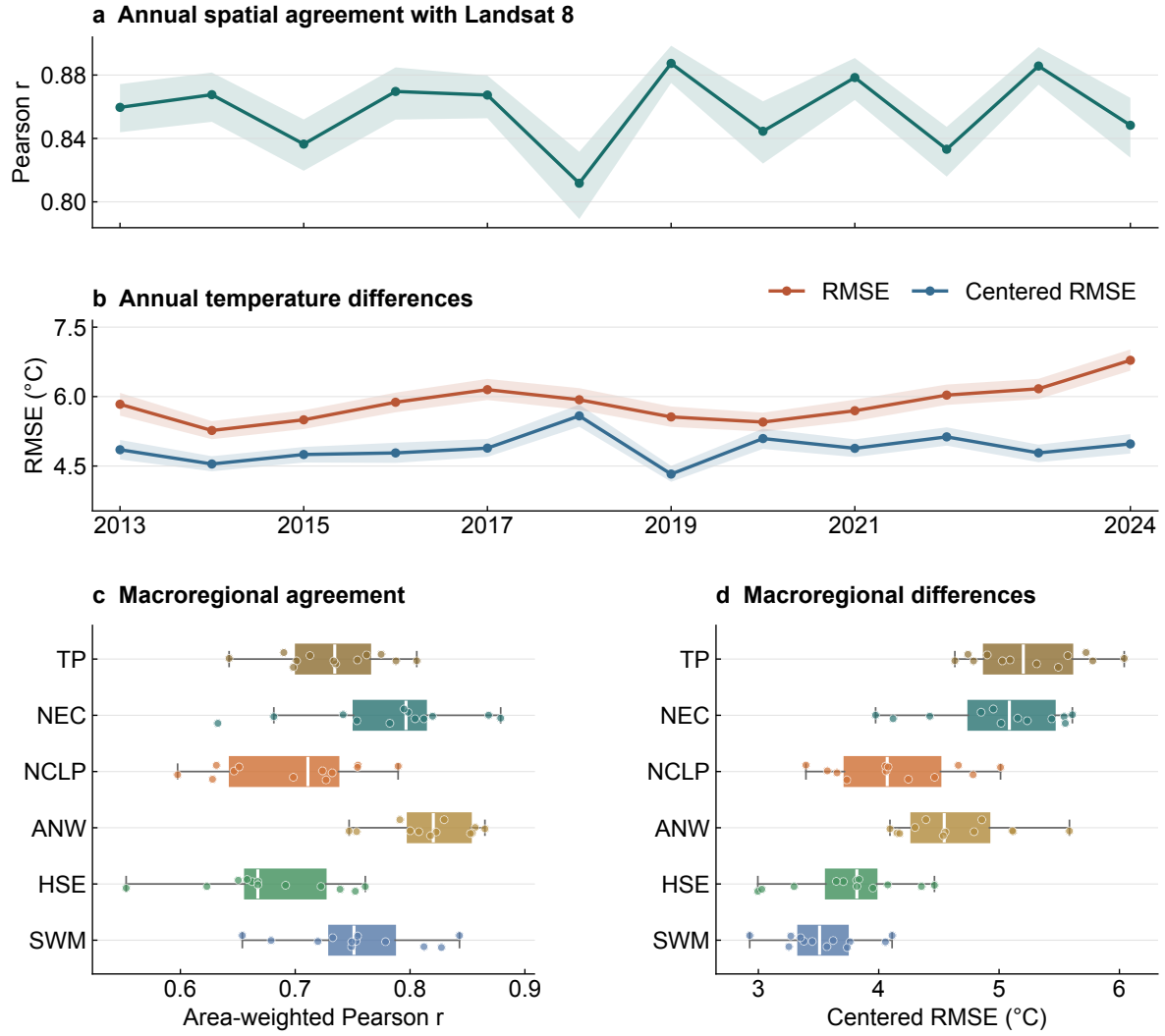


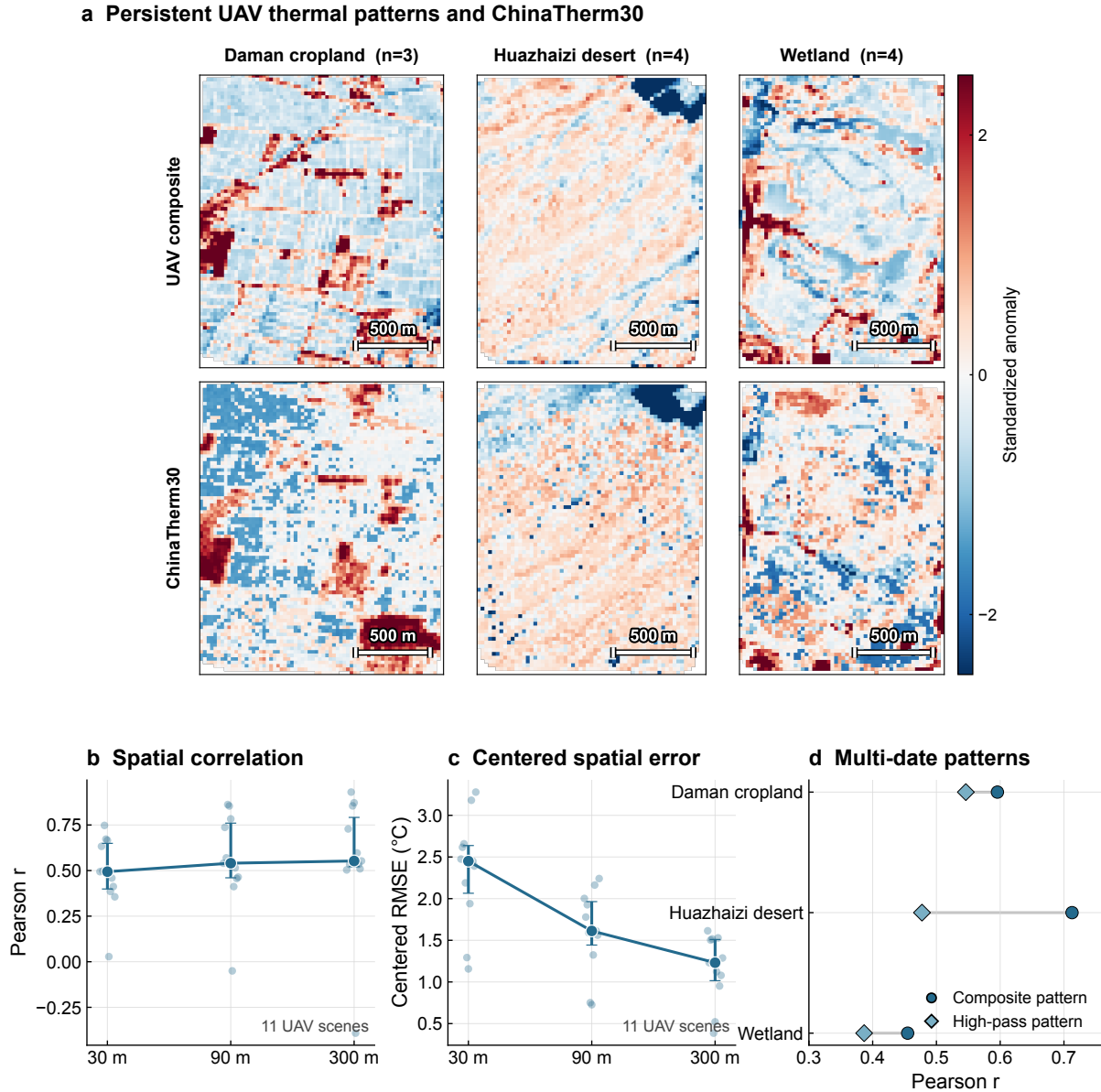
Figure 7: Nationwide spatially stratified comparison of ChinaTherm30 with Landsat 8 Collection 2 surface temperature during 2013–2024. a, Annual national area-weighted spatial Pearson correlation, with 95% confidence intervals from a 2° spatial-block bootstrap. b, Annual national RMSE and centred RMSE with 95% confidence intervals. Centred RMSE removes the national area-weighted mean difference between the two datasets. c, Twelve-year distributions of annual spatial Pearson correlations in TP, NEC, NCLP, ANW, HSE and SWM. d, Corresponding distributions of annual centred RMSE. In c and d, points represent individual years, boxes show the interquartile range, white lines mark medians, and whiskers extend to the most extreme values within 1.5 interquartile ranges of the box.

4.4 Independent UAV evaluation of thermal spatial structure

Across the 11 UAV scenes, increasing the common aggregation scale from 30 to 300 m raised the median scene-level spatial correlation from 0.494 to 0.553 and reduced centred RMSE from 2.450 to 1.231 °C (Fig. 8b–c). Improved agreement at coarser scales indicates more stable representation of field- and landscape-scale thermal patterns, whereas comparisons at the finest scale are more sensitive to instantaneous surface conditions and spatial registration.

Correlations for the standardized multidade composites over Daman cropland, Huazhaizi desert and the wetland were 0.596, 0.713 and 0.455, respectively; corresponding high-frequency correlations were 0.546, 0.477 and 0.387 (Fig. 8d). In the southeastern part of the Daman scene, ChinaTherm30 shows a more pronounced warm anomaly than the multidade UAV composite (Fig. 8a). Individual UAV acquisitions show this area to be relatively cool in July, warmer in August and closer to the scene mean in September. The

354 local warm contrast in ChinaTherm30 is stronger than in each of these three observations.



355 **Figure 8:** Spatial-structure comparison of UAV thermal infrared brightness temperature and ChinaTherm30 in the
 356 middle Heihe basin. a, Standardized multiday UAV thermal patterns over Daman cropland, Huazhaizi desert and the
 357 wetland, with corresponding ChinaTherm30 patterns. UAV composites are pixelwise medians of spatially standard-
 358 ized scenes. b–c, Spatial Pearson correlations and centred RMSE for the 11 UAV scenes at 30, 90 and 300 m; lighter
 359 points show individual scenes, while filled points and error bars show medians and interquartile ranges. d, Pearson
 360 correlations of ChinaTherm30 with the multiday composite patterns and their high-frequency components for the
 361 three surface types.

362 4.5 Ground evaluation and spatial representativeness

363 Ground evaluation included 23 sites and 131 site-years spanning 16 calendar years within 2008–2024.
 364 Twenty-one sites belong to the upper, middle and lower Heihe network, while Guantao and Daxing provide
 365 two additional sites in the Haihe basin (Fig. 9a). Heihe site numbers follow the 1–23 numbering in Table 1
 366 of Liu et al.³⁶; H1 and H2 denote Guantao and Daxing, respectively. Station metadata are given in Supple-

mentary Table S1. Annual coverage, paired-IRT consistency screening and comparisons before and after quality control are provided in Supplementary Figs. S4–S7.

The Pearson correlation between ChinaTherm30 3×3 neighbourhood medians and annual ground-IRT composites was 0.840, with RMSE of 5.397 °C, MAE of 4.135 °C and bias of 0.560 °C (Fig. 9b). Site-cluster bootstrap 95% intervals were 0.681–0.931 for r , 3.640–6.788 °C for RMSE and –1.960–2.852 °C for bias.

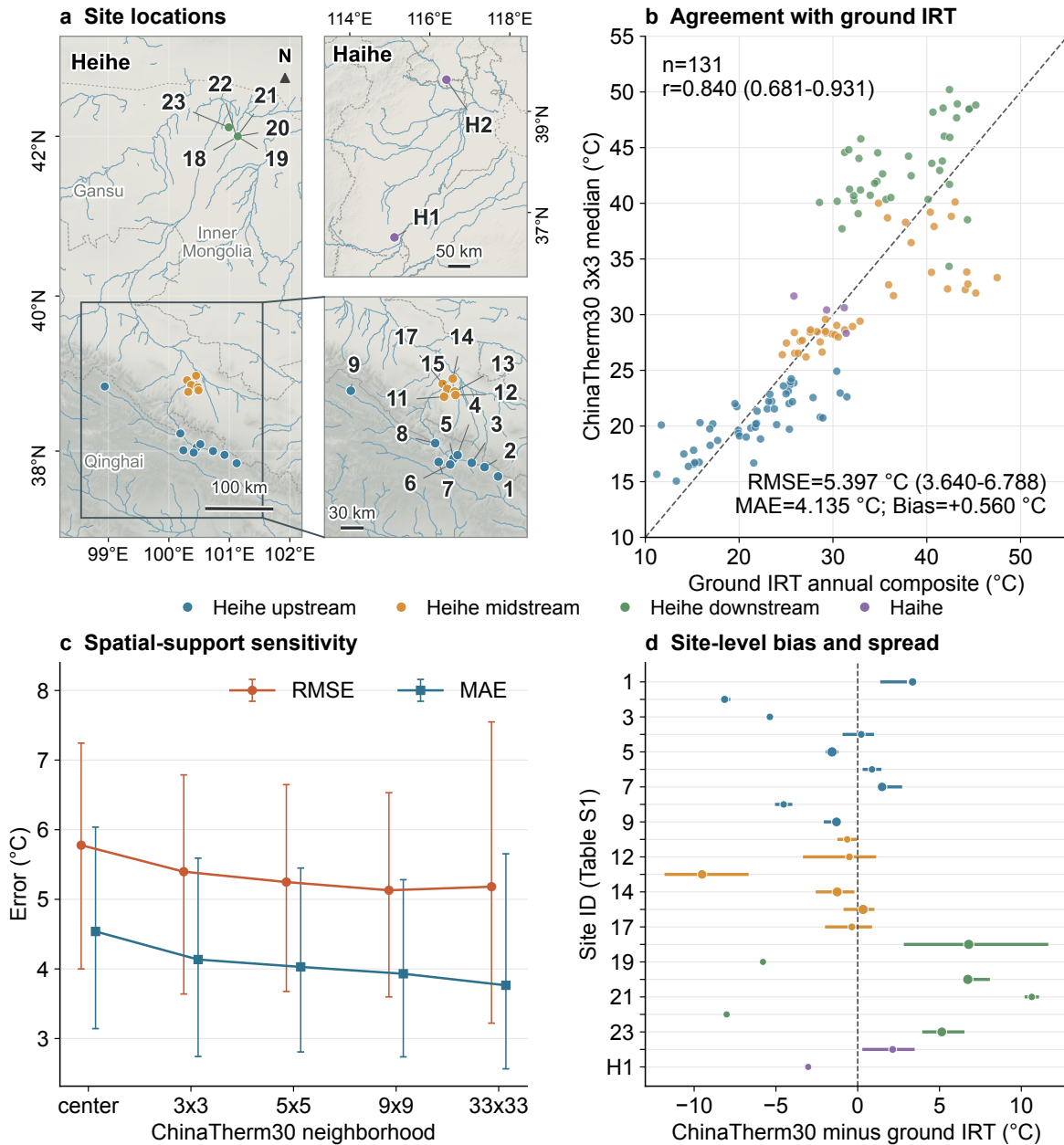


Figure 9: Independent evaluation of ChinaTherm30 using surface infrared radiometric temperatures from NCDC automatic stations. All panels use the 131 site-years passing ground-reference consistency screening. a, Locations of the 23 sites in the Heihe and Haihe basins, with an enlarged view of the upper and middle Heihe reaches. b, ChinaTherm30 3×3 neighbourhood medians against annual ground-IRT composites, with overall metrics and site-cluster bootstrap 95% intervals. c, RMSE and MAE for the centre pixel and neighbourhoods up to 33×33 pixels. d, Site-level mean bias and interquartile range of the 3×3 residuals, with point size indicating site-year count. Site numbers in a and d correspond to Supplementary Table S1.

Agreement changed gradually with spatial support. For the centre pixel and 3×3 , 5×5 , 9×9 and 33×33 neighbourhood medians, correlations were 0.820, 0.840, 0.848, 0.851 and 0.832, respectively. Corresponding RMSE values were 5.778, 5.397, 5.248, 5.130 and 5.181 °C, and biases were 0.889, 0.560, 0.508, 0.348 and -0.756 °C. The modest decrease in error with larger neighbourhoods indicates differences in spatial representativeness among point IRT measurements, pixel locations and heterogeneous surrounding surfaces.

Sub-basin results further revealed this heterogeneity. Centre-pixel RMSE values were 3.533, 5.750 and 7.930 °C for the upper, middle and lower Heihe reaches, with biases of -0.922 , -1.946 and 6.224 °C, respectively. Centre-pixel RMSE at the two Haihe sites was 3.511 °C. Site-level 3×3 bias ranged from -9.517 °C at Heihe Remote Sensing to $+10.641$ °C at Cropland (Fig. 9d). Removing each site's mean residual reduced RMSE to 2.448 °C.

4.6 Long-term thermal responses to landscape change

Yan'an New District and Lanzhou New Area illustrate two settings where urban construction and vegetation change have occurred together. Historical Landsat imagery records the expansion of construction and changes in surrounding vegetation, while ChinaTherm30 shows the evolution of leaf-on daytime thermal conditions during 2000–2024 (Figs. 10 and 11).

In Yan'an, thermal conditions in the construction zone progressively diverged from those of the surrounding loess hills. During 2000–2010, the area that later became the new district was still predominantly hilly terrain. Extensive land levelling was visible by 2015, followed by the development of roads and buildings (Fig. 10a–f). The construction zone Y1 and surrounding hills Y2 initially followed similar temperature trajectories, which began to separate around 2012 (Fig. 10j). Between 2000–2004 and 2020–2024, mean LST in Y1 increased from 29.36 to 30.30 °C, while that in Y2 decreased from 29.28 to 26.54 °C. Their temperature difference widened from 0.08 to 3.76 °C. Cooling in the surrounding hills contrasted spatially with concentrated warming patches within the construction zone (Fig. 10g–i). Over the same periods, NDVI in Y2 increased from approximately 0.33 to 0.66; NDVI in Y1 declined markedly during construction and subsequently recovered to some extent (Fig. 10k). Together, the temperature record and optical imagery capture the concurrent development of the new district and greening of the surrounding hills.

Lanzhou shows a different contrast between airport development and agricultural landscape change. The airport surroundings and cropland belt evolved into an interspersed landscape of construction areas and contiguous farmland, with extensive engineering works visible within the airport window in recent imagery (Fig. 11a–f). Phase III expansion of Lanzhou Zhongchuan International Airport began in 2020, and its main works were completed in 2024, consistent with the recent changes visible in the imagery⁴⁴. Between 2000–2004 and 2020–2024, mean LST in airport window L3 increased from 32.67 to 35.00 °C, while NDVI decreased from approximately 0.18 to 0.11. In western cropland L2, mean LST decreased from 31.45 to 29.28 °C as NDVI increased from approximately 0.24 to 0.42. The airport–cropland temperature difference widened from 1.21 to 5.72 °C, with airport warming and cropland cooling clearly expressed in the period-difference maps (Fig. 11g–i). Mean LST in the main built-up zone L1 changed less, from 32.30 to 32.90 °C, with both warming and cooling patches within the zone.

Annual curves in both cases retain substantial year-to-year variation, while thermal differences among surface types widen as the landscapes evolve. Yan'an shows increasing separation between construction areas and surrounding greening hills, whereas Lanzhou exhibits contrasting changes between the airport and cropland. These cases illustrate the ability of ChinaTherm30 to represent local thermal contrasts and their long-term evolution against a background of shared regional interannual variability.

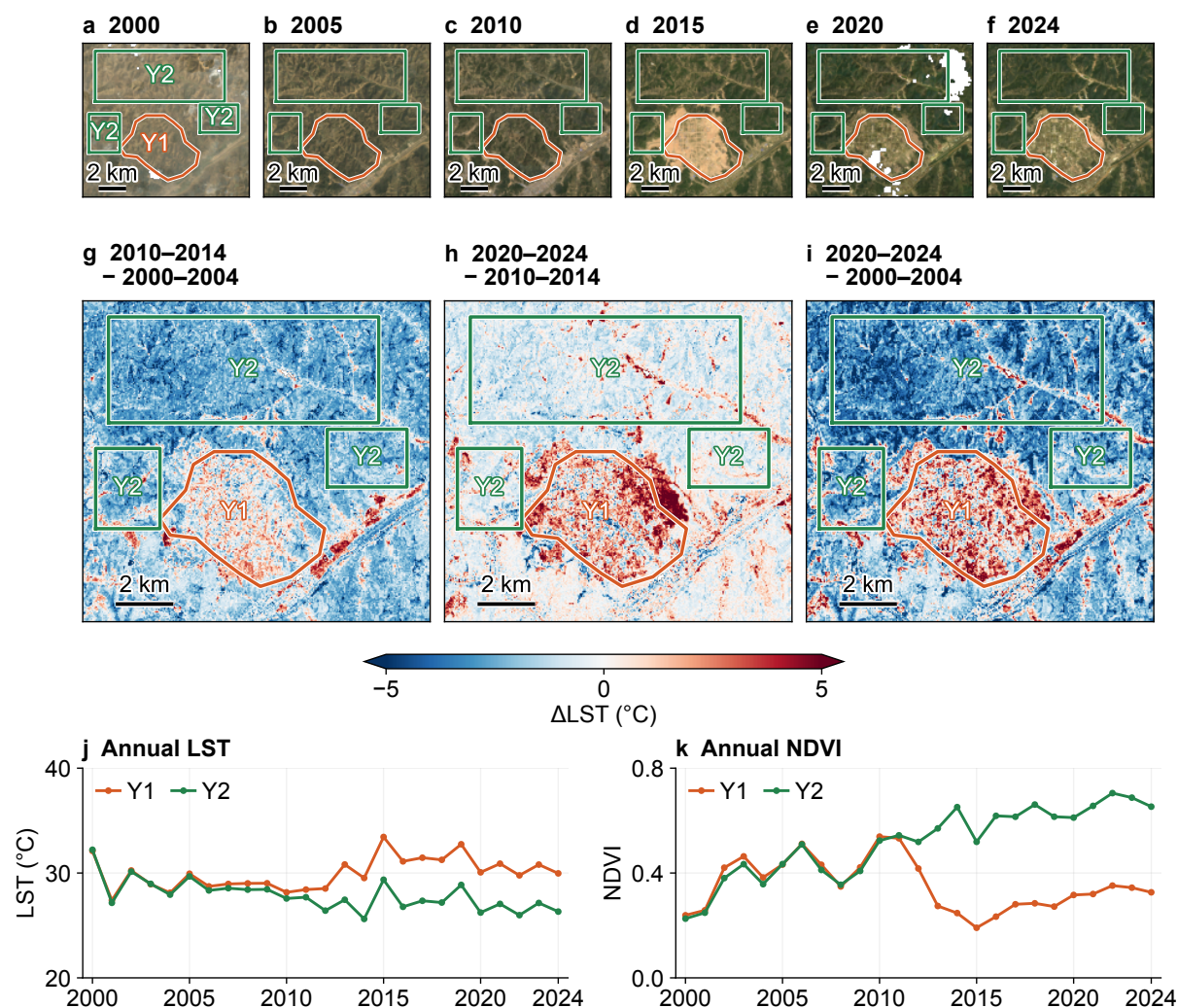


Figure 10: Landscape change and long-term thermal evolution in Yan'an New District and the surrounding hills. a–f, Annual Landsat true-colour composites for 2000, 2005, 2010, 2015, 2020 and 2024. Y1 denotes the main construction zone; Y2 comprises the three surrounding hill polygons shown. g–i, Mean LST differences for 2010–2014 minus 2000–2004, 2020–2024 minus 2010–2014, and 2020–2024 minus 2000–2004, respectively. j, k, Annual ChinaTherm30 LST and Landsat NDVI for Y1 and Y2.

5 Usage Notes

The record represents annual composite thermal conditions during the leaf-on daytime period and supports seasonal thermal comparisons in urban, vegetated and agricultural landscapes. Each annual value is the pixelwise median of Terra eight-day daytime LST composites passing Mandatory QA screening and having nominal start dates within DOY 150–300. The standard sequence contains 19 candidate eight-day periods, with the final period potentially extending to DOY 304. The record does not represent full-year mean temperatures, nighttime conditions or individual extreme-heat events.

The representation of regional interannual changes varies geographically. In the 2013–2024 Landsat 8 comparison, correlations between consecutive-year temperature changes were 0.870 in HSE, 0.465 in ANW and 0.399 in SWM. The standard-deviation ratios of these changes ranged from 0.349 to 0.826 across the six macroregions, indicating generally smaller year-to-year changes in ChinaTherm30 in this comparison

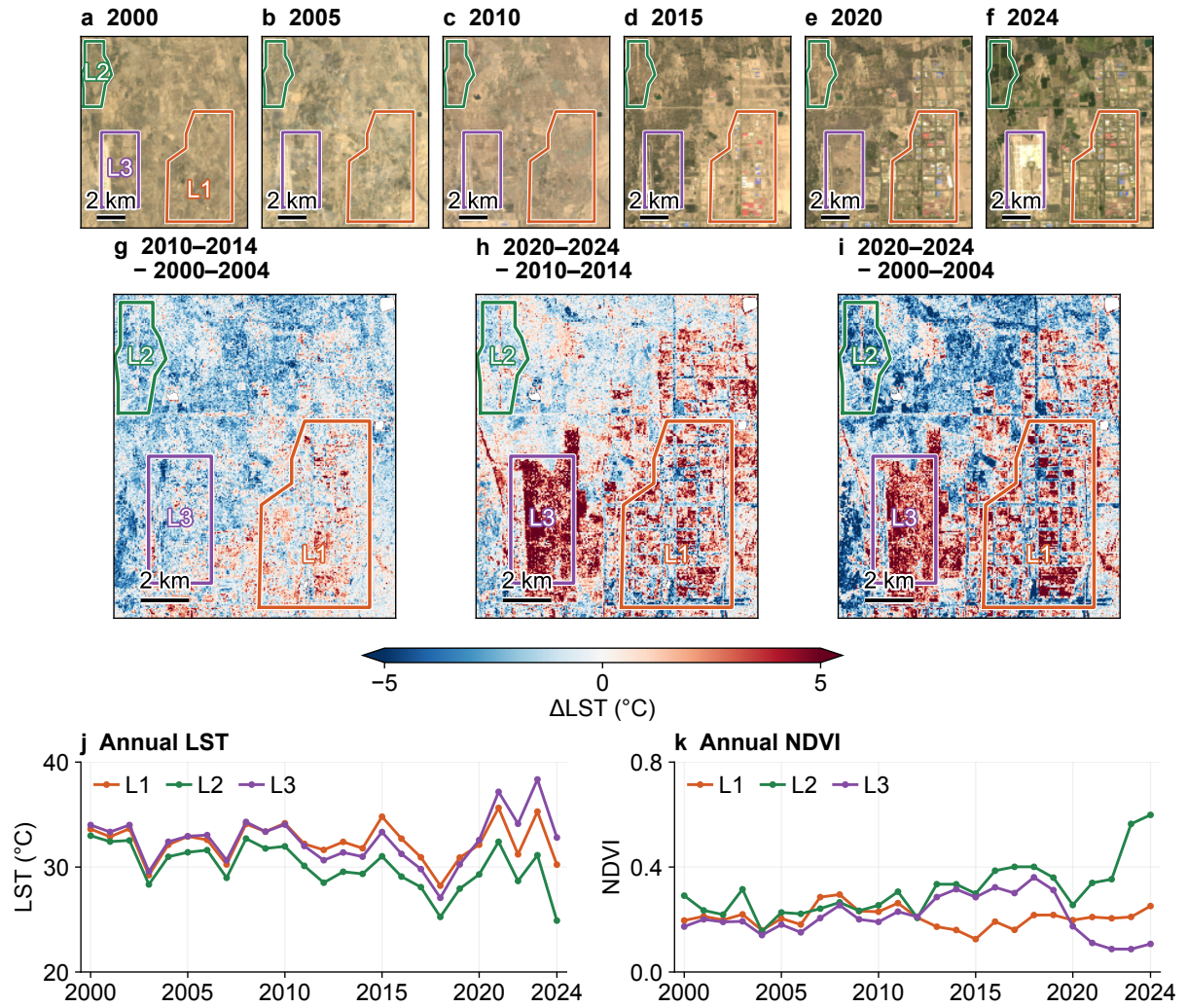


Figure 11: Landscape change and long-term thermal evolution across built-up, cropland and airport zones in Lanzhou New Area. a–f, Annual Landsat true-colour composites for 2000, 2005, 2010, 2015, 2020 and 2024. L1 denotes the main built-up zone, L2 the western contiguous cropland belt, and L3 the airport and surrounding window. g–i, Mean LST differences for 2010–2014 minus 2000–2004, 2020–2024 minus 2010–2014, and 2020–2024 minus 2000–2004, respectively. j, k, Annual ChinaTherm30 LST and Landsat NDVI for each zone.

(Supplementary Fig. S8 and Tables S4–S5). Studies of long-term change can combine the record with regional observations and meteorological information to assess change magnitudes and their drivers.

The 30 m spatial patterns in ChinaTherm30 are inferred from fine-resolution optical, topographic and geographic predictors, while the regional low-frequency thermal background is constrained by kilometre-scale annual targets. Areas with high elevation, strong radiation, limited training support or rapid surface change may benefit from targeted evaluation using independent observations and regional reference data. Of the 23 ground-IRT sites, 21 are in the Heihe basin; these comparisons primarily characterize site-scale agreement in arid, alpine and oasis environments of northwestern China. Other climatic regions require additional long-term ground observations.

6 Data Availability

ChinaTherm30 can be explored interactively at:

<https://ee-liangerzheng377.projects.earthengine.app/view/chinatherm30-explorer>

The complete 25-year GeoTIFF record, English README and data dictionary are publicly available through ScienceDB⁴³ at [10.57760/sciencedb.00zzg](https://doi.org/10.57760/sciencedb.00zzg).

7 Code Availability

The core production code for MODIS thermal-target preparation, random forest training and 30 m inference, coarse-grid aggregation and residual adjustment is publicly available on Zenodo⁴⁵ at [10.5281/zenodo.22894495](https://doi.org/10.5281/zenodo.22894495) under the MIT License. The archive includes a README, software dependencies and a synthetic end-to-end test. Prepared optical and topographic predictor tiles are required to run the workflow.

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Author Contributions

E.L. conceived the study, developed the methodology and software, produced and validated the data, prepared the visualizations and wrote the original draft. Y.C. provided the China Earth Observation Data Cube. Y.C. and F.G. provided methodological support and research guidance and contributed to study design and manuscript review. L.W. and Z.Z. contributed to study design, interpretation, manuscript review and research guidance. Z.Z. supervised the project.

Competing Interests

The authors declare no competing interests.

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Supplementary information

Annual 30 m leaf-on daytime land surface temperature composites across China from 2000 to 2024

Contents

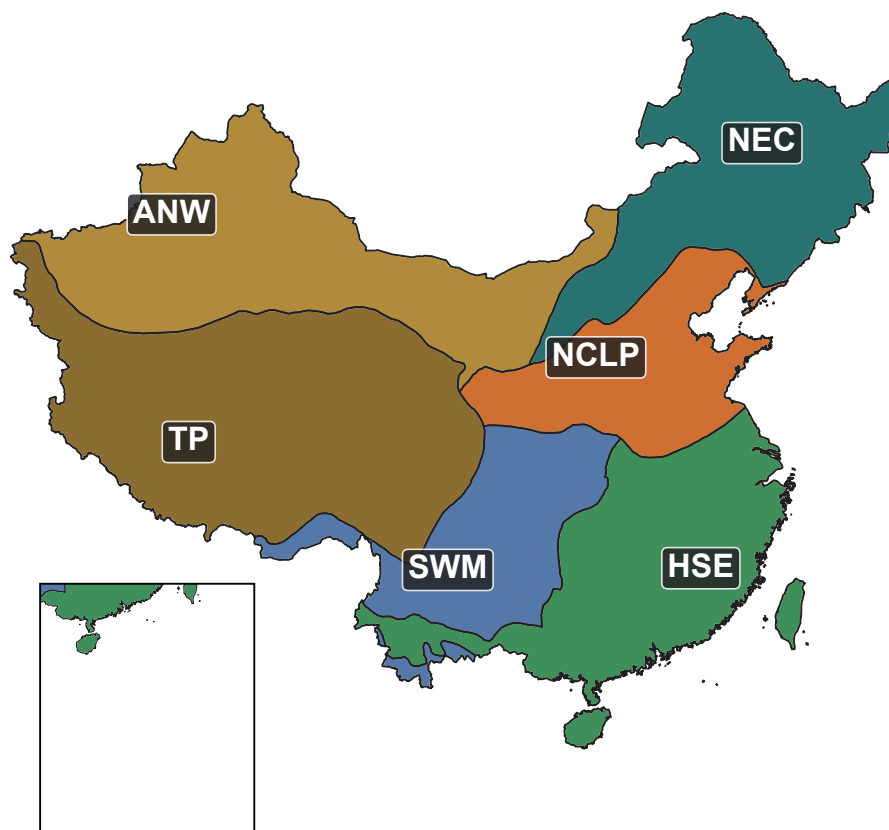
Supplementary figures

Figure S1. Six macroregions	2
Figure S2. Spatial support of the multisensor Landsat comparison	3
Figure S3. Annual support of the multisensor Landsat comparison	4
Figure S4. Ground-observation coverage	5
Figure S5. Paired-IRT consistency	6
Figure S6. Ground evaluation before and after quality control	7
Figure S7. Spatial-support sensitivity	8
Figure S8. Regional interannual-change consistency	9

Supplementary tables

Table S1. Station metadata and ground-validation coverage	10
Table S2. Ground-IRT processing and validation protocol	11
Table S3. Station-years excluded by paired-IRT screening	11
Table S4. Regional interannual-change metrics	13
Table S5. Bootstrap confidence intervals	14
Table S6. Paired-year changes and observation support	14
Regional interannual consistency: methods and results	13
References	16

Six macroregions used for stratification and reporting



TP Tibetan Plateau
 NCLP North China-Loess Plateau
 HSE Humid Southeast
 NEC Northeast China
 ANW Arid Northwest
 SWM Southwest Mountains

6 **Figure S1:** Six macroregions used for stratified sampling and regional reporting. The boundaries aggregate 46 ecological
 7 regions from the China eco-geographical regionalization: TP, Tibetan Plateau; NEC, Northeast China; NCLP, North China–
 8 Loess Plateau; ANW, Arid Northwest; HSE, Humid Southeast; and SWM, Southwest Mountains. These abbreviations are
 9 used consistently in the main text and figures.

Spatial support of the 2000-2024 Landsat validation sample

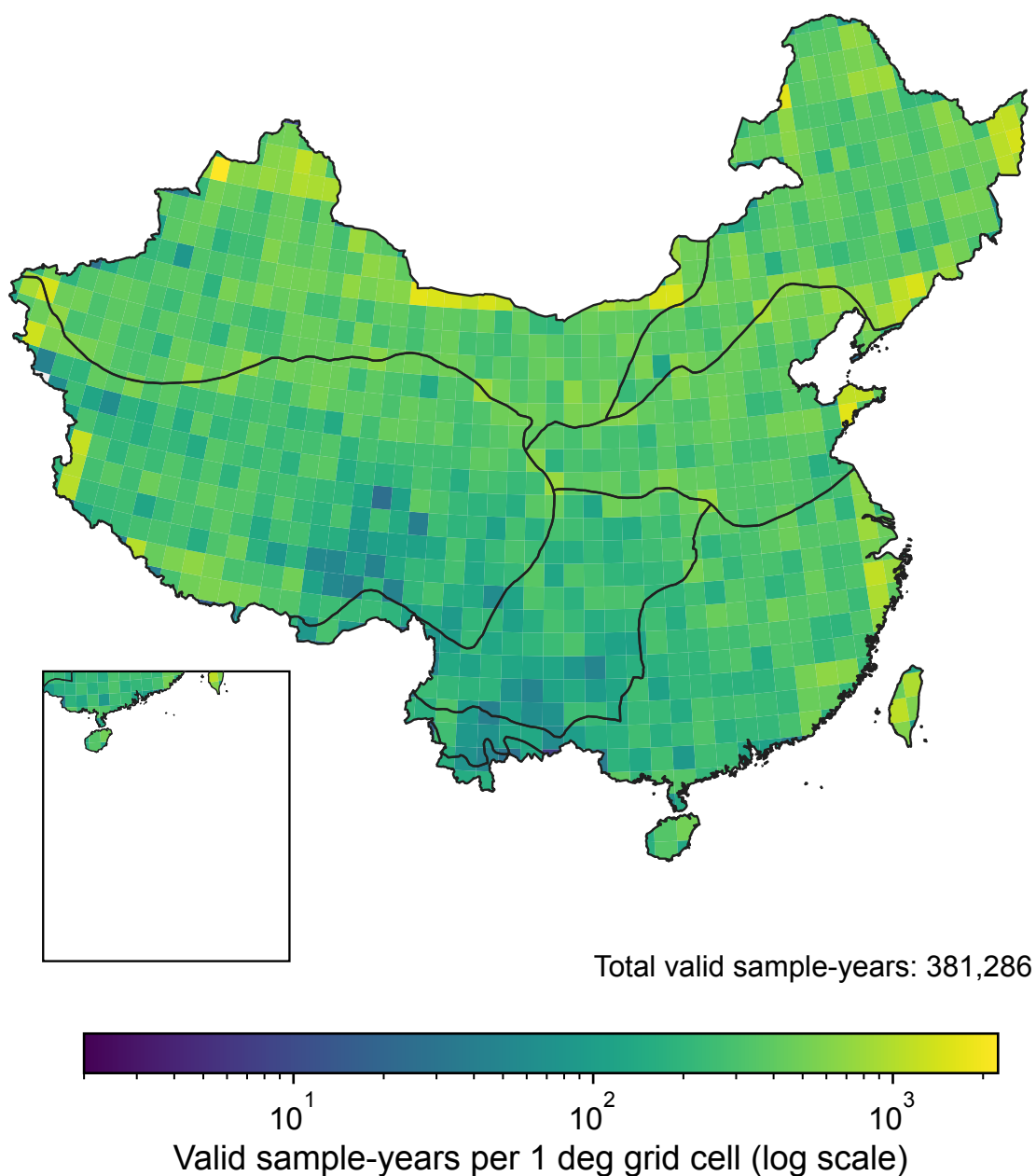
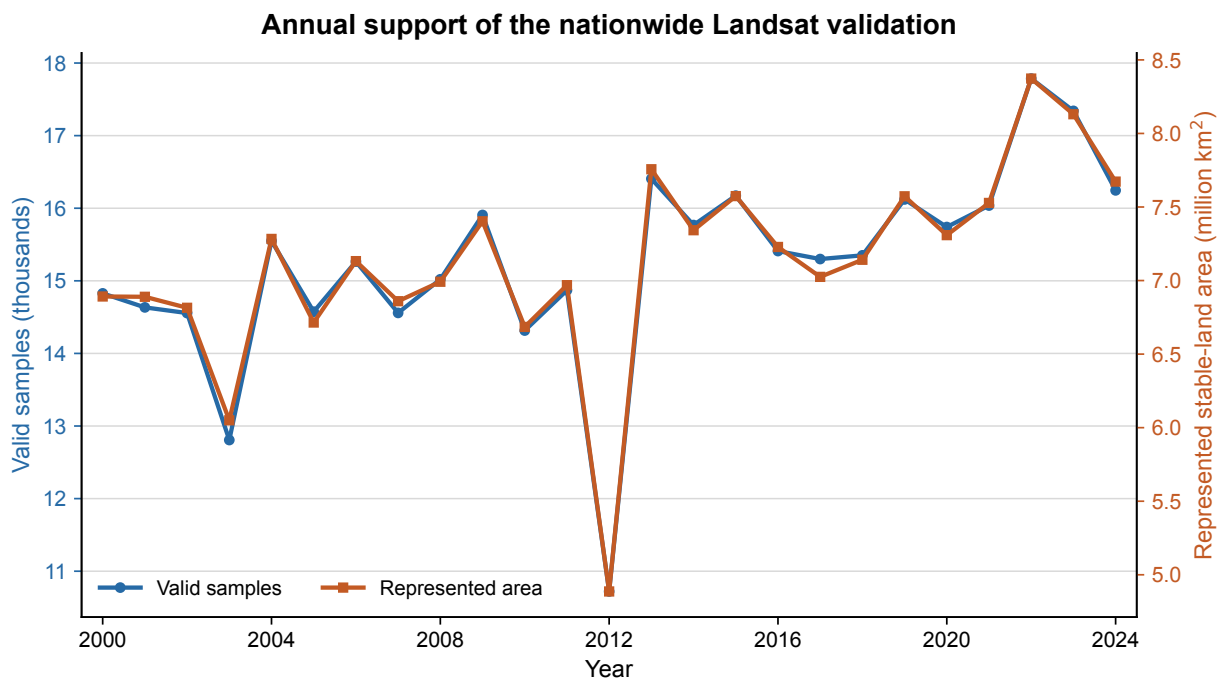
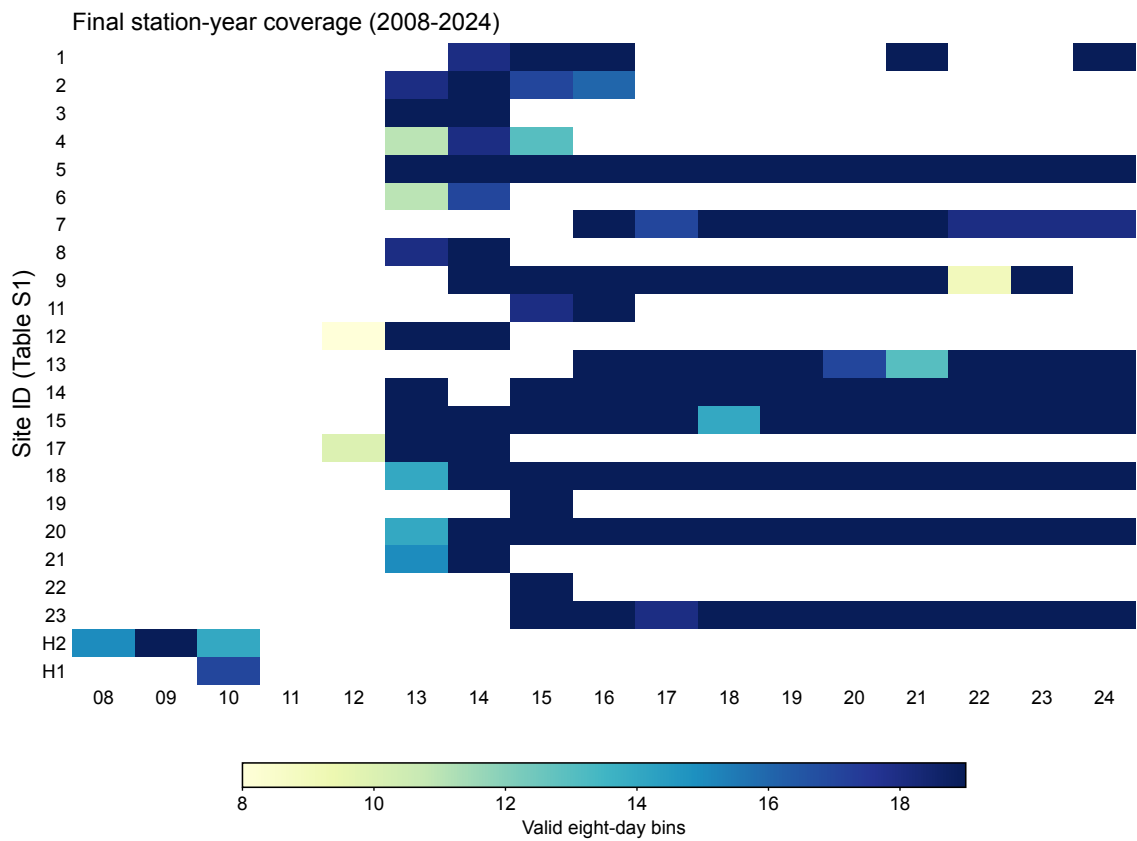


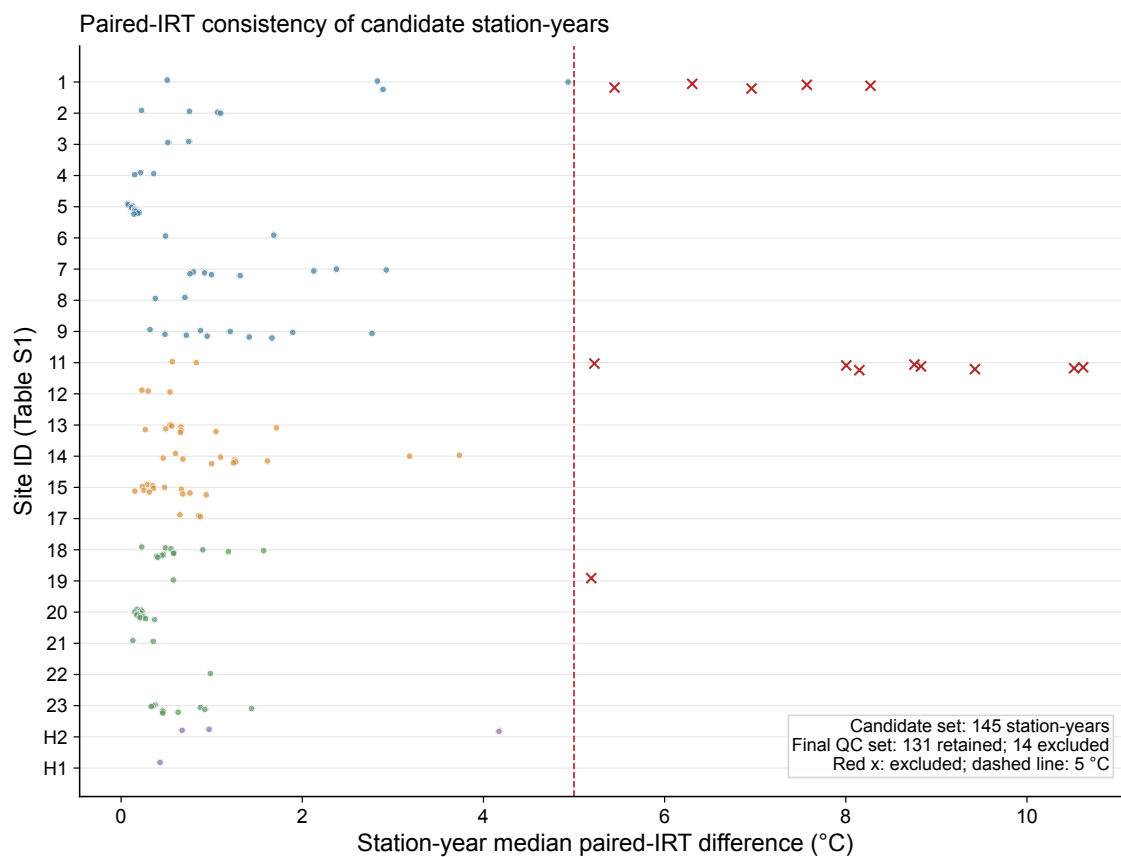
Figure S2: Spatial support of the supplementary nationwide multisensor Landsat comparison, 2000–2024. This extended archive combines Landsat 5, 7, 8 and 9, whereas the main-text comparison uses Landsat 8 alone during 2013–2024. Valid sample-years are aggregated to 1° grid cells. A sample-year requires strict cloud, shadow, snow and radiometric-saturation screening, at least three valid Landsat observations, available 3×3 ChinaTherm30 and RF-LST baseline means, and a water fraction no greater than 10%. Macroregion boundaries follow Figure S1.



15 **Figure S3:** Annual support of the supplementary nationwide multisensor Landsat comparison, 2000–2024. Valid sample
 16 counts and represented land area correspond to the Landsat 5/7/8/9 archive in Figure S2. Counts reflect at least three quality-
 17 screened observations per sample-year, while area totals use the original stratified-sampling weights. The Landsat 8-only
 18 comparison in the main text uses its own annual valid samples during 2013–2024.



19 **Figure S4:** Temporal coverage of the final ground-validation set. Colours indicate the number of valid MOD11A2-aligned
 20 eight-day bins contributing to each station-year annual IRT composite. The final set contains 131 station-years across all 23
 21 sites and 16 calendar years. Site IDs follow Table S1.



22 **Figure S5:** Paired-IRT consistency within the 145 candidate station-years. A paired-sensor diagnostic was available for 143
 23 records. Fourteen station-years with a median daily paired-IRT absolute difference greater than 5 °C were excluded from
 24 the final ground-reference set; the remaining 131 station-years retained all 23 sites. The criterion uses only ground-sensor
 25 measurements.

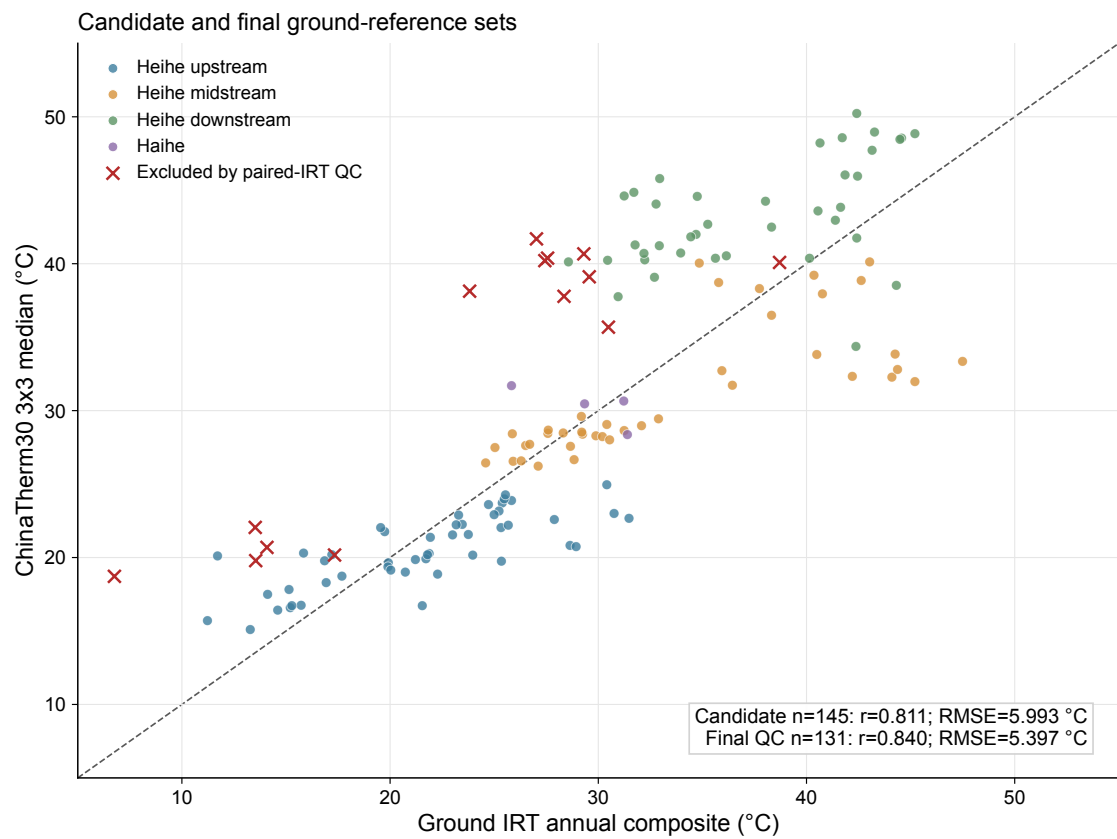


Figure S6: ChinaTherm30 3×3 neighbourhood medians compared with annual ground-IRT composites before and after ground-reference quality control. Coloured circles are the 131 final station-years, and red crosses are the 14 records excluded by the paired-IRT criterion. Summary statistics report the complete 145-record candidate set and the 131-record final set.

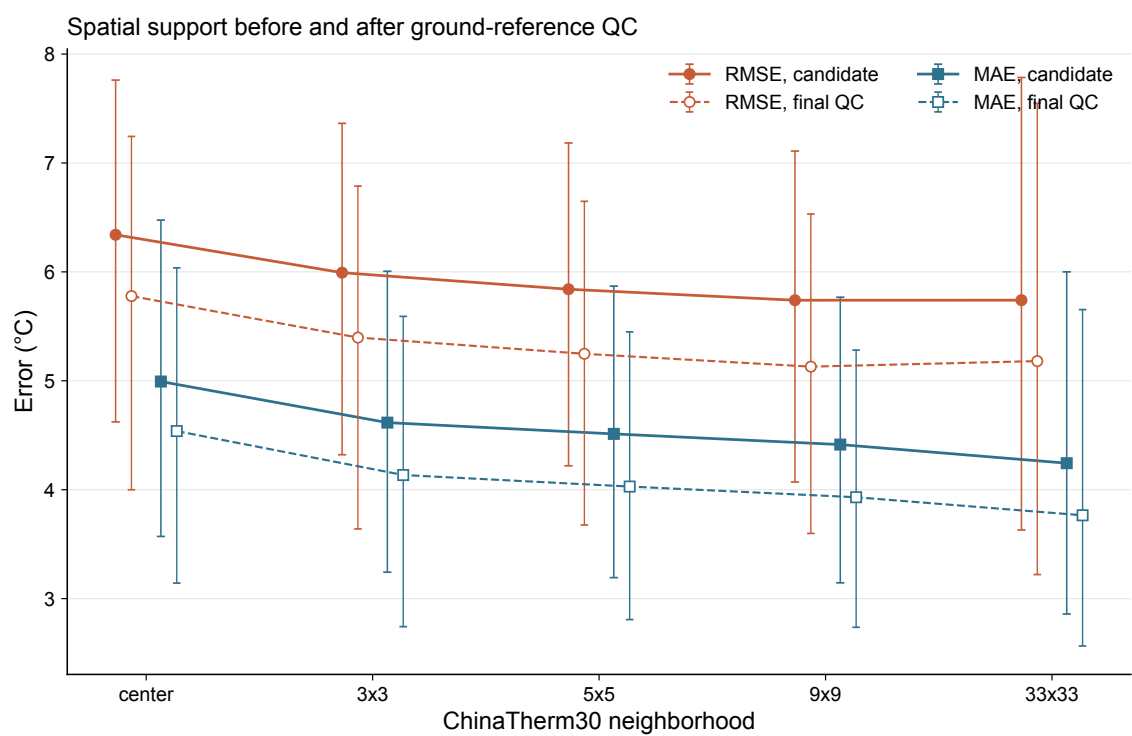


Figure S7: Spatial-support sensitivity before and after ground-reference quality control. Points show RMSE and MAE for the ChinaTherm30 centre pixel and median neighbourhoods from 3×3 to 33×33 pixels; error bars are 95% site-cluster bootstrap intervals.

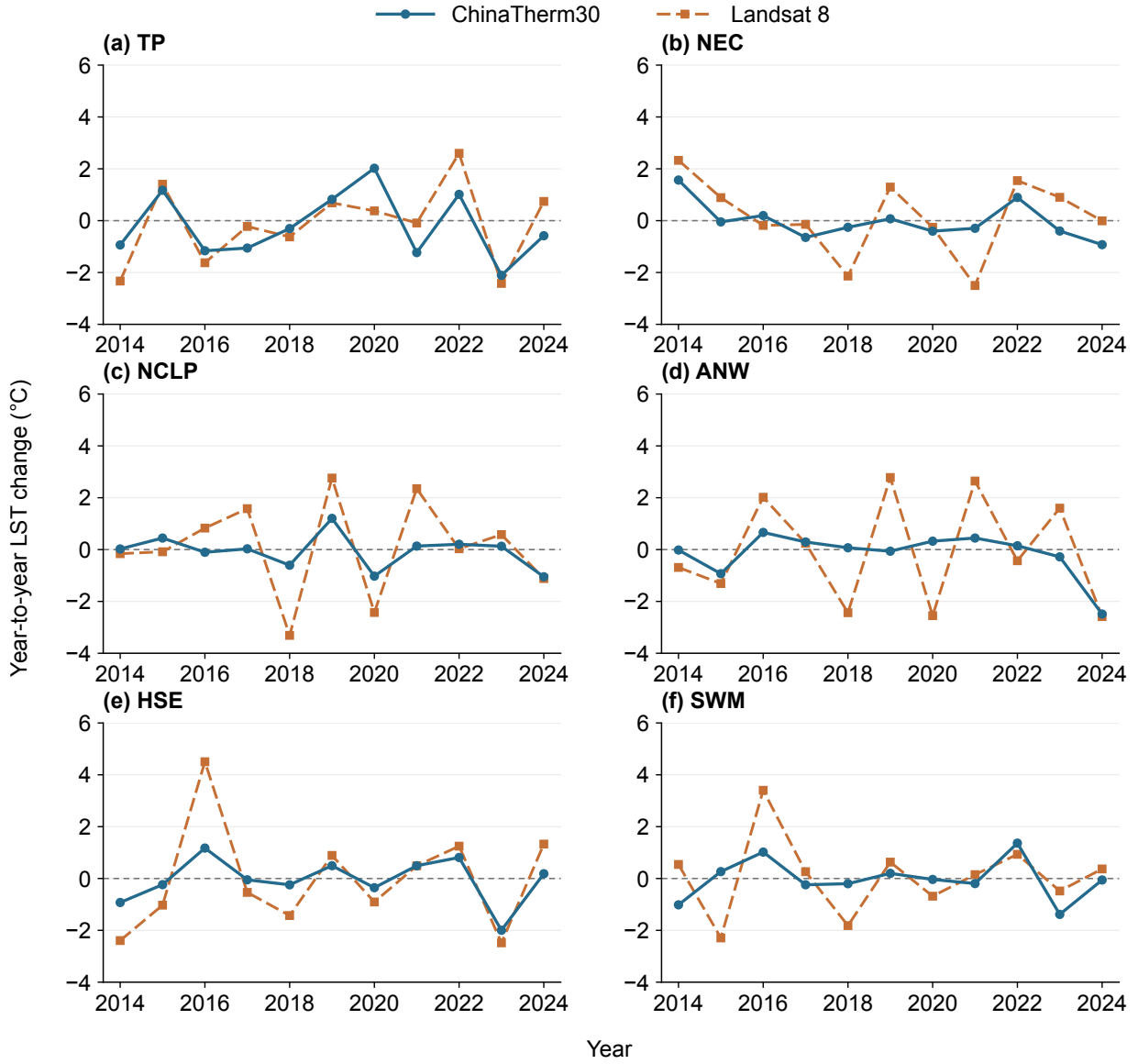


Figure S8: Interannual consistency of regional LST changes. Panels a–f show TP, NEC, NCLP, ANW, HSE and SWM. Curves show area-weighted changes between consecutive annual composites of ChinaTherm30 and Landsat 8; year t denotes the change from $t - 1$ to t . Each macroregion uses the same supported spatial strata across all 11 year pairs during 2013–2024, with fixed stratum-area weights. Both datasets use the same eligible locations within each year pair, while locations may differ among pairs. Horizontal dashed lines indicate zero change.

37 Supplementary Tables

Table S1: Station metadata and ground-validation coverage. Heihe Site IDs 1–23 follow Liu et al.¹; H1 and H2 denote the Guantao and Daxing sites in the Haihe basin. Candidate records use $K \geq 0.65$, 10:30 local mean solar time ± 30 min, and at least eight valid MOD11A2-aligned eight-day bins; evaluated records additionally satisfy the paired-IRT ground-reference criterion. Observation durations are reproduced from source metadata; evaluated year ranges may contain gaps.

Site ID	Station	Network	Reach	Landscape	Lon.	Lat.	Elev.	Duration reported	Years evaluated	Site-years	Status
1	Jingyangling	Heihe	Up.	alpine meadow	101.120	37.840	3750	Aug. 2013-present	2014-2024	5	Final QC
2	E'bao	Heihe	Up.	alpine meadow	100.920	37.950	3294	June 2013-Oct. 2016	2013-2016	4	Final QC
3	Huangcaogou	Heihe	Up.	alpine meadow	100.730	38.000	3137	June 2013-Apr. 2015	2013-2014	2	Final QC
4	Arou Sunny	Heihe	Up.	alpine meadow	100.520	38.090	3529	Aug. 2013-Aug. 2015	2013-2015	3	Final QC
5	Arou	Heihe	Up.	subalpine meadow	100.460	38.050	3033	June 2008-present	2013-2024	12	Final QC
6	Arou Shady	Heihe	Up.	alpine meadow	100.410	37.980	3536	Aug. 2013-Aug. 2015	2013-2014	2	Final QC
7	Yakou	Heihe	Up.	alpine meadow	100.240	38.010	4148	Jan. 2014-present	2016-2024	9	Final QC
8	Huangzangsi	Heihe	Up.	wheat	100.190	38.230	2612	June 2013-Apr. 2015	2013-2014	2	Final QC
9	Dashalong	Heihe	Up.	alpine marsh	98.940	38.840	3739	Aug. 2013-present	2014-2023	10	Final QC
10	Guantan	Heihe	Up.	Qinghai spruce	100.250	38.530	2835	2008-2011	–	0	No IRT work-book
11	Huazhaizi	Heihe	Mid.	Kalidium desert	100.320	38.770	1731	June 2012-present	2015-2016	2	Final QC
12	Shenshawo	Heihe	Mid.	sandy desert	100.490	38.790	1594	June 2012-Apr. 2015	2012-2014	3	Final QC
13	Heihe RS	Heihe	Mid.	grassland	100.480	38.830	1560	Aug. 2014-present	2016-2024	9	Final QC
14	Zhangye wetland	Heihe	Mid.	reed	100.450	38.980	1460	June 2012-present	2013-2024	11	Final QC
15	Daman	Heihe	Mid.	maize	100.370	38.860	1556	May 2012-present	2013-2024	12	Final QC
16	Yingke	Heihe	Mid.	maize	100.410	38.860	1519	2008-2011	–	0	No IRT work-book
17	Bajitan Gobi	Heihe	Mid.	Reaumuria	100.300	38.920	1562	May 2012-Apr. 2015	2012-2014	3	Final QC
18	Mixed Forest	Heihe	Down.	Populus-Tamarix	101.130	41.990	874	July 2013-present	2013-2024	12	Final QC
19	Barren Land	Heihe	Down.	bare land	101.130	42.000	878	July 2013-Mar. 2016	2015	1	Final QC
20	Sidaoqiao	Heihe	Down.	Tamarix	101.140	42.000	873	July 2013-present	2013-2024	12	Final QC
21	Cropland	Heihe	Down.	melon	101.130	42.000	875	July 2013-Nov. 2015	2013-2014	2	Final QC
22	Populus	Heihe	Down.	Populus	101.120	41.990	876	July 2013-Apr. 2016	2015	1	Final QC
23	Desert	Heihe	Down.	Reaumuria	100.990	42.110	1054	Apr. 2015-present	2015-2024	10	Final QC
H1	Guantao	Haihe	–	–	115.117	36.500	–	2008-2010 dataset scope	2010	1	Final QC
H2	Daxing	Haihe	–	–	116.416	39.616	–	2008-2010 dataset scope	2008-2010	3	Final QC

Table S2: Ground-IRT processing and validation protocol.

Step	Definition
Source screening	Identify station and observation year; retain records with interpretable timestamps and surface IRT measurements, and remove duplicate observations.
Time basis	Interpret station timestamps as China Standard Time and convert to local mean solar time using station longitude.
Nominal overpass	Use 10:30 local mean solar time with a +/-30 min primary window; +/-60 and +/-90 min are sensitivity tests.
IRT consensus	Average IRT-1 and IRT-2 when both are valid; reject paired observations differing by more than 5 degrees C; retain a single valid sensor when only one is available.
Daily aggregation	Take the median of valid observations within each station-day and overpass window.
Clear-sky protocol	Use downward shortwave radiation to calculate a clear-sky index; $K \geq 0.65$ is primary, with all-sky and $K \geq 0.60$ alternatives.
Eight-day alignment	Assign daily values to MOD11A2 nominal eight-day bins whose start DOY is 150-300; average valid daily values within each bin.
Annual composite	Take the median of qualified eight-day means and require at least eight valid bins per station-year.
Ground-reference QC	Apply the paired-IRT consistency criterion to 145 candidate station-years and retain 131 records across all 23 sites. Exclude a station-year when its median daily paired-IRT absolute difference exceeds 5 degrees C; product values and residuals are not used.
Product extraction	Extract the colocated ChinaTherm30 center pixel and median neighborhoods of 3x3, 5x5, 9x9, and 33x33 pixels.
Metrics and uncertainty	Report Pearson r , RMSE, MAE, bias, site-stratified results, and 2,000-replicate site-cluster bootstrap intervals.

38 The temporal, clear-sky and annual-support filters yielded 145 candidate station-years. Ground-reference
39 quality control excluded a station-year when the median of its daily paired-IRT absolute differences exceeded
40 5 °C; no ChinaTherm30 or RF-LST value was used in this decision. The final set retained 131 station-years across
41 all 23 sites and excluded 14 records (eight at Huazhaizi Desert Steppe, five at Jingyangling, and one at Barren
42 Land). For the ChinaTherm30 3×3 comparison, r and RMSE changed from 0.811 and 5.993 °C in the candidate
43 set to 0.840 and 5.397 °C in the final set. Table S3 provides the complete exclusion audit.

Table S3: Station-years excluded from the final ground-reference set by paired-IRT inconsistency. Paired days count days with a finite IRT-1/IRT-2 diagnostic; medians and 95th percentiles are daily absolute paired-sensor differences. No satellite-product residual was used in the criterion.

Station	Chinese name	Year	Paired days	Median (°C)	P95 (°C)	Status
Barren Land	裸地	2013	85	5.190	6.098	Excluded
Huazhaizi Desert Steppe	花 寨 子 荒漠	2017	112	5.225	7.202	Excluded
Huazhaizi Desert Steppe	花 寨 子 荒漠	2018	108	8.757	11.329	Excluded
Huazhaizi Desert Steppe	花 寨 子 荒漠	2019	117	8.005	13.871	Excluded
Huazhaizi Desert Steppe	花 寨 子 荒漠	2020	122	8.830	14.162	Excluded
Huazhaizi Desert Steppe	花 寨 子 荒漠	2021	109	10.620	15.492	Excluded

Table S3 continued

Station	Chinese name	Year	Paired days	Median (°C)	P95 (°C)	Status
Huazhaizi Desert Steppe	花寨子荒漠	2022	89	10.520	13.713	Excluded
Huazhaizi Desert Steppe	花寨子荒漠	2023	120	9.425	13.892	Excluded
Huazhaizi Desert Steppe	花寨子荒漠	2024	115	8.150	12.877	Excluded
Jingyangling	景阳岭	2018	107	6.305	10.326	Excluded
Jingyangling	景阳岭	2019	115	7.570	16.906	Excluded
Jingyangling	景阳岭	2020	110	8.273	12.861	Excluded
Jingyangling	景阳岭	2022	106	5.447	9.921	Excluded
Jingyangling	景阳岭	2023	121	6.960	9.720	Excluded

Regional interannual consistency

Sampling and temporal pairing

The analysis compares consecutive-year changes in ChinaTherm30 and Landsat 8 annual LST composites during 2013–2024. The Landsat date window, temperature conversion and strict quality screening follow the main-text Landsat 8 comparison. Each year requires at least three valid observations; both annual ChinaTherm30 3×3 means must be available, and neighbourhood water fractions must not exceed 10%. The original 20,000 candidate points were supplemented by a pool of 59,626 candidates to improve representation where cloud screening had reduced temporal support. Within each 4° tile–macroregion–elevation stratum, eligible original points were retained first, followed by eligible reserve points in their preassigned order until the original stratum quota was reached.

For each of the 11 adjacent-year pairs, both datasets use exactly the same selected locations. A stratum is included only if it has at least three paired points and a Kish effective sample size of at least three in every year pair. The retained stratum set and its area weights remain fixed across all pairs; individual points may change between pairs. Original 2° sampling weights are normalized within each retained stratum to its original area. Supported area fractions are relative to the full macroregional sampling-design area, not the fraction of pixels directly observed.

Metrics and uncertainty

For product P , the regional change ending in year t is

$$\Delta T_{r,t}^P = \frac{\sum_{s \in S_r} A_s \left[\sum_{i \in I_{s,t}} w_i (T_{i,t}^P - T_{i,t-1}^P) / \sum_{i \in I_{s,t}} w_i \right]}{\sum_{s \in S_r} A_s}, \quad (1)$$

where S_r is the fixed set of supported strata in region r , A_s is stratum area, and $I_{s,t}$ contains the paired locations. Pearson correlation and RMSE are calculated from the 11 regional change values for the two datasets. The standard-deviation ratio is $\text{SD}(\Delta T^{\text{CT30}}) / \text{SD}(\Delta T^{\text{L8}})$; it describes variability in adjacent-year changes, not the variability or trend of annual temperature levels. Direction agreement counts year pairs for which both changes have the same sign.

Confidence intervals use 1,000 spatial-cluster bootstrap replicates over 4° tiles. They are conditional on the observed years and supported domain and do not quantify uncertainty over unobserved regions or resampled years. SWM contains only nine spatial blocks. Observation-date summaries first calculate the median valid-observation DOY for each point and year, then take an area-weighted median across paired points; they are not the first and last acquisition dates of a season.

Results

Regional change correlations range from 0.399 in SWM to 0.870 in HSE, and change RMSE ranges from 1.017 to 1.752 $^\circ\text{C}$ (Figure S8; Tables S4–S5). HSE agrees in change direction for all 11 pairs and TP for ten pairs; ANW and SWM agree for six. Standard-deviation ratios of 0.349–0.826 indicate smaller adjacent-year changes in ChinaTherm30 than in Landsat 8 across all six regions. Fixed strata represent more than 99% of the design area in TP, NEC, NCLP and ANW, compared with 83.3% in HSE and 62.5% in SWM. Year-pair sample sizes, temperature changes and observation support are reported in Table S6.

Table S4: Regional interannual-change metrics for 2013–2024 (11 year pairs). Supported area denotes the fixed-stratum fraction of the design area. SD ratio is ChinaTherm30/Landsat 8.

Region	Area (%)	Paired points	r	RMSE ($^\circ\text{C}$)	SD ratio	Same sign
TP	99.2	3,841–4,228	0.734	1.017	0.826	10/11
NEC	99.9	3,689–3,691	0.592	1.158	0.481	8/11
NCLP	99.3	1,871–1,883	0.773	1.363	0.349	8/11
ANW	99.6	4,381–4,417	0.465	1.752	0.423	6/11
HSE	83.3	1,665–2,334	0.870	1.269	0.432	11/11

Region	Area (%)	Paired points	r	RMSE (°C)	SD ratio	Same sign
SWM	62.5	407–674	0.399	1.329	0.520	6/11

Table S5: Spatial-cluster bootstrap 95% intervals for the metrics in Table S4 (1,000 replicates).

Region	Tile blocks	r	RMSE (°C)	SD ratio
TP	28 [0.394, 0.874]	[0.857, 1.344]	[0.706, 1.113]	
NEC	24 [0.213, 0.764]	[0.790, 2.000]	[0.311, 0.673]	
NCLP	14 [0.496, 0.858]	[1.018, 2.062]	[0.272, 0.494]	
ANW	27 [0.200, 0.689]	[1.445, 2.159]	[0.360, 0.529]	
HSE	15 [0.759, 0.905]	[0.836, 1.904]	[0.325, 0.613]	
SWM	9 [0.158, 0.475]	[1.226, 1.839]	[0.318, 0.655]	

Table S6: Paired-year regional changes and observation support. Temperature changes are in degrees Celsius. Count and DOY columns give area-weighted medians for the earlier/later year, respectively; DOY summarizes point-level median observation dates.

Region	Year pair	Points	ΔT_{CT30}	ΔT_{L8}	Count	DOY
TP	2013–2014	4,080	-0.938	-2.330	5/5	224/238
TP	2014–2015	4,113	1.173	1.405	5/6	238/242
TP	2015–2016	4,165	-1.161	-1.624	6/5	242/238
TP	2016–2017	4,025	-1.057	-0.224	5/5	239/248
TP	2017–2018	3,841	-0.305	-0.627	5/5	247/239
TP	2018–2019	3,843	0.823	0.685	5/5	237/237
TP	2019–2020	4,022	2.021	0.377	5/6	237/250
TP	2020–2021	4,224	-1.232	-0.091	6/5	251/242
TP	2021–2022	4,158	1.014	2.598	6/5	242/221
TP	2022–2023	4,121	-2.110	-2.422	5/5	222/242
TP	2023–2024	4,228	-0.581	0.741	5/6	242/235
NEC	2013–2014	3,691	1.566	2.327	6/7	246/238
NEC	2014–2015	3,691	-0.048	0.889	7/8	238/233
NEC	2015–2016	3,691	0.196	-0.185	8/7	233/234
NEC	2016–2017	3,691	-0.647	-0.144	7/8	234/234
NEC	2017–2018	3,691	-0.257	-2.139	8/7	236/246
NEC	2018–2019	3,691	0.071	1.295	7/7	246/250
NEC	2019–2020	3,691	-0.405	-0.255	7/6	250/232
NEC	2020–2021	3,691	-0.295	-2.504	7/6	232/249
NEC	2021–2022	3,689	0.895	1.545	6/7	250/248
NEC	2022–2023	3,689	-0.400	0.901	7/8	248/249
NEC	2023–2024	3,691	-0.926	-0.007	8/7	249/242
NCLP	2013–2014	1,878	0.024	-0.158	6/5	235/232
NCLP	2014–2015	1,877	0.445	-0.085	6/7	232/239
NCLP	2015–2016	1,877	-0.104	0.829	7/5	238/239
NCLP	2016–2017	1,871	0.029	1.579	5/5	238/216
NCLP	2017–2018	1,874	-0.604	-3.310	5/6	217/248
NCLP	2018–2019	1,883	1.203	2.760	6/6	249/229
NCLP	2019–2020	1,878	-1.025	-2.427	6/5	229/241
NCLP	2020–2021	1,877	0.135	2.351	5/6	241/227
NCLP	2021–2022	1,882	0.204	0.031	5/7	226/223
NCLP	2022–2023	1,883	0.128	0.577	6/6	224/235
NCLP	2023–2024	1,882	-1.050	-1.118	6/6	234/232
ANW	2013–2014	4,417	-0.018	-0.689	8/9	227/228
ANW	2014–2015	4,416	-0.930	-1.310	9/9	228/230
ANW	2015–2016	4,412	0.662	2.018	9/8	230/226
ANW	2016–2017	4,408	0.293	0.245	9/9	226/228
ANW	2017–2018	4,397	0.069	-2.436	9/9	228/236

Region	Year pair	Points	ΔT_{CT30}	ΔT_{L8}	Count	DOY
ANW	2018–2019	4,392	-0.063	2.781	9/9	236/224
ANW	2019–2020	4,398	0.324	-2.550	9/9	224/233
ANW	2020–2021	4,417	0.445	2.644	9/9	233/228
ANW	2021–2022	4,410	0.147	-0.431	9/9	228/231
ANW	2022–2023	4,396	-0.281	1.598	9/9	231/227
ANW	2023–2024	4,381	-2.488	-2.585	9/8	227/224
HSE	2013–2014	2,334	-0.926	-2.395	5/4	239/247
HSE	2014–2015	2,105	-0.238	-1.028	4/4	248/257
HSE	2015–2016	2,015	1.174	4.504	4/4	259/227
HSE	2016–2017	1,785	-0.051	-0.537	4/4	223/230
HSE	2017–2018	1,808	-0.244	-1.430	4/4	230/233
HSE	2018–2019	2,094	0.493	0.890	4/4	233/246
HSE	2019–2020	1,840	-0.354	-0.906	5/4	247/239
HSE	2020–2021	1,881	0.493	0.491	4/4	241/251
HSE	2021–2022	2,231	0.810	1.247	4/5	251/245
HSE	2022–2023	1,868	-1.997	-2.483	5/4	245/239
HSE	2023–2024	1,665	0.183	1.327	4/4	239/238
SWM	2013–2014	648	-1.016	0.542	5/4	238/221
SWM	2014–2015	547	0.265	-2.293	4/4	218/235
SWM	2015–2016	534	1.019	3.402	4/4	239/217
SWM	2016–2017	407	-0.242	0.262	4/4	215/223
SWM	2017–2018	443	-0.201	-1.817	4/4	219/227
SWM	2018–2019	624	0.198	0.632	4/4	227/225
SWM	2019–2020	474	-0.037	-0.683	4/4	227/214
SWM	2020–2021	448	-0.196	0.148	4/4	214/239
SWM	2021–2022	582	1.364	0.932	4/4	227/228
SWM	2022–2023	674	-1.384	-0.482	4/4	226/225
SWM	2023–2024	670	-0.057	0.368	4/4	225/232

79 **References**

- 80 [1] Liu, S. et al. The Heihe Integrated Observatory Network: A basin-scale land surface processes observatory
81 in China. In: *Vadose Zone Journal* **17.1** (2018), p. 180072. <https://doi.org/10.2136/vzj2018.04.0072>.