

## Divergent urbanization-induced impacts on global surface urban heat island trends since 1980s



Long Li<sup>a</sup>, Wenfeng Zhan<sup>a,b,\*</sup>, Leiqiu Hu<sup>c</sup>, TC Chakraborty<sup>d</sup>, Zhihua Wang<sup>e</sup>, Peng Fu<sup>f</sup>, Dazhong Wang<sup>a</sup>, Weilin Liao<sup>g</sup>, Fan Huang<sup>a</sup>, Huyan Fu<sup>a</sup>, Jiufeng Li<sup>a</sup>, Zihan Liu<sup>a</sup>, Huilin Du<sup>a</sup>, Shasha Wang<sup>a</sup>

<sup>a</sup> Jiangsu Provincial Key Laboratory of Geographic Information Science and Technology, International Institute for Earth System Science, Nanjing University, Nanjing, Jiangsu 210023, China

<sup>b</sup> Jiangsu Center for Collaborative Innovation in Geographical Information Resource Development and Application, Nanjing, Jiangsu 210023, China

<sup>c</sup> Department of Atmospheric Science, University of Alabama in Huntsville, Huntsville, AL 35899, USA

<sup>d</sup> Pacific Northwest National Laboratory, Richland, WA 99354, USA

<sup>e</sup> School of Sustainable Engineering and the Built Environment, Arizona State University, Tempe, AZ 85287, USA

<sup>f</sup> Center for Environment, Energy, and Economy, Harrisburg University of Science and Technology, PA 17101, USA

<sup>g</sup> Guangdong Key Laboratory for Urbanization and Geo-simulation, School of Geography and Planning, Sun Yat-sen University, Guangzhou, Guangdong 510006, China

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### ABSTRACT

Urbanization experiences different speeds and forms under diverse development stages across the globe. However, urbanization-induced impacts on long-term surface urban heat island intensity ( $I_s$ ) trends across global cities and the regulators of such impacts remain understudied. Here we estimate interannual trends in daytime  $I_s$  (i.e., urban-rural differences in surface temperatures) across 511 major cities for 1985–2020 using annual averages calculated using reconstructed land surface temperature data derived from >250,000 Landsat thermal images. Our study reveals that the global mean  $I_s$  growth rate is 0.156 °C/decade. We further examine  $I_s$  change associated with per 1% impervious land growth (denoted as  $\beta$ ) in each city throughout the research period and during different periods. The global mean  $\beta$  is  $0.018 \pm 0.025$  °C/% (mean  $\pm$  1 standard deviation) for the whole period, with greater values in humid than in arid climates; and the  $\beta$  may change during different periods, e.g., it has more than tripled when urban impervious land exceeds 30%, indicating the spatiotemporally divergent impacts of urbanization on  $I_s$  trends across global cities. The spatial variations in  $\beta$  across global cities are well correlated with rural vegetation abundance and precipitation but not with urban population. Among these three factors, rural vegetation abundance possesses the greatest standardized regression coefficient of partial least-squares model, signifying the critical role of biome background in regulating  $\beta$ . The finding implies that future urbanization over densely vegetated regions should be more carefully and strategically planned due to the greater urbanization-induced surface warming effect.

### 1. Introduction

The world has witnessed widespread urbanization in recent decades (Liu et al., 2020). One of the consequences is the urban heat island (UHI) effect, which is usually characterized by higher temperatures over urban areas than their rural surroundings (Oke, 1982). The UHI can impact weather through modification of surface energy budget and boundary layer dynamics (Kalnay and Cai, 2003; Qian et al., 2022). One consequence of this is the exacerbation of heat extremes (Sun et al., 2014;

Wang et al., 2021; Yang et al., 2017), which adversely impacts the lives and health of urban residents. Accurate understanding of the impact of continued urbanization on UHI trends is critical for both understanding urban impact at the local scale and for informing urban planning strategies towards heat mitigations (UNEP, 2021).

The key of examining urbanization-induced impacts on UHI trends lies in the accurate quantification of UHI trends. Satellite-based land surface temperature (LST) overcomes the under-representation of in-situ air temperature measurements over large areas (Zhou et al., 2022) and it

\* Corresponding author at: Nanjing University, Xianlin Campus, No. 163 Xianlin Avenue, Qixia District, Nanjing, Jiangsu, 210023, China.  
E-mail address: [zhanwenfeng@nju.edu.cn](mailto:zhanwenfeng@nju.edu.cn) (W. Zhan).

has been frequently used to investigate surface UHI intensity ( $I_s$ ) trends, either for studies at city (Dewan et al., 2021; Meng et al., 2018; Quan et al., 2016), national (Li et al., 2020a; Yao et al., 2018), or global scales (Chakraborty and Lee, 2019; Si et al., 2022; Yao et al., 2019). However, the research periods of investigations of  $I_s$  trends have been mostly limited to the recent two decades (i.e., post-2000), mostly due to the lack of high-quality and temporally consistent satellite-derived LST products before 2000. Global cities should possess highly diverse expansion processes due to divergent urbanization rates during different periods. For example, much faster urbanization has been witnessed in the United States before 2000 than afterwards, while China has experienced more rapid urbanization after 2000 (Liu et al., 2020). Such contrasting urbanization processes are expected to cause divergent  $I_s$  trends across global cities during different periods (Supplementary Fig. S1). Therefore, long-term LST observations are required to identify such spatio-temporal disparities in  $I_s$  trends. The long-term  $I_s$  trends (especially for pre-2000s) are potentially derivable with LST data acquired by Landsat-series satellites, as Landsat-series satellites have sampled the thermal status of the earth's surface for approximately four decades. However, Landsat thermal data are characterized by long sampling interval (~16 days) and strongly impacted by cloud contamination and the stripe-gap effect, making the derivation of  $I_s$  trends based on Landsat thermal data extremely difficult (Li et al., 2022a). Therefore, variations in the  $I_s$  trends since the 1980s across global cities remain unknown.

Increase in urban impervious land can serve as a proxy for urbanization (Gong et al., 2020; Liu et al., 2020). Numerically, the urbanization-induced impacts on  $I_s$  trends are usually evaluated as the  $I_s$  change associated per 1% urban impervious land (or urban-rural difference in impervious surface percentage,  $\delta ISP$ ) growth (Li et al., 2021; Li et al., 2022b; Rizvi et al., 2020), denoted here as  $\beta$ . Investigating the pattern and dynamics of  $\beta$  can deepen the understanding of urbanization-induced impacts on  $I_s$  trends (Fu and Weng, 2016; Tran et al., 2017). Previous assessments revealed that  $\beta$  reaches 0.020 °C%/ in Beijing-Tianjin-Hebei metropolitan region, China, with a warm temperate climate (Li et al., 2022b). By contrast,  $\beta$  is very small (0.001 °C/%) in Karachi, Pakistan, characterized by an arid climate (Rizvi et al., 2020). However, preceding estimations on  $\beta$  are spatio-temporally constrained in individual cities and/or in relatively short periods (often after 2000); and a global pattern of  $\beta$  remains lacking. Furthermore, the daytime absolute  $I_s$  (not the  $I_s$  trends) has been shown to be jointly regulated by precipitation, vegetation, and urban population (Li et al., 2019; Manoli et al., 2019; Zhao et al., 2014). Whether  $\beta$  is controlled by these three factors and which factor among these exerts the greatest impacts, especially from a global perspective, remain unknown.

Here, we investigate the  $I_s$  trends since the 1980s across 511 cities worldwide with reconstructed LST data obtained based on >250,000 Landsat thermal images, with the MODIS LST data used to validate the

reliability in depicting the long-term  $I_s$  trends. We further combine  $I_s$  and impervious surface data to analyze the urbanization-induced impacts on  $I_s$  trends (i.e.,  $\beta$ ) by establishing their temporal relationships. We also use several other datasets (vegetation abundance, precipitation, and population) to examine the associated regulators of  $\beta$ . The findings of this study should help to deepen the understanding of the change in the urban thermal environment due to continued urbanization over the last four decades.

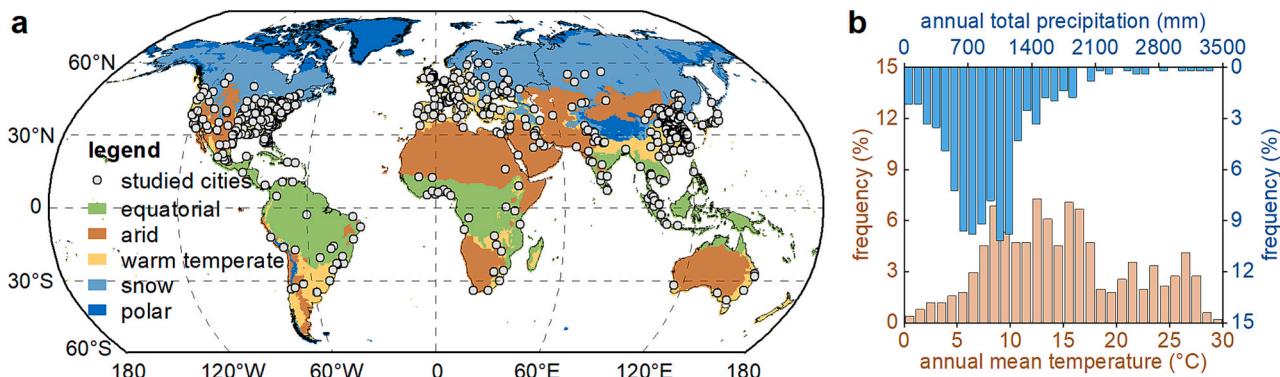
## 2. Methods

### 2.1. Study area and data

We focused on the 511 major cities worldwide with an urban area > 200 km<sup>2</sup> in 2018 (Fig. 1a). These cities are distributed in Africa (34 cities), Asia (194 cities), Europe (82 cities), North America (172 cities), Oceania (6 cities), and South America (23 cities). They are typified by various climate types according to the Köppen-Geiger classification scheme (Kottek et al., 2006), including equatorial (52 cities), arid (51 cities), warm temperate (290 cities), and snow (118 cities) climates. These cities have undergone rapid urbanization in recent decades (Gong et al., 2020) and possess remarkable differences in annual mean temperature and annual total precipitation (Fig. 1b). Moreover, large cities also offer more pixels and make them more suitable for statistical analysis than small cities. Therefore, these characteristics should be useful for assessing and understanding the impacts of urbanization on  $I_s$  trends and the regulators of such impacts in different background climates.

We employed LST observations from both Landsat and MODIS Terra satellites. Across the 511 major cities, we processed >250,000 LST images acquired from Landsat-5, -7, and -8 for the period of 1985–2020, with a spatial resolution of ~100 m as well as overpass time of approximately 10:30–12:00 local time. These LSTs were retrieved by a statistical mono-window algorithm and have been demonstrated to possess an acceptable accuracy (Ermida et al., 2020). These Landsat LSTs were used to reconstruct LST time series and to derive the  $I_s$  trends for the period of 1985–2020. The MODIS LSTs for the period of 2000–2020 were extracted from the MOD11A2 V6.1 product. The MODIS LST products have a spatial resolution of 1 km and also possess reliable retrieval accuracy (Wan, 2008). The MODIS LSTs were used to validate the LSTs reconstructed from Landsat thermal data in capturing long-term  $I_s$  dynamics and  $I_s$  trends.

We also processed impervious surface, urban boundary, elevation, land cover type, vegetation abundance, precipitation, and population data. The impervious surface data (<http://data.ess.tsinghua.edu.cn/gaia.html>) for 1985–2018 were derived from Landsat images and they hold a relatively high overall accuracy (Gong et al., 2020). These data were employed to characterize urban impervious land growth (i.e.,



**Fig. 1.** Spatial distribution and climate characteristics of the 511 studied cities. Distribution of cities and their corresponding climate zones (a) and frequency distribution of annual mean temperature and annual total precipitation (b).

urbanization). The urban boundary data (<http://data.ess.tsinghua.edu.cn/gub.html>) in 2018 were generated by combining the impervious surface data and a kernel density estimation method (Li et al., 2020b). The urban boundary data were used to delineate urban and rural surfaces. The elevation data were obtained from <https://srtm.csi.cgiar.org/>. The elevation data possess a spatial resolution of 90 m, and they were applied to suppress the impacts of large elevation variations on the  $I_s$  estimation. The land cover type data (<https://search.earthdata.nasa.gov/>) were obtained from the MCD12Q1 product. They have a spatial resolution of 500 m and were employed to exclude the pixels labeled as ‘water’, ‘wetlands’, and ‘permanent snow and ice’ over urban and rural surfaces. The vegetation abundance data were obtained from the VIP-PHEN data product. We retrieved the normalized difference vegetation index (NDVI) in 1985 from VIPPHEN (with a resolution of 0.05°) to examine the impacts from vegetation abundance on  $\beta$ . The reanalysis precipitation data in 1985 were obtained from [https://psl.noaa.gov/odata/gridded/data.UDel\\_AirT\\_Precip.html](https://psl.noaa.gov/odata/gridded/data.UDel_AirT_Precip.html). The precipitation data (with a resolution of 0.5°) were employed to examine the impacts from precipitation on  $\beta$ . The population data in 1990 (with a resolution of 1 km) were collected from Global Human Settlement Layer (<http://data.europa.eu/89h/d6d86a90-4351-4508-99c1-cb074b022c4a>). The population data were used to examine the impacts from urban population on  $\beta$ .

We processed all data to a spatial resolution of 1 km for analysis, mainly aiming to match the resolution of LST data and to reduce computational complexity. The continuous (Landsat LST, elevation, vegetation abundance and precipitation data) and discrete (land cover data) variables were resampled by bilinear interpolation and nearest neighbor interpolation, respectively. The impervious surface percentage data were generated based on the proportion of impervious surface within a 1 km<sup>2</sup> rectangle. The MODIS LST and population data preserve their original 1 km resolution. Note that the Landsat LST data were reconstructed at 1 km resolution, mainly because we aim to assess the impacts of urbanization on long-term  $I_s$  trends at the city scale and due to the huge data volume involved in reconstructing high-resolution LSTs.

## 2.2. Estimation of long-term $I_s$ trends using Landsat data

The Landsat LST data cannot be used directly to estimate  $I_s$  trends and assess urbanization-induced impacts on  $I_s$  trends, due to the long sampling interval (~16 days) and the large differences in data acquisition dates impacted by cloud contamination, stripe gaps, and missing images (Ahmed et al., 2023; Zhou et al., 2019). There is thus a need to reconstruct the Landsat LST with higher spatiotemporal continuity to reduce the sampling bias. The Prophet model can reconstruct data with periodic variability (Taylor and Letham, 2018). The critical capability of the Prophet model is to utilize all available time-series data to simulate the interannual and seasonal dynamics. This model can reduce the sampling bias of LST data arising from cloud contamination, stripe gaps, and missing images by enabling the reconstructed LST dataset with enough values within a year and the relatively consistent dates across years. This method therefore helps estimate LST trends by overcoming the deficiencies of Landsat-derived LST (i.e., with intra-annual periodic variability) time series with severe missing and large differences in acquisition dates (Li et al., 2022a).

Here we employed the Prophet model to reconstruct spatiotemporally continuous Landsat LSTs at 1 km resolution for 1985–2020. The method includes three main steps. We first pre-processed the acquired Landsat LST data by setting all Landsat LST gaps arising from cloud contamination, stripe gaps, and data missing as null values and eliminating LST outliers based on the ‘3σ (standard deviation)’ rule (Lehmann, 2013). With all the pre-processed Landsat LSTs, we then solved for the coefficients of the Prophet model and obtained its interannual, seasonal, and residual components. Using the model coefficients and associated components, we finally generated spatiotemporally

continuous LST data under clear-sky conditions across global cities. We compared the Landsat observations with the reconstructed data to evaluate the accuracy of the reconstructed Landsat LST with the mean absolute error (MAE). Note that the LST data were reconstructed at a temporal resolution of 16 days by referring to the revisit period of Landsat satellites. To facilitate understanding, a case in Beijing, China, is presented to show the procedure of the Prophet model to reconstruct Landsat LST (refer to Supplementary Fig. S2).

We delineated the urban areas as the pixels within the urban boundary of 2018 while the rural areas as the buffer zone with an equivalent area to the urban (Zhou et al., 2014). The pixels labeled as ‘water’, ‘wetlands’, ‘permanent snow and ice’, and those pixels with an elevation beyond ±50 m of the urban mean elevation were excluded to suppress their impacts on the  $I_s$  estimation (Imhoff et al., 2010; Peng et al., 2012). We then calculated  $I_s$  as the difference between the urban and rural mean LSTs:

$$I_s = LST_{\text{urban}} - LST_{\text{rural}} \quad (1)$$

where  $I_s$  denotes the surface urban heat island intensity; and  $LST_{\text{urban}}$  and  $LST_{\text{rural}}$  denote the urban and rural mean LSTs, respectively.

We estimated the interannual  $I_s$  trends for each city using linear regression and tested the significance of  $I_s$  trends at the 0.05 level. Only cities with significant  $I_s$  trends (i.e.,  $p < 0.05$ ) were considered in the global and regional analysis. Considering that we used static urban boundary to estimate  $I_s$ , the detected  $I_s$  trend mainly reflects the increase in areas affected by  $I_s$  due to urban expansion. We further validated the Landsat-derived  $I_s$  with those derived from MODIS LST data during 2000–2020. MODIS data have been commonly used to derive  $I_s$  trends (Quan et al., 2016; Si et al., 2022; Yao et al., 2018). Thus, the  $I_s$  trends derived from MODIS data can be regarded as ‘ground truth’ under clear-sky conditions, both because of the estimates available from previous studies and also because of the relatively high retrieval accuracy of and high-frequency (i.e., daily) revisit of MODIS LST data (Chakraborty et al., 2021). We assessed the accuracy of the Landsat-derived  $I_s$  and  $I_s$  trends with the determination coefficient ( $R^2$ ), MAE, and bias.

## 2.3. Assessment of urbanization-induced impacts on $I_s$ trends

Urbanization is often described as the increase of impervious surfaces (Gong et al., 2020; Liu et al., 2020). Here we used the impervious surface percentage (ISP, i.e., the percentage within a 1 km<sup>2</sup> rectangle) to investigate the urbanization-induced impacts on  $I_s$  trends. Corresponding to the  $I_s$  calculation, the urban-rural contrast in ISP (denoted as  $\delta\text{ISP}$ ) were used to represent the urbanization level, expressed by the following formula:

$$\delta\text{ISP} = ISP_{\text{urban}} - ISP_{\text{rural}} \quad (2)$$

where  $\delta\text{ISP}$  denotes the urban-rural contrast in ISP;  $ISP_{\text{urban}}$  and  $ISP_{\text{rural}}$  denotes the urban and rural mean ISP, respectively. Analogous to the  $I_s$  trend estimation, we examined the  $\delta\text{ISP}$  trends for each city using linear regression.

Global cities are expected to possess highly diverse expansion processes due to varying urbanization rates across cities and periods. Such contrasting urbanization processes across global cities usually lead to divergent  $I_s$  trends. To quantify the urbanization-induced impacts on  $I_s$  trends, we calculated the  $I_s$  change associated with per 1% urban land growth (denoted as  $\beta$ ) from a temporal perspective, i.e., the slope of the linear relationship between the temporal changes in  $I_s$  and  $\delta\text{ISP}$  (Supplementary Fig. S3). That is, we compared the  $\beta$  in different cities by assessing changes in  $I_s$  due to same increase in urban land proportion (i.e.,  $\delta\text{ISP}$ ). The  $\beta$  can be calculated by:

$$\beta = \frac{\Delta I_s - b}{\Delta \delta\text{ISP}} \quad (3)$$

where  $\Delta I_s$  and  $\Delta \delta\text{ISP}$  denote the temporal changes in  $I_s$  and  $\delta\text{ISP}$ ,

respectively; and  $b$  is a constant denoting the offset of the linear relationship between  $\Delta I_s$  and  $\Delta \delta\text{ISP}$ . We used the static urban boundary in 2018 to assess  $\beta$ , mainly because it contains most of the areas experiencing rapid urbanization and can reflect the changes in  $\delta\text{ISP}$  and the resulting changes in  $I_s$  compared to urban boundaries in earlier years.

#### 2.4. Potential drivers of $\beta$

According to previous findings, precipitation (a climate parameter), vegetation abundance (a surface-property parameter), and population (a proxy for human activity intensity) are the main regulators on the spatial pattern of  $I_s$  (Li et al., 2019; Manoli et al., 2019; Zhao et al., 2014). We therefore also employed precipitation, vegetation abundance (rural NDVI), and urban population to investigate their roles in regulating the spatial pattern of  $\beta$  (i.e., urbanization-induced impacts on  $I_s$  trends) by establishing their spatial relationships across global cities. We first used ordinary correlation analysis to preliminarily examine the relationships of  $\beta$  with precipitation, rural NDVI, and urban population across global cities. Nevertheless, there is often co-linearity between precipitation and rural NDVI (Supplementary Figs. S4 & S5), and the role of vegetation and precipitation cannot be well differentiated in regulating  $\beta$  with ordinary correlation analysis. We therefore employed the partial least-squares model (i.e., a common strategy to solve co-linearity) (Wold et al., 1984) to differentiate the role of these three variables. We used the partial correlation coefficients between  $\beta$  and precipitation, rural NDVI, and urban population as well as the associated standardized coefficients to determine the relative importance of these three variables on regulating the spatial pattern of  $\beta$  across global major cities. Note that the impacts from precipitation, vegetation abundance, and urban population on  $\beta$  described in the study mainly reflect the controls of spatial differences in  $\beta$  between different cities.

#### 2.5. Uncertainties of the method

We conducted the uncertainty analysis to examine the impacts from image number, urban definition, and factor selection on our results. First, we investigated the effects of the number difference in available Landsat images on the estimated  $I_s$  and  $I_s$  trend. This aims to examine the possible effect of the number differences in available Landsat LST across cities on the analysis associated with the  $I_s$  and  $I_s$  trend. Second, we analyzed the influence of urban definition on the magnitudes of  $I_s$ ,  $I_s$  trend, and  $\beta$  by dividing the urban areas into urban cores (defined by the areas within the urban boundary in 1990) and urban fringes (defined as the newly expanded areas between the urban boundaries of 1990 and 2018). This analysis aims to assess the uncertainties in the estimates of  $I_s$ ,  $I_s$  trend, and  $\beta$  caused by different urban definitions. Third, we used urban NDVI, rural NDVI, and urban-rural contrast in NDVI to detect the relationship between  $\beta$  and vegetation cover. This aims to analyze the

effect of such factor selections on the obtained results.

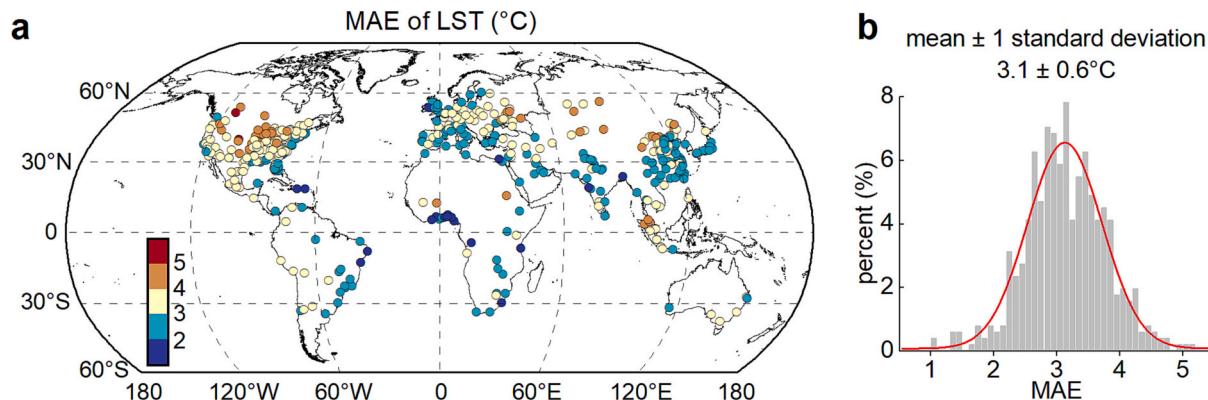
### 3. Results

#### 3.1. Validation of the reconstructed Landsat LST dataset

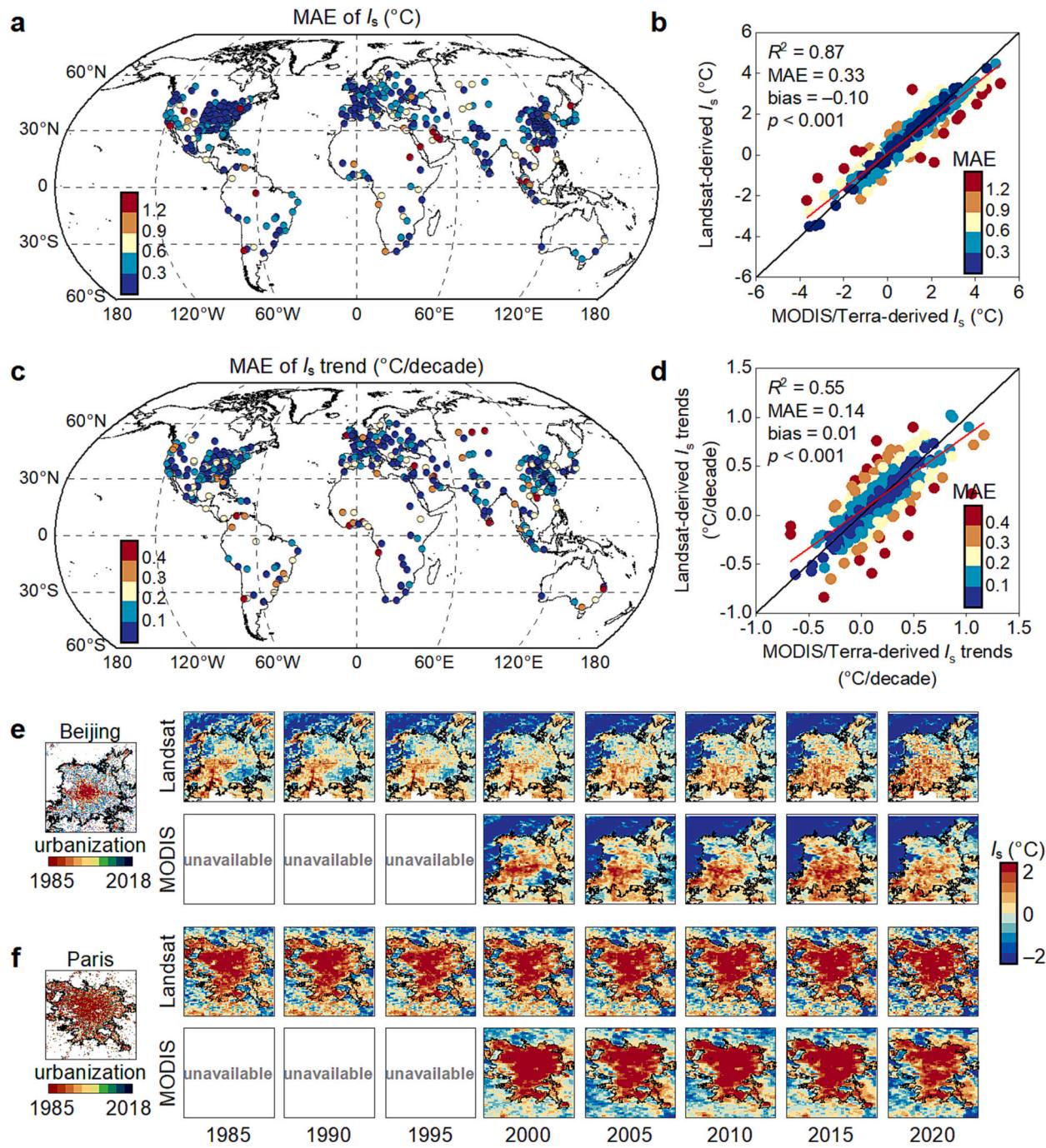
We evaluated the accuracy of the reconstruction by comparing the Landsat observations with the reconstructed LST. The results show that the mean absolute error (MAE) of the reconstructed Landsat LST is about 3 °C across global cities (Fig. 2), e.g., the MAE is 2.9 °C for one sample point in Beijing (Supplementary Fig. S2). This error may be caused by the impacts of weather system on LST. The magnitude for this error is close to that of  $I_s$  and the reliability of the reconstructed Landsat LST may therefore be doubtful in accurately portraying  $I_s$  and  $I_s$  trends. We therefore further compared the Landsat-derived  $I_s$  and  $I_s$  trends with those estimated from MODIS data for the period of 2000–2020. The comparisons show that  $I_s$  and  $I_s$  trends estimated from these two types of satellite data are in good agreement, with  $R^2$  of 0.87 for  $I_s$  ( $p < 0.001$ ) and  $R^2$  of 0.55 for  $I_s$  trends ( $p < 0.001$ ; Fig. 3b & 3d). The estimated  $I_s$  and  $I_s$  trends are also relatively consistent for individual cities (Fig. 4) and at the pixel level (e.g., Fig. 3e & 3f). When compared with those obtained from MODIS data, the mean absolute error (MAE) of the Landsat-derived  $I_s$  and  $I_s$  trends are 0.33 °C and 0.14 °C/decade, respectively. These two MAEs account for <10% of the dynamic ranges of the  $I_s$  (−4 to 5 °C) and of the associated trends (−0.7 to 1.2 °C/decade). The mean biases for the  $I_s$  and  $I_s$  trends are even lower, being equivalent to −0.10 °C and 0.01 °C/decade, respectively (Fig. 3b to 3d). These assessments indicate that the Landsat-derived  $I_s$  and  $I_s$  trends are generally reliable across global cities. The MAE of  $I_s$  and  $I_s$  trend estimates is obviously smaller than that of the reconstructed LST, probably because the  $I_s$  calculation (i.e., the difference between urban and rural mean LSTs) significantly offsets the influence of weather systems on  $I_s$  estimates (Huang et al., 2016). Note that there exist spatial differences of the estimated  $I_s$  at the pixel level (e.g., Fig. 3e & 3f) due to the differences between MODIS LST and the reconstructed Landsat LST (Supplementary Fig. S6). Such LST differences could be caused by the differences in various factors between these two types of data, such as the imaging style and LST retrieval algorithm; besides, the annual MODIS LST averages were influenced by missing data, which may cause a bias compared to the true LST values and therefore lead to the spatial difference of the estimated  $I_s$ . The final resulting annual averages of Landsat LST data at 1 km resolution for 1985–2020 are freely available at <https://osf.io/qgewa/>.

#### 3.2. Global long-term $I_s$ trends accompanied by increased urban land

From the global perspective,  $I_s$  shows a nearly linear increasing pattern since the 1980s, resembling to the growth of the urban-rural



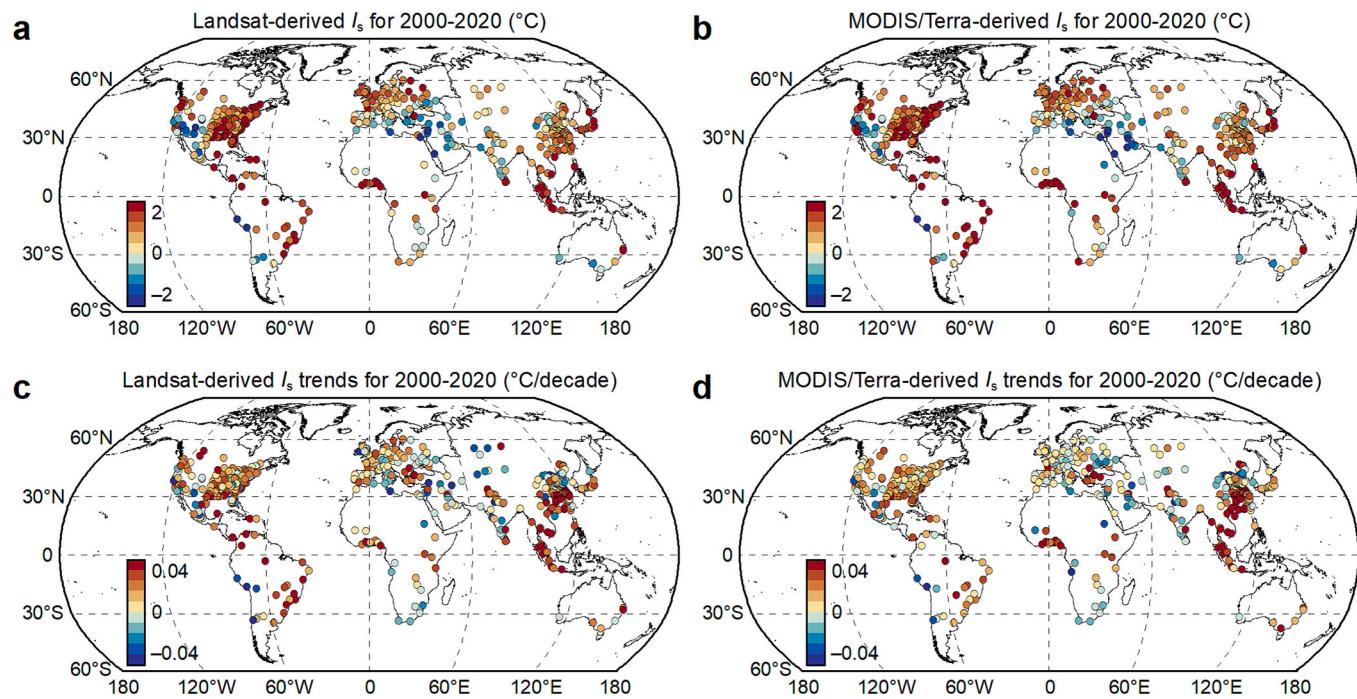
**Fig. 2.** The accuracy of the Prophet model for Landsat land surface temperature (LST) reconstruction across global cities. Mean absolute error (MAE) of LST reconstruction across global cities (a); and frequency histogram of MAE of LST reconstruction (b).



**Fig. 3.** Comparison of the surface urban heat island intensity ( $I_s$ ) and  $I_s$  trends derived from the Landsat and MODIS annual mean thermal data. The mean absolute errors (MAEs) of the  $I_s$  (a) and  $I_s$  trends (c) across global cities; comparison of the global  $I_s$  (b) and  $I_s$  trends (d) derived from these two types of satellite data; and pixel-based comparison of the  $I_s$  over time derived from these two data sources for Beijing, China (e) and Paris, France (f), with black lines indicating the urban boundaries in 2018. The ‘unavailable’ label in (e) and (f) denotes the unavailability of MODIS data in these three years (1985, 1990, and 1995).

contrast in impervious surface percentage ( $\delta ISP$ ; Fig. 5a & 5b). The global mean  $I_s$  increases from  $0.63\text{ }^{\circ}\text{C}$  around 1985 to  $1.14\text{ }^{\circ}\text{C}$  in 2020, with an increasing rate of  $0.156 \pm 0.002\text{ }^{\circ}\text{C}/\text{decade}$  (mean  $\pm$  95% confidence interval,  $p < 0.001$ ), while the global mean  $\delta ISP$  grows from 16.4% to 52.6% during the same period at a rate of  $9.7 \pm 0.3\%/\text{decade}$  ( $p < 0.001$ ). The strong temporal correlation between the  $I_s$  and  $\delta ISP$  trends over individual cities is understandable, because urbanization (i.e., increase of  $\delta ISP$ ) significantly regulates the  $I_s$  change over time (Li et al., 2021; Li et al., 2022b). However, there is a large difference in the spatial variability of  $I_s$  and  $\delta ISP$  growths among global cities (Fig. 5c & 5d). From the spatial perspective, the correlation between the  $I_s$  and  $\delta ISP$

trends over global cities becomes insignificant (Fig. 5f). This implies that the more rapid urbanization rate in a city does not necessarily lead to faster  $I_s$  trends than in other cities. For example, a stagnant increase of  $\delta ISP$  (7.7%/decade) is associated with a relatively fast increase of  $I_s$  ( $0.200\text{ }^{\circ}\text{C}/\text{decade}$ ) for cities in North America. While a rapid growth of  $\delta ISP$  (15.1%/decade) is accompanied with a relatively low  $I_s$  increase ( $0.057\text{ }^{\circ}\text{C}/\text{decade}$ ) in African cities. Such a contrast suggests the presence of other regulators in modulating urbanization-induced impacts on  $I_s$  trends across global cities (refer to the next section for elaborate analysis).



**Fig. 4.** Comparison of surface urban heat island intensity ( $I_s$ ) and  $I_s$  trends derived from Landsat and MODIS land surface temperature (LST) data across global major cities. The mean  $I_s$  ( $^{\circ}$ C) for the period of 2000–2020 derived from Landsat (a) and MODIS (b) data; the  $I_s$  trends ( $^{\circ}$ C/decade) for the same period derived from Landsat (c) and MODIS (d) data.

### 3.3. Divergent urbanization-induced impacts on $I_s$ trends and their regulators

The global mean  $\beta$  (i.e.,  $I_s$  change associated with per 1% growth of  $\delta$ ISP) is  $0.018 \pm 0.025$   $^{\circ}$ C/% (mean  $\pm$  1 SD; Fig. 6). We find an inflection point of  $\beta$  on the increase of  $I_s$  along with urbanization, at which  $\delta$ ISP is around 30%. When urban fraction  $\delta$ ISP < 30%,  $\beta$  remains at a rather low rate of 0.005  $^{\circ}$ C/>. As the cluster of urban areas reaches a certain density ( $\delta$ ISP > 30%), its impact on  $I_s$  triples (0.018  $^{\circ}$ C/%) (Fig. 6c). This implies urbanization can accelerate the increase of  $I_s$  as cities grow bigger or denser. This may be due to the phenomenon that urbanization is initially characterized by the occupation of bare land or areas with little vegetation, while later urban encroachment on forest land leads to a significant reduction in vegetation and accelerates the  $I_s$  growth. Moreover, the threshold for the inflection point of  $\beta$  varies across climate zones, generally with a smaller threshold yet larger change magnitude of  $\beta$  in humid climates (Fig. 7), which may be associated with greater vegetation abundance.

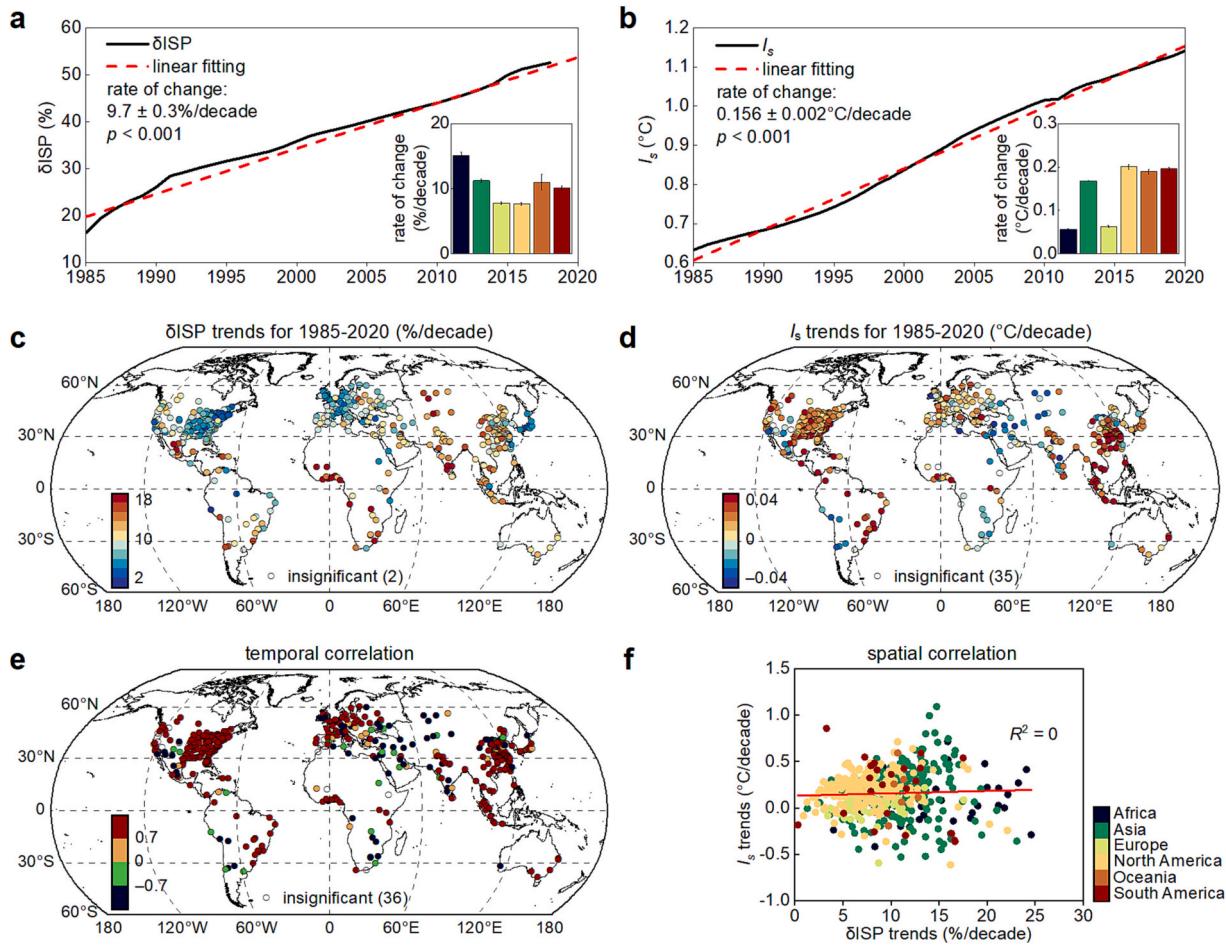
Regarding the spatial variations,  $\beta$  is greater in most cities in eastern North America, eastern South America, and Southeastern Asia, yet it is smaller in southwestern North America, western South America, central Euro-Asia, and Africa. We identified the top ten countries with the greatest  $\beta$  (Table S1). The identification reveals that the  $\beta$  is the greatest in Indonesia, followed by Brazil and the United States. In terms of climate zone, the  $\beta$  is the largest in equatorial zone, followed by warm temperate and then snow zones, while  $\beta$  is the smallest and can even be negative for many cities in arid zone. The urbanization in arid zones increases irrigation and vegetation fraction in cities than in surrounding desert environment (Fan et al., 2017; Wang, 2021), leading to a negative urbanization-induced daytime  $I_s$  and therefore a negative  $\beta$ .

Our analysis shows that precipitation and vegetation background are both closely related to the changing rate of  $I_s$  during the urbanization process, while the influence of urban population is negligible (Fig. 8). The  $\beta$  shows a non-linear relationship with precipitation (Fig. 8a). This corresponds well to previous findings that  $I_s$  correlates nonlinearly with precipitation (Manoli et al., 2019). Nevertheless, the  $\beta$  is more strongly

related to rural normalized difference vegetation index (NDVI) compared with precipitation and urban population (Fig. 8a to 8c). Furthermore, the partial correlation coefficient of rural NDVI with  $\beta$  is greater than those of precipitation and urban population with  $\beta$  (Fig. 8d); and the standardized regression coefficient for rural NDVI is almost twice that for precipitation and is close to zero for urban population when co-explaining  $\beta$  ( $R^2 = 0.33, p < 0.001$ ; Fig. 8e). This suggests that the  $\beta$  could be controlled mainly by rural NDVI. This finding is comparable to previous ones that  $I_s$  should be strongly regulated by evapotranspiration (Li et al., 2019), although our focus is on  $\beta$  (i.e., urbanization-induced impacts on the  $I_s$  trends) rather than on  $I_s$ . In fact, the strong influence of rural NDVI on the  $\beta$  can be intuitively understood as that, as urbanization happens over regions with more vegetation and therefore naturally higher evapotranspiration, cooling efficiency over these regions gets reduced, which leads to larger  $I_s$ . In other words, the heating potential induced by urbanization (increase of  $\delta$ ISP) can be significantly larger over regions with abundant vegetation (mostly in humid climate) than those sparsely vegetated regions (mostly in arid climate) (Supplementary Fig. S3).

### 3.4. Uncertainty analysis

Several uncertainty analyses were performed on image number, urban definition, and factor selection. In terms of image number, the number of available Landsat thermal images exceeds 300 views in most cities, and the MAEs of estimated  $I_s$  and  $I_s$  trend show a slight negative correlation with image number (Supplementary Fig. S9). This indicates the disparities in the amount of available Landsat LST across cities have relatively small impacts on the analysis associated with the  $I_s$  and  $I_s$  trend. Regarding urban definition, urban cores possess significantly distinct magnitudes of  $I_s$  and  $I_s$  trends relative to urban fringes (Supplementary Fig. S10). This implies that static urban boundary does have impacts on estimation of  $I_s$  and  $I_s$  trends and may not accurately describe the magnitudes of  $I_s$  and  $I_s$  trends (or ISP) across urban categories. Nevertheless, the assessment of  $\beta$  is similar across urban categories; particularly, the estimated  $\beta$  in different urban categories is highly



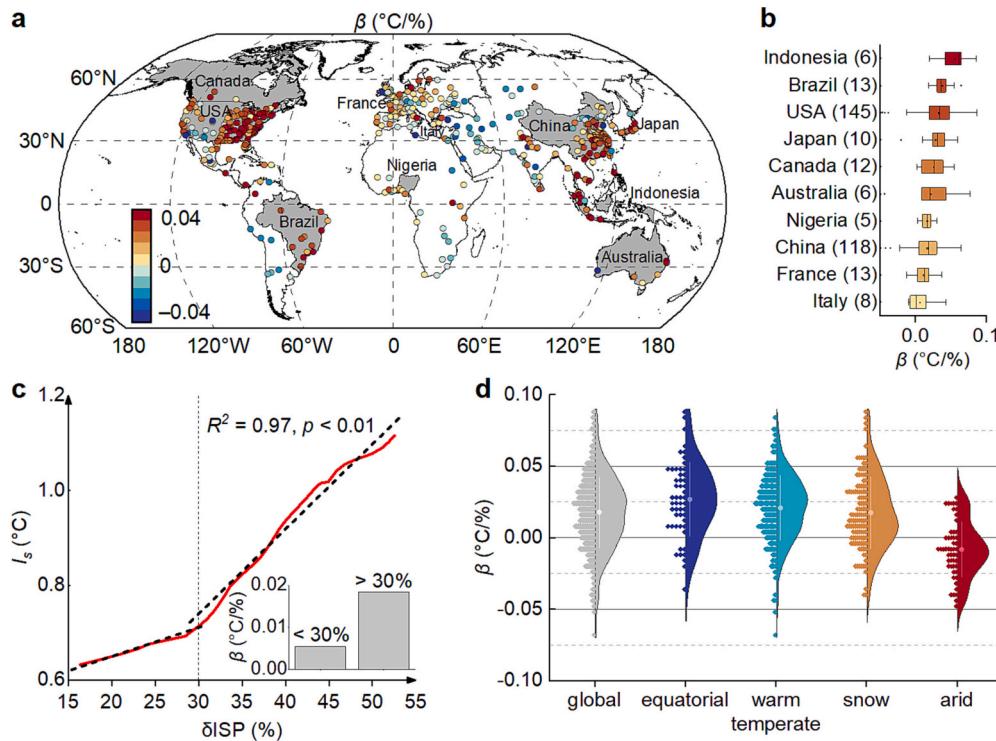
**Fig. 5.** The trends of urban-rural contrast in impervious surface percentage ( $\delta\text{ISP}$ ) and surface urban heat island intensity ( $I_s$ ) as well as their correlations across global cities for the period of 1985–2020. The  $\delta\text{ISP}$  trends (a) and  $I_s$  trends (b) at global and continental scales; the  $\delta\text{ISP}$  trends (c) and  $I_s$  trends (d) for the period of 1985–2020 across global cities; the temporal correlation between  $\delta\text{ISP}$  and  $I_s$  over time for each city (e); and the spatial correlation between  $\delta\text{ISP}$  and  $I_s$  trends across global cities (f). Both the trend and correlation analyses are based on significance tests at the 0.05 level. The  $\delta\text{ISP}$  and  $I_s$  trends for cities in Asia, North America, and Europe are enlarged as Supplementary Figs. S7 & S8.

correlated with that without distinguishing between urban categories, and the fitting line between the two is close to the 1:1 line (Supplementary Fig. S11). This implies that the static urban boundary used in this study should not significantly affect the estimation of  $\beta$ . The sensitivity analysis of factor selection shows that  $\beta$  is more correlated with rural NDVI compared to urban NDVI and urban-rural contrast in NDVI (Supplementary Fig. S12a to S12c). This difference in correlation may be due to larger differences in vegetation coverage among cities in rural areas than in urban areas (Supplementary Fig. S12d). The former may therefore better reflect the potential degree of urbanization-induced impacts on vegetation cover (and thus  $I_s$  change) by transforming vegetation into urban land. This indicates that our selection of rural NDVI should be appropriate for understanding the potential causes of differences in  $\beta$  across cities. Besides, data accuracy may also induce uncertainty in the results. For instance, the generated ISP at 1 km resolution calculated using 30 m impervious surfaces may overestimate the true ISP in urban areas; and such an overestimation may vary across cities and urban regions, therefore affecting the assessment of  $\beta$ . Nevertheless, such a kind of errors mainly affects the ISP magnitude and has relatively little effects on the estimates of temporal ISP trend, mainly because systematic errors can be significantly offset when fitting the overall overestimated ISP time series. That is, the effects of systematic overestimation on the slope of relationship tend to be small by fitting the relationship between overall overestimated ISP and  $I_s$ . Therefore, the overestimated ISP should not significantly affect our main findings

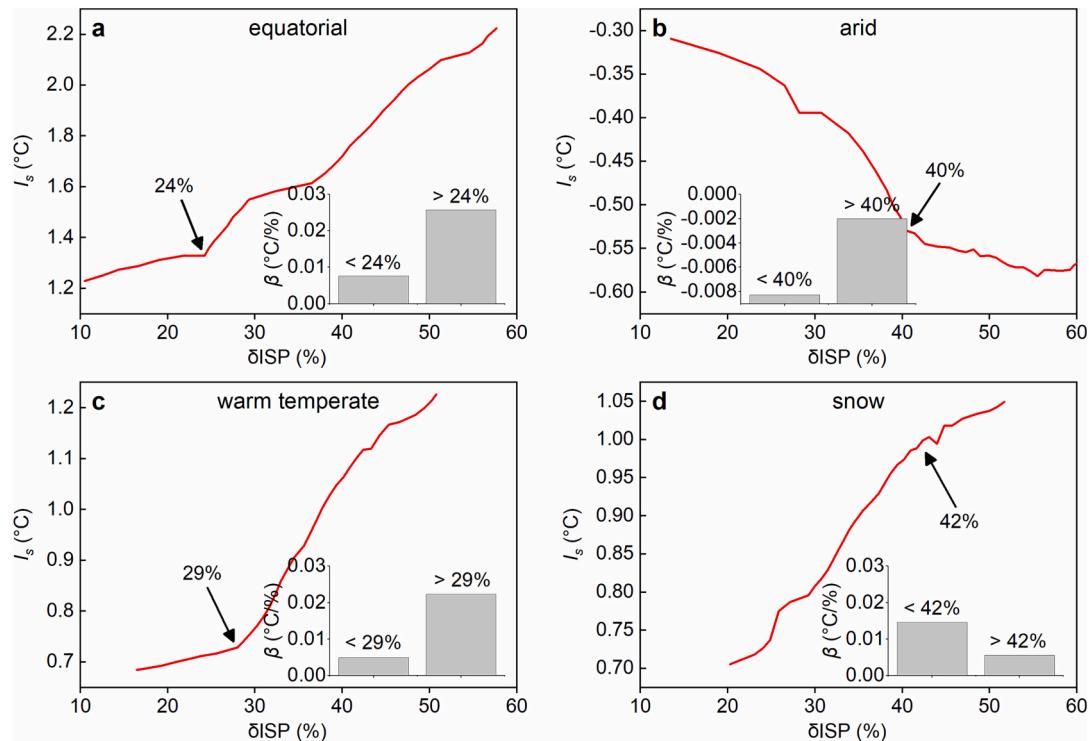
related to  $\beta$ .

#### 4. Discussion and implications

The Landsat satellites possess major advantages of global periodic and long-term observations. Several studies revealed the impacts of urbanization on  $I_s$  changes using multiple clear-sky Landsat images and land cover data (Rizvi et al., 2020; Yu et al., 2019). However, the issue of temporal discontinuity becomes a major challenge for  $I_s$  trend analysis using Landsat data due to the relatively low temporal resolution and the large amount of missing data caused by cloud cover (Ahmed et al., 2023; Zhou et al., 2019). Therefore, there may be large uncertainties associated with employing LST data from only a few time nodes to assess the impacts of urbanization on  $I_s$  trends. Several studies attempted to reconstruct Landsat (or MODIS) LST data to improve the temporal continuity of LST data to better assess the impacts of urbanization on  $I_s$  trends (Fu and Weng, 2016; Li et al., 2022b). Nevertheless, previous investigations are mainly limited to individual cities/urban agglomerations and limited to the recent two decades. A comprehensive assessment of urbanization-induced impacts on  $I_s$  trends remains lacking, especially from a global and long-term perspective. As an attempt, we reconstructed a spatiotemporally continuous LST dataset for global cities using >250,000 Landsat thermal images. We demonstrated that the reconstructed LST matches well with the MODIS LST data in quantifying  $I_s$  and its trends (Fig. 3); and the reconstructed Landsat LST data have a



**Fig. 6.** Spatial variations of urbanization-induced impacts on surface urban heat island intensity trends ( $\beta$ ) across global cities. The spatial variations of  $\beta$  (a); the top 10 countries with the highest  $\beta$ , with the number in the parentheses after the country name denoting the number of cities (b); temporal variations of global mean surface urban heat island intensity ( $I_s$ ) with the increase of urban-rural contrast in impervious surface percentage ( $\delta\text{ISP}$ , i.e., the red curve), with the slope characterizing  $\beta$  (c); and variations in  $\beta$  for cities in each background climate (d). Note that in (b) only countries containing five or more cities are included in the ranking. An inflection point was identified along the red curve in (c):  $\beta$  before this inflection point (i.e.,  $\delta\text{ISP} = 30\%$ ) is significantly lower ( $\beta = 0.005 ^{\circ}\text{C}/\%$ ) than that after this inflection point ( $\beta = 0.018 ^{\circ}\text{C}/\%$ ). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

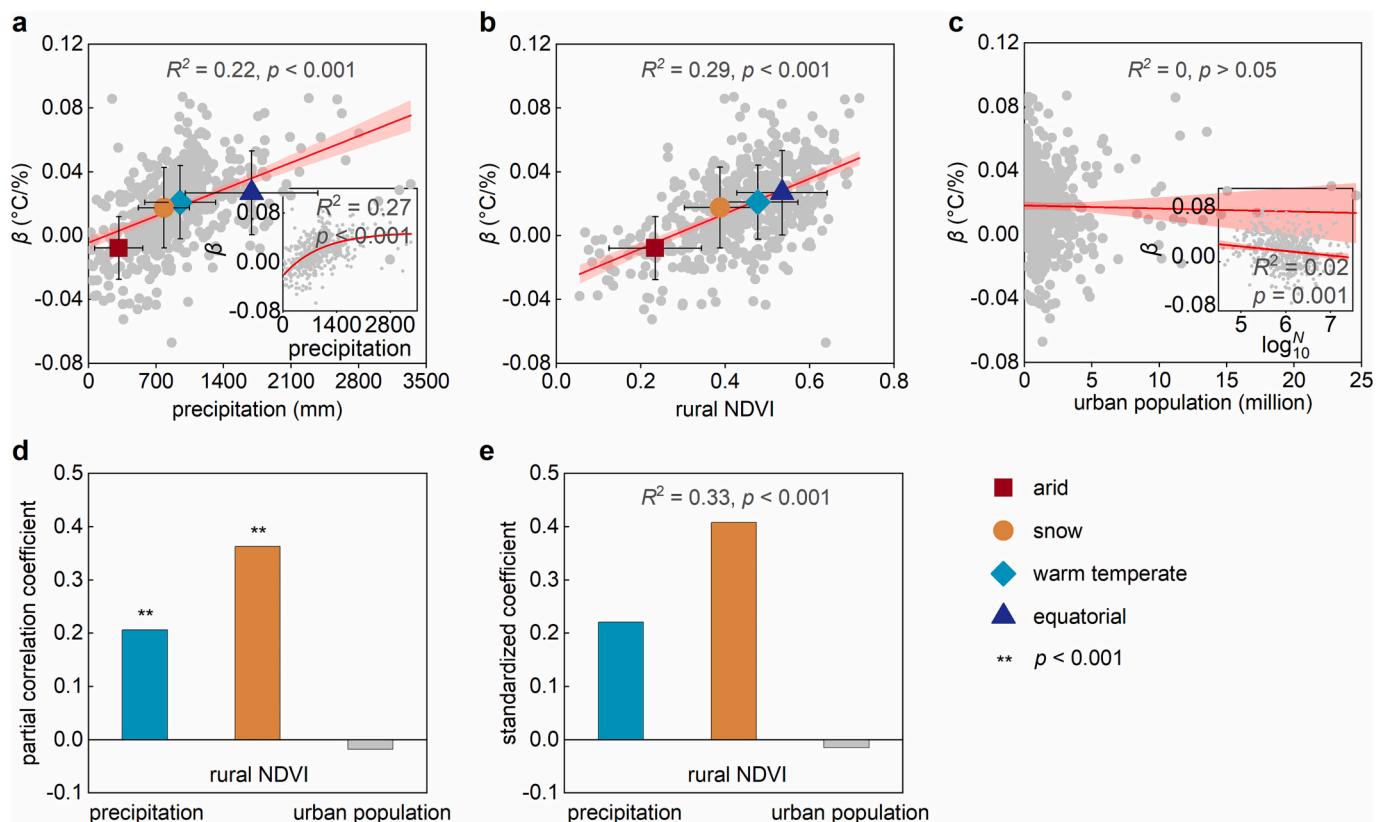


**Fig. 7.** Surface urban heat island intensity ( $I_s$ ) variations depending on the variations in urban-rural contrast of impervious surface percentage ( $\delta\text{ISP}$ ) across climate zones, with the slopes of the red curves denoting urbanization-induced impacts on  $I_s$  trends (i.e., the  $\beta$ ). The inflection points were identified along each red curve. There is a significant difference in the slope of the red curve (i.e., the  $\beta$ ) before and after the inflection points. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

high reliability for  $I_s$  analysis. We further analyzed the impacts of urbanization on long-term  $I_s$  trends by combining  $I_s$  and Landsat impervious surface data. This is perhaps the first effort to assess global  $I_s$  trends since the 1980s and to evaluate the role of urbanization in regulating

such long-term trends using Landsat LST data.

The urbanization rates vary considerably across cities and during different periods (Liu et al., 2020). Such disparities in urban expansion processes may lead to significantly different  $I_s$  trends across cities and



**Fig. 8.** Responses of urbanization-induced impacts on surface urban heat island intensity trends ( $\beta$ ) to three factors including precipitation, rural normalized difference vegetation index (NDVI), and urban population. Correlations of  $\beta$  with precipitation (a), rural NDVI (b), and urban population (c); and partial correlation coefficients of  $\beta$  (d) and partial least-squares based standardized regression coefficients of  $\beta$  (e) with these three factors. The inserted subplots in (a) and (c) show the non-linear relation between  $\beta$  and precipitation and the relationship between  $\beta$  and logarithm of urban population, respectively.

periods (e.g., Supplementary Fig. S1). Accurately identifying the long-term  $I_s$  trends from a global perspective is critical to understand the impacts of urbanization on such trends. By establishing a long-term relationship between  $I_s$  and ISP in each city worldwide, we find a noteworthy ‘marginal effect’ of urbanization on  $I_s$  trends – the same increase of ISP can lead to significantly different amounts of  $I_s$  increase across different climates and along different urbanization stages (Figs. 6 and 7). For example, the impacts of urbanization on  $I_s$  trends are larger in humid climates (Fig. 6) that are characterized by denser vegetation and heavier precipitation (Hossain and Li, 2021; Yang et al., 2008). This implies that over cities in humid tropical regions (e.g., some African cities), urban population exposure to heat may become even more prominent in the future due to the projected increase in urban population (Rohat et al., 2019) and the notably larger  $I_s$  trends associated with urbanization (Fig. 6a). Furthermore, urbanization can impact temperature extremes (Sun et al., 2014; Wang et al., 2021; Yang et al., 2017), especially by increasing heat wave periods in humid climates (Liao et al., 2018) due to the complex interactions between UHI and temperature extremes (Zhao et al., 2018). This implies that urban population exposure to extreme heat events can therefore be further augmented over humid cities due to urbanization. We also find an evident threshold for the urbanization-induced impacts on  $I_s$  trends, e.g., the  $I_s$  trends can accelerate when urban impervious land exceeds 30% (Fig. 6c). The enhanced impacts of urbanization with the proportion of urban impervious land may be associated with the increasing magnitude of the reduction in evapotranspiration due to local urbanization (Zhou et al., 2022). This implies that the increase in heat exposure of urban residents may be amplified with the advance of urbanization. Special care should therefore be taken on such a threshold in sustainable urban planning, although this threshold may change for individual cities (Fig. 7).

Besides, previous studies interestingly showed that surface temperatures are higher in regions near barren land and lower in those close to vegetation and water bodies, described as the ‘proximity effect’ (Mansourmoghadam et al., 2021; Mansourmoghadam et al., 2023). Here we further find that cities with larger  $I_s$  (or  $I_s$  trend) in urban cores also have stronger  $I_s$  (or  $I_s$  trend) in urban fringes (Supplementary Fig. S10). This implies that the ‘proximity effect’ exists not only between small urban patches (e.g., barren land, vegetated areas and water bodies) and their surroundings, but may also occur among regional urban thermal environments at a larger spatial scale. This finding indicates that the ‘proximity effect’ needs to be considered in the design of future urban heat mitigation strategies to hinder the effects of urbanization-induced rapid surface warming on the surrounding thermal environment.

Satellite thermal data with high spatial resolution are required to better understand inner-city  $I_s$  changes and their controlling factors (Sobrino et al., 2012). Compared to reanalysis data and other satellite data (e.g., MODIS and AVHRR LSTs), Landsat LST data have a much higher spatial resolution, enabling the monitoring of thermal environmental characteristics at the landscape scale. However, due to the huge computational burden involved in reconstructing 100-m Landsat LST, here we only reconstructed the Landsat LST dataset for 1985–2020 at 1-km spatial resolution, as our primary purpose is to assess the impacts of global urbanization on long-term  $I_s$  trends at the city scale. Our method should be able to reconstruct 100-m Landsat LST if the computational capacity permits. This implies that our approach should be useful to assess local thermal environmental changes and their responses to urban landscape or landscape change from a fine-scale perspective for future studies. For example, the Landsat LST reconstruction method may help better assess the long-term and fine-scale changes in urban thermal environments (Li et al., 2022a), the impacts of land cover change on

surface temperatures (Fu and Weng, 2016), as well as identify the cooling and heating effects of blue-green space (Gunawardena et al., 2017) and industrial plants (Gao et al., 2022) on their surroundings, respectively.

Previous studies have revealed urbanization-induced impacts on the evolution of the urban thermal environment (Li et al., 2021; Li et al., 2022b; Sun et al., 2014; Wang et al., 2021; Yang et al., 2017) and assessed the relative importance of controlling factors of  $I_s$  (Lai et al., 2021; Li et al., 2019). While urbanization-induced vegetation reduction is traditionally considered as the dominant factor affecting  $I_s$  (Peng et al., 2012; Zhou et al., 2014), background precipitation and urban population have been also shown to exert a strong control (Manoli et al., 2019; Zhao et al., 2014). Nevertheless, studies that found strong control of background precipitation are not contradictory to those that stressed the control of vegetation, because the rural vegetation depend strongly on background precipitation (Supplementary Fig. S5). This is analogous to previous findings from a spatial perspective that the change trends of LST with increasing impervious surface percentage are largely regulated by both evapotranspiration and background precipitation (Zhou et al., 2022). Here, by differentiating the relative importance of rural vegetation, precipitation, and urban population based on partial least-squares model, we further find that while such urbanization-induced impacts on  $I_s$  trends are closely related to the background precipitation where cities are located, they are more strongly induced by differences in vegetation abundance (Fig. 8). We therefore provide evidence that, resembling the absolute  $I_s$ , the  $I_s$  trends could be more influenced by vegetation abundance relative to background precipitation and urban population. Our study thus highlights the potential of urban green spaces as an effective strategy to reduce  $I_s$  growth during the urbanization process.

#### Credit author statement

W. Zhan and L. Li conceived and designed project. L. Li performed data analysis. L. Li and W. Zhan wrote manuscript. D. Wang provides technical assistance in data reconstruction. L. Hu, T. Chakraborty, Z. Wang, P. Fu, W. Liao, F. Huang, H. Fu, J. Li, Z. Liu, H. Du, and S. Wang contributed ideas to data analysis, results interpretation, and manuscript revision. All authors have read and approved the paper.

#### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

#### Data availability

Data will be made available on request.

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#### Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.rse.2023.113650>.

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