Responses to Review Comments

Dear Editor,

Thank you and all the reviewers for their careful review and valuable comments. We have carefully addressed all of the comments and revised our manuscript accordingly. Below please find our item-by-item responses to all comments raised by two reviewers and the topic editor. Please note that the review comments are in black, our responses are highlighted in blue, the extracts from the manuscript are in red, and **the new texts that have been added or changed** are in bold. Thank you very much for your time.

Best regards,

Ming Luo and Yongquan Zhao, on behalf of all authors

Comments by Reviewer #1

Major comments.

The dataset is very import to study the climate change during this period over this region. The high spatial resolution and the monthly temporal resolution are basically reasonable, based on the previous datasets. The use of homogenous meteorological observation data is the right way to evaluate. This research is novel and belongs to the application of big data for large volume of Satellite data used, and machine learning algorithm. The authors are from 8 universities/colleges. The results supply important reference for other research fields like the field of geoscience, biology, sociology, and medicine and engineering.

Response: Many thanks for your appreciation of our work and the constructive comments. We have carefully revised our manuscript according to your comments and gave the following responses for your further review.

1) Line 415, harm, it is suggested to change the word. All 11 indices are calculated based on SAT, so the accuracy of this dataset is up to the accuracy of the dataset (Zhang 2022b) and the algorithm. SAT has important influence to the other 11 indices. How to understand these?

Response: Thank you for your comment. We have changed “harm” to “influence”. The 11 human thermal indices were calculated from SAT at a daily scale (see Table 2 in the main text) for each station. Then, the daily thermal indices were monthly averaged and used for training together with the other predictors (e.g., LST, land cover, topography, and temporal variation) to estimate the spatial distribution of the 11 monthly indices at the 1 km grids. Ideally, the spatial prediction should be conducted based on monthly or even daily SAT. However, the SAT observations with full spatial coverage are not available, so we used monthly LST as an alternative to predict the spatial distribution of the monthly human thermal indices. In this case, the accuracy of monthly LST may influence the accuracy of our HiTIC-monthly dataset. We thereby performed multiple accuracy assessments at various spatial (e.g., individual stations, the mainland of China, and its urban agglomerations) and temporal scales (e.g., monthly, yearly, and overall). The assessment results indicate that our dataset shows a desirable performance and exhibits good agreement with the observations in both spatial and temporal dimensions (see Section 4.1 of the main text), demonstrating the broad applicability of our dataset.

2) (Zhang 2022b) SAT is LST, but not Tair (1.5 meters above the surface). Why use LST but not Tair in Table 1 to compute the other 11 indices?

Response: As shown in our response to your comment #1, we first computed daily thermal indices observed at the weather stations based on daily SAT and other meteorological observations (see Table 2), and then aggregated them to monthly values. These spatially-discrete (station-based) monthly indices were then used for predicting spatially-continuous human thermal indices on 1 km grids, which adopted seamless monthly LST (seamless SAT is not available) and other related variables as predictors. Previous studies have shown that LST is highly correlated with SAT and can be used as a proxy to predict SAT and SAT-related human thermal indices (Shamir & Georgakakos, 2014; W. Zhu, Lű, & Jia, 2013; X. Zhu, Zhang, Xu, Sun, & Hu, 2019). Our results also demonstrate that using LST can generate a desirable accuracy in predicting monthly human thermal indices.

3) Line 157-158 "Section 6 compares our products with two existing datasets, and the main findings of this paper are summarized in Section 7". Where is section 6 and section 7? They are data availability and conclusions.

Response: Thank you for pointing out this issue. We have revised the description as (Lines 157–159): "**Comparisons on our products with two existing datasets are in Section 5, data availability is provided in Section 6. The main findings of this paper are summarized in Section 7.**"

4) Why not keep Figures S1-S9, Tables S1-S5 as formal ones? Please consider again which to keep in the manuscript.

Response: Thanks a lot for your advice. We have moved Tables S1–S2 to the main text in the current revision, and we decided to keep Figures S1–S9 and Tables S3–S5 in the supplementary material because there are already 14 figures and 4 tables in the main text. Including more figures and tables may not meet the requirement of the journal of ESSD and influence the readability of our manuscript.

5) How to get monthly data from MODIS daily mid-daytime 13:30 and mid-nighttime 01:30 LST? The monthly mean is different considering of the diurnal variation and satellite observations from ascending orbits and descending orbits.

Response: Thank you for the comment. Our monthly LST values were calculated by averaging daily LST in the corresponding month in the calendar years of 2003−2020. The daily mean LST values were obtained by averaging four MODIS observations in a day, which correspond to mid-daytime and mid-nighttime observations from ascending and descending orbits. In the current revised version, we have added the following explanations (Lines 178–183): "**We used monthly LST as one of the inputs to predict the spatial distribution of 12 thermal indices. Monthly LST values were calculated by averaging daily LST, which was obtained by averaging four observations in a day, including mid-daytime and mid-nighttime observations from ascending and descending orbits of MOD11A1 (Terra) and MYD11A1 (Aqua). More details about the LST data are described in Zhang et al. (2022b).**"

6) Line 190-191, how to compute and use the covariates?

Response: Thank you for the question. The covariates directly come from the data providers or producers, and these information is listed in Table 1. All these covariates were pre-processed to have the same spatial extent, projection, and spatial resolution for predicting human thermal indices with full spatial coverage at the 1 km resolution.

7) HiTIC? What is i? Is it HTI (human thermal index)? No "I" after "human" and before " thermal".

Response: "HiTIC" stands for **Hi**gh spatial resolution **T**hermal **I**ndex **C**ollection. We have changed the title to "**HiTIC-Monthly: A Monthly High Spatial Resolution (1 km) Human Thermal Index Collection over China during 2003−2020**" to avoid misunderstanding.

Minor comments.

1) Add abbr. of LGBM when it is first used. Light Gradient Boosting Machine. Check others, please.

Response: Thank you for your suggestion. The full name of LGBM has been added (Lines 38–39): "In this collection, 12 commonly-used thermal indices were generated by **the Light Gradient Boosting Machine (LGBM)** learning algorithm from multi-source gridded data."

2) Author contribution. It seems only H.Z is responsible for analysis and data processing, others are all involved in writing. For computations, are there anyone else in the author list?

Response: The first author H.Z. and two corresponding authors of M.L. and Y.Z. are responsible for data analysis and computation. We also wish to clarify that this work involves a large number of tasks (including but not limited to the selection of predictors, the accuracy assessment, the discussion and interpretation of the results, and the comparison with other datasets), and all other authors in the list contributed to discussion, investigation, and writing.

3) Line 439. The unit of the dataset is degree or 0.01 degree? Is 0.01 the scale factor?

Response: Yes, the unit of the dataset is 0.01 degree Celsius (°C). The values are stored in integer type (Int16) for saving storage and need to be multiplied by 100 when in use. The following updates have been made in the main text (Lines 472–474): "The unit of the dataset is 0.01 degree Celsius (°C)**, and the values are stored in an integer type (Int16) for saving storage space, and need to be divided by 100 to get the values in degree Celsius when in use.**"

4) Please revise the followings.

- Line 247-248, as the figure displays

Response: Revised.

- Line 384, Figures S8j&m. "Figure S8", not figures, and add a blank before j.

Response: Revised.

It is suggested to delete equations (1-2) and (3-6), add the reference.

Response: Thanks for the suggestion. With respect, we believe that these equations are helpful for readers to understand the details more easily, and thus can be kept in the main text. As suggested, we have added the relevant references in the current revision:

Lines 205–206: "E_a is derived from T and RH rather than directly observed at meteorological stations (Eqs. 1~2; **Bolton (1980)**)."

Lines 238–239: "Four statistic metrics, namely, determination coefficient (R^2), Mean Absolute Error (*MAE*), *RMSE*, and *Bias* **(Rice, 2006)**."

- If necessary, please keep the same description of the time period for there are many kinds in the manuscript, like 2003~2020, from 2003 to 2020, during the year

2003~2020, (2003 to 2020), during 2003~2020, from January 2003 to December 2020, 2003-2020.

Response: Thanks for your suggestion. We have changed all descriptions of the time period to "**during 2003−2020**".

- Line 755. Delete the last sentence. Line 759, change : to . after 2003~2020.

Response: Revised.

- Add longitude and latitude (or the numerical scope signs) in Fig 1, 4-7, 9-12, 14.

Response: Added.

Figure 8. Prediction accuracies of 12 human thermal indices… Add 12. In individual years, change the description. Time series? Add the description of (a) (b) (c).

Response: Added.

- Figure 10. Spatial distributions of 12 human thermal indices... Add 12.

Response: Added.

- Line 780. Figure 11. National average, are you sure to write like this? Check it in other places in the manuscript. Just use average is fine. Delete "straight". Line 789, Figure 13, national, delete this. Add 12, 12 human thermal indices.

Response: Thank you. We have revised these sentences accordingly. For example, we have revised the caption of Figure 11 as (Lines 843–844): "Temporal changes of **the 12 annually-averaged human thermal indices over the mainland of China during 2003−2020**."

- Line 785, Figure 12, add 12. "the trends of annual mean", please consider how to express better. Inter-annual variation?

Response: Thank you for the comment. The sentence has been rewritten as (Lines 849–850): "Spatial distributions of the **linear** trends (unit: °C per decade) in **the 12**

annually-averaged human thermal indices over the mainland of China **during 2003−2020**.”

- Line 795, Figure 14. HITIC, is it “i”? in mainland China, is it over mainland of China? Please check the description of “mainland China” in the manuscript. In July 2018, move to the end of four major UAs. Delete i.e., change to :.

Response: Thank you for the comment. We have revised these sentences as follows (Lines 858-861):

“Comparison of the spatial patterns among HDI_0p25_1970_2018 (HDI), HiTiSEA, and **HiTIC-Monthly** for AT_{in} **over the mainland of China and its four largest UAs** in July 2018: Beijing-Tianjin-Hebei (BTH), Yangtze River Delta (YRD), middle Yangtze River Valley (mYRV) and Pearl River Delta (PRD). Colored circles indicate the observed AT_{in} values at individual meteorological stations.”

Comments by Reviewer #2

The authors have produced a high-resolution (1 km×1 km) thermal index collection at a monthly scale (HiTIC-Monthly) in China during 2003 to 2020, with 12 widely used human thermal indices. The authors have created a high-resolution products for quantifying thermal index in China, which is valuable to the scientific community. I have some comments to be addressed by the authors.

Response: Thank you very much for your helpful comments and suggestions. We have carefully revised our manuscript based on your comments. Below please find our item-by-item responses.

1. The biggest concern is the temporal resolution. Why do the authors choose monthly resolution, rather than daily? Daily products would be extremely useful to characterize extreme events, which are of societal importance.

Response: Thank you very much for your comment. We agree with you that daily products could be useful to characterize extreme events. However, a daily thermal indices dataset with full spatial coverage requires daily covariates that have full spatial coverage as well, and these data are not available. We produced a long-term monthly thermal indices dataset with high accuracies. The monthly dataset could be useful for the studies of climate change and urban climate and environment across China and has the potential for investigations of heat-related illnesses and deaths. A daily high-resolution human thermal index collection (HiTIC-Daily) will be produced and released in our future studies.

2. Lines 168-169: How about the impacts of precipitation on thermal indices? Have the authors considered precipitation as a covariate?

Response: Thank you for bringing our attention to precipitation. We did not include precipitation as a covariate because the precipitation data are not normally distributed.

More importantly, they exhibit many zero values in many regions of China (especially in the dry season), which would increase the uncertainty of the spatial prediction.

3. Figures 7 and 8: The results indicate spatial variability of bias in the thermal indices. What factors drive the spatial variability of the bias? Meanwhile, there is also temporal variability in the bias (Figure 8), and what is the drivers of this variability? Are the spatial and temporal variabilities of the bias related to background climates?

Response: Thank you for the comment. Yes, the spatial and temporal variabilities of the bias are related to background climates. As shown in Figure 7, the biases exhibit zonal variations across the space, i.e., positive bias values tend to distribute in northern China and negative values are mainly located in the south. The spatial variability is likely caused by the generally lower temperatures in the north and higher temperatures in the south. The extremely small values in the north and the extremely large values in the south may be overestimated and underestimated to some extent, respectively. The overestimation and underestimation issues caused by limited training samples of extreme values are quite common in machine learning (Cho, Yoo, Im, & Cha, 2020; Li, Li, Li, & Liu, 2020; Uddin, Nash, Mahammad Diganta, Rahman, & Olbert, 2022; Wu et al., 2022), due to limited samples of extreme low and high values compared to the rest of the samples. The temporal variability of the bias is relative to climate warming. Under climatic warming, the lower temperatures appear in early periods (e.g., 2003–2005) while relatively higher temperatures occur in more recent periods (e.g., 2016–2019). The overestimation of lower temperature in early periods and the underestimation of higher temperature in recent periods result in the temporal variability of the bias (Figure 8). It should be noted that, although the bias has spatial and temporal variabilities, these variations are quite small (i.e., ranging from -0.3 °C to +0.3 °C). Overall, the estimations in our study are reliable (see the evaluation results in Section 4.1).

In this revision, we have added the following discussions:

Lines 282–290: "**Positive *Bias* values tend to distribute in northern China while negative values are mainly located in the south. This spatial variability is likely caused by the generally lower temperatures in the north and higher temperatures in the south. In particular, the extremely small values in the north and the extremely large values in the south may be overestimated and underestimated to some extent, respectively, due to limited samples of extremely small and large values (compared with the rest of the samples) when training the machine learning model. The overestimation and underestimation issues caused by limited training samples of extreme values are quite common in machine learning (Cho et al., 2020; Li et al., 2020; Uddin et al., 2022; Wu et al., 2022).** "

Lines 297–304: "*Biases* vary between -0.04 °C and 0.04 °C across all years. **This temporal variability of the *Bias* is related to the yearly climate variations, and is characterized by a marginal overestimation of lower temperatures that mainly appeared in early periods (e.g., 2003–2005) and the underestimation of higher temperatures mostly in recent periods (e.g., 2016–2019). Under climatic warming over the past decades, the lower temperatures tended to appear in early periods while relatively higher temperatures more likely occurred in more recent periods. Extremely small values of temperature in earlier periods and the large values in the later periods may be slightly overestimated (i.e., with positive *Bias* values) and underestimated (i.e., with negative *Bias* values), respectively, thereby characterizing the temporal variations of the *Bias*.**".

4. One way of evaluating the quality of these products is to evaluate the EOFs of these products. For example, what are the first three EOFs in each product? How do the temporal coefficients change over time across these products? Such spatial-temporal evaluation would be desirable.

Response: Thank you very much for this suggestion. We have followed your suggestion and evaluated the first three EOF modes of the 12 thermal indices. The spatial patterns and corresponding temporal coefficients of these EOFs are depicted in Figures R1−R4 (see also Figure S10−S13 in the Supporting Information). As Figure R1 shows, the leading EOF (EOF1) of all 12 thermal indices exhibit highly consistent spatial distribution with higher values in the north and lower values in the south. Their temporal variations are also similar to each other (Figure R2). The second and third EOF modes (EOF2 and EOF3) are also similar among different thermal indices (except EOF3 of NET, Figures R2−R4). These results demonstrate the desirable quality of our products. We have thus included the following discussions in the revised manuscript (Lines 350-356):

"**The dominant modes of these indices are further examined by applying the empirical orthogonal function (EOF) analysis (Figures S10−S13). As Figure S10 shows, the leading EOF (EOF1) of all 12 thermal indices exhibit highly consistent spatial distribution with higher values in the northern region and lower values in the south. Their temporal variations are also similar to each other (Figure S11). The second and third EOF modes (EOF2 and EOF3) are also similar among different thermal indices (except EOF3 of NET, Figures S11−S13). These results demonstrate the desirable quality of our products.**"

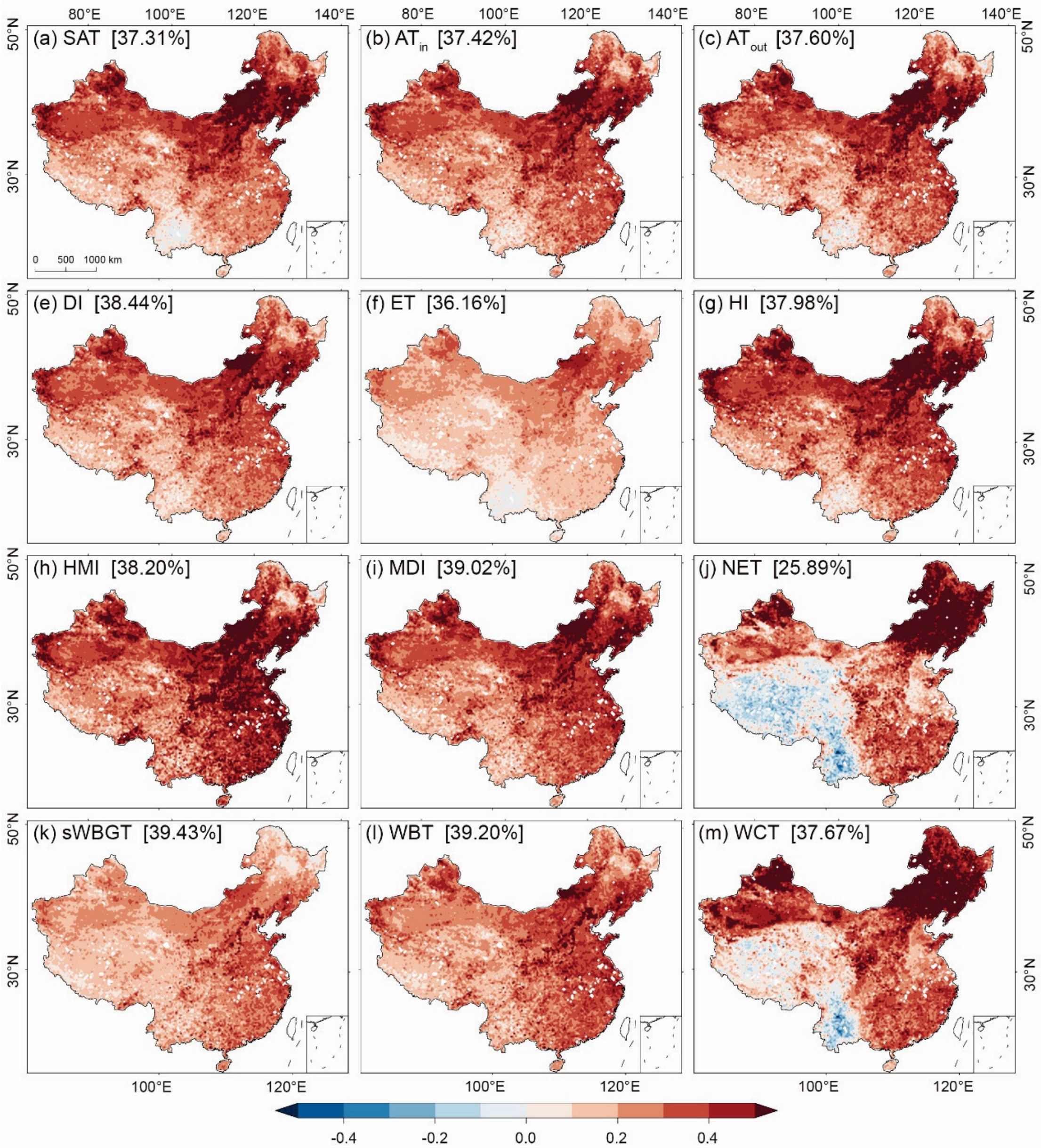

Figure R1. Spatial distributions of the leading empirical orthogonal function (EOF1) of the 12 human thermal indices over the mainland of China. The numbers in square brackets represent the percentage of the variance explained by the corresponding EOF mode.

Figure R2. Time series of the principal components (PCs) corresponding to the first three EOF modes of the 12 human thermal indices over the mainland of China during 2003–2020.

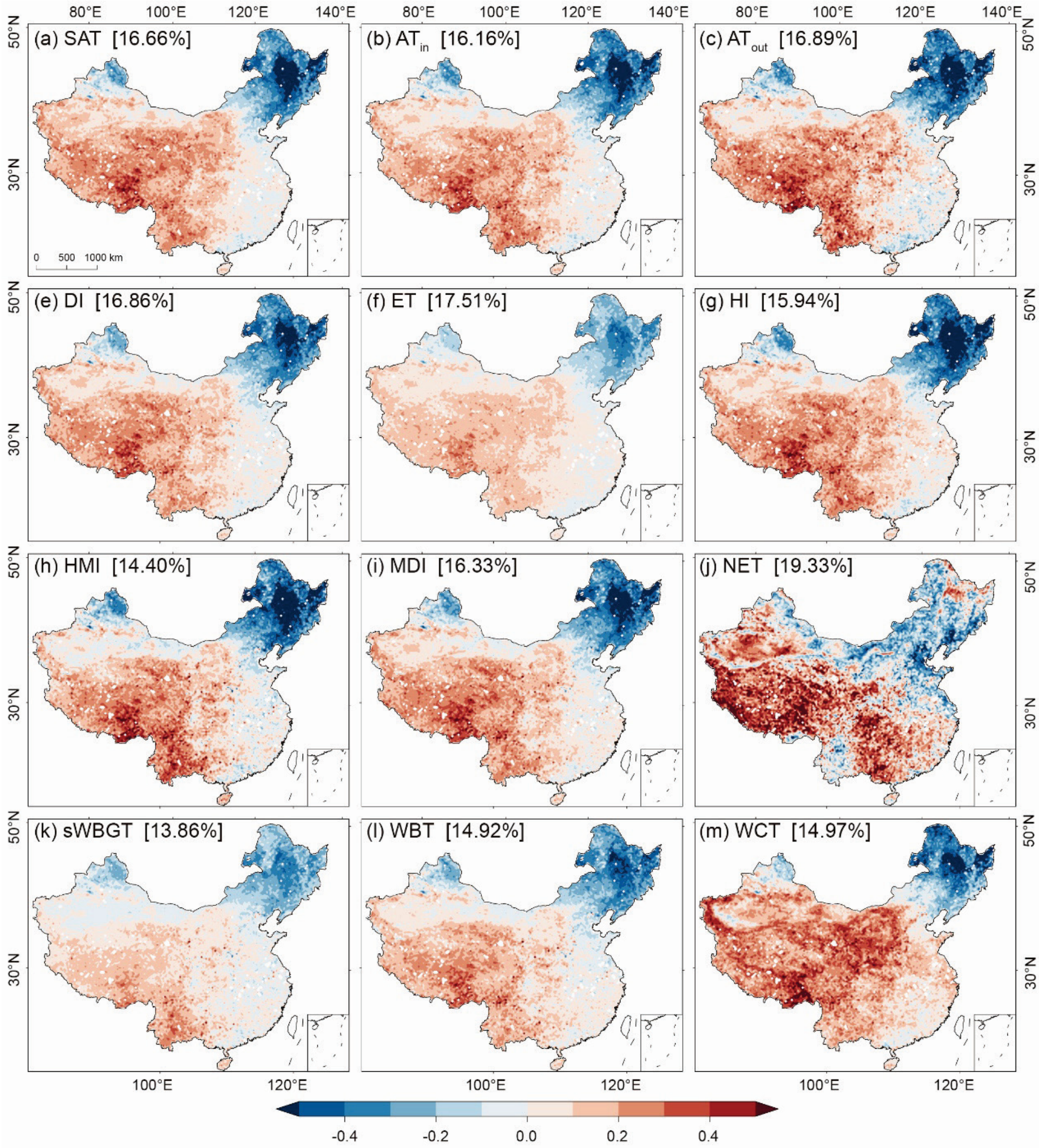

Figure R3. As Figure R1 but for the second EOF (EOF2).

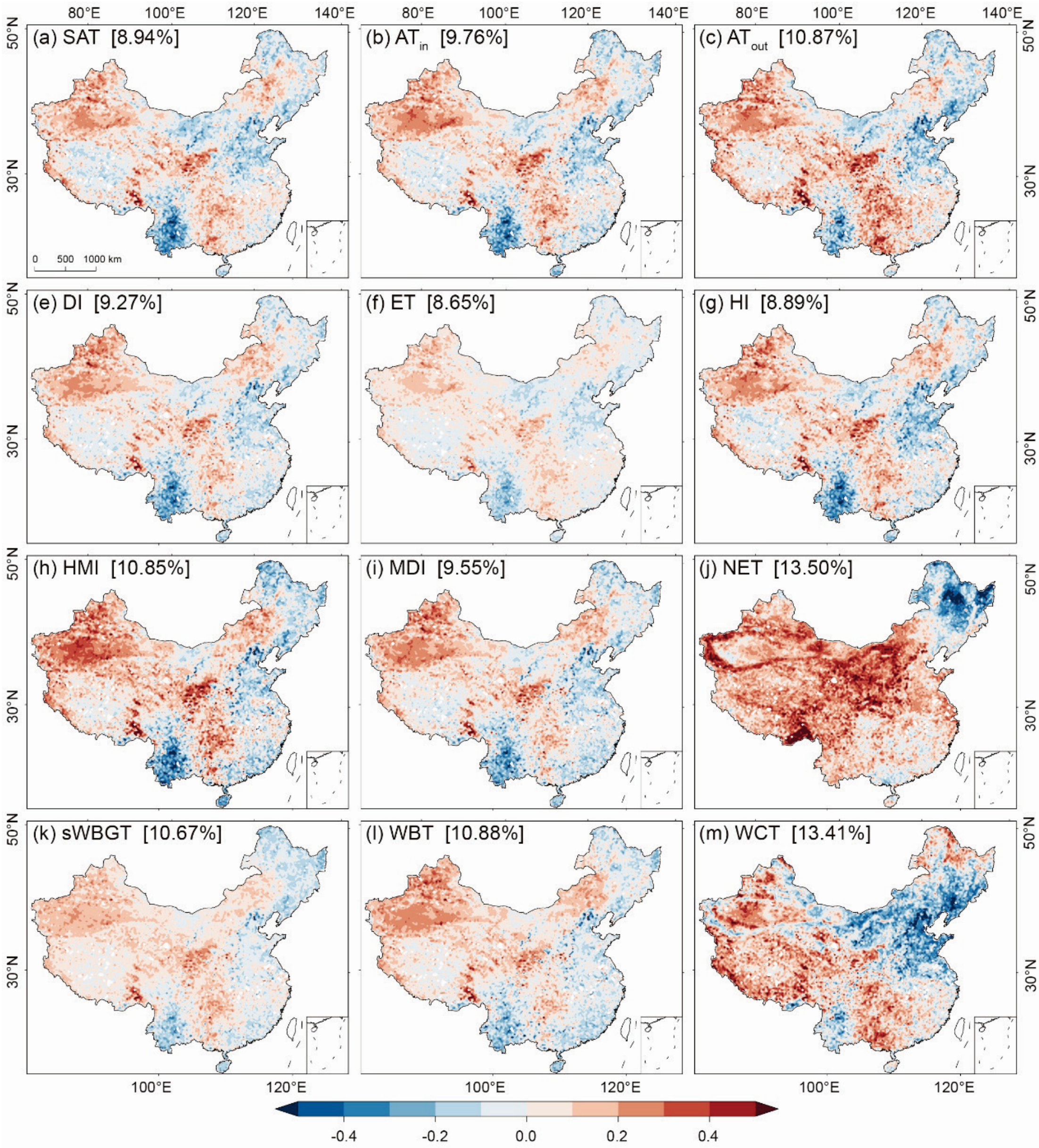

Figure R4. As Figure R1 but for the third EOF (EOF3).

Second-round Comments by Reviewer #1

1. Line 157-158, suggest: Comparisons on our products with two existing datasets are in Section 5, data availability is provided in Section 6, ...

Response: Revised per your suggestion.

2. The 3rd response to the reviewer2 (spatial variability, temporal variability, background climates), Please consider how to answer the question directly.

Response: Thank you very much for your comment. Below please see our updated and direct responses (please note that our response to reviewer #2 has also been updated accordingly in the current version):

Yes, the spatial and temporal variabilities of the bias are related to background climates. As shown in Figure 7, the biases exhibit zonal variations across the space, i.e., positive bias values tend to distribute in northern China and negative values are mainly located in the south. The spatial variability is likely caused by the generally lower temperatures in the north and higher temperatures in the south. The extremely small values in the north and the extremely large values in the south may be overestimated and underestimated to some extent, respectively. The overestimation and underestimation issues caused by limited training samples of extreme values are quite common in machine learning (Cho et al., 2020; Li et al., 2020; Uddin et al., 2022; Wu et al., 2022), due to limited samples of extreme low and high values compared to the rest of the samples. The temporal variability of the bias is relative to climate warming. Under climatic warming, the lower temperatures appear in early periods (e.g., 2003–2005) while relatively higher temperatures occur in more recent periods (e.g., 2016–2019). The overestimation of lower temperature in early periods and the underestimation of higher temperature in recent periods result in the temporal variability of the bias (Figure 8). It should be noted that, although the bias has spatial and temporal variabilities, these variations are quite small (i.e., ranging from -0.3 °C to

+0.3 °C). Overall, the estimations in our study are reliable (see the evaluation results in Section 4.1).

In this revision, we have added the following discussions:

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Comments by Topic Editor

There is still a minor comment from one of the reviewers. In order to save time for the publication of the MS, I forward his opinion to you here. Please consider it.

The 3rd response to the reviewer 2 is still not directly answered. The question from the reviewer 2 is good, but the authors almost use the same answer on Oct 1st. What factors drive the spatial variability of the bias? What are the drivers of the temporal variability? Are the spatial and temporal variabilities of the bias related to background climates? If the answers are in the listed references, how about answer the questions directly and add some discussion or explanations in the manuscript?

Response: Thank you very much for your comment. Below please see our updated and direct responses. Please be reminded that, in the current version we have also updated our responses to the corresponding comment raised by reviewers #2 and #3.

Yes, the spatial and temporal variabilities of the bias are related to background climates. As shown in Figure 7, the biases exhibit zonal variations across the space, i.e., positive bias values tend to distribute in northern China and negative values are mainly located in the south. The spatial variability is likely caused by the generally lower temperatures in the north and higher temperatures in the south. The extremely small values in the north and the extremely large values in the south may be overestimated and underestimated to some extent, respectively. The overestimation and underestimation issues caused by limited training samples of extreme values are quite common in machine learning (Cho et al., 2020; Li et al., 2020; Uddin et al., 2022; Wu et al., 2022), due to limited samples of extreme low and high values compared to the rest of the samples. The temporal variability of the bias is relative to climate warming. Under climatic warming, the lower temperatures appear in early periods (e.g., 2003–2005) while relatively higher temperatures occur in more recent periods (e.g., 2016–2019). The overestimation of lower temperature in early periods and the underestimation of higher temperature in recent periods result in the temporal variability of the bias (Figure 8). It should be noted that, although the bias has spatial and temporal variabilities, these variations are quite small (i.e., ranging from -0.3 °C to +0.3 °C). Overall, the estimations in our study are reliable (see the evaluation results in Section 4.1).

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HiTIC-Monthly: A Monthly High Spatial Resolution (1 km) Human Thermal Index Collection over China during 2003–2020

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Abstract

Human-perceived thermal comfort (also known as human-perceived temperature) measures the combined effects of multiple meteorological factors (e.g., temperature, humidity, and wind speed) and can be aggravated under the influences of global warming and local human activities. With the most rapid urbanization and the largest population, China is being severely threatened by aggravating human thermal stress. However, the variations of thermal stress in China at a fine scale have not been fully understood. This gap is mainly due to the lack of a high-resolution gridded dataset of human thermal indices. Here, we generated the first high spatial resolution (1 km) dataset of monthly human thermal index collection (HiTIC-Monthly) over China during 2003–2020. In this collection, 12 commonly-used thermal indices were generated by the Light Gradient Boosting Machine (LGBM) learning algorithm from multi-source data, including land surface temperature, topography, land cover, population density, and impervious surface fraction. Their accuracies were comprehensively assessed based on the observations at 2419 weather stations across the mainland of China. The results show that our dataset has desirable accuracies, with the mean R^2, root mean square error, and mean absolute error of 0.996, 0.693°C, and 0.512°C, respectively, by averaging the 12 indices. Moreover, the data exhibit high agreements with the observations across spatial and temporal dimensions, demonstrating the broad applicability of our dataset. A comparison with two existing datasets also suggests that our high-resolution dataset can describe a more explicit spatial distribution of the thermal information, showing great potentials in fine-scale (e.g., intra-urban) studies. Further investigation reveals that nearly all thermal indices exhibit increasing trends in most parts of China during 2003–2020. The increase is especially significant in North China, Southwest China, the Tibetan Plateau, and parts of Northwest China, during spring and summer. The HiTIC-Monthly dataset is publicly available from Zenodo at https://zenodo.org/record/6895533 and the National Tibetan Plateau Data Center (TPDC) of China at https://data.tpdc.ac.cn/disallow/036e67b7-7a3a-4229-956f-40b8cd11871d (Zhang et al., 2022a).

1 Introduction

Global climate change has brought significant challenges to human society and natural systems (Arias et al., 2021; Haines and Ebi, 2019) by inducing higher air temperature and more frequent extreme weather and climate events around the world (Arias et al., 2021; Schwingshackl et al., 2021). Heat-related disasters, e.g., heatwaves, droughts, and wildfires, are occurring more frequently and becoming more intense (Tong et al., 2021; Arias et al., 2021; Luo et al., 2022), exacerbating the thermal environment and threatening the tolerance limits of humans, animals, and plants (Raymond et al., 2020). Substantial warming and increasing extreme weather and climate events aggravate human thermal comfort and increase the exposures to uncomfortable thermal environments (Brimicombe et al., 2021), thus posing adverse impacts on public health, socio-economy, and agricultural productivities (Budhathoki and Zander, 2019; Moda et al., 2019; Tuholske et al., 2021; Sun et al., 2019; Zhao et al., 2017).

The thermal stress that human beings actually perceive is not only related to air temperature, but also jointly influenced by other environmental variables such as humidity, wind, and/or direct sunlight (Mistry, 2020; Djongyang et al., 2010). These variables alter the heat balance that maintains the core temperature of human bodies by influencing the heat exchange (e.g., radiation, convection, conduction, and evaporation) between humans and the surrounding environment (Periard et al., 2021; Stolwijk, 1975). High atmospheric humidity can exacerbate the thermal stress on human bodies by reducing evaporation from the skin through sweating when the air temperature is high (Li et al., 2018; Rogers et al., 2021; Luo and Lau, 2021). Furthermore, abnormal weather with a combination of extremely high air temperature, humidity, and/or wind can reduce labor capacity and human performance (Roghanchi and Kocsis, 2018; Lazaro and Momayez, 2020; Enander and Hygge, 1990), leading to temperature-related discomfort, stress, morbidity, and even death (Di Napoli et al., 2018; Kuchcik, 2021; Nastos and Matzarakis, 2011), particularly during heatwaves. For example, in the summer of 2017, 2018, and 2019, there were 1489, 1700, and 161 heatwave-related deaths, respectively, in the United Kingdom (Rustemeyer and Howells, 2021). Additionally, vulnerable groups including children, the elderly, chronic patients, and poor communities are at higher risk of being affected by thermal stress (Patz et al., 2005; Wang et al., 2019), which is likely to be further exacerbated as global population aging and climate warming (United Nations, 2017).

The changes and impacts of human thermal stress have attracted increasing attention in recent years (Schwingshackl et al., 2021; Krzysztof et al., 2021; Li et al., 2018; Rahman et al., 2022; Ren et al., 2022; Luo and Lau, 2021). For instance, Szer et al. (2022) estimated the impact of heat stress on construction workers based on the Universal Thermal Climate Index (UTCI). Ren et al. (2022) and Luo and Lau (2021) quantified the contribution of urbanization and climate change to urban human thermal comfort in China. Schwingshackl et al. (2021) assessed the future severity and trend of global heat stress based on Coupled Model Intercomparison Project phase 6 (CMIP6). These studies were mainly based on meteorological stations or coarse-gridded data. However, the meteorological stations are sparsely distributed (Peng et al., 2019), particularly in undeveloped and mountainous areas, which cannot reveal continuously spatial distributions of air temperature and thermal stress conditions (He et al., 2021). Additionally, existing low spatial resolution image products (Mistry, 2020; Di Napoli et al., 2020) cannot be applied to fine-scale studies because they cannot provide information with spatial details and variations. However, the changes in human thermal stress at a fine scale (e.g., 1 km×1 km) remain much less understood. This research gap is mainly inhabited by the unavailability of a high spatial resolution (high-resolution) gridded dataset of human thermal stress.

Although extensive studies have been conducted to generate high-resolution land surface temperature (LST) [such as the Land Surface Temperature in China (LSTC; (Zhao et al., 2020) and the global seamless land surface temperature dataset (Zhang et al., 2022b; Hong et al., 2022)], or near surface air temperatures (SAT) products [such as ERA5 (ECMWF, 2017), TerraClimate (Abatzoglou et al., 2018), and GPRChinaTemp1km (He et al., 2021)], human thermal stress datasets were generally produced at low-resolution levels, such as ERA5-HEAT (Di Napoli et al., 2020), HDI_0p25_1970_2018 (hereafter, HDI) (Mistry, 2020), and HiTiSEA (Yan et al., 2021). ERA5-HEAT was derived from ERA5 and includes two global hourly human thermal stress indices (UTCI and mean radiant temperature (MRT)) from January 1979 to the present (Di Napoli et al., 2020). The HDI dataset was generated using 3-hourly climate variables of the global land data assimilation system (GLDAS), and it contains ten daily indices with a spatial resolution of 0.25° × 0.25°, covering 90°N–60°S from 1970 to 2018 (Mistry, 2020). HiTiSEA contains ten daily human thermal stress indices from 1981 to 2017, with a spatial resolution of

0.1° × 0.1° over South and East Asia (Yan et al., 2021), which was derived from the ERA5-Land and ERA5 reanalysis products. However, these existing thermal index datasets have very coarse spatial resolutions. There is an urgent need for a high-resolution (e.g., 1 km) data collection of multiple human thermal stress indices.

Various indices have been proposed to measure human thermal stress, but there is no universal thermal stress index that works in all climate zones (Schwingshackl et al., 2021; Brake and Bates, 2002; Roghanchi and Kocsis, 2018; Luo and Lau, 2021). Existing human thermal stress indices considered different climate conditions, direct or indirect exposures to weather elements, human metabolism, and the local working environment (Di Napoli et al., 2020), which were designed to evaluate or quantify the comprehensive environmental pressure of meteorological factors (e.g., temperature, humidity, wind) on human bodies (Epstein and Moran, 2006). These indices are based on the thermal exchange between the human and surrounding environments or empirical relationships gained by studying human responses to various environmental factors, varying in complexity, applicability, and capacity (Staiger et al., 2019). For example, the heat index (HI) is used for meteorological service (NWS, 2011); wet-bulb temperature (WBT) is used to measure the upper physiological limit of human beings (Raymond et al., 2020); physiologically equivalent temperature (PET) and UTCI are used to estimate human thermal comfort (Varentsov et al., 2020). Therefore, a high-resolution dataset that contains different commonly used human thermal stress indices is urgently called for in global and regional studies, particularly for those with complex climate conditions (e.g., China).

China has been threatened by deteriorating thermal environments under global climate change and rapid local urbanization over the past decades (Ren et al., 2022; Luo and Lau, 2019). The changes and characteristics of human thermal stress across China have attracted extensive attention in recent years (Yan, 2013; Tian et al., 2022; Li et al., 2022). Wang et al. (2021) found that the frequency of extreme human-perceived temperature events increases in summer and decreases in winter in most urban agglomerations (UAs) of China. Li et al. (2022) showed that the frequency of thermal discomfort days in China exhibits a significant increasing trend from 1961 to 2014, and there will be more threats from thermal discomfort in the future. Therefore, a long-term and high-resolution dataset with multiple human thermal stress indices in China is of great importance for investigating detailed spatial and temporal variations of human thermal stress across the country. Such a dataset has the potential to (1) assess population exposure to extreme thermal conditions and heat-related health risks, (2) reveal the spatiotemporal evolution of human thermal stress and its influence on public health, tourism, industries, military, epidemiology, and biometeorology at a fine scale, and (3) provide policymakers with data in manipulating targeted strategies to mitigate heat stress and protect vulnerable people.

In this study, we produced a high-resolution (1 km × 1 km) thermal index collection at a monthly scale (HiTIC-Monthly) in China over a long period (2003–2020). This collection contains 12 widely-used human thermal indices, including Surface Air Temperature (SAT), indoor Apparent Temperature (AT_{in}), outdoor shaded Apparent Temperature (AT_{out}), Discomfort Index (DI), Effective Temperature (ET), Heat Index (HI), Humidex (HMI), Modified Discomfort Index (MDI), Net Effective Temperature (NET), Wet-Bulb Temperature (WBT), simplified Wet Bulb Globe Temperature (sWBGT), and Wind Chill Temperature (WCT). The remainder of this paper is structured as follows. Sections 2 and 3 describe the data sources and the methodology, respectively. Section 4 presents a comprehensive analysis of the accuracies and trends of the human thermal indices. Comparisons on our products with two existing datasets are in Section 5, data availability is provided in Section 6. The main findings of this paper are summarized in Section 7.

2 Data

2.1 Meteorological data

Daily mean surface air temperature, relative humidity, and wind speed recorded at the 2419 weather stations across China (Figure 1) during 2003–2020 were collected from the China Meteorological Data Service Center (CMDC) at http://data.cma.cn/en. All station records were subjected to strict quality control and evaluation, including homogenization based on a statistical approach (Xu et al., 2013) and evaluation of temporal inhomogeneity based on the Easterling-Peterson method (Li et al., 2004).

2.2 Covariates

Human thermal stress is related to temperature, topography, land cover, population density, surface water, and vegetation (Wang et al., 2020; Rahman et al., 2022; Krzysztof et al., 2021). In this study, eight variables reflecting the changes and spatial distribution characteristics of temperature were used to predict human thermal indices (Table 1) in addition to the meteorological variables. As LST is one of the most essential parameters for predicting human thermal indices, the seamless LST dataset created by Zhang et al. (2022b) was introduced into our model training. This LST dataset used a spatiotemporal gap-filling algorithm to fill the missing or invalid value caused by clouds in the Moderate Resolution Imaging Spectroradiometer (MODIS) LST dataset (MOD11A1 and MYD11A1). It includes daily mid-daytime (13:30) and mid-nighttime (01:30) LST with 1 km spatial resolution. The mean root mean squared errors (*RMSEs*) of daytime and nighttime LST are 1.88°C and 1.33°C, respectively. We used monthly LST as one of the inputs to predict the spatial distribution of 12 thermal indices. Monthly LST values were calculated by averaging daily LST, which was obtained by averaging four observations in a day, including mid-daytime and mid-nighttime observations from ascending and descending orbits of MOD11A1 (Terra) and MYD11A1 (Aqua). More details about the LST data are described in Zhang et al. (2022b). The land cover dataset (MCD12Q1 Version 6) developed by Sulla-Menashe and Friedl (2019) based on a supervised classification method was downloaded via Google Earth Engine (GEE). The Multi-Error-Removed Improved-Terrain (MERIT) elevation dataset developed by Yamazaki et al. (2017) was downloaded from GEE. This dataset was generated after removing the errors from existing Digital Elevation Models (DEMs), such as SRTM3 and AW3D-30m, based on multi-source satellite data and filtering algorithms. The spatial resolution of this dataset is 3″ (i.e., ~90 meters at the equator). In addition, the slope was also extracted from the elevation data to act as the topography predictor. As the artificial surface is closely related to human activities (Zhao and Zhu, 2022), the dataset of global artificial impervious area (GAIA) produced by Gong et al. (2020) from the Google Earth Engine (GEE) was used to delineate human footprints. The overall accuracy of GAIA is greater than 90% (Gong et al., 2020). The population dataset was downloaded from the WorldPop Project (Gaughan et al., 2013). Then, the abovementioned eight datasets were pre-processed to have the same spatial extend, projection, and spatial resolution (1 km) through image mosaicking, reprojection, resampling, clipping, aggregating, and monthly synthesizing. Moreover, year and month of the year were also used as covariates. Note that we did not include precipitation as a covariate because the precipitation data are not normally distributed. More importantly, they exhibit many zero values in many regions of China (especially in the dry season), which would increase the uncertainty of the spatial prediction.

3 Methodology

3.1 Calculation of human thermal indices

In addition to SAT, the calculation of human thermal indices used in this study is described in Table 2. These indices are first calculated based on SAT (also simply denoted as T), relative humidity (RH), wind speed (V), and actual vapor pressure (E_a) at daily scale. E_a is derived from T and RH rather than directly observed at meteorological stations (Eqs. 1~2; (Bolton, 1980)). Furthermore, monthly human thermal indices were derived by averaging daily values in each month.

$$E_s = 6.112 \times exp^{(17.67 \times T/(T+243.5))} \tag{1}$$

$$E_a = \frac{RH}{100} \times E_s \tag{2}$$

Here E_s is saturation vapor pressure (hPa) near the surface, T (°C) is air temperature at 2 m above the ground, and RH (%) is relative humidity at 2 m above the ground.

3.2 Prediction of human thermal indices using LGBM

The Light Gradient Boosting Machine (LGBM) algorithm was employed to predict human thermal indices during 2003–2020. LGBM is one of the gradient boosting decision tree (GBDT) algorithms developed by Microsoft Research (Ke et al., 2017). This algorithm has become a very popular nonlinear machine learning algorithm due to its superior performance in machine learning competitions and efficiency (Candido et al., 2021). Its performance has been evaluated and shows desirable results in different applications, such as evapotranspiration estimation (Fan et al., 2019), land cover classification (Candido et al., 2021; Mccarty et al., 2020), air quality prediction (Su, 2020; Zeng et al., 2021; Tian et al., 2021), subsurface temperature reconstruction (Su et al., 2021), and above-ground biomass estimation (Tamiminia et al., 2021).

Furthermore, LGBM adopts the Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB) algorithms to improve the training speed (Su et al., 2021). Here, GOSS is used to select data instances with larger gradients and to exclude a considerable proportion of small gradient data instances (Ke et al., 2017), and EFB is used to merge features (Ke et al., 2017). Compared with traditional GBDT algorithms including eXtreme gradient boosting (XGBoost) and Stochastic Gradient Boosting (SGB), LGBM effectively decreases the training time without reducing the accuracy (Los et al., 2021; Ke et al., 2017).

We used the Python package *Scikit-Learn* to perform the LGBM training, and hyperparameters of LGBM were tuned based on Grid Search Methods. The observed monthly human thermal indices at the 2419 weather stations across the mainland of China during 2003–2020 were randomly classified into a training set (80%) for hyperparameters tuning and model training and a testing set (20%) for model evaluation.

3.3 Accuracy assessment

Four statistic metrics, namely, determination coefficient (R^2), Mean Absolute Error (*MAE*), *RMSE*, and *Bias* (Rice, 2006), were used to evaluate the prediction accuracy of the human thermal indices. Ranging from 0 to 1, R^2 measures the proportion of variance explained by the model, representing how well the human thermal indices were predicted compared to the observations. *MAE* represents the average absolute error between the predictions and the observations. *RMSE* is the standard deviation of the residuals and is sensitive to outliers. *Bias* describes the differences between the predictions and the observations. These metrics are computed as follows.

$$MAE = \frac{1}{N} \times \sum_{i=1}^{N} |y_i - \hat{y}| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{N} \times \sum_{i=1}^{N} (y_i - \hat{y})^2} \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y})^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \tag{5}$$

$$Bias = \frac{1}{N} \times \sum_{i=1}^{N} (y_i - \hat{y}) \tag{6}$$

where $\hat{y}$ is the predicted value of human thermal indices, $\bar{y}$ is the mean of the observed human thermal indices calculated from meteorological stations, and *N* is the number of samples.

4 Results

4.1 Evaluation of the predicted human thermal indices

4.1.1 Overall accuracy

The prediction accuracies of the 12 human thermal indices were evaluated based on the validation data introduced in Section 3.2. All predicted human thermal indices exhibit high accuracies. Figure 2 shows the scatter plots of the observed versus the predicted values of the 12 human thermal indices. As the figure displays, the data points of all indices are concentrated around the corresponding 1:1 line, indicating a good consistency between the observed and the predicted values. Figure 3 and Table 3 present the R^2, *MAE*, *RMSE,* and *Bias* values of 12 thermal indices during 2003–2020. The R^2 values of the 12 indices are all higher than 0.99, and their *RMSE*, *MAE,* and *Bias* are lower than 0.9 °C, 0.7 °C, and 0.003 °C, respectively. Particularly, HMI has the largest *RMSE* (0.859 °C) and *MAE* (0.645 °C), while ET shows the smallest *RMSE* (0.377 °C) and *MAE* (0.281 °C). The larger errors of NET are likely caused by the incorporation of wind speed during the computation (see Table 2). Overall, the accuracy metrics demonstrate that the 12 predicted human thermal indices are of good quality.

The spatial distributions of R^2, *MAE, RMSE*, and *Bias* at individual stations across the mainland of China are depicted in Figures 4–7, respectively. The predicted indices have high R^2 values (i.e., >0.98, Figure 4) at almost all stations across China, demonstrating the superiority of LGBM. Better predictions (with higher R^2) are distributed in eastern China, particularly in the North China Plain (NCP) and the Yangtze River Delta (YRD), while southwestern China (e.g., the Yunnan-Guizhou Plateau (YGP)) has relatively lower R^2 values (<0.98). For *MAE* and *RMSE*, all indices have small values <1 °C at most stations across China. HMI has the largest *MAE* and *RMSE* values (Figures 5g and 6g), followed by NET and WCT, and ET has the smallest *MAE* and *RMSE* values (i.e., < 0.4 °C, Figures 5e and 6e). The *MAE* and *RMSE* of NET and WCT decrease from northwestern to southeastern China (Figures 5i, 5l, 6i, 6l). For other indices, small *MAE* and *RMSE* values are mainly observed in plains including NCP, while large values tend to appear in regions with complex topography, such as arid Northwest China, mountainous Northeast and South China, and the Hengduan Mountains. These differences are related to the uneven distribution of weather stations, i.e., dense in plains and coarse in complex terrain areas. The *Bias* values range from -0.3 °C to 0.3 °C (Figure 7). Positive *Bias* values tend to distribute in northern China while negative values are mainly located in the south. This spatial variability is likely caused by the generally lower temperatures in the north and higher temperatures in the south. In particular, the extremely small values in the north and the extremely large values in the south may be overestimated and underestimated to some extent, respectively, due to limited samples of extremely small and large values (compared with the rest of the samples) when training the machine learning model. The overestimation and underestimation issues caused by limited training samples of extreme values are quite common in machine learning (Wu et al., 2022; Li et al., 2020; Uddin et al., 2022; Cho et al., 2020).

4.1.2 Annual and monthly accuracies

The annual accuracies regarding *RMSE*, *MAE,* and *Bias* of the 12 human thermal indices during 2003–2020 are shown in Figure 8. *RMSEs* and *MAEs* of all indices in nearly all years are less than 1.0 °C (Figures 8a-b). Yearly *RMSE* (*MAE)* of ET fluctuates around 0.3 °C (0.2 °C) during 2003–2020. *RMSEs* (*MAEs)* of other indices range from 0.5 to 1.1 °C (0.4–0.8 °C) with marginal variations from year to year. *Biases* vary between -0.04 °C and 0.04 °C across all years. This temporal variability of the *Bias* is related to the yearly climate variations, and is characterized by a marginal overestimation of lower temperatures that mainly appeared in early periods (e.g., 2003–2005) and the underestimation of higher temperatures mostly in recent periods (e.g., 2016–2019). Under climatic warming over the past decades, the lower temperatures tended to appear in early periods while relatively higher temperatures more likely occurred in more recent periods. Extremely small values of temperature in earlier periods and the large values in the later periods may be slightly overestimated (i.e., with positive *Bias* values) and underestimated (i.e., with negative *Bias* values), respectively, thereby characterizing the temporal variations of the *Bias*. Moreover, Figure S1 displays the monthly *RMSEs*, *MAEs,* and *Biases* of all human thermal indices. For *RMSE*, all the indices in 12 months are lower than 1.4 °C, and their *MAEs* are less than 1 °C. HI and HMI have relatively higher *RMSE* and *MAE* values in summer than in other seasons; whereas, other indices tend to have larger errors in winter than in summer. Additionally, the magnitude of *Bias* is smaller than 0.03 °C for all the indices in 12 months.

4.1.3 Accuracies in major urban agglomerations

More than half of the national population in China lives in cities, particularly in UAs (i.e., also known as city clusters). Here we assessed the prediction accuracies in 20 major UAs in China, which hold 62.83% and 80.57% of the total population and gross domestic product (GDP) of the country (Fang, 2016). These accuracy assessments are presented in Tables S1–S4. As shown in Table S1, all UAs have R^2 values higher than 0.9837, with an average of 0.9947. Table S2 also shows that these UAs have small *RMSE* values, most of which are smaller than 1 °C, except for the UA of North Tianshan Mountain in arid Northwest China. As the biggest UA in China, YRD has the lowest *RMSE* of 0.288 °C among all 20 UAs. The *MAEs* of the thermal indices in all UAs are smaller than 1 °C and with an average value of 0.477 °C (Table S3). The *Biases* in the 20 UAs range from -0.160 °C to 0.123 °C (Table S4). These results suggest that all predicted human thermal indices in different UAs across China are of good quality at the local scale. It implies that our prediction model and results have great potential in evaluating local thermal environment changes (e.g., in urban areas or cities).

4.2 Spatial variations of the human thermal indices

The abovementioned assessments show that our model based on LGBM can yield high-accuracy predictions at both national and local scales. Therefore, this model is employed to generate a high-resolution human thermal index collection at a monthly scale over China (HiTIC-Monthly) during 2003–2020. By taking monthly ET in 2020 as an example, we examined the monthly evolution of spatial patterns of the HiTIC-Monthly dataset in this subsection.

Figure 9 shows the monthly distribution of the predicted ET in 2020, which exhibits obvious seasonality with higher temperatures in summer and lower in winter. The temperature shows a significant zonal difference with colder temperatures in northern than in southern China. The temperature has a close relationship with topography and decreases with elevation, varying from plateaus to plains. The Qinghai-

Tibet Plateau (TP) has the lowest temperature, while southern China, the Sichuan Basin, and the Gobi regions in Northwest China witness the highest temperature. The distribution of temperature exhibits different patterns among the four seasons, especially between winter (e.g., January) and summer (e.g., July). In winter, the temperature increases from northern to southern areas and is the coldest in Northeast and Northwest China and the warmest on the Hainan Island. In summer, the hottest temperature appears in the Tarim and Jungar Basins of Xinjiang. The NCP region also has a high temperature in summer, which might be related to local urbanization (Liu et al., 2008) and irrigation (Kang and Eltahir, 2018).

The spatial variations of the predicted human thermal indices in summer (which is often characterized by severe heat stress) are examined in Figure 10 by taking July 2020 as an example. As it shows, the 12 indices exhibit similar distribution patterns. There are significant differences in temperature among northwest, northeast, and southeast China. Generally, the temperature decreases from the southeast to the northwest, and the southeast and northwest parts have the highest and lowest temperatures, respectively.

HMI exhibits the highest temperature while NET shows the lowest in July 2020. The dominant modes of these indices are further examined by applying the empirical orthogonal function (EOF) analysis (Figures S10–S13). As Figure S10 shows, the leading EOF (EOF1) of all 12 thermal indices exhibit highly consistent spatial distribution with higher values in the northern region and lower values in the south. Their temporal variations are also similar to each other (Figure S11). The second and third EOF modes (EOF2 and EOF3) are also similar among different thermal indices (except EOF3 of NET, Figures S11–S13). These results demonstrate the desirable quality of our products.

4.3 Temporal changes in the human thermal indices

The yearly evolutions of the annual mean human thermal indices during 2003–2020 are displayed in Figure 11. Despite the interannual fluctuation in the time series, all indices exhibit upward trends except for NET and WCT, of which the decreasing trends are mainly affected by the recovering wind speed in the recent decade (Zeng et al., 2019). The fastest warming appears in HMI (0.303 °C/decade), and the slowest is in ET (0.111 °C/decade). These warming trends are stronger than the rising rate of global mean near surface temperature (IPCC, 2021), demonstrating China as one of the severest hotspots suffering from dramatic climate warming under global change. The detailed spatial variations regarding the trends of the human thermal indices across China are further depicted in Figure 12. Most parts of China experience are seen with increases in nearly all the indices during 2003–2020. These increases are especially more profound in North China, Southwest China, TP, and parts of Northwest China. The possible reasons for the prominent warming trends in North China are explained as follows. The urbanization process has been prevailing in this area, with rapid growth in the economy and population. This process is accompanied by dramatic increases in impervious surfaces and decreases in green spaces. These changes lead to warmer surface and near surface air temperature, known as urban heat islands (UHI), thus increasing thermal stress in this region. The urbanization effects on local heat stress have also been reported by (Luo and Lau, 2021). Moreover, North China has a large amount of croplands with prominent irrigation activities, which may increase air humidity near the surface and exacerbate the combined effects of temperature and humidity, leading to increased heat stress (Kang and Eltahir, 2018). In addition, this area has experienced a weakening of surface wind speed (Zhang et al., 2021), which also exacerbates thermal stress, especially in NET and WCT.

Furthermore, different indices have different degrees of increasing trends. HMI has the largest increasing magnitude (Figure 12h), and ET is seen with relatively slight increases across China (Figure 12f). The trends of NET and WCT have similar spatial distribution patterns, with large proportions having cooling trends since 2003 (Figures 12j&l). Most parts of Xinjiang, northeastern and southern China have obvious decreasing trends, and the Inner Mongolia Plateau (IMP), NCP, eastern TP, YRD, and YGP have slightly increasing trends.

The temporal trends of the human thermal indices in different seasons were also examined (Figure 13). The fastest warming tendency is observed in the spring season. The rising trends of spring HMI, HI, MDI, AT_{in}, and AT_{out} exceed 0.4 °C/decade, and the trends of other indices (except ET and NET) are larger than 0.3 °C/decade (Figure S2). Summer also has been experiencing significant increasing trends in all indices, i.e., at a rate of > 0.2 °C/decade (except ET and NET). The trends in summer HMI, HI, WBT, MDI, DI, sWBGT, AT_{in}, and AT_{out} exceed 0.3 °C/decade (Figure S3). Differing from spring and summer, the human thermal indices (except WCT and NET) in the autumn season show slightly cooling trends

(Figure S4). Autumn WCT and NET have significantly strong decreasing trends, i.e., -0.349 and -0.507 °C/decade, respectively. Similar strong cooling trends of WCT and NET appear in winter, i.e., -0.661 and -0.453 °C/decade, respectively, while other indices experience marginal long-term changes (Figure S5).

Figure S6 maps the spatial patterns of the trends of summer mean human thermal indices over the mainland of China during 2003–2020. All indices show warming trends in most parts of China, particularly in NCP and TP. As one of the most densely populated regions in China, the prominent increases in thermal indices in NCP indicate that the local has been experiencing increasing threats of intensifying heat stress. Among the 12 indices, AT_{out}, HI, NET and WCT tend to have a slight cooling trend in southeastern China. This cooling trend is consistent with the corresponding summer SAT.

The spatial distributions of the changing trends in winter across the mainland of China during 2003–2020 are depicted in Figure S7. The trend patterns in winter are similar to that in summer to some degree. The warming trends are concentrated in Southwest China, most parts of Northwest China, and parts of East China (e.g., YRD). The cooling trends are located in TP, parts of Northeast and South China. The cooling tendencies are especially significant in Northeast China, and most parts of Northwest and South China (Figures S7 j&m). Parts of central China are seen with even stronger cooling thermal comfort.

In spring, increases in all thermal indices are observed in most parts of China (Figure S8), particularly in northern regions, such as central Inner Mongolia, parts of NCP, and Northeast China, while parts of southern China have slight decreases. These decreases are noticeable in NET and WCT (Figures S8 j&m). In contrast to spring, the autumn season is observed with decreased thermal temperature in the north and increases in the south (e.g., Southwest China, Figure S9).

5 Discussion

5.1 Comparison with existing human thermal index datasets

We compared our HITIC-Monthly with two existing datasets, i.e., HDI (Mistry, 2020) and HiTiSEA (Yan et al., 2021), which have coarser spatial resolutions of 0.25°×0.25° and 0.1°×0.1° (Table 4), respectively. We derived monthly mean AT_{in} in July 2018 from HDI and HiTiSEA and compared them with HITIC-Monthly over the mainland of China, with a particular highlight in the four largest UAs, including Beijing-Tianjin-Hebei (BTH), YRD, middle Yangtze River Valley (mYRV) and Pearl River Delta (PRD) (Figure 14). The summer of 2018 was selected because it was included in all three datasets and frequent heat events occurred in this summer (Zhou et al., 2020). Generally, the three datasets depict similar spatial patterns. However, our HiTIC-Monthly dataset obviously provides more detailed and clearer spatial information on human thermal stress than the other two. Additionally, the observed AT_{in} values at individual weather stations are also compared (Figure 14). It can be seen that HDI and HiTISEA overestimate AT_{in}, and such overestimation is especially severe for HDI, while our dataset is in good agreement with the observed AT_{in} at individual weather stations. Therefore, our predicted temperature can describe the spatial variations in the city areas well, thereby providing fundamental support for fine-scale climate studies, such as urban climate research.

5.2 Limitations and future works

There are 12 commonly used human thermal indices in the HiTIC-Monthly dataset produced in this study. Nine of these indices were computed from temperature and humidity (or water vapor) and the other three (i.e., AT_{out}, NET, and WCT) were derived from temperature, humidity, and wind speed. In addition, other indices considering the combined effect of environmental variables such as sunlight (Blazejczyk, 1994; Fanger, 1970; Höppe, 1999; Yaglou and Minaed, 1957) were proposed, including wet bulb globe temperature (WBGT), predicted mean vote (PMV), UTCI, physiological equivalent temperature (PET), etc. These thermal indices were not included in our study due to the lack of sunshine and radiative flux data.

Since LST is the most important variable for predicting the 11 human thermal indices, the uncertainty in the LST dataset may influence the accuracy of the human thermal indices. The LST variable in our prediction is collected from a global seamless 1 km resolution daily LST dataset (Zhang et al., 2022b). This dataset was generated based on spatiotemporal gap-filling algorithms and the MODIS LST data. It may overestimate LST in some cases because the LST under cloudy weather was filled based on the data in clear sky conditions (Zhang et al., 2022b). A high-quality LST dataset would further improve the prediction accuracy of the human thermal indices.

The human thermal indices dataset is at a monthly scale, but the temporal resolution may not be sufficient for the research of extreme weather events (e.g., heatwaves and cold spells) and related environmental health (e.g., heat-related mortality). A daily high-resolution human thermal index collection (HiTIC-Daily) will be produced and released in our future studies. In the current study, we provided the first national-level dataset over the mainland of China with multiple high-resolution human thermal indices in a monthly interval, which shows high prediction accuracies in all climate regimes across China. A global dataset of multiple human thermal indices dataset is also expected in the near future.

6 Data availability

The high spatial resolution monthly human thermal index collection (HiTIC-Monthly) generated in this study is freely available to the public in network common data form (NetCDF) from Zenodo at https://zenodo.org/record/6895533 and the National Tibetan Plateau Data Center (TPDC) of China at https://data.tpdc.ac.cn/disallow/036e67b7-7a3a-4229-956f-40b8cd11871d (Zhang et al., 2022a). The human thermal indices include surface air temperature (SAT), indoor Apparent Temperature (AT_{in}), outdoor shaded Apparent Temperature (AT_{out}), Discomfort Index (DI), Effective Temperature (ET), Heat Index (HI), Humidex (HMI), Modified Discomfort Index (MDI), Net Effective Temperature (NET), simplified Wet Bulb Globe Temperature (sWBGT), Wet-Bulb Temperature (WBT), and Wind Chill Temperature (WCT). This dataset has a spatial resolution of 1 km×1 km and covers the mainland of China from 2003 to 2020, stacking by year. Each stack is composed of 12 monthly images. The unit of the dataset is 0.01 degree Celsius (°C), and the values are stored in an integer type (Int16) for saving storage space, and need to be divided by 100 to get the values in degree Celsius when in use. The projection coordinate system is Albers Equal Area Conic Projection. The naming rule and other detailed information can be found in “README.pdf”.

7 Conclusions

A long-term and high-resolution dataset of multiple human thermal indices is of great significance for monitoring detailed spatiotemporal changes of human thermal stress in different climate regions across China and assessing the health risks of people exposed to extreme heat at a fine scale. However, the current datasets of human thermal indices (e.g., HDI and HiTiSEA) only have coarse spatial resolutions (> 0.1°). In this study, we generated a dataset of monthly human thermal index collection with a high spatial resolution of 1 km over the mainland of China (HiTIC-Monthly). In this collection, 12 human thermal indices from 2003 to 2020 were predicted, including SAT, AT_{in}, AT_{out}, DI, ET, HI, HMI, MDI, NET, sWBGT, WBT, and WCT.

The HiTIC-Monthly dataset was produced by LGBM based on multi-source data, including MODIS LST, DEM, land cover, population density, and impervious surface fraction. This dataset shows a desirable performance, with mean R^2, *RMSE*, *MAE,* and *Bias* of 0.996, 0.693°C, 0.512°C, and 0.003°C, respectively. Our predictions also exhibit good agreements with the observations in both spatial and temporal dimensions, demonstrating the broad applicability of our dataset. Moreover, the comparison with two existing datasets (i.e., HDI and HiTiSEA) suggests that HiTIC-Monthly has more detailed spatial information, indicating that our dataset can well support fine-scale studies. Further investigation shows that almost all the indices show warming trends in most parts of China during 2003–2020, particularly for North China, Southwest China, TP, and parts of Northwest China. Additionally, the warming tendency is faster in spring and summer. WCT and NET show similar and strong cooling trends in autumn and winter, while other indices exhibit slight long-term changes.

Author contribution

H.Z.: Data curation, Formal analysis, Investigation, Methodology, Writing – original draft preparation; M.L.: Formal analysis, Conceptualization, Investigation, Funding acquisition, Methodology, Supervision Writing – review & editing; Y.Z.: Formal analysis, Conceptualization, Investigation, Supervision, Writing – review & editing; L.J.: Investigation, Writing – review & editing; E.G.: Investigation, Writing – review & editing; Y.Y.: Investigation, Writing – review & editing; G.N.: Investigation, Writing – review

& editing; J.G.: Investigation, Writing – review & editing; Z.Z.: Investigation, Writing – review & editing; K.G.: Investigation, Writing – review & editing; J.L.: Investigation, Writing – review & editing; X.L.: Investigation, Writing – review & editing; S.W.: Investigation, Writing – review & editing; P.W.: Investigation, Writing – review & editing; X.W.: Investigation, Writing – review & editing.

Competing interests

The authors declare that they have no conflict of interest.

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Figures

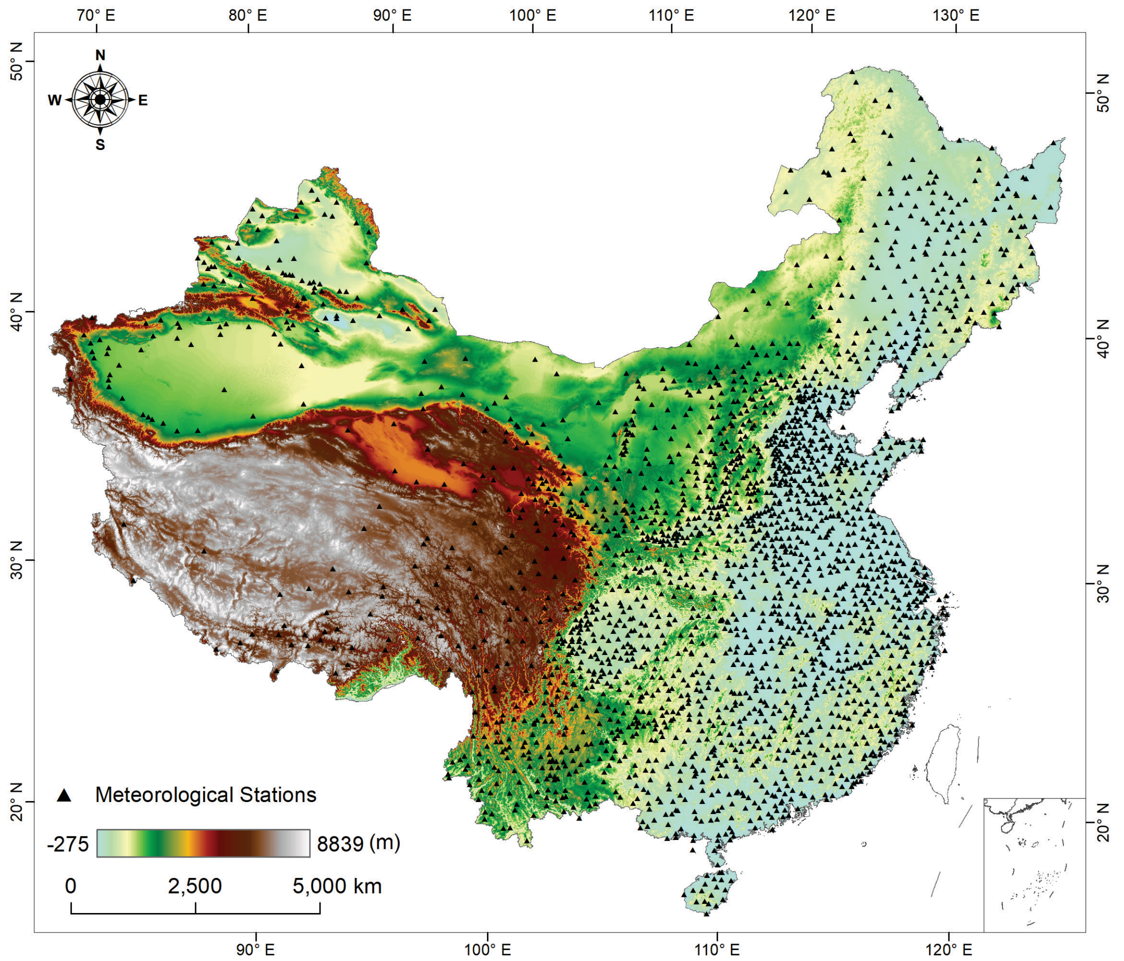

Figure 1. Spatial distribution of meteorological stations in the mainland of China, with color shadings indicating the elevation in meters.

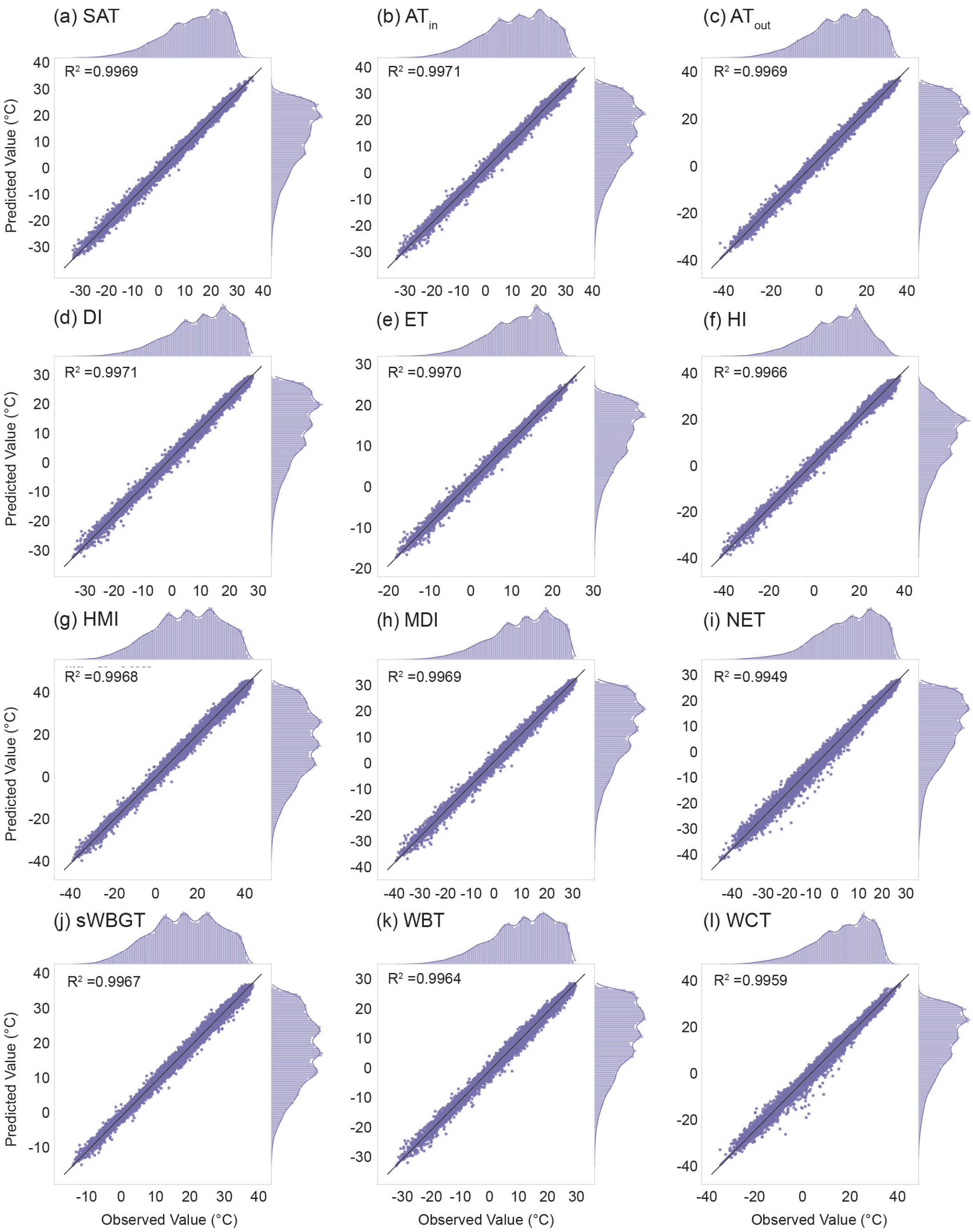

Figure 2. Scatter plots of predictions versus observations of the 12 human thermal indices over the mainland of China during 2003–2020. (a) SAT, (b) AT$_{in}$, (c) AT$_{out}$, (d) DI, (e) ET, (f) HI, (g) HMI, (h) MDI, (i) NET, (j) sWBGT, (k) WBT, and (l) WCT.

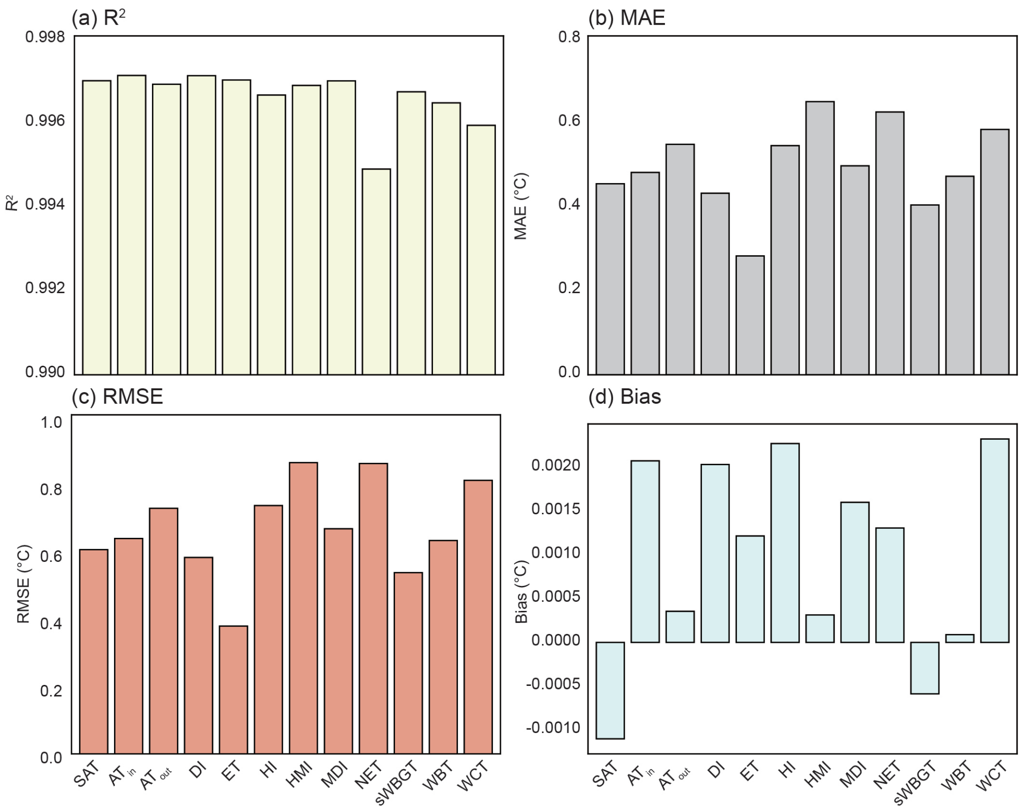

Figure 3. Overall prediction accuracies of the 12 human thermal indices over the mainland of China during 2003–2020. (a) R^2, (b) *MAE*, (c) *RMSE*, (d) *Bias*.

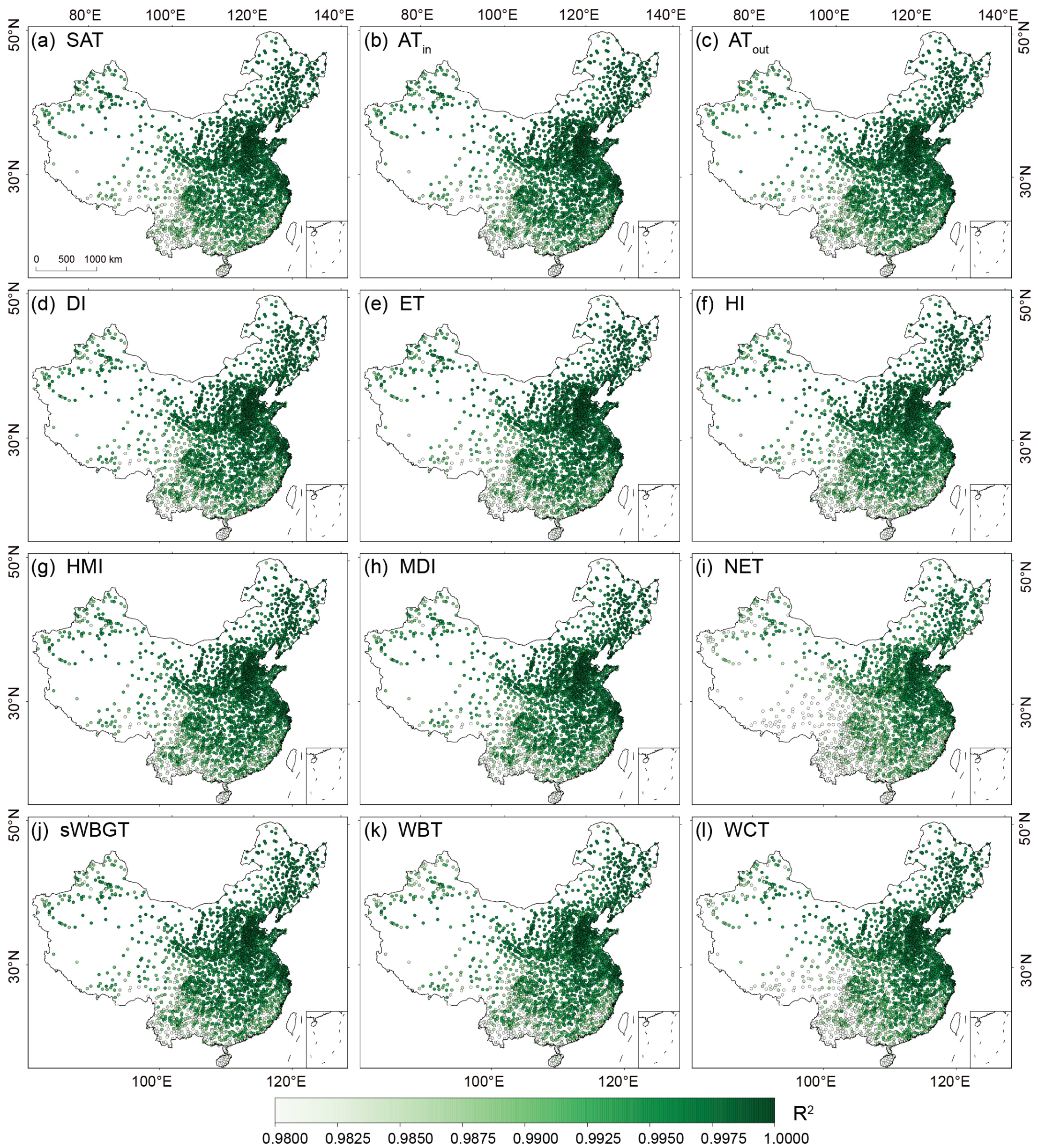

Figure 4. Spatial distribution of R^2 of the 12 human thermal index predictions at individual meteorological stations over the mainland of China during 2003–2020.

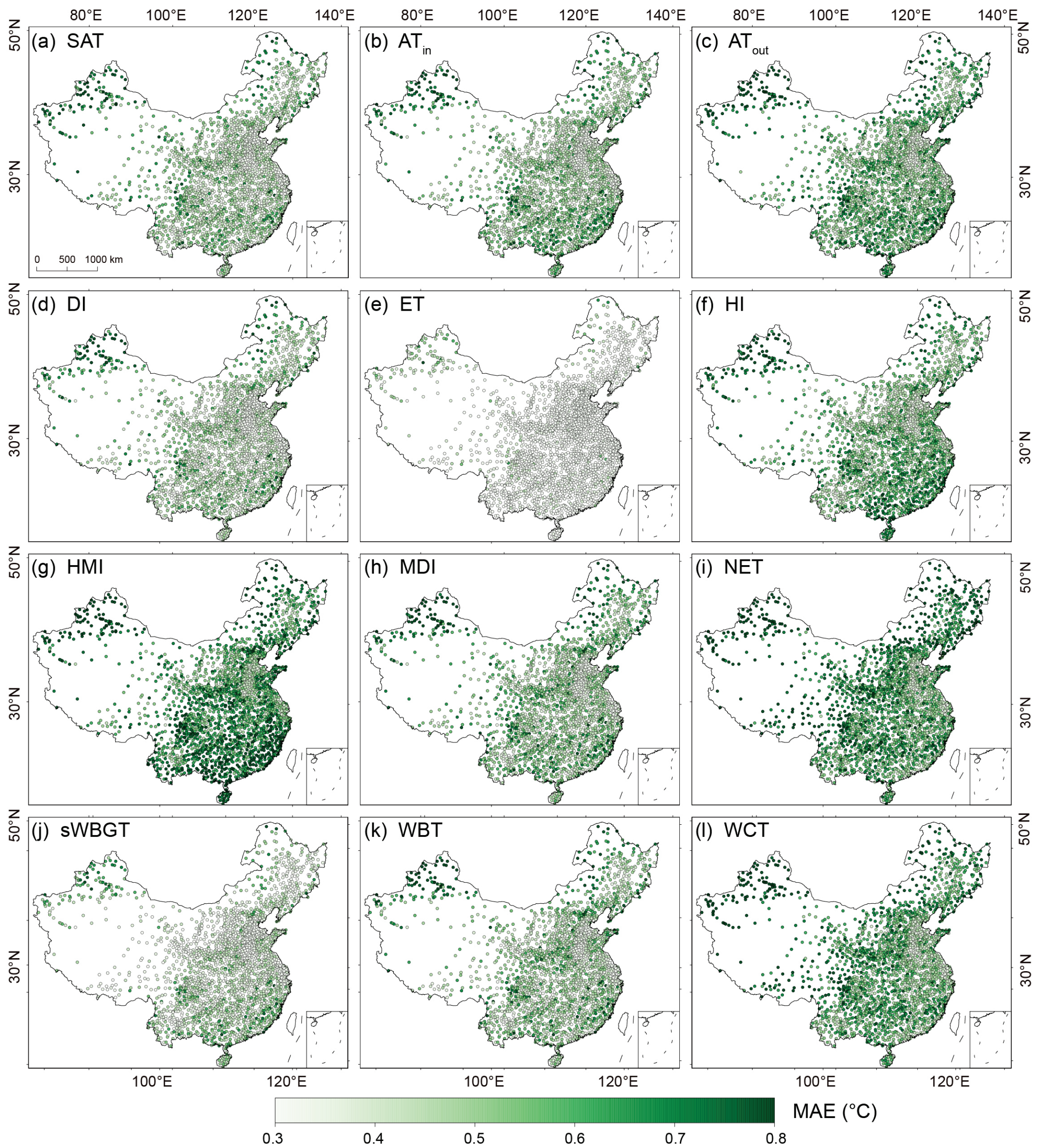

Figure 5. As Figure 4 but for *MAE*.

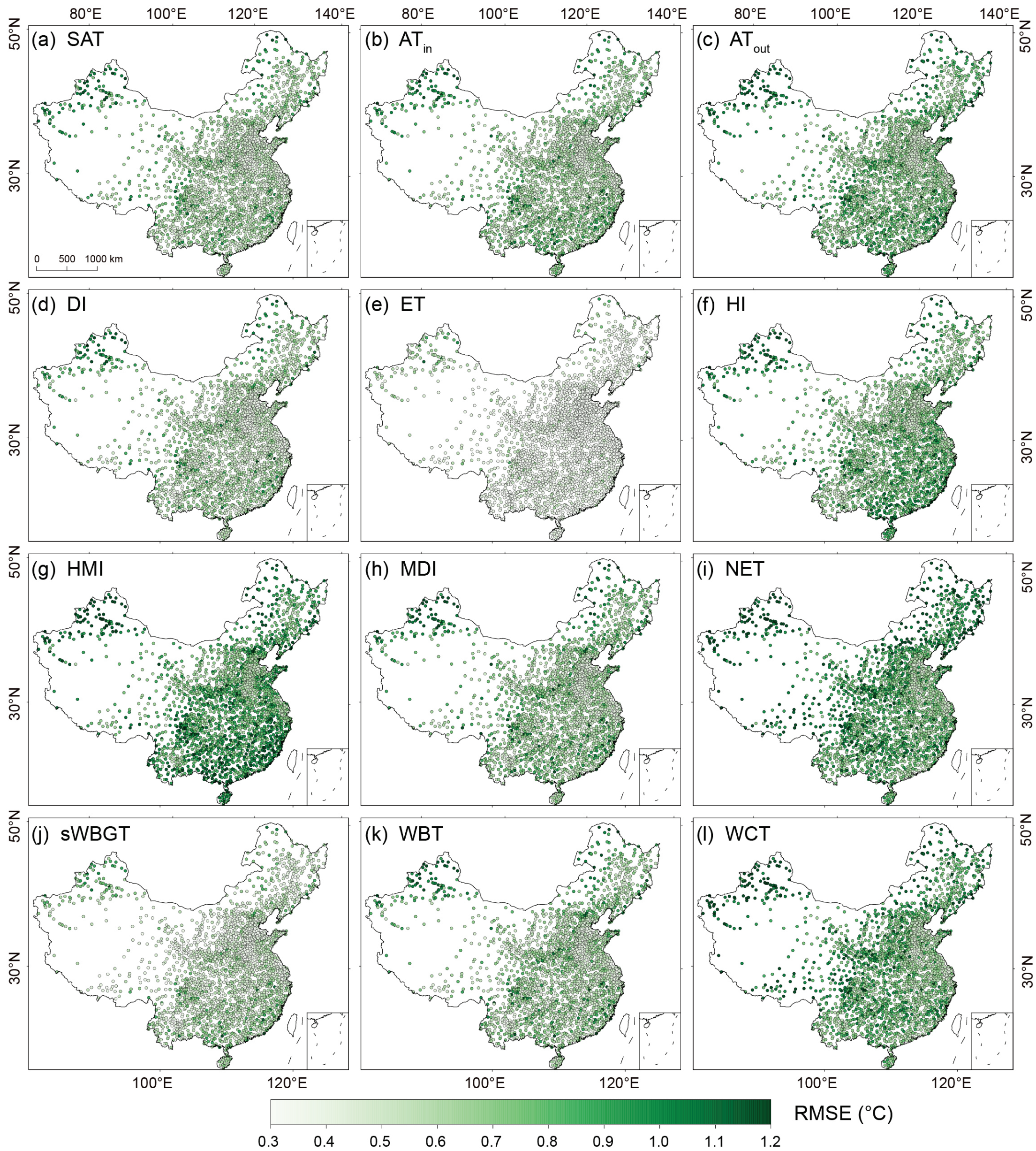

Figure 6. As Figure 4 but for *RMSE*.

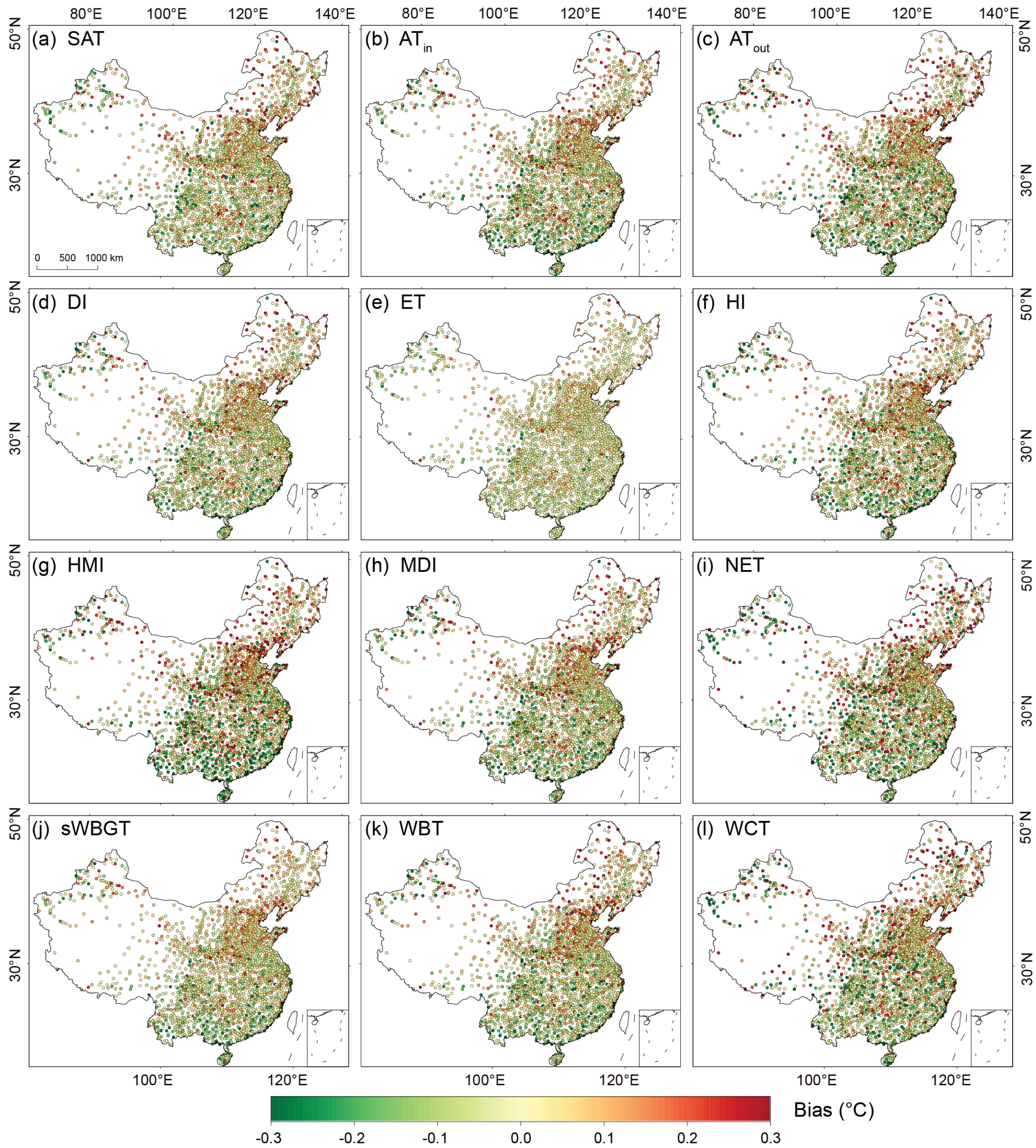

Figure 7. As Figure 4 but for *Bias*.

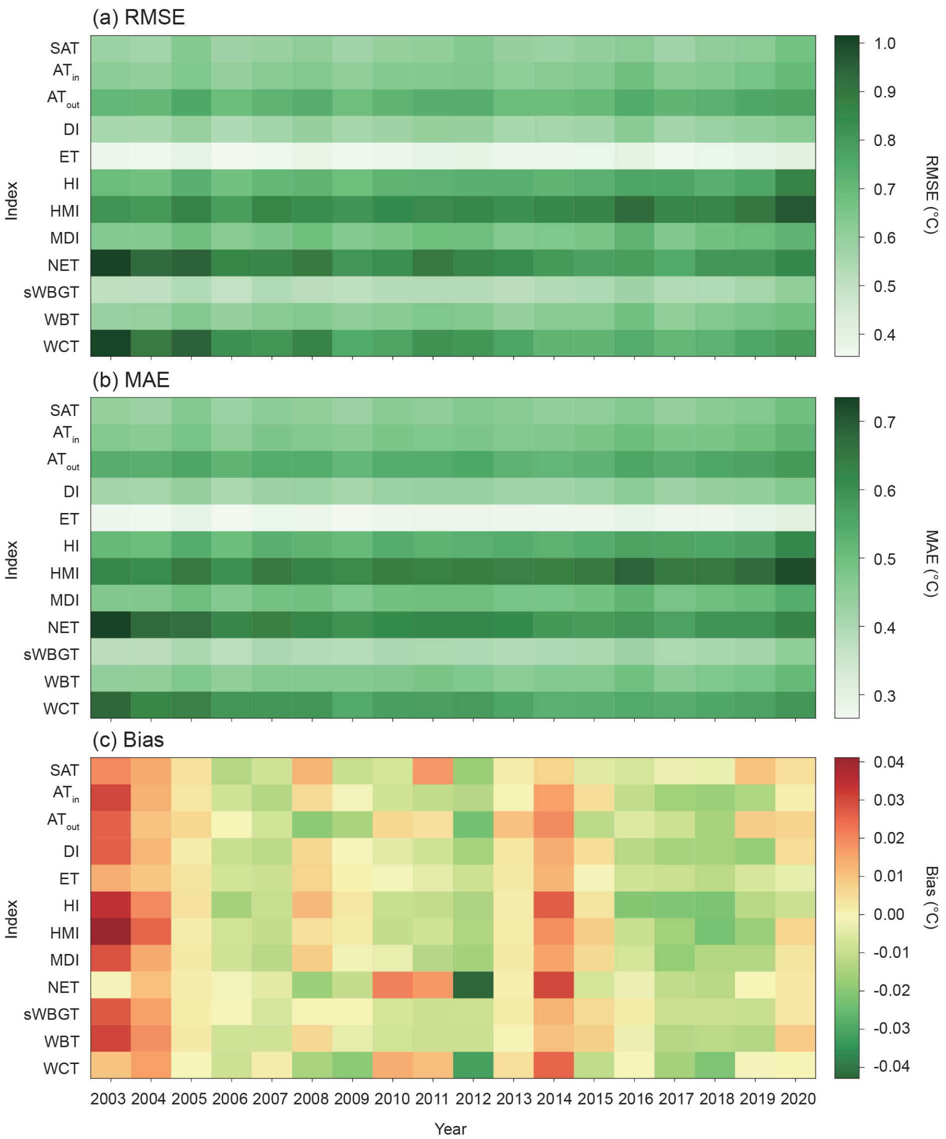

Figure 8. Annual prediction accuracies of the 12 human thermal indices over the mainland of China during 2003–2020: (a) *RMSE*, (b) *MAE*, (c) *Bias*.

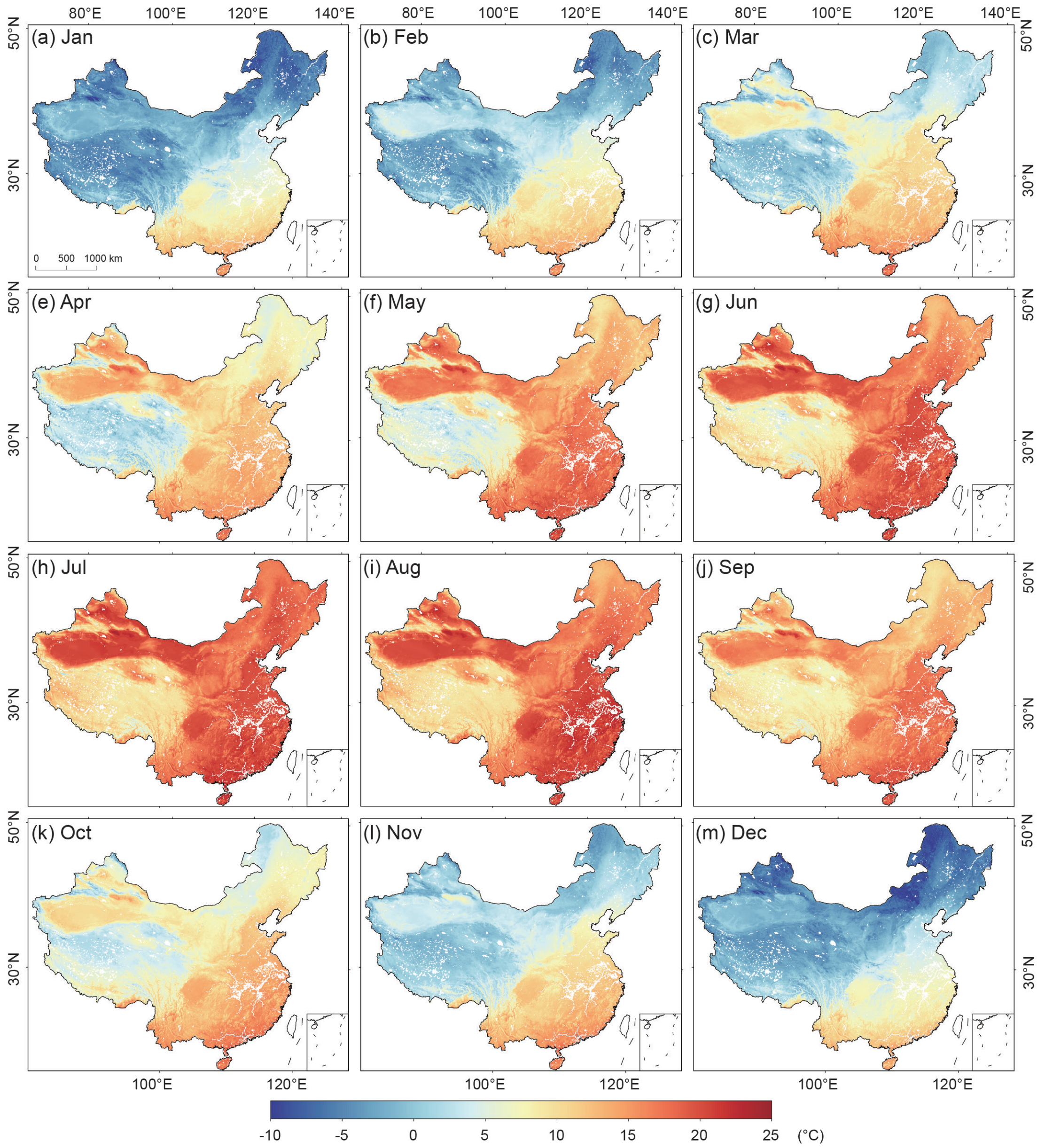

Figure 9. Spatial distributions of the monthly mean ET over the mainland of China in 2020.

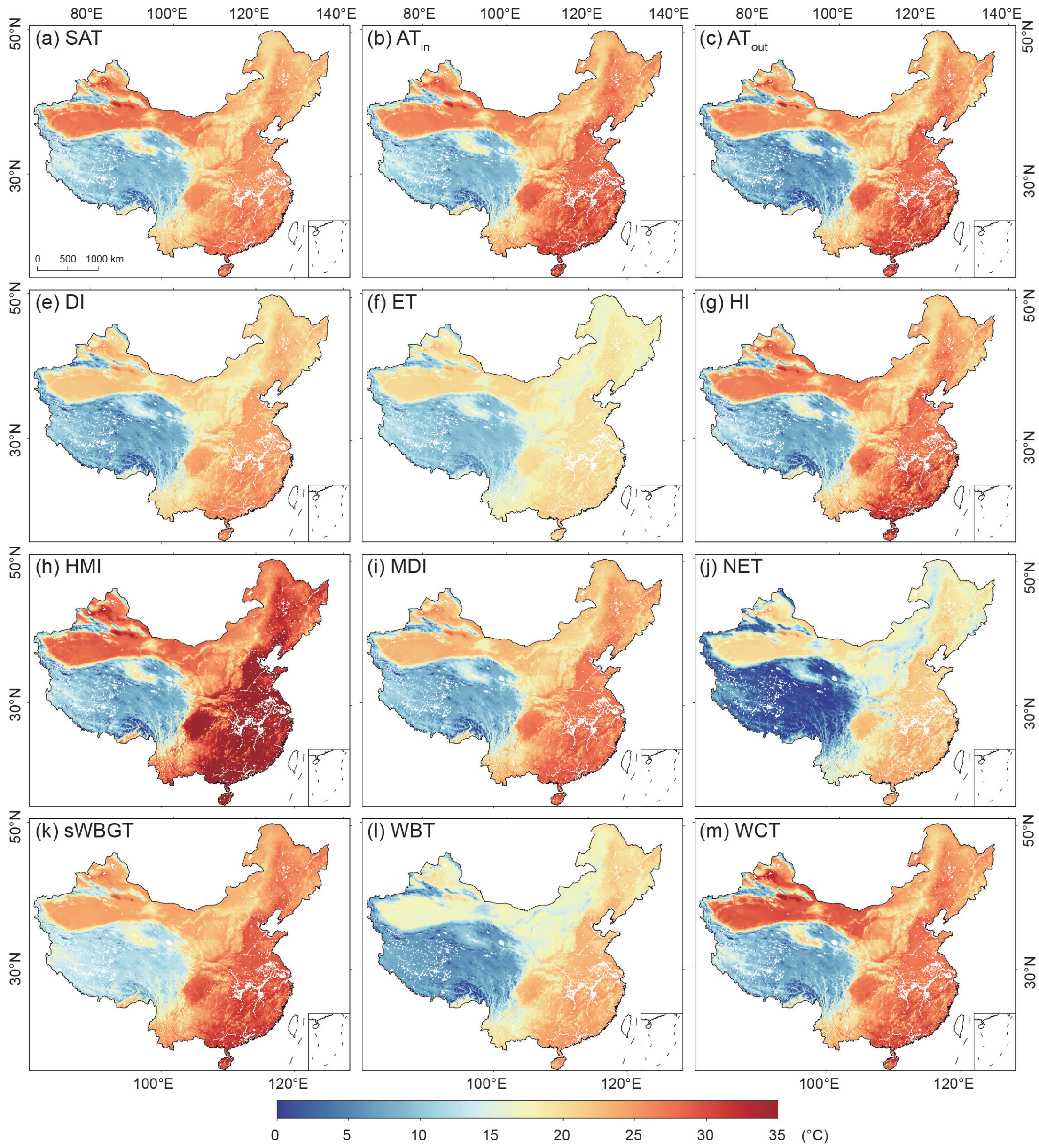

Figure 10. Spatial distributions of the 12 human thermal indices over the mainland of China in July 2020.

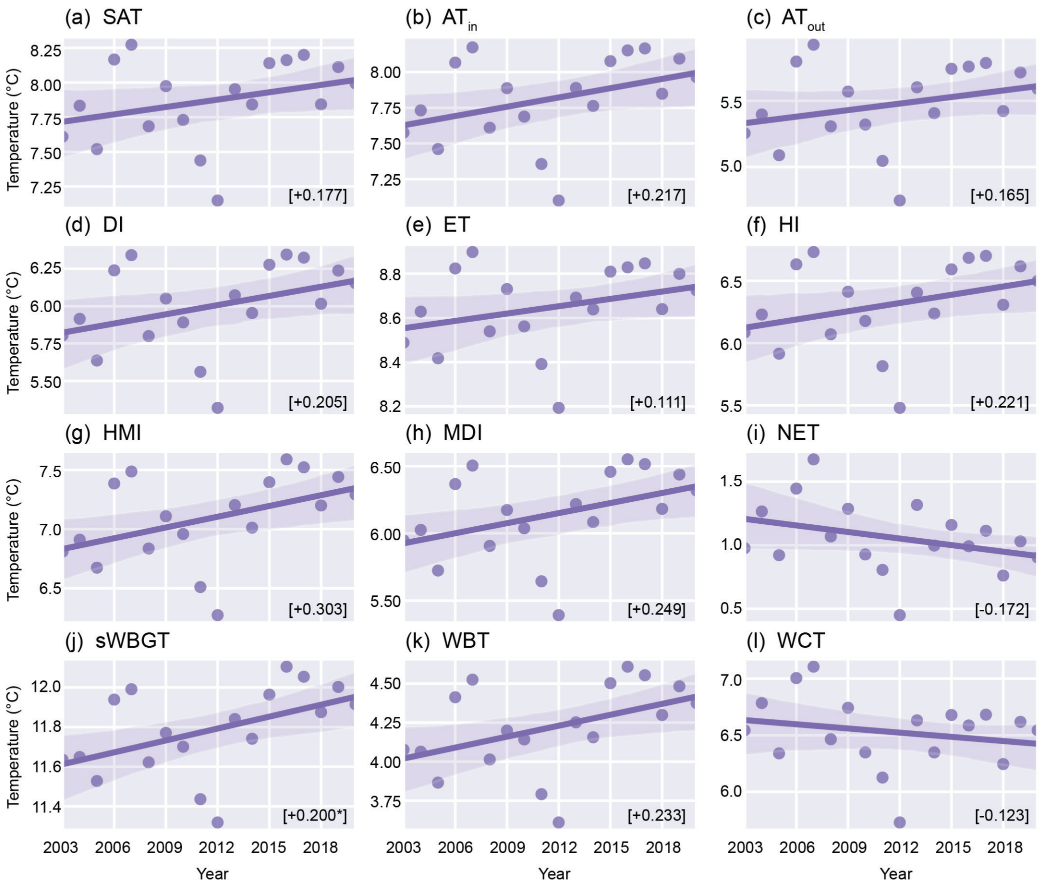

Figure 11. Temporal changes of the 12 annually-averaged human thermal indices over the mainland of China during 2003–2020. The line illustrates the linear trend, the number in the square bracket means the corresponding trend per decade, and the asterisk next to the number indicates that the trends are significant at the 0.05 level.

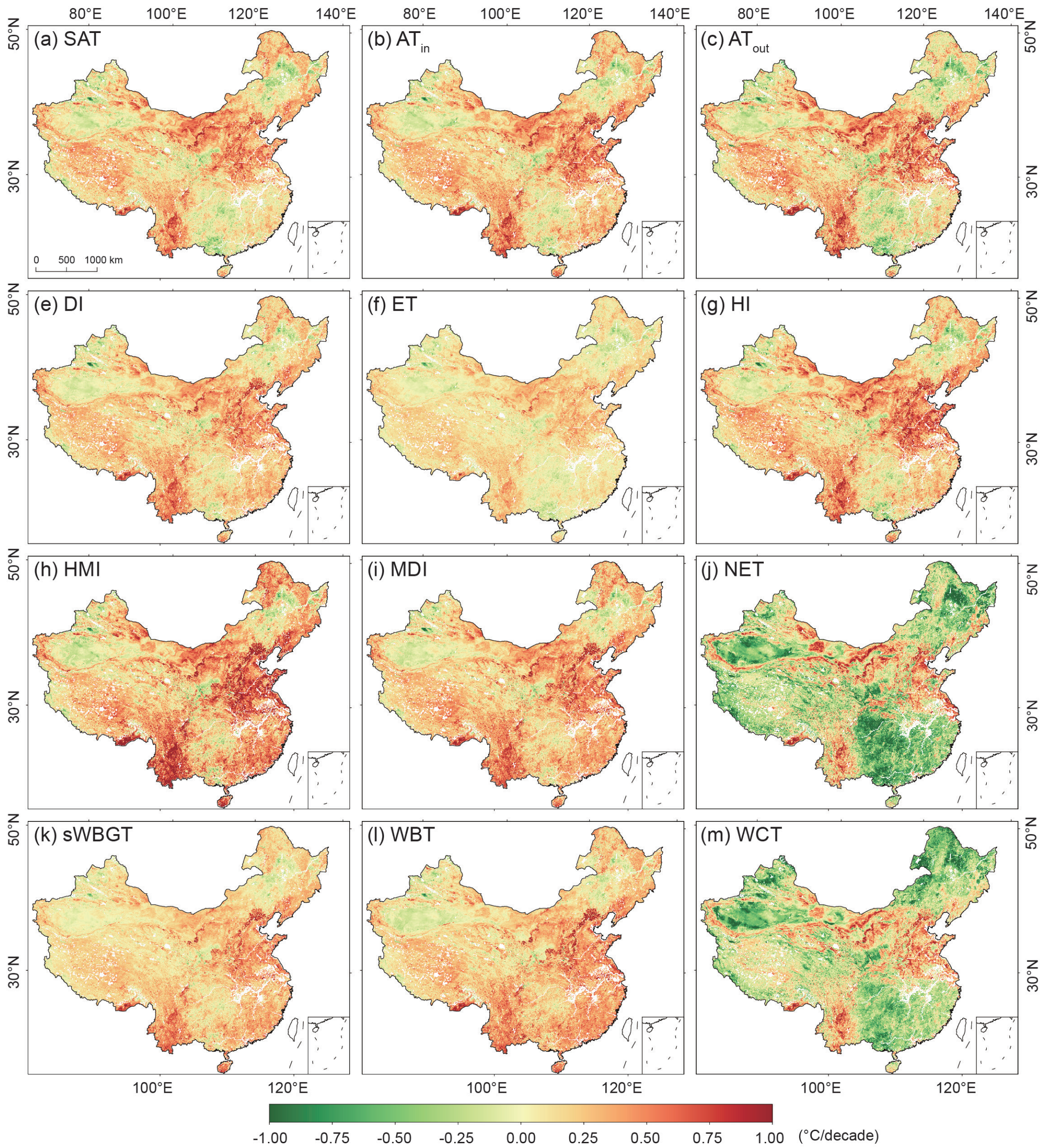

Figure 12. Spatial distributions of the linear trends (unit: °C per decade) in the 12 annually-averaged human thermal indices over the mainland of China during 2003–2020.

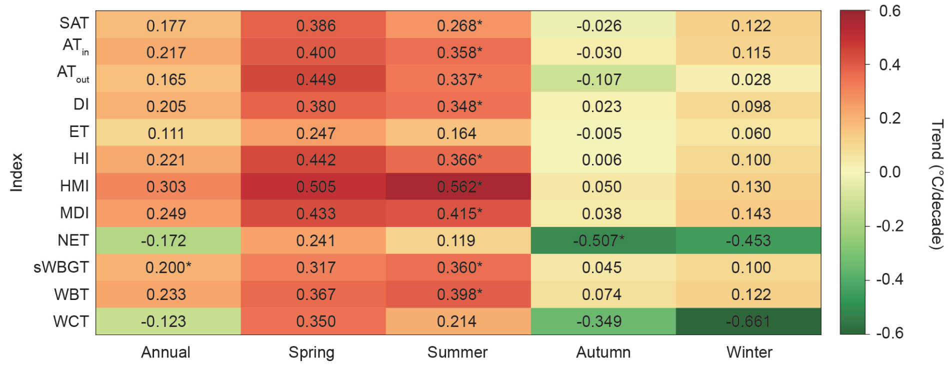

Figure 13. Temporal trends of the 12 annually- and seasonally-averaged human thermal indices over the mainland of China during 2003–2020. The number means linear trend per decade. The asterisk indicates that the trends are significant at the 0.05 level.

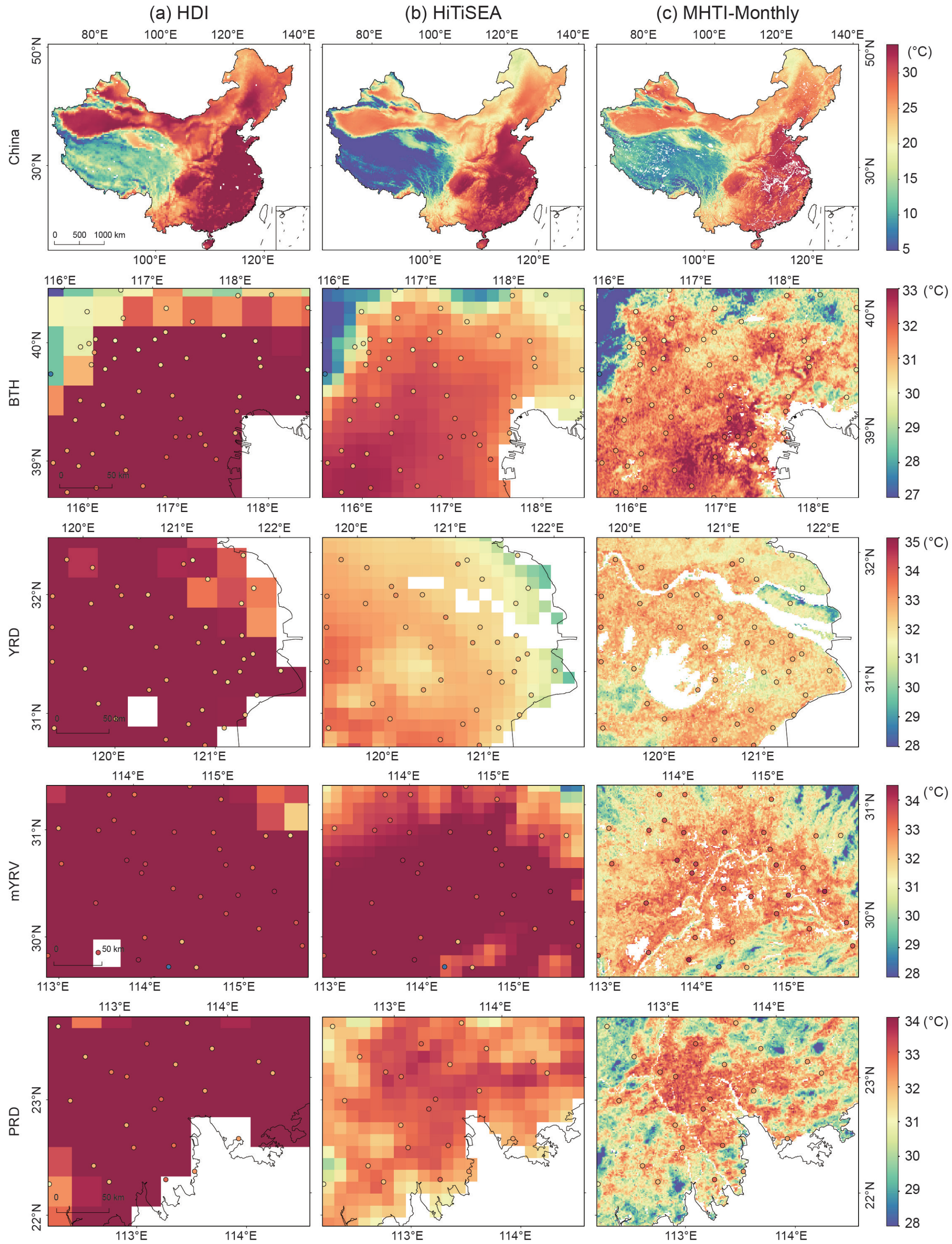

Figure 14. Comparison of the spatial patterns among HDI_0p25_1970_2018 (HDI), HiTiSEA, and HiTIC-Monthly for AT_{in} over the mainland of China and its four largest UAs in July 2018: Beijing-Tianjin-Hebei (BTH), Yangtze River Delta (YRD), middle Yangtze River Valley (mYRV) and Pearl River Delta (PRD). Colored circles indicate the observed AT_{in} values at individual meteorological stations.

Tables

Table 1. Grided datasets used in this study.

Category	Dataset	Spatial Resolution	Temporal Resolution	Variables	Data Source
Land surface temperature	A global seamless 1 km resolution daily land surface temperature dataset (2003-2020)	1 km	Daily	Land surface temperature	Zhang et al. (2022b)
Land cover	MCD12Q1.006	500 m	Annual	Land cover classes in 1 km grids	Sulla-Menashe and Friedl (2019)
Elevation	MERIT DEM: Multi-Error-Removed Improved-Terrain DEM	90 m	/	Aggregated elevation and slope in 1 km grids	Yamazaki et al. (2017)
Impervious surface	Tsinghua/FROM-GLC/GAIA/v10	30 m	Annual	Proportion of impervious surface in 1 km grids	Gong et al. (2020)
Population density	WorldPop	1 km	Annual	Population density	Gaughan et al. (2013)
Temporal variation	/	/	/	Year, Month	/

Table 2. Equations of the human thermal indices for each station.

Abbreviation	Human thermal index	Computation model	Reference
AT_{in}	Apparent Temperature (indoors)	$AT_{in} = -1.3 + 0.92 \times SAT + 2.2 \times E_a$	Steadman (1979)
AT_{out}	Apparent Temperature (outdoors, in the shade)	$AT_{out} = -2.7 + 1.04 \times SAT + 2 \times E_a - 0.65 \times \mathrm{V}$	Steadman (1984)
DI	Discomfort Index	$DI = 0.5 \times WBT + 0.5 \times SAT$	Sohar et al. (1963)
ET	Effective Temperature	$ET = SAT - 0.4 \times (SAT - 10) \times (1 - 0.001 * RH)$	Gagge et al. (1972)
HI	Heat Index*	$HI^* = -8.784695 + 1.61139411 \times SAT - 2.338549 \times RH - 0.14611605 \times SAT \times RH - 1.2308094 \times 10^{-2} \times SAT^2 - 1.6424828 \times 10^{-2} \times RH^2 + 2.211732 \times 10^{-3} \times SAT^2 \times RH + 7.2546 \times 10^{-4} \times SAT \times RH^2 + 3.582 \times 10^{-6} \times SAT^2 \times RH^2$	Rothfusz and Headquarters (1990)
HMI	Humidex	$HMI = SAT + 0.5555 \times (0.1 \times E_a - 10)$	Masterton et al. (1979)
MDI	Modified discomfort index	$MDI = 0.75 \times WBT + 0.38 \times SAT$	Moran et al. (1998)
NET	Net Effective Temperature	$NET = 37 - \dfrac{37 - SAT}{0.68 - 0.0014 \times RH + \dfrac{1}{1.76 + 1.4 \times V^{0.75}}} - 0.29 \times SAT \times (1 - 0.01 \times RH)$	Houghton and Yaglou (1923)
sWBGT	simplified Wet Bulb Globe Temperature	$sWBGT = 0.567 \times SAT + 0.0393 \times E_a + 3.94$	Gagge and Nishi (1976)
WBT	Wet-bulb Temperature	$WBT = SAT \times atan(0.151977 \times (RH + 8.313659)^{0.5}) + atan(T + RH) - atan(RH - 1.676331) + 0.00391838 \times RH^{1.5} \times atan(0.02301 \times RH) - 4.686035$	Stull (2011)
WCT	Wind Chill Temperature	$WCT = 13.12 + 0.6215 \times SAT - 11.37 \times (V \times 3.6)^{0.16} + 0.3965 \times SAT \times (V \times 3.6)^{0.16}$	Osczevski and Bluestein (2005)

SAT is observed air temperature (°C), RH is relative humidity (%), V is wind speed (m/s), and E_a is actual water vapor pressure (kPa). Asterisk means that an adjustment is needed. All units of human thermal indices in this study are in degrees Celsius (°C).

Table 3. Overall prediction accuracies of the 12 human thermal indices over the mainland of China during 2003–2020.

Indices	R^2	*RMSE* (°C)	*MAE* (°C)	*Bias* (°C)
SAT	0.9969	0.603	0.451	-0.001
AT_{in}	0.9971	0.635	0.478	0.002
AT_{out}	0.9969	0.724	0.544	0.000
DI	0.9971	0.579	0.429	0.002
ET	0.9970	0.377	0.281	0.001
HI	0.9966	0.733	0.541	0.002
HMI	0.9968	0.859	0.645	0.000
MDI	0.9969	0.664	0.493	0.002
NET	0.9949	0.856	0.620	0.001
sWBGT	0.9967	0.535	0.401	-0.001
WBT	0.9964	0.629	0.469	0.000
WCT	0.9959	0.807	0.579	0.002

Table 4. Comparisons of the four thermal index datasets.

	ERA5-HEAT	HDI	HiTiSEA	HiTIC-Monthly
Spatial Resolution	0.25°×0.25°	0.25°×0.25°	0.1°×0.1°	1 km×1 km
Temporal Resolution	Hourly	Daily	Daily	Monthly
Spatial Coverage	Global	Global	South and East Asia	Mainland of China
Period	1979–present	1970–2018	1981–2019	2003–2020
Thermal Indices	Mean Radiant Temperature (MRT), Universal Thermal Climate Index (UTCI)	Apparent Temperature indoors (ATind), two variants of Apparent Temperature outdoors in shade (ATot), Heat Index (HI), Humidex (HDEX), Wet Bulb Temperature (WBT), two variants of Wet Bulb Globe Temperature (WBGT), Thom Discomfort Index (DI), Windchill Temperature (WCT)	UTCI, indoor UTCI, outdoor shaded UTCI, MRT, Environment Stress Index (ESI), HI, Humidex, WBGT, WBT, WCT, AT, NET	SAT, AT_{in}, AT_{out}, DI, ET, HI, HMI, MDI, NET, sWBGT, WBT, WCT