

Supplementary Materials

for

Irrigation cooling effect reduced by water-saving practices

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Supplementary Text 1. Changes in annual mean land surface temperature (Δ LST) due to agricultural irrigation averaged during 2001–2020

Pronounced annual daytime cooling effect was found in arid regions (-2.34 ± 0.04 K, mean $\pm$ one standard deviation averaged for 2001–2020), followed by semi-arid/humid regions (-0.23 ± 0.01 K), but was quite weak in humid regions (Supplementary Fig. 2). We found a demarcation line ($\sim 34^\circ\text{N}$), above and below which showed evident cooling (mean: -0.75 K) and negligible temperature changes (mean: 0.031 K) (Supplementary Fig. 2a), respectively. Slight daytime warming effects were observed in some areas in humid South China (e.g., Sichuan Basin, Jiangnan Plain), possibly due to the different vegetation types (e.g., irrigated paddy rice and non-irrigated corn), consistent with the findings of a slight irrigation warming effect in the Mississippi Embayment²⁰. Δ LST at night was quite smaller, but more geographically homogeneous compared to that in the daytime. Clear seasonal patterns were observed for Δ LST, especially in the daytime, characterized by evident cooling in summer (June, July, and August) and slight cooling (or warming) in winter (December, January, and February; Supplementary Fig. 2c), because irrigation practices are mainly implemented in the growing season (May to September).

Supplementary Text 2. Changes in annual mean energy fluxes due to agricultural irrigation during 2001–2020

Based on the energy balance equation (Methods, Eq. (5)), we obtained the twenty-year averaged changes in latent heat flux (ΔLE), sensible and ground heat fluxes (ΔHE), reflected shortwave solar radiation (ΔSW_{out}), and emitted longwave radiation (ΔLW_{out}) (Supplementary Fig. 4). LE showed the most prominent changes of $3.10 \pm 0.50 \text{ W m}^{-2}$, contributed most by the increase in the arid region ($11.31 \pm 1.42 \text{ W m}^{-2}$). HE decreased across the country, especially in the arid region ($-4.67 \pm 1.31 \text{ W m}^{-2}$). SW_{out} was negligible across the country, and LW_{out} showed a slight decrease in arid (semi-arid) regions and an increase in humid regions, respectively. Changes in all four energy fluxes except HE have a clear precipitation-temperature gradient, with SW_{out} and LW_{out} increasing from cold-dry to warm-wet regions and the opposite pattern for LE .

Supplementary Text 3. Partial correlation analysis of irrigation-induced LST changes

To further assess the individual influence of each variable on the observed trends in irrigation-induced land surface temperature (Δ LST), we conducted a partial correlation analysis between Δ LST and six explanatory variables: irrigation water use (IWU), precipitation, air temperature, solar radiation, wind speed, and vegetation greenness (Δ EVI). This analysis allows us to isolate the effect of each factor while controlling the influence of the others.

The results demonstrate that IWU is the dominant driver of both daytime and nighttime Δ LST changes across China. After controlling for other variables, IWU exhibited strong and statistically significant partial correlations with Δ LST nationally (daytime: $r = -0.87$; nighttime: $r = +0.86$; $p < 0.01$), underscoring the central role of reduced irrigation intensity under WSI adoption in modulating surface temperature patterns (Supplementary Fig. 9a, e).

In addition, we found regionally varying effects of vegetation greening. In semi-arid and semi-humid regions, Δ EVI was significantly negatively correlated with daytime Δ LST ($r = -0.72$, $p < 0.05$; Supplementary Fig. 9c), suggesting that enhanced crop vigor may have partially counterbalanced the loss of evaporative cooling due to reduced soil evaporation. However, in arid and humid regions, Δ EVI exhibited weaker and non-significant correlations with Δ LST.

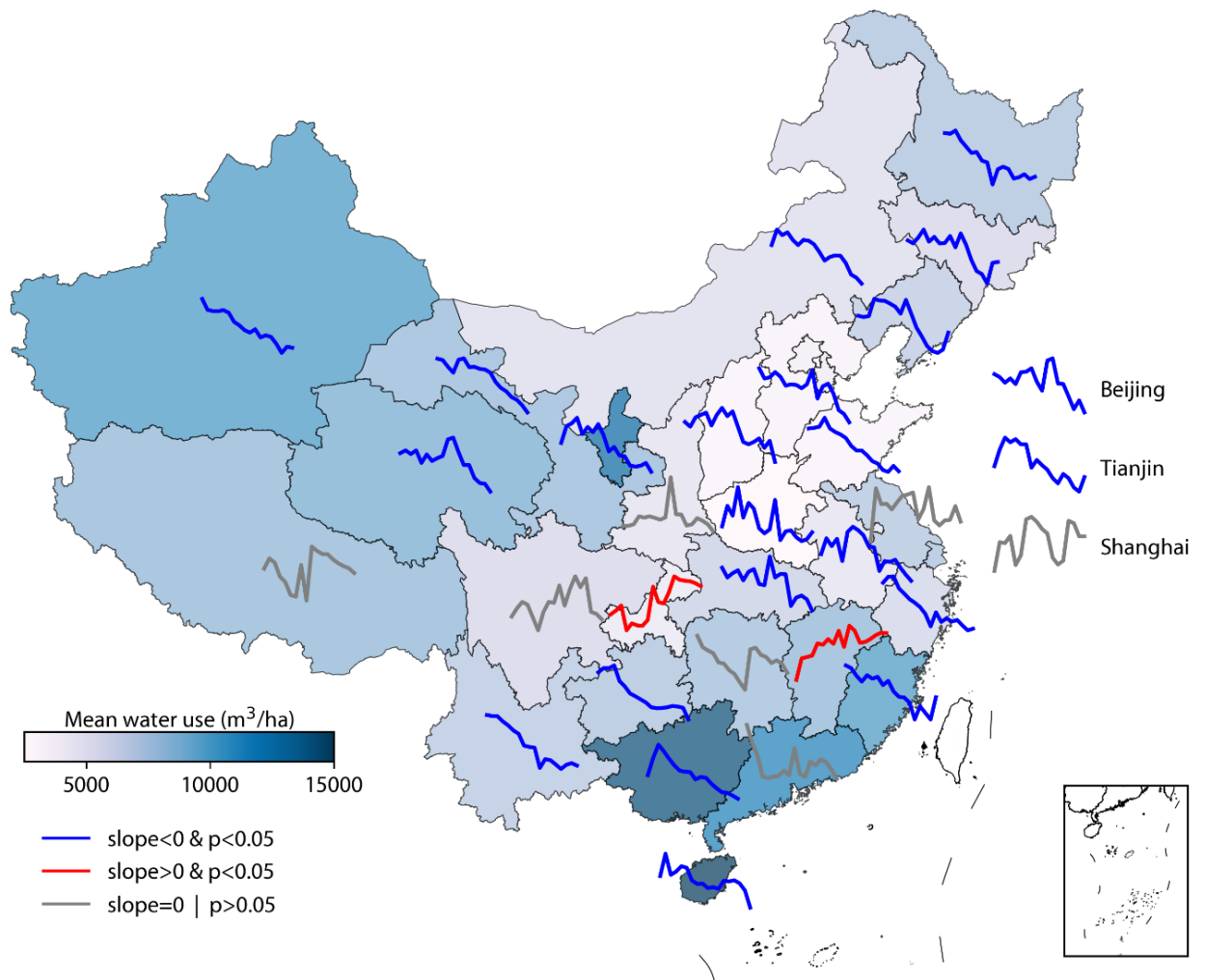
At night, IWU remained significant driver in most climate zones, except the humid region (Supplementary Fig. 9e–h). This pattern implies that nighttime LST changes are primarily governed by changes in soil moisture and thermal properties—both closely tied to irrigation intensity—rather than by vegetation dynamics or meteorological drivers.

Together, the partial correlation results reinforce the regression-based attribution findings, providing strong statistical evidence that the widespread reduction in water use under WSI is

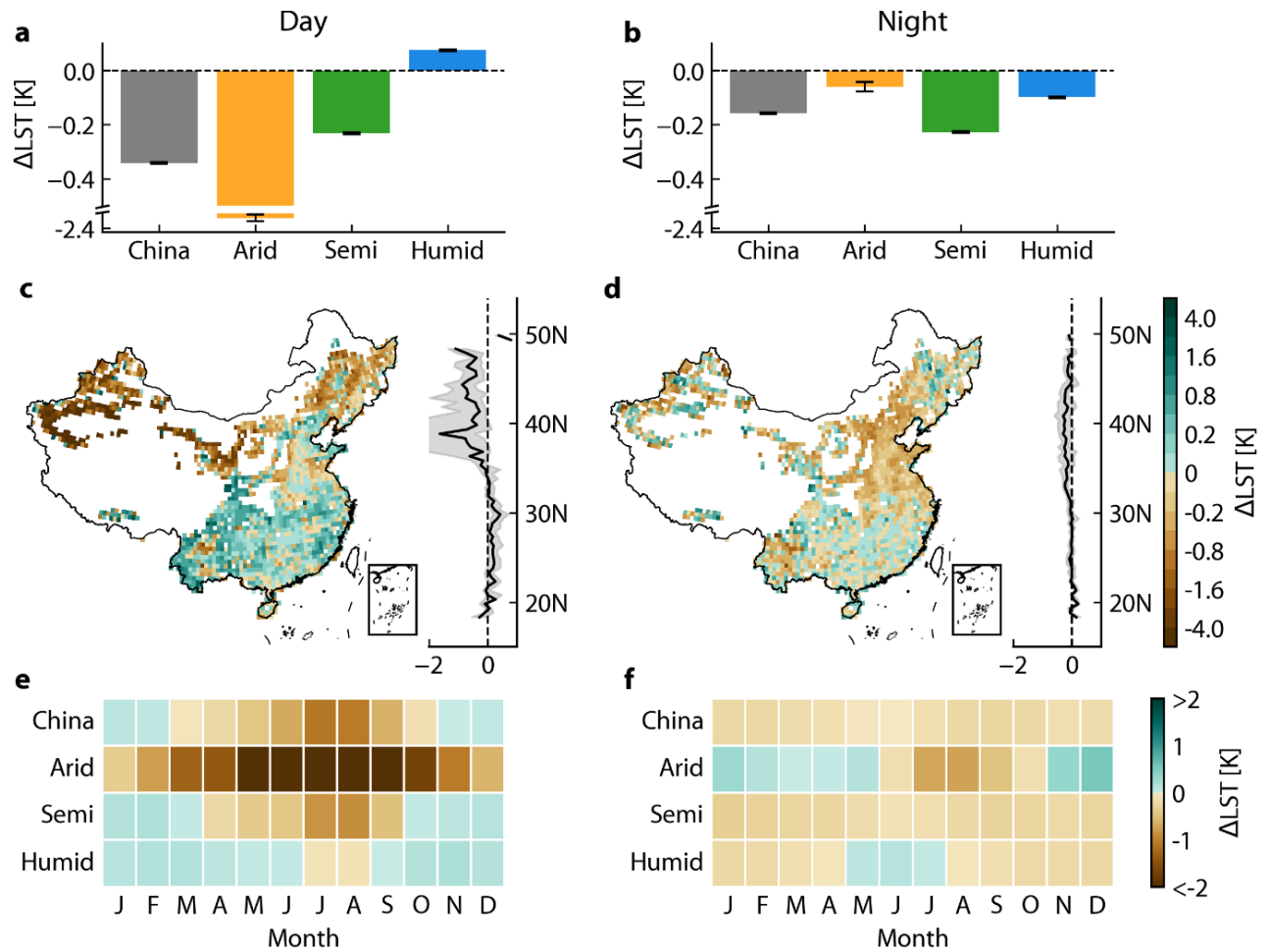
the key driver of evolving irrigation-climate interactions across China.

Supplementary Table 1 | Datasets used in this study. This table summarizes the key datasets employed in the analysis, including satellite products, model outputs, and national statistics. NLCD-China refers to the National Land Cover Dataset of China; LST: land surface temperature; EVI: enhanced vegetation index; T: vegetation transpiration; Ecanopy: evaporation from canopy interception; Esoil: soil evaporation; Ta: air temperature; Pre: precipitation; SW: solar shortwave radiation; Ws: wind speed; LW: longwave radiation; IWU: Irrigation water use.

Dataset	Spatial resolution	Temporal period	Variables	Reference
NLCD-China	1,000 m	1980s-2020 (5-year)	Land use and land cover	60
IrriMap_CN	500 m	2001-2019	Irrigated croplands	26,55
IrriMap_Meier	1000 m	1999-2012	Irrigated croplands	56
MOD11A2	1,000 m, 8-day	2001-2020	LST (daytime, nighttime)	61
MCD43A3	500 m, daily	2001-2020	Albedo	80
MOD13A2	1,000 m, 8-day	2001-2020	EVI	64
MOD16A2	500 m, 8-day	2001-2020	ET	67
PML_V2	500 m, 8-day	2001-2020	T, Ecanopy, Esoil	34
TerraClimate	4,000 m, monthly	1980-2020	Ta, Pre, SW, Ws	68
FLDAS	10,000 m, monthly	2000 - 2021	Downward LW	70
SRTM	1000 m	static	Elevation	71
IWU	provincial	2003-2020	Mean irrigation water use	-

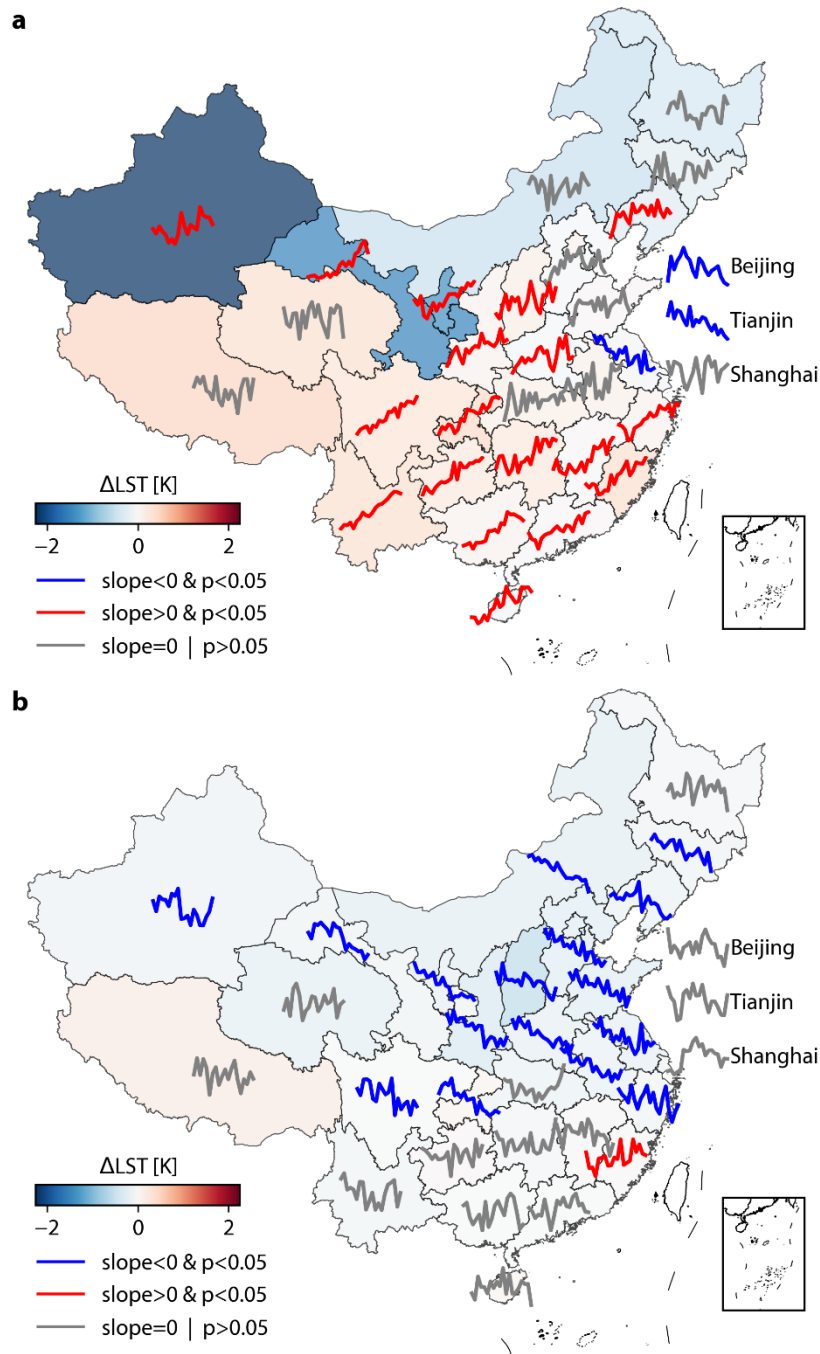


Supplementary Fig. 1 | Provincial patterns and trends in irrigation water use per hectare (2003–2020). Background shading indicates the multi-year mean irrigation water use (IWU) per hectare for each province. Overlaid curves represent temporal trends in IWU across provinces from 2003 to 2020, highlighting regional variability in irrigation intensity change.

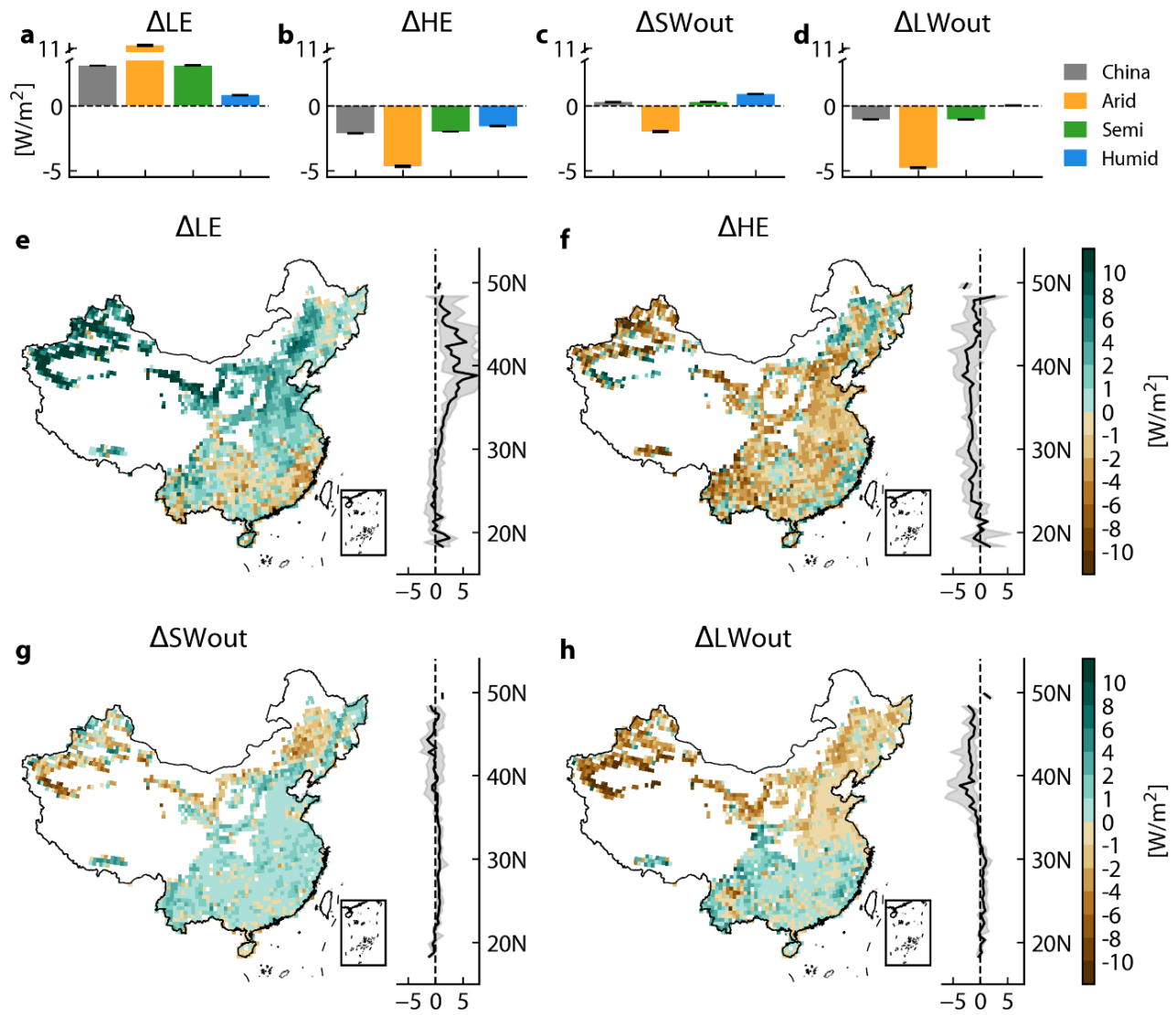


Supplementary Fig. 2 | Mean irrigation-induced land surface temperature changes (ΔLST)

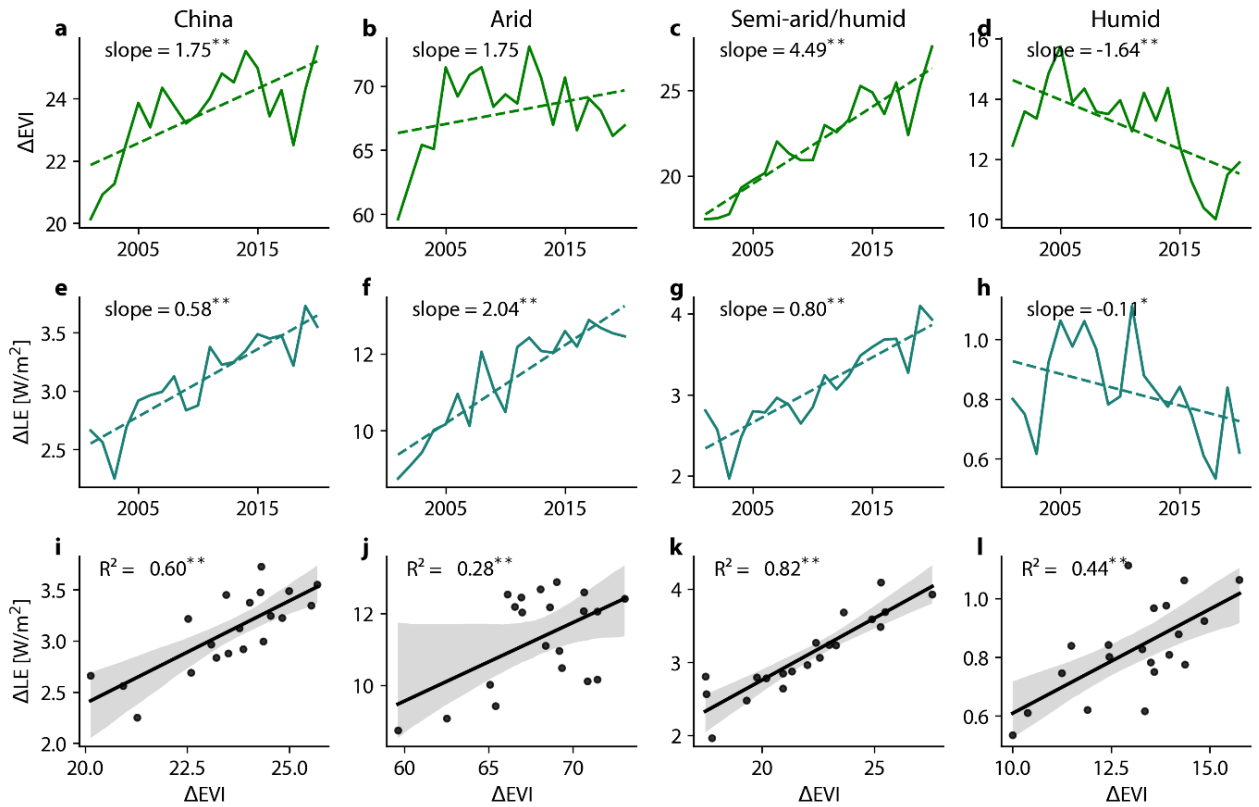
during 2001–2020. a, b National mean ΔLST for daytime and nighttime, respectively. **c, d** Spatial distribution of mean ΔLST at 0.5° resolution for daytime and nighttime, respectively. Right-side panels show the latitudinal median (solid line) and interquartile range (shaded area). **e, f** Monthly mean ΔLST for daytime and nighttime, respectively, aggregated across arid, semi-arid/semi-humid (Semi), and humid climate zones.



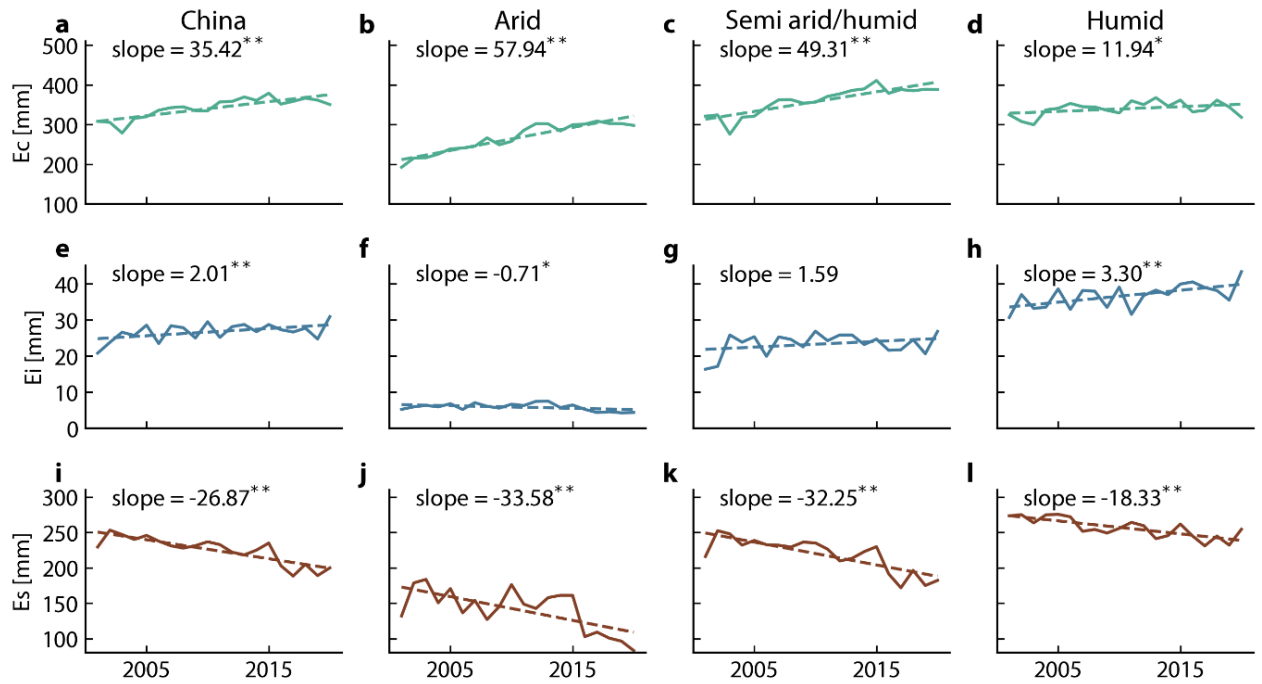
Supplementary Fig. 3 | Provincial mean and trends of irrigation-induced land surface temperature change (Δ LST) during 2001–2020. a, Daytime Δ LST; b, Nighttime Δ LST. The base map shows the provincial average Δ LST, with blue indicating cooling and red indicating warming. Inset line plots illustrate temporal trends for each province: red lines indicate a significant upward trend ($p < 0.05$), blue lines indicate a significant downward trend ($p < 0.05$), and gray lines indicate non-significant trends. Hong Kong, Macao, and Taiwan are excluded.



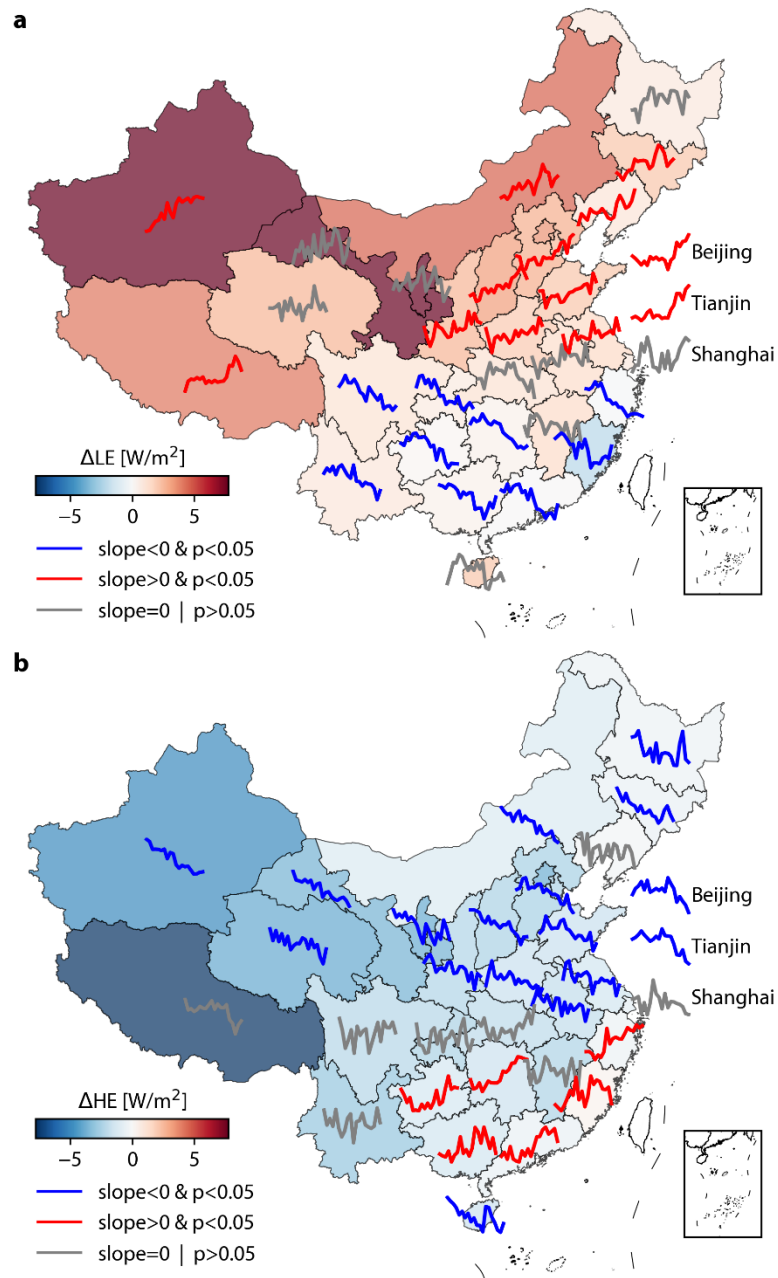
Supplementary Fig. 4 | Mean irrigation-induced changes in surface energy fluxes averaged over 2001–2020. a–d, National annual mean changes in latent heat flux (ΔLE), sensible heat flux (ΔHE), reflected shortwave radiation (ΔSW_{out}), and emitted longwave radiation (ΔLW_{out}) due to irrigation. **e–h**, Spatial patterns of 20-year mean ΔLE , ΔHE , ΔSW_{out} , and ΔLW_{out} at 0.5° grid resolution. Right-side panels show latitudinal profiles with solid lines indicating the median and shaded areas representing the interquartile range (25th to 75th percentiles).



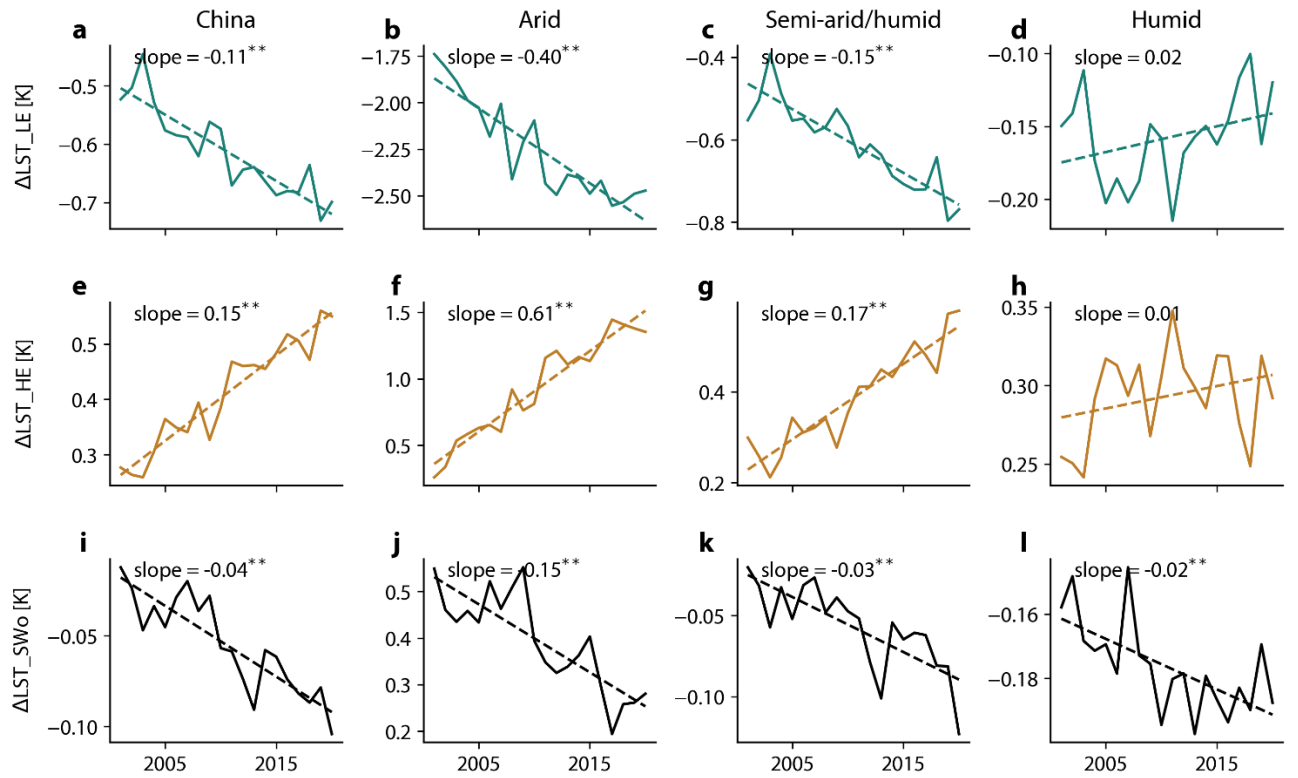
Supplementary Fig. 5 | Temporal trends of annual ΔEVI and ΔLE across irrigated croplands over 2001–2020. Top row: ΔEVI ; Middle row: ΔLE ; Bottom row: scatter plots depict the relationship between ΔEVI and changes in ΔLE , highlighting the role of vegetation greening in modulating evapotranspiration. ** $p < 0.05$ and * $p < 0.1$ based on Student's t -test.



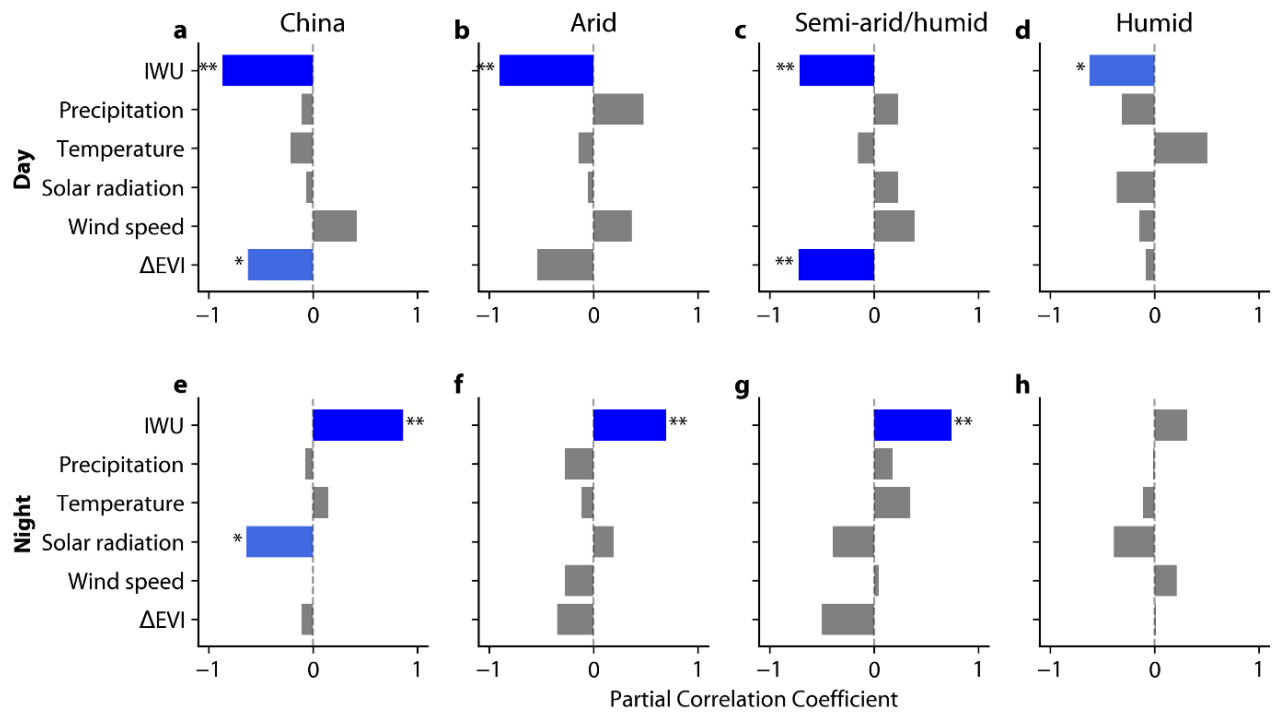
Supplementary Fig. 6 | Temporal trends of annual evapotranspiration (ET) components over irrigated croplands (2001–2020). a–d Vegetation transpiration (E_c). **e–h** Canopy interception loss (E_i). **i–l** Soil evaporation (E_s). ** $p < 0.05$ and * $p < 0.1$ based on the Student's t -test.



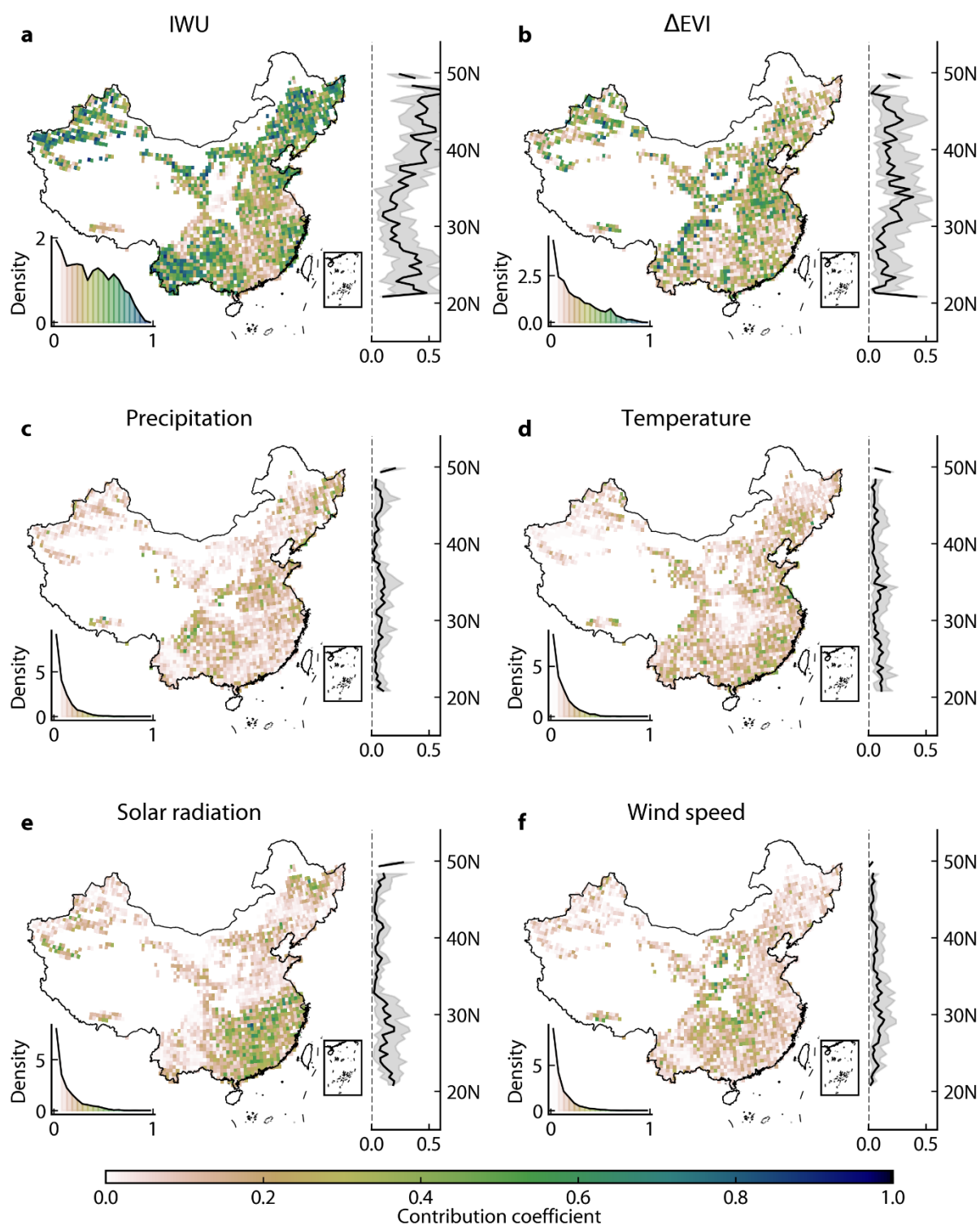
Supplementary Fig. 7 | Provincial mean and trends of irrigation-induced latent and sensible heat flux changes (2001–2020). **a** Mean and temporal trend of latent heat flux change (ΔLE). **b** Same as (a), but for sensible heat flux (ΔHE). Maps show the 20-year averaged annual ΔLE or ΔHE at the provincial level (excluding Hong Kong, Macao, and Taiwan), with green indicating positive values and purple indicating negative values. Inset plots depict temporal trends from 2001 to 2020: red lines denote significant upward trends ($p < 0.05$), blue lines indicate significant downward trends ($p < 0.05$), and gray lines represent non-significant trends.



Supplementary Fig. 8 | Time series of ΔLST forcing components derived from surface energy flux changes (2001–2020). Top row: Latent heat flux (ΔLE); Middle row: Sensible heat flux (ΔHE); Bottom row: Reflected shortwave radiation (ΔSWo). Each panel shows the estimated ΔLST contribution from the corresponding energy component, calculated using Equation (7) in the *Methods*. $^{**}p < 0.05$ and $^{*}p < 0.10$ based on the Student's t -test.

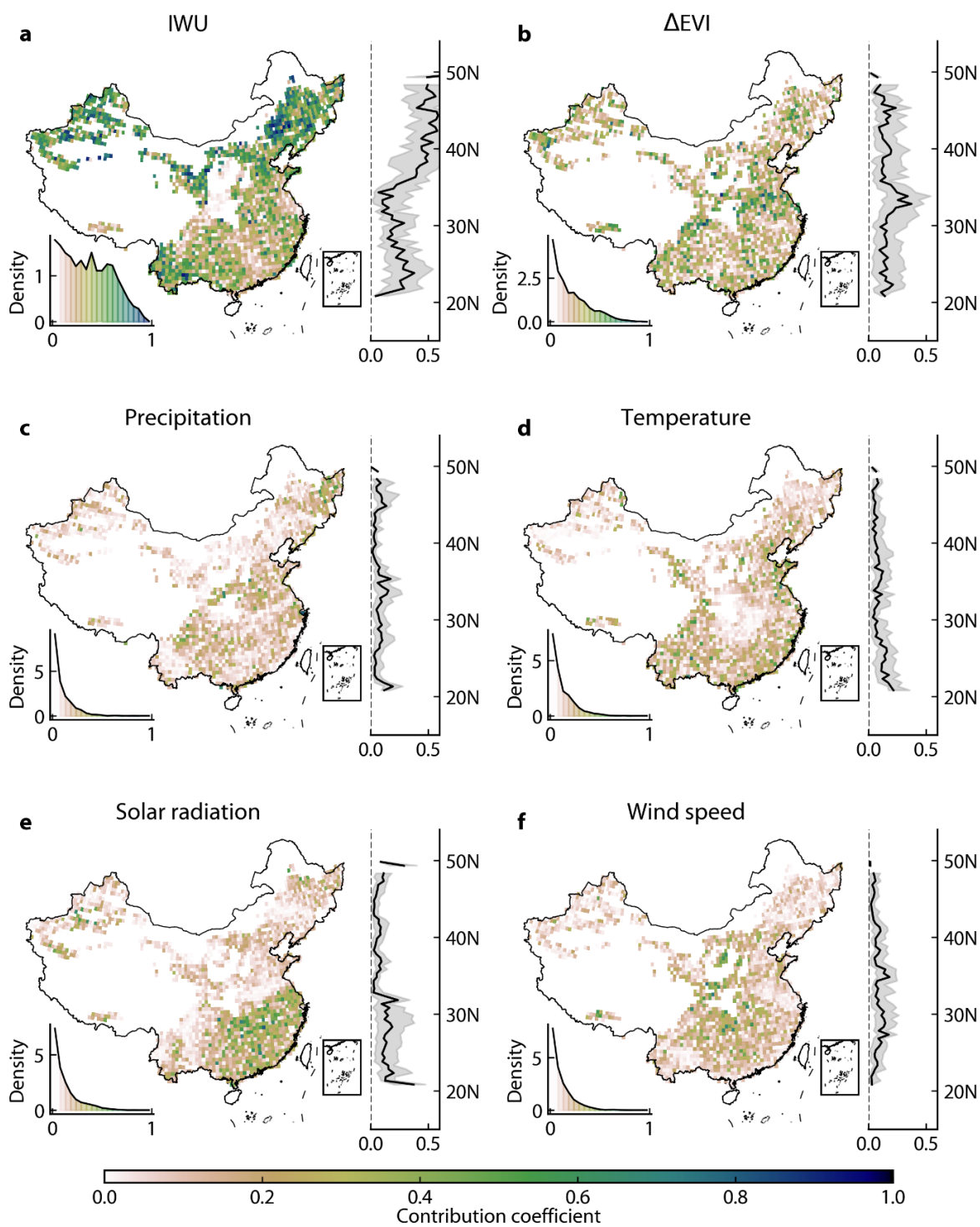


Supplementary Fig. 9 | Partial correlation analyses of factors influencing irrigation-induced Δ LST changes. Panels **a–d** show the partial correlation coefficients between daytime Δ LST and five explanatory variables: irrigation water use (IWU), precipitation, air temperature, solar radiation, and enhanced vegetation index (Δ EVI). Panels **e–h** present the same for nighttime Δ LST. Correlations are computed while controlling for the other variables to isolate independent effects. $p < 0.01$ and $*p < 0.05$ based on Student's t -test. IWU = irrigation water use.

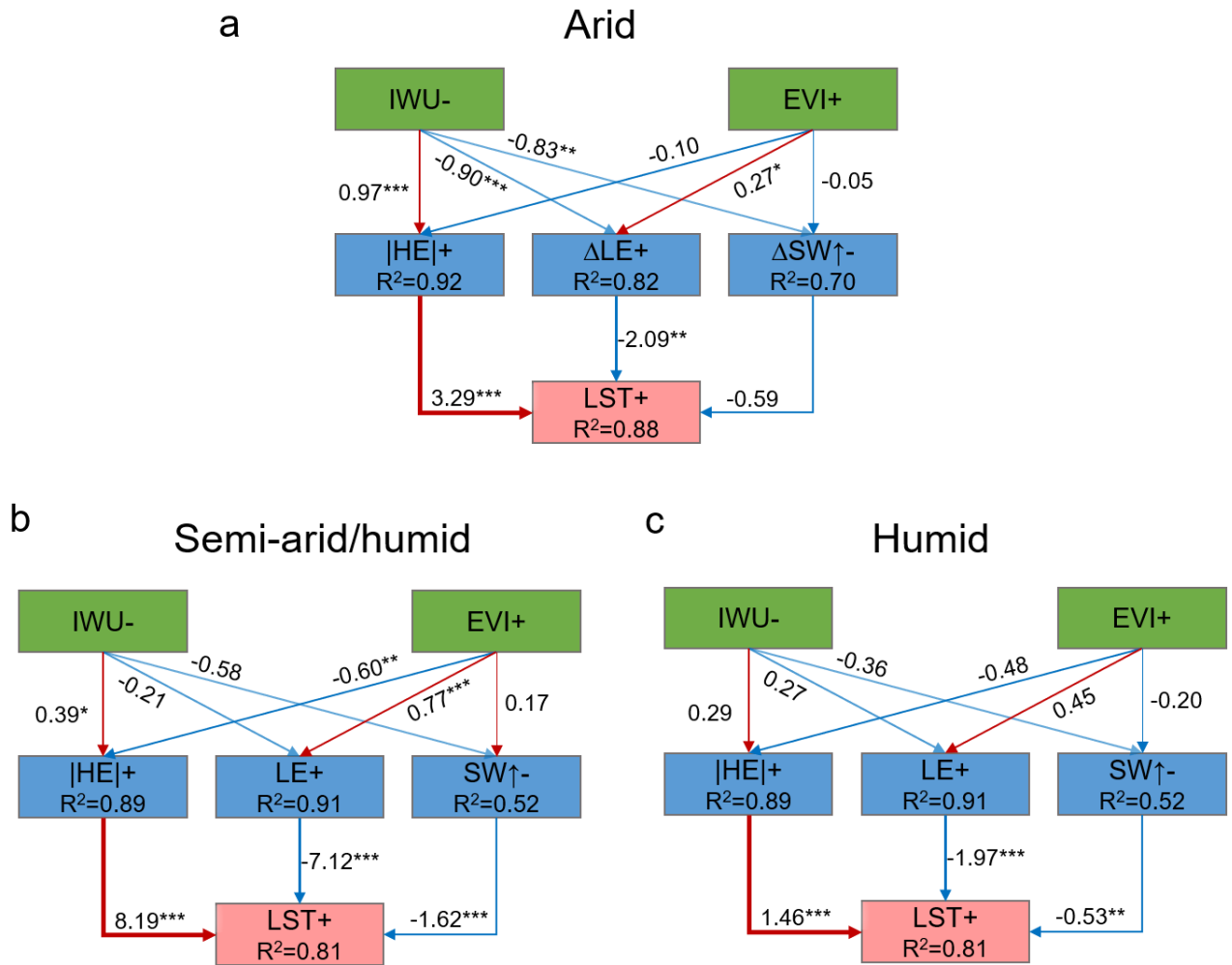


Supplementary Fig. 10 | Contribution coefficients of driving factors to interannual variations in daytime ΔLST at the 0.5° grid scale. Spatial patterns of contribution coefficients quantify the extent to which interannual variations in daytime ΔLST are explained by each factor: (a) irrigation water use (IWU), (b) enhanced vegetation index (ΔEVI), (c) precipitation,

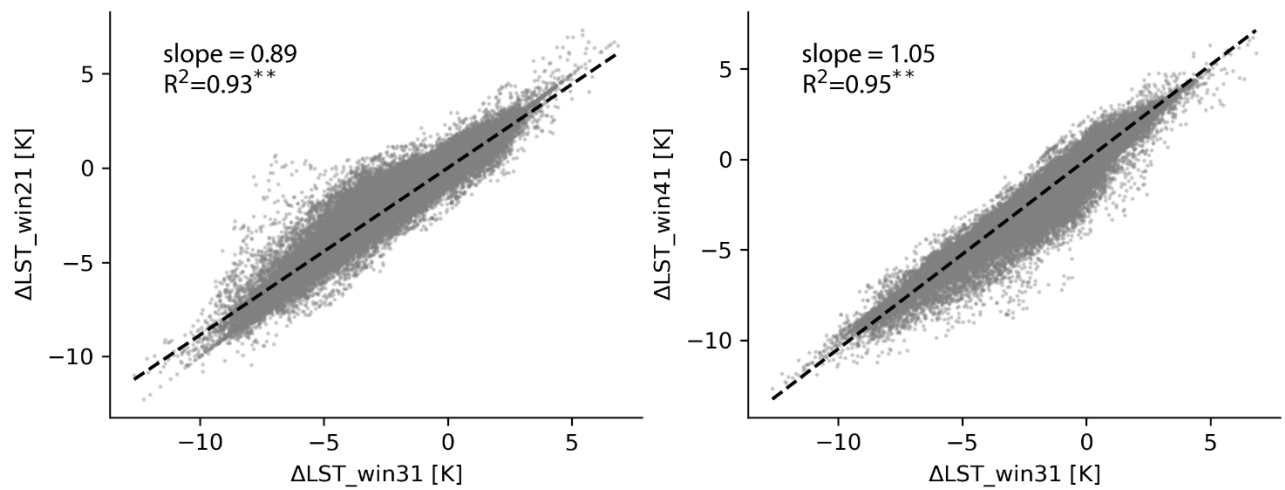
(d) air temperature, (e) solar radiation, and (f) wind speed, based on the attribution framework (*Methods*, Eq. (10)). Right-side panels display latitudinal distributions of the contribution coefficients (solid line: median; shaded area: 25th–75th percentiles). The lower-left inset in each map shows the probability distribution of the coefficients across all valid grid cells.



Supplementary Fig. 11 | Same as Supplementary Fig. 10, but for nighttime ΔLST .

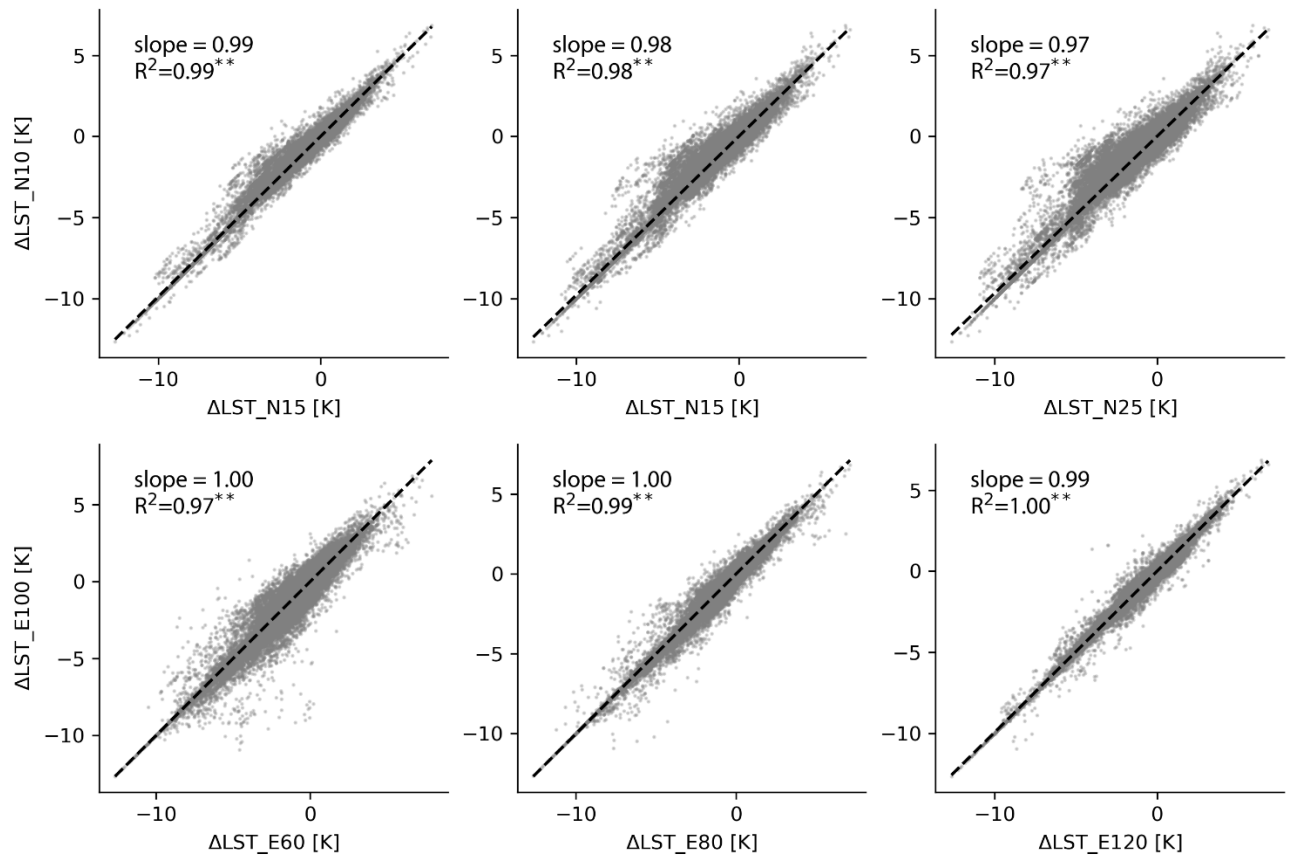


Supplementary Fig. 12 | Same as Fig. 5a in the main text, but for regional statistics including arid (a), semi-arid/humid (b), and humid (c) climate zones.

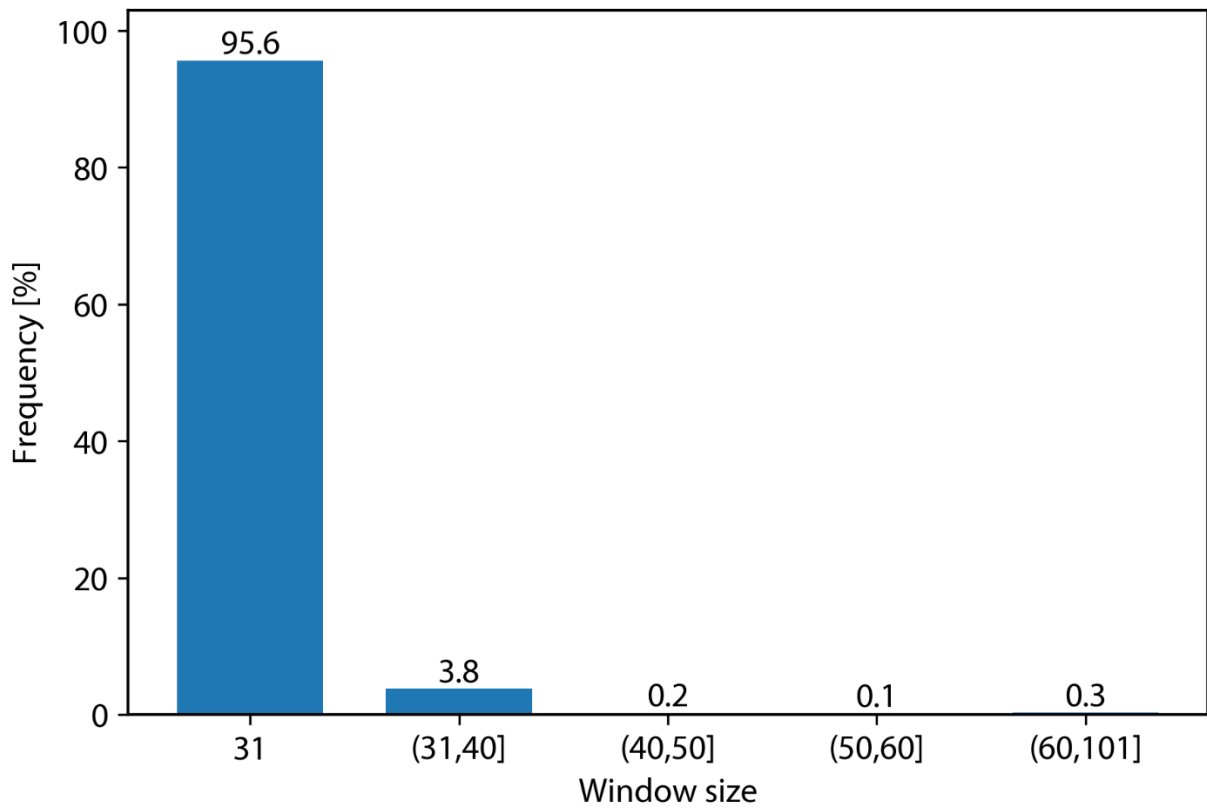


Supplementary Fig. 13 | Sensitivity analysis of Δ LST estimates to window size in the pairwise comparison method. **a** Scatterplot comparing Δ LST in 2010 using 21×21 km versus 31×31 km moving windows. **b** Scatterplot comparing Δ LST using 41×41 km versus 31×31 km windows. Each point represents a grid cell where Δ LST was estimated for irrigated croplands. High correlations indicate the robustness of Δ LST estimates to window size.

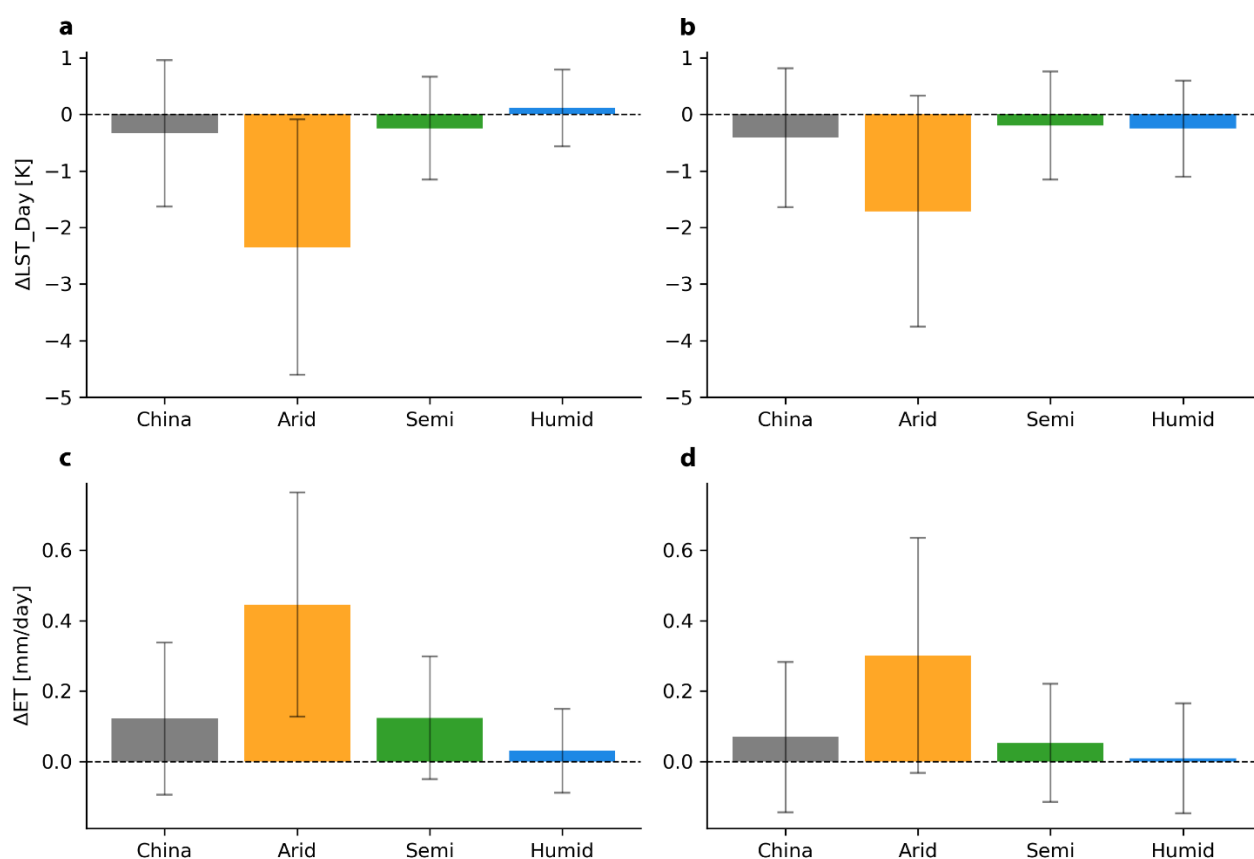
** $p < 0.01$, * $p < 0.05$ based on Student's t -test.



Supplementary Fig. 14 | Sensitivity analysis of the pairwise comparison method using different window parameters in 2010. Sensitivity tests were conducted by varying two key parameters: the number of reference (non-irrigated) pixels (N) and the elevation difference threshold (E) used to match irrigated and control pixels. Results show how estimated ΔLST values respond to different parameter settings. $**p < 0.01$, $*p < 0.05$ based on Student's t -test.



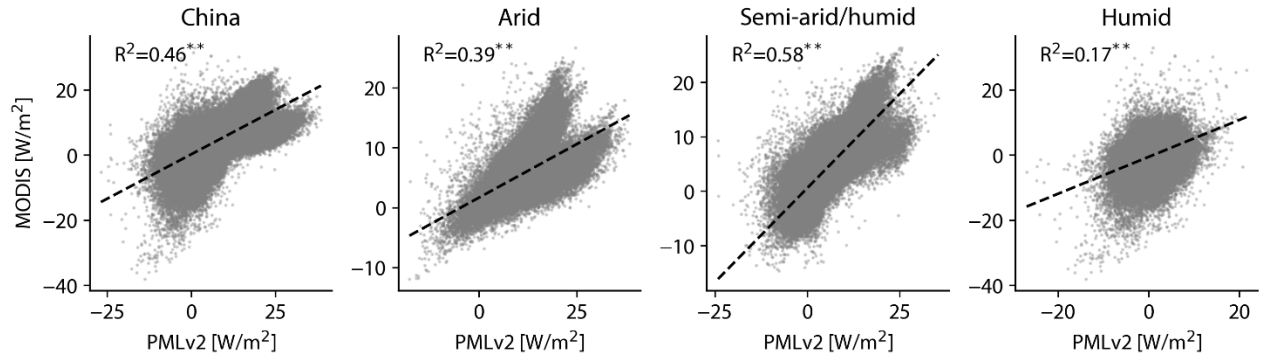
Supplementary Fig. 15. | Probability distribution of window sizes in the flexible window-searching algorithm. Histogram of final window sizes selected by the flexible window-searching algorithm used for identifying matched non-irrigated reference pixels. The initial search window size was 31×31 km, and the algorithm adaptively adjusted the window size based on matching criteria.



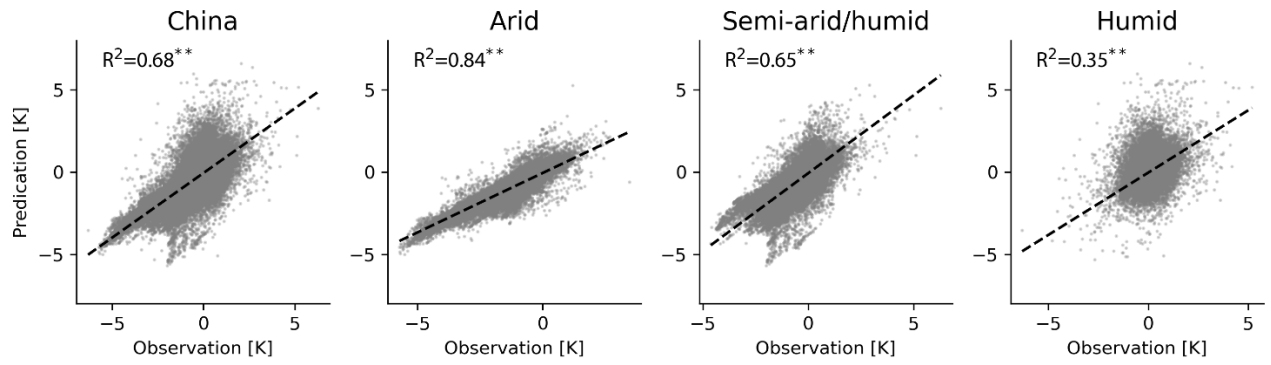
Supplementary Fig. 16 | Comparison of ΔLST and ΔET based on two irrigation datasets.

a, c Results derived using the IrriMap_CN dataset. **b, d** Results derived using the IrriMap_Meier dataset.

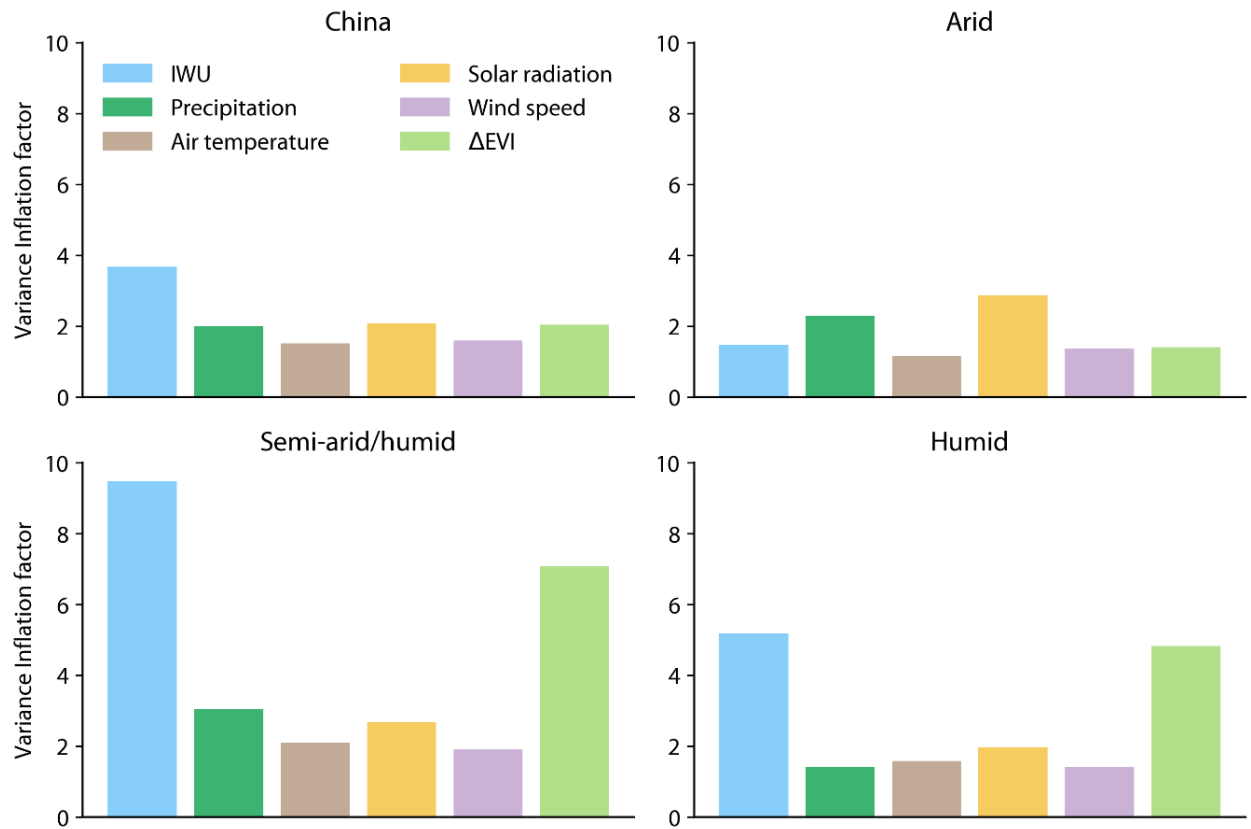
ΔLST : irrigation-induced change in land surface temperature; ΔET : change in evapotranspiration. “Semi” denotes semi-arid and semi-humid regions. Error bars represent the standard error of the mean.



Supplementary Fig. 17 | Inter-comparison of temporal trends in irrigation-induced latent heat flux (ΔLE) from two remote sensing products. Time series of ΔLE from PML_V2 and MODIS latent heat flux datasets across irrigated croplands in China. The comparison highlights consistency and discrepancies in irrigation-driven ΔLE between the two products.



Supplementary Fig. 18 | Comparison of observed and calculated irrigation-induced land surface temperature changes (ΔLST) across China and climate zones in 2010. Scatter plots of observed ΔLST versus calculated ΔLST using Eq. (7) in *Methods*. Each dot represents the value from underlying 1-km resolution data. Results are shown for China overall and for each climate zone to assess consistency between observed and modeled thermal responses to irrigation.



Supplementary Fig. 19 | Collinearity diagnostics of predictors used in the multiple linear regression model. Variance inflation factor (VIF) analysis of the explanatory variables included in the attribution model. All variables exhibit VIF values well below the conventional threshold of 10, indicating no severe multicollinearity and supporting the robustness of the regression analysis.