

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. 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

#Reviewer 1

Major comments.

The dataset is very important 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, Lú, & 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 156–158): **“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 177–182):

“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 it? Is it HTI (human thermal index)? No “I” after “human” and before “thermal”.

Response: “HiTIC” stands for **High** spatial resolution **Thermal Index Collection**. 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 ($^{\circ}\text{C}$). 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 454–456): **“The unit of the dataset is 0.01 degree Celsius ($^{\circ}\text{C}$), 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 204–205: **“ E_a is derived from T and RH rather than directly observed at meteorological stations (Eqs. 1~2; Bolton (1980)).”**

Lines 237–238: **“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 811–812): “**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 817–818): “**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 826-829):

“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.”

#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. As shown in Figure 7, the bias exhibits a zonal variation across the space, i.e., positive bias values tend to distribute in northern China and 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, and extremely small values in the north may be overestimated while extremely large values in the south may be underestimated to some extent. Such an issue of overestimation of low values and underestimation of high values is a common problem in machine learning prediction (Cho, Yoo, Im, & Cha, 2020; Li, Li, Li, & Liu, 2020; Uddin, Nash, Mahammad Diganta, Rahman, & Olbert, 2022; Wu et al., 2022). The same reason can also explain the temporal variability of the bias (Figure 8). Positive bias values are more likely seen in early periods with lower temperatures, and negative bias values tend to appear in more recent periods with higher temperatures. Although there exist some spatial and temporal variabilities of the bias, these variations are quite small (i.e., ranging from $-0.3\text{ }^{\circ}\text{C}$ to $+0.3\text{ }^{\circ}\text{C}$), and the overall estimations in our study are still reliable (see the evaluation results in Section 4.1).

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 334–340):

“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.”

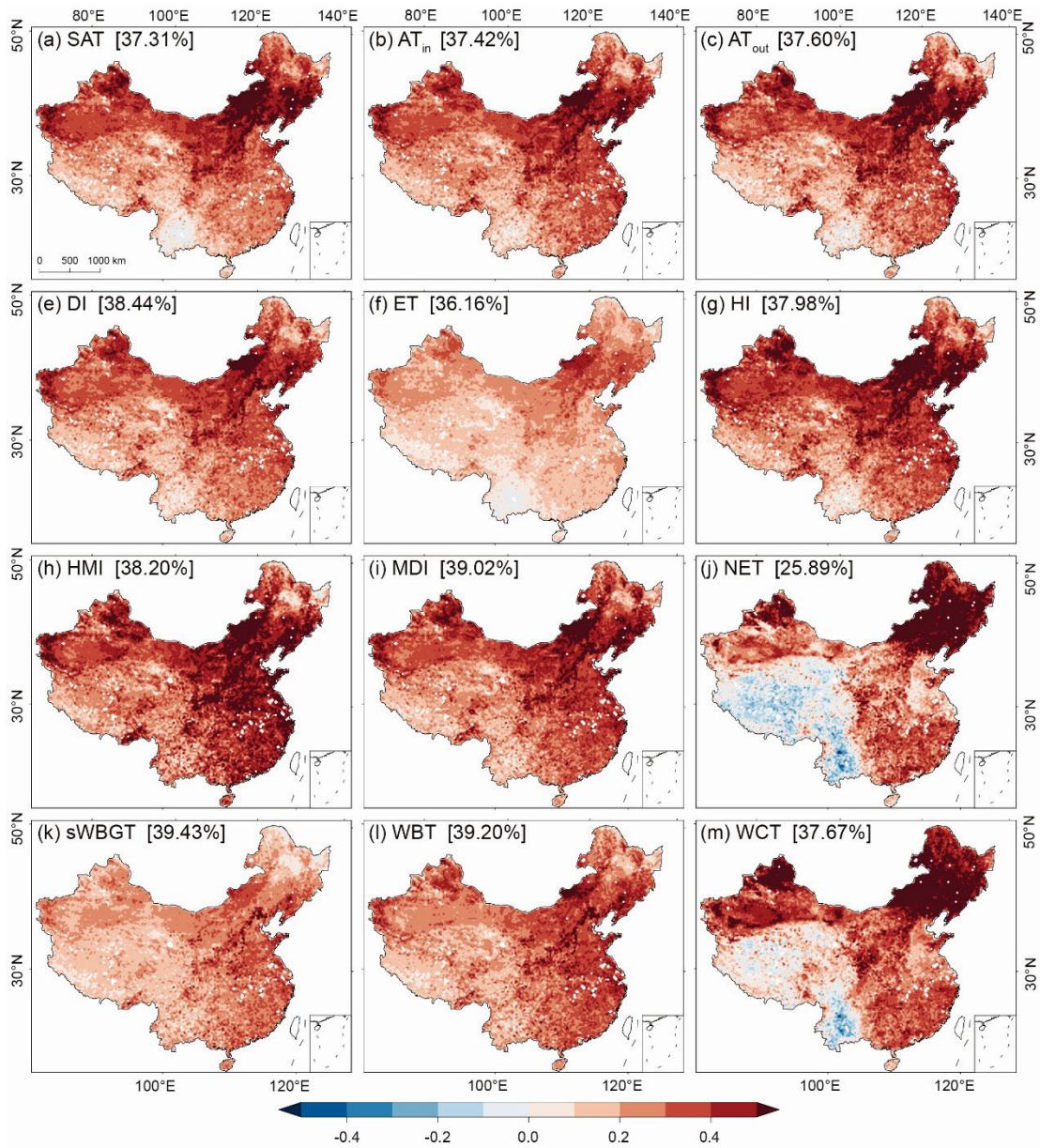


Figure R1. Spatial distributions of the leading empirical orthogonal function (EOF1) of the 12 human thermal indices over the mainland of China. The numbers in square brackets represent the percentage of the variance explained by the corresponding EOF mode.

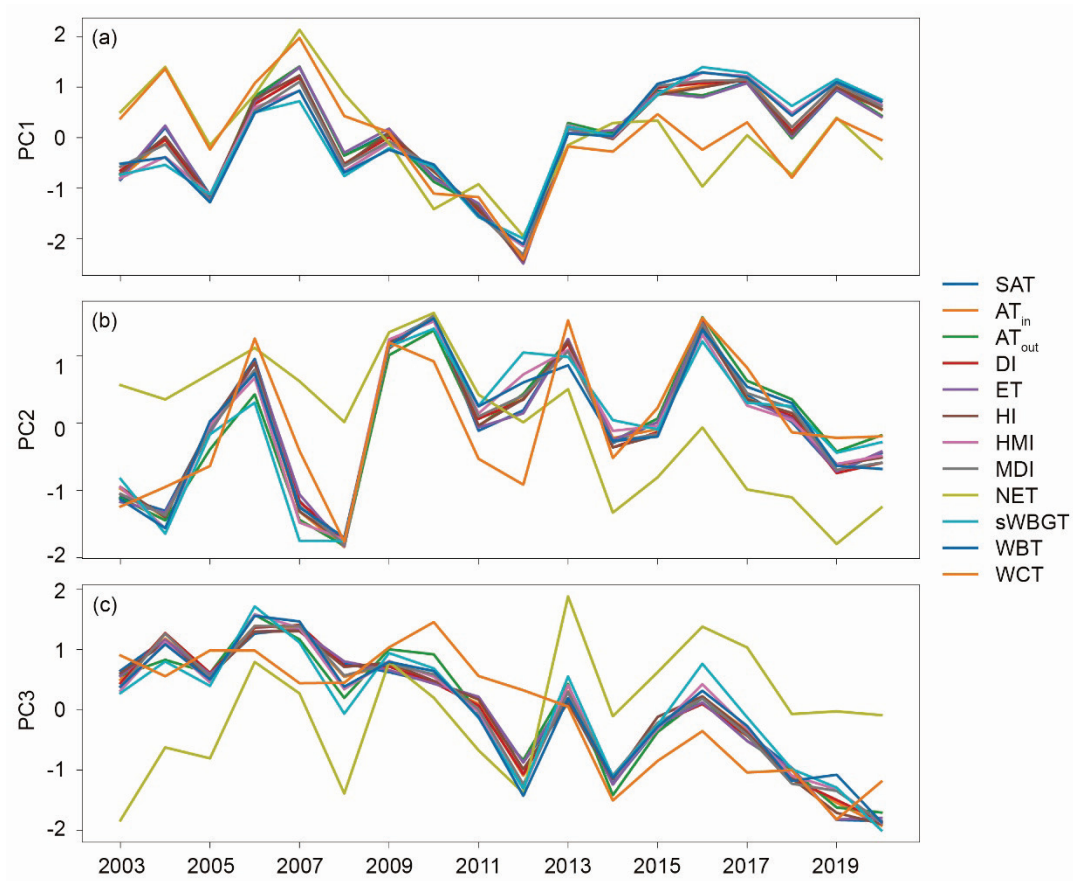


Figure R2. Time series of the principal components (PCs) corresponding to the first three EOF modes of the 12 human thermal indices over the mainland of China during 2003–2020.

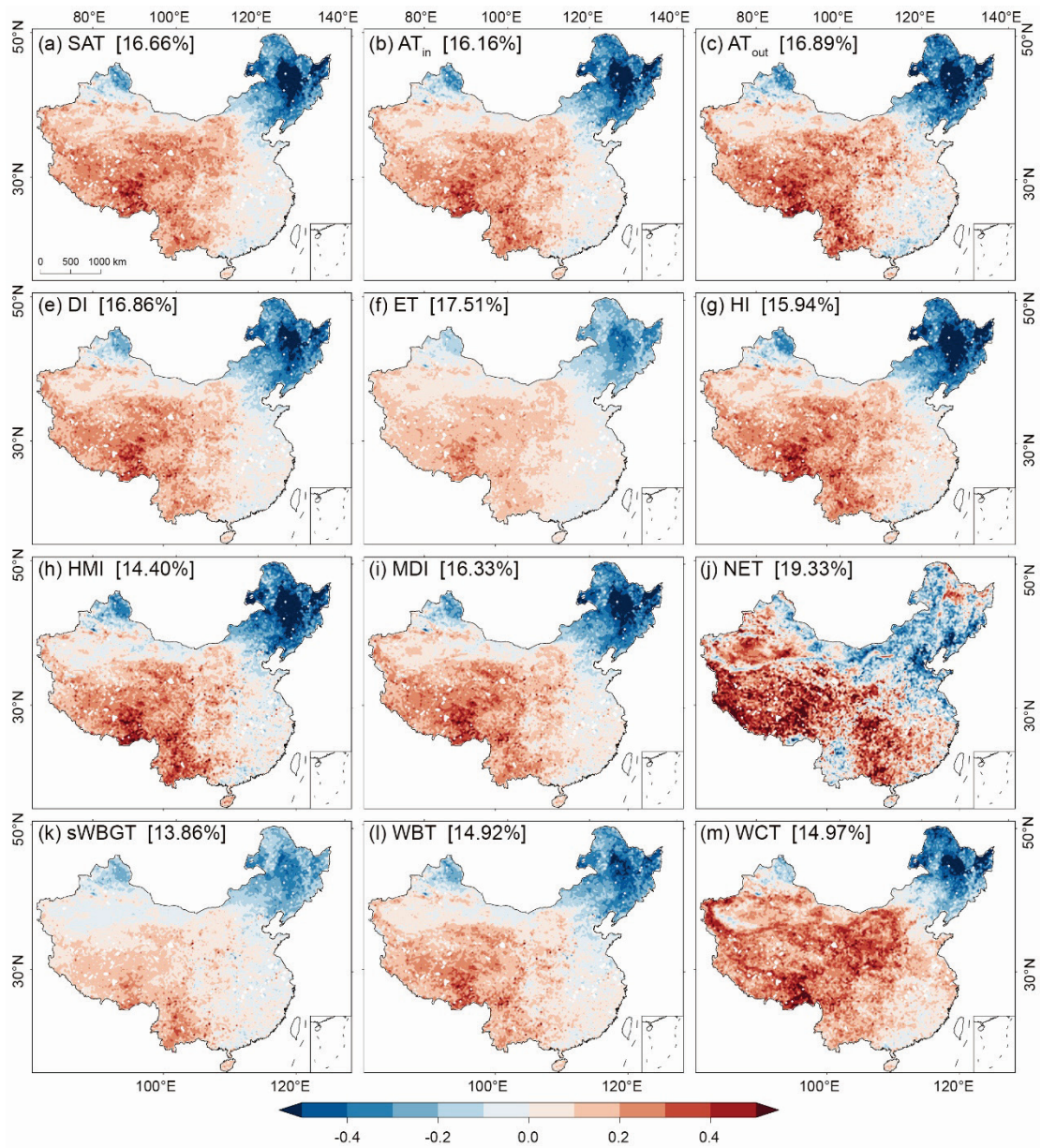


Figure R3. As Figure R1 but for the second EOF (EOF2).

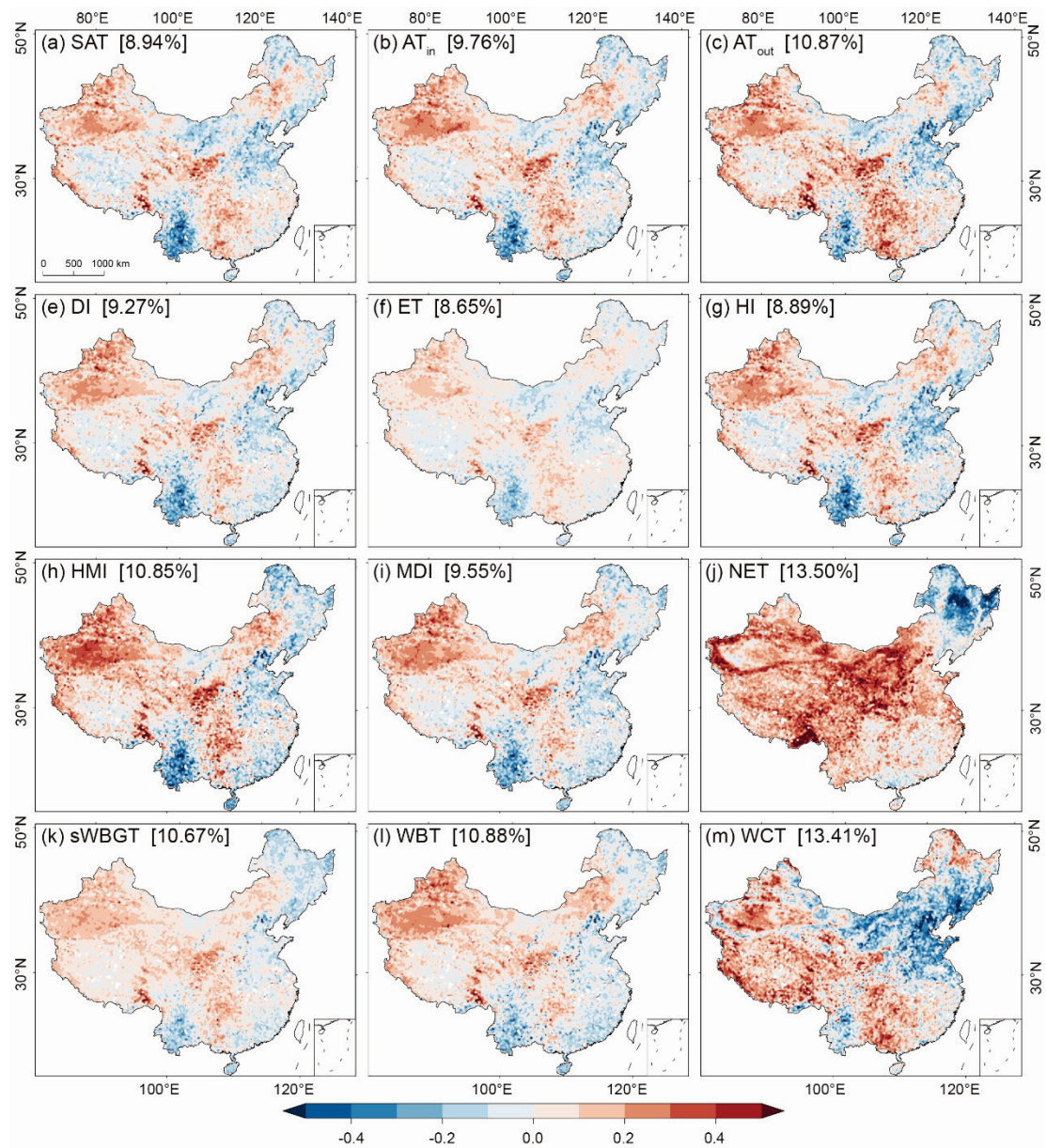


Figure R4. As Figure R1 but for the third EOF (EOF3).

#Reviewer 3

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:

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. This spatial variability is likely caused by the generally low and high temperatures in the north and south, respectively. The extremely small values in the north may be overestimated while the extremely large values in the south may be underestimated to some extent. The overestimation and underestimation issues are quite common in machine learning (Cho et al., 2020; Li et al., 2020; Uddin et al., 2022; Wu et al., 2022). This can explain the temporal variability of the bias (Figure 8) as well. Positive bias values are more likely to be seen in early periods with lower temperature, and negative bias values tend to appear in more recent periods with higher temperature. Although the biases have spatial and temporal variabilities, these variations are quite small (i.e., ranging from $-0.3\text{ }^{\circ}\text{C}$ to $+0.3\text{ }^{\circ}\text{C}$). Overall, the estimations in our study are reliable (see the evaluation results in Section 4.1).

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1 **HiTIC-Monthly: A Monthly High Spatial Resolution (1**
2 **km) Human Thermal Index Collection over China during**
3 **2003–2020**

4
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30 **Abstract**

31 Human-perceived thermal comfort (also known as human-perceived temperature) measures the
32 combined effects of multiple meteorological factors (e.g., temperature, humidity, and wind speed) and
33 can be aggravated under the influences of global warming and local human activities. With the most
34 rapid urbanization and the largest population, China is being severely threatened by aggravating human
35 thermal stress. However, the variations of thermal stress in China at a fine scale have not been fully
36 understood. This gap is mainly due to the lack of a high-resolution gridded dataset of human thermal
37 indices. Here, we generated the first high spatial resolution (1 km) dataset of monthly human thermal
38 index collection (HiTIC-Monthly) over China during 2003–2020. In this collection, 12 commonly-used
39 thermal indices were generated by the **Light Gradient Boosting Machine (LGBM)** learning algorithm
40 from multi-source data, including land surface temperature, topography, land cover, population density,
41 and impervious surface fraction. Their accuracies were comprehensively assessed based on the
42 observations at 2419 weather stations across the mainland of China. The results show that our dataset
43 has desirable accuracies, with the mean R^2 , root mean square error, and mean absolute error of 0.996,
44 0.693°C, and 0.512°C, respectively, by averaging the 12 indices. Moreover, the data exhibit high
45 agreements with the observations across spatial and temporal dimensions, demonstrating the broad
46 applicability of our dataset. A comparison with two existing datasets also suggests that our high-
47 resolution dataset can describe a more explicit spatial distribution of the thermal information, showing
48 great potentials in fine-scale (e.g., intra-urban) studies. Further investigation reveals that nearly all
49 thermal indices exhibit increasing trends in most parts of China during 2003–2020. The increase is
50 especially significant in North China, Southwest China, the Tibetan Plateau, and parts of Northwest
51 China, during spring and summer. The HiTIC-Monthly dataset is publicly available via
52 <https://zenodo.org/record/6895533> (Zhang et al., 2022a).

53

54 **1 Introduction**

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

65
66 The thermal stress that human beings actually perceive is not only related to air temperature, but also
67 jointly influenced by other environmental variables such as humidity, wind, and/or direct sunlight (Mistry,
68 2020; Djongyang et al., 2010). These variables alter the heat balance that maintains the core temperature
69 of human bodies by influencing the heat exchange (e.g., radiation, convection, conduction, and
70 evaporation) between humans and the surrounding environment (Periard et al., 2021; Stolwijk, 1975).
71 High atmospheric humidity can exacerbate the thermal stress on human bodies by reducing evaporation
72 from the skin through sweating when the air temperature is high (Li et al., 2018; Rogers et al., 2021; Luo
73 and Lau, 2021). Furthermore, abnormal weather with a combination of extremely high air temperature,
74 humidity, and/or wind can reduce labor capacity and human performance (Roghanchi and Kocsis, 2018;
75 Lazaro and Momayez, 2020; Enander and Hygge, 1990), leading to temperature-related discomfort,
76 stress, morbidity, and even death (Di Napoli et al., 2018; Kuchcik, 2021; Nastos and Matzarakis, 2011),
77 particularly during heatwaves. For example, in the summer of 2017, 2018, and 2019, there were 1489,
78 1700, and 161 heatwave-related deaths, respectively, in the United Kingdom (Rustemeyer and Howells,
79 2021). Additionally, vulnerable groups including children, the elderly, chronic patients, and poor
80 communities are at higher risk of being affected by thermal stress (Patz et al., 2005; Wang et al., 2019),
81 which is likely to be further exacerbated as global population aging and climate warming (United Nations,
82 2017).

83

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

99

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

112 0.1° × 0.1° over South and East Asia (Yan et al., 2021), which was derived from the ERA5-Land and
113 ERA5 reanalysis products. However, these existing thermal index datasets have very coarse spatial
114 resolutions. There is an urgent need for a high-resolution (e.g., 1 km) data collection of multiple human
115 thermal stress indices.

116

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

132

133 China has been threatened by deteriorating thermal environments under global climate change and rapid
134 local urbanization over the past decades (Ren et al., 2022; Luo and Lau, 2019). The changes and
135 characteristics of human thermal stress across China have attracted extensive attention in recent years
136 (Yan, 2013; Tian et al., 2022; Li et al., 2022). Wang et al. (2021) found that the frequency of extreme
137 human-perceived temperature events increases in summer and decreases in winter in most urban
138 agglomerations (UAs) of China. Li et al. (2022) showed that the frequency of thermal discomfort days
139 in China exhibits a significant increasing trend from 1961 to 2014, and there will be more threats from
140 thermal discomfort in the future. Therefore, a long-term and high-resolution dataset with multiple human

141 thermal stress indices in China is of great importance for investigating detailed spatial and temporal
142 variations of human thermal stress across the country. Such a dataset has the potential to (1) assess
143 population exposure to extreme thermal conditions and heat-related health risks, (2) reveal the
144 spatiotemporal evolution of human thermal stress and its influence on public health, tourism, industries,
145 military, epidemiology, and biometeorology at a fine scale, and (3) provide policymakers with data in
146 manipulating targeted strategies to mitigate heat stress and protect vulnerable people.

147

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

159

160 **2 Data**

161 **2.1 Meteorological data**

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

167 2.2 Covariates

168 Human thermal stress is related to temperature, topography, land cover, population density, surface water,
169 and vegetation (Wang et al., 2020; Rahman et al., 2022; Krzysztof et al., 2021). In this study, eight
170 variables reflecting the changes and spatial distribution characteristics of temperature were used to
171 predict human thermal indices (Table 1) in addition to the meteorological variables. As LST is one of the
172 most essential parameters for predicting human thermal indices, the seamless LST dataset created by
173 Zhang et al. (2022b) was introduced into our model training. This LST dataset used a spatiotemporal
174 gap-filling algorithm to fill the missing or invalid value caused by clouds in the Moderate Resolution
175 Imaging Spectroradiometer (MODIS) LST dataset (MOD11A1 and MYD11A1). It includes daily mid-
176 daytime (13:30) and mid-nighttime (01:30) LST with 1 km spatial resolution. The mean root mean
177 squared errors (*RMSEs*) of daytime and nighttime LST are 1.88°C and 1.33°C, respectively. We used
178 monthly LST as one of the inputs to predict the spatial distribution of 12 thermal indices. Monthly LST
179 values were calculated by averaging daily LST, which was obtained by averaging four observations in a
180 day, including mid-daytime and mid-nighttime observations from ascending and descending orbits of
181 MOD11A1 (Terra) and MYD11A1 (Aqua). More details about the LST data are described in Zhang et al.
182 (2022b). The land cover dataset (MCD12Q1 Version 6) developed by Sulla-Menashe and Friedl (2019)
183 based on a supervised classification method was downloaded via Google Earth Engine (GEE). The Multi-
184 Error-Removed Improved-Terrain (MERIT) elevation dataset developed by Yamazaki et al. (2017) was
185 downloaded from GEE. This dataset was generated after removing the errors from existing Digital
186 Elevation Models (DEMs), such as SRTM3 and AW3D-30m, based on multi-source satellite data and
187 filtering algorithms. The spatial resolution of this dataset is 3" (i.e., ~90 meters at the equator). In addition,
188 the slope was also extracted from the elevation data to act as the topography predictor. As the artificial
189 surface is closely related to human activities (Zhao and Zhu, 2022), the dataset of global artificial
190 impervious area (GAIA) produced by Gong et al. (2020) from the Google Earth Engine (GEE) was used
191 to delineate human footprints. The overall accuracy of GAIA is greater than 90% (Gong et al., 2020).
192 The population dataset was downloaded from the WorldPop Project (Gaughan et al., 2013). Then, the
193 abovementioned eight datasets were pre-processed to have the same spatial extend, projection, and spatial
194 resolution (1 km) through image mosaicking, reprojection, resampling, clipping, aggregating, and
195 monthly synthesizing. Moreover, year and month of the year were also used as covariates. Note that we

196 did not include precipitation as a covariate because the precipitation data are not normally distributed.
197 More importantly, they exhibit many zero values in many regions of China (especially in the dry season),
198 which would increase the uncertainty of the spatial prediction.

199

200 **3 Methodology**

201 **3.1 Calculation of human thermal indices**

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

$$207 \quad E_s = 6.112 \times \exp^{(17.67 \times T / (T + 243.5))} \quad (1)$$

$$208 \quad E_a = \frac{RH}{100} \times E_s \quad (2)$$

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

211

212 **3.2 Prediction of human thermal indices using LGBM**

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

222

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

230

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

235

236 3.3 Accuracy assessment

237 Four statistic metrics, namely, determination coefficient (R^2), Mean Absolute Error (MAE), $RMSE$, and
 238 $Bias$ (Rice, 2006), were used to evaluate the prediction accuracy of the human thermal indices. Ranging
 239 from 0 to 1, R^2 measures the proportion of variance explained by the model, representing how well the
 240 human thermal indices were predicted compared to the observations. MAE represents the average
 241 absolute error between the predictions and the observations. $RMSE$ is the standard deviation of the
 242 residuals and is sensitive to outliers. $Bias$ describes the differences between the predictions and the
 243 observations. These metrics are computed as follows.

$$244 \quad MAE = \frac{1}{N} \times \sum_{i=1}^N |y_i - \hat{y}| \quad (3)$$

$$245 \quad RMSE = \sqrt{\frac{1}{N} \times \sum_{i=1}^N (y_i - \hat{y})^2} \quad (4)$$

$$247 \quad R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y})^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (5)$$

$$248 \quad Bias = \frac{1}{N} \times \sum_{i=1}^N (y_i - \hat{y}) \quad (6)$$

249 where \hat{y} is the predicted value of human thermal indices, \bar{y} is the mean of the observed human thermal

250 indices calculated from meteorological stations, and N is the number of samples.

251

252 **4 Results**

253 **4.1 Evaluation of the predicted human thermal indices**

254 **4.1.1 Overall accuracy**

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

266

267 The spatial distributions of R^2 , MAE , $RMSE$, and $Bias$ at individual stations across the mainland of
268 China are depicted in Figures 4–7, respectively. The predicted indices have high R^2 values
269 (i.e., >0.98, Figure 4) at almost all stations across China, demonstrating the superiority of LGBM.
270 Better predictions (with higher R^2) are distributed in eastern China, particularly in the North China
271 Plain (NCP) and the Yangtze River Delta (YRD), while southwestern China (e.g., the Yunnan-
272 Guizhou Plateau (YGP)) has relatively lower R^2 values (<0.98). For MAE and $RMSE$, all indices
273 have small values <1 °C at most stations across China. HMI has the largest MAE and $RMSE$ values
274 (Figures 5g and 6g), followed by NET and WCT, and ET has the smallest MAE and $RMSE$ values
275 (i.e., < 0.4 °C, Figures 5e and 6e). The MAE and $RMSE$ of NET and WCT decrease from
276 northwestern to southeastern China (Figures 5i, 5l, 6i, 6l). For other indices, small MAE and $RMSE$
277 values are mainly observed in plains including NCP, while large values tend to appear in regions

278 with complex topography, such as arid Northwest China, mountainous Northeast and South China,
279 and the Hengduan Mountains. These differences are related to the uneven distribution of weather
280 stations, i.e., dense in plains and coarse in complex terrain areas. The *Bias* values range from -0.3°
281 C to $0.3^{\circ}C$ (Figure 7). Positive and negative *Bias* values are mainly distributed in northern and
282 southern China, respectively.

283

284 **4.1.2 Annual and monthly accuracies**

285 The annual accuracies regarding *RMSE*, *MAE*, and *Bias* of the 12 human thermal indices during 2003–
286 2020 are shown in Figure 8. *RMSEs* and *MAEs* of all indices in nearly all years are less than $1.0^{\circ}C$
287 (Figures 8a-b). Yearly *RMSE* (*MAE*) of ET fluctuates around $0.3^{\circ}C$ ($0.2^{\circ}C$) during 2003–2020. *RMSEs*
288 (*MAEs*) of other indices range from 0.5 to $1.1^{\circ}C$ (0.4 – $0.8^{\circ}C$) with marginal variations from year to year.
289 *Biases* vary between $-0.04^{\circ}C$ and $0.04^{\circ}C$ across all years. *Biases* seem to be slightly positive in 2003,
290 2004, and 2014 and negative in 2012, 2017, and 2018. Moreover, Figure S1 displays the monthly *RMSEs*,
291 *MAEs*, and *Biases* of all human thermal indices. For *RMSE*, all the indices in 12 months are lower than
292 $1.4^{\circ}C$, and their *MAEs* are less than $1^{\circ}C$. HI and HMI have relatively higher *RMSE* and *MAE* values in
293 summer than in other seasons; whereas, other indices tend to have larger errors in winter than in summer.
294 Additionally, the magnitude of *Bias* is smaller than $0.03^{\circ}C$ for all the indices in 12 months.

295

296 **4.1.3 Accuracies in major urban agglomerations**

297 More than half of the national population in China lives in cities, particularly in UAs (i.e., also known as
298 city clusters). Here we assessed the prediction accuracies in 20 major UAs in China, which hold 62.83%
299 and 80.57% of the total population and gross domestic product (GDP) of the country (Fang, 2016). These
300 accuracy assessments are presented in Tables S1–S4. As shown in Table S1, all UAs have the R^2 values
301 higher than 0.9837, with an average of 0.9947. Table S2 also shows that these UAs have small *RMSE*
302 values, most of which are smaller than $1^{\circ}C$, except for the UA of North Tianshan Mountain in arid
303 Northwest China. As the biggest UA in China, YRD has the lowest *RMSE* of $0.288^{\circ}C$ among all 20 UAs.
304 The *MAEs* of the thermal indices in all UAs are smaller than $1^{\circ}C$ and with an average value of $0.477^{\circ}C$
305 (Table S3). The *Biases* in the 20 UAs range from $-0.160^{\circ}C$ to $0.123^{\circ}C$ (Table S4). These results suggest

306 that all predicted human thermal indices in different UAs across China are of good quality at the local
307 scale. It implies that our prediction model and results have great potential in evaluating local thermal
308 environment changes (e.g., in urban areas or cities).

309

310 **4.2 Spatial variations of the human thermal indices**

311 The abovementioned assessments show that our model based on LGBM can yield high-accuracy
312 predictions at both national and local scales. Therefore, this model is employed to generate a high-
313 resolution human thermal index collection at a monthly scale over China (HiTIC-Monthly) during 2003–
314 2020. By taking monthly ET in 2020 as an example, we examined the monthly evolution of spatial
315 patterns of the HiTIC-Monthly dataset in this subsection.

316

317 Figure 9 shows the monthly distribution of the predicted ET in 2020, which exhibits obvious seasonality
318 with higher temperatures in summer and lower in winter. The temperature shows a significant zonal
319 difference with colder temperatures in northern than southern China. Temperature has a close relationship
320 with topography and decreases with elevation, varying from plateaus to plains. The Qinghai-Tibet Plateau
321 (TP) has the lowest temperature, while southern China, the Sichuan Basin, and the Gobi regions in
322 Northwest China witness the highest temperature. The distribution of temperature exhibits different
323 patterns among the four seasons, especially between winter (e.g., January) and summer (e.g., July). In
324 winter, the temperature increases from northern to southern areas and is the coldest in Northeast and
325 Northwest China and the warmest on the Hainan Island. In summer, the hottest temperature appears in
326 the Tarim and Jungar Basins of Xinjiang. The NCP region also has a high temperature in summer, which
327 might be related to local urbanization (Liu et al., 2008) and irrigation (Kang and Eltahir, 2018).

328

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

334

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

342

343 4.3 Temporal changes in the human thermal indices

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

364

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

371

372 The temporal trends of the human thermal indices in different seasons were also examined (Figure 13).
373 The fastest warming tendency is observed in the spring season. The rising trends of spring HMI, HI, MDI,
374 AT_{in} , and AT_{out} exceed $0.4\text{ }^{\circ}\text{C}/\text{decade}$, and the trends of other indices (except ET and NET) are larger
375 than $0.3\text{ }^{\circ}\text{C}/\text{decade}$ (Figure S2). Summer also has been experiencing significant increasing trends in all
376 indices, i.e., at a rate of $> 0.2\text{ }^{\circ}\text{C}/\text{decade}$ (except ET and NET). The trends in summer HMI, HI, WBT,
377 MDI, DI, sWBGT, AT_{in} , and AT_{out} exceed $0.3\text{ }^{\circ}\text{C}/\text{decade}$ (Figure S3). Differing from spring and summer,
378 the human thermal indices (except WCT and NET) in the autumn season show slightly cooling trends
379 (Figure S4). Autumn WCT and NET have significantly strong decreasing trends, i.e., -0.349 and $-$
380 $0.507\text{ }^{\circ}\text{C}/\text{decade}$, respectively. Similar strong cooling trends of WCT and NET appear in winter, i.e., $-$
381 0.661 and $-0.453\text{ }^{\circ}\text{C}/\text{decade}$, respectively, while other indices experience marginal long-term changes
382 (Figure S5).

383

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

390

391 The spatial distributions of the changing trends in winter across the mainland of China during 2003–2020
392 are depicted in Figure S7. The trend patterns in winter are similar to that in summer to some degrees. The

393 warming trends are concentrated in Southwest China, most parts of Northwest China, and parts of East
394 China (e.g., YRD). The cooling trends are located in TP, parts of Northeast and South China. The cooling
395 tendencies are especially significant in Northeast China, and most parts of Northwest and South China
396 (Figures S7 j&m). Parts of central China are seen with even stronger cooling thermal comfort.

397

398 In spring, increases in all thermal indices are observed in most parts of China (Figure S8), particularly in
399 northern regions, such as central Inner Mongolia, parts of NCP, and Northeast China, while parts of
400 southern China have slight decreases. These decreases are noticeable in NET and WCT (Figures S8 j&m).

401 In contrast to spring, the autumn season is observed with decreased thermal temperature in the north and
402 increases in the south (e.g., Southwest China, Figure S9).

403

404 **5 Discussion**

405 **5.1 Comparison with existing human thermal index datasets**

406 We compared our HITIC-Monthly with two existing datasets, i.e., HDI (Mistry, 2020) and HiTiSEA (Yan
407 et al., 2021), which have coarser spatial resolutions of $0.25^\circ \times 0.25^\circ$ and $0.1^\circ \times 0.1^\circ$ (Table 4), respectively.

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

420 **5.2 Limitations and future works**

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

429

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

437

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

445

446 **6 Data availability**

447 The high spatial resolution monthly human thermal index collection (HiTIC-Monthly) generated in this

448 study is freely available to the public in network common data form (NetCDF) at
449 <https://zenodo.org/record/6895533> (Zhang et al., 2022a). The human thermal indices include surface air
450 temperature (SAT), indoor Apparent Temperature (AT_{in}), outdoor shaded Apparent Temperature (AT_{out}),
451 Discomfort Index (DI), Effective Temperature (ET), Heat Index (HI), Humidex (HMI), Modified
452 Discomfort Index (MDI), Net Effective Temperature (NET), simplified Wet Bulb Globe Temperature
453 (sWBGT), Wet-Bulb Temperature (WBT), and Wind Chill Temperature (WCT). This dataset has a spatial
454 resolution of $1\text{ km} \times 1\text{ km}$ and covers the mainland of China from 2003 to 2020, stacking by year. Each
455 stack is composed of 12 monthly images. The unit of the dataset is 0.01 degree Celsius ($^{\circ}\text{C}$), and the
456 values are stored in an integer type (Int16) for saving storage space, and need to be divided by 100 to get
457 the values in degree Celsius when in use. The projection coordinate system is Albers Equal Area Conic
458 Projection. The naming rule and other detailed information can be found in “README.pdf”.

459

460 **7 Conclusions**

461 A long-term and high-resolution dataset of multiple human thermal indices is of great significance for
462 monitoring detailed spatiotemporal changes of human thermal stress in different climate regions across
463 China and assessing the health risks of people exposed to extreme heat at a fine scale. However, the
464 current datasets of human thermal indices (e.g., HDI and HiTiSEA) only have coarse spatial resolutions
465 ($> 0.1^{\circ}$). In this study, we generated a dataset of monthly human thermal index collection with a high
466 spatial resolution of 1 km over the mainland of China (HiTIC-Monthly). In this collection, 12 human
467 thermal indices from 2003 to 2020 were predicted, including SAT, AT_{in} , AT_{out} , DI, ET, HI, HMI, MDI,
468 NET, sWBGT, WBT, and WCT.

469

470 The HiTIC-Monthly dataset was produced by LGBM based on multi-source data, including MODIS LST,
471 DEM, land cover, population density, and impervious surface fraction. This dataset shows a desirable
472 performance, with mean R^2 , $RMSE$, MAE , and $Bias$ of 0.996, 0.693°C , 0.512°C , and 0.003°C ,
473 respectively. Our predictions also exhibit good agreements with the observations in both spatial and
474 temporal dimensions, demonstrating the broad applicability of our dataset. Moreover, the comparison
475 with two existing datasets (i.e., HDI and HiTiSEA) suggests that HiTIC-Monthly has more detailed

476 spatial information, indicating that our dataset can well support fine-scale studies. Further investigation
477 shows that almost all the indices show warming trends in most parts of China during 2003–2020,
478 particularly for North China, Southwest China, TP, and parts of Northwest China. Additionally, the
479 warming tendency is faster in spring and summer. WCT and NET show similar and strong cooling trends
480 in autumn and winter, while other indices exhibit slight long-term changes.

481

482 **Author contribution**

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493 **Competing interests**

494 The authors declare that they have no conflict of interest.

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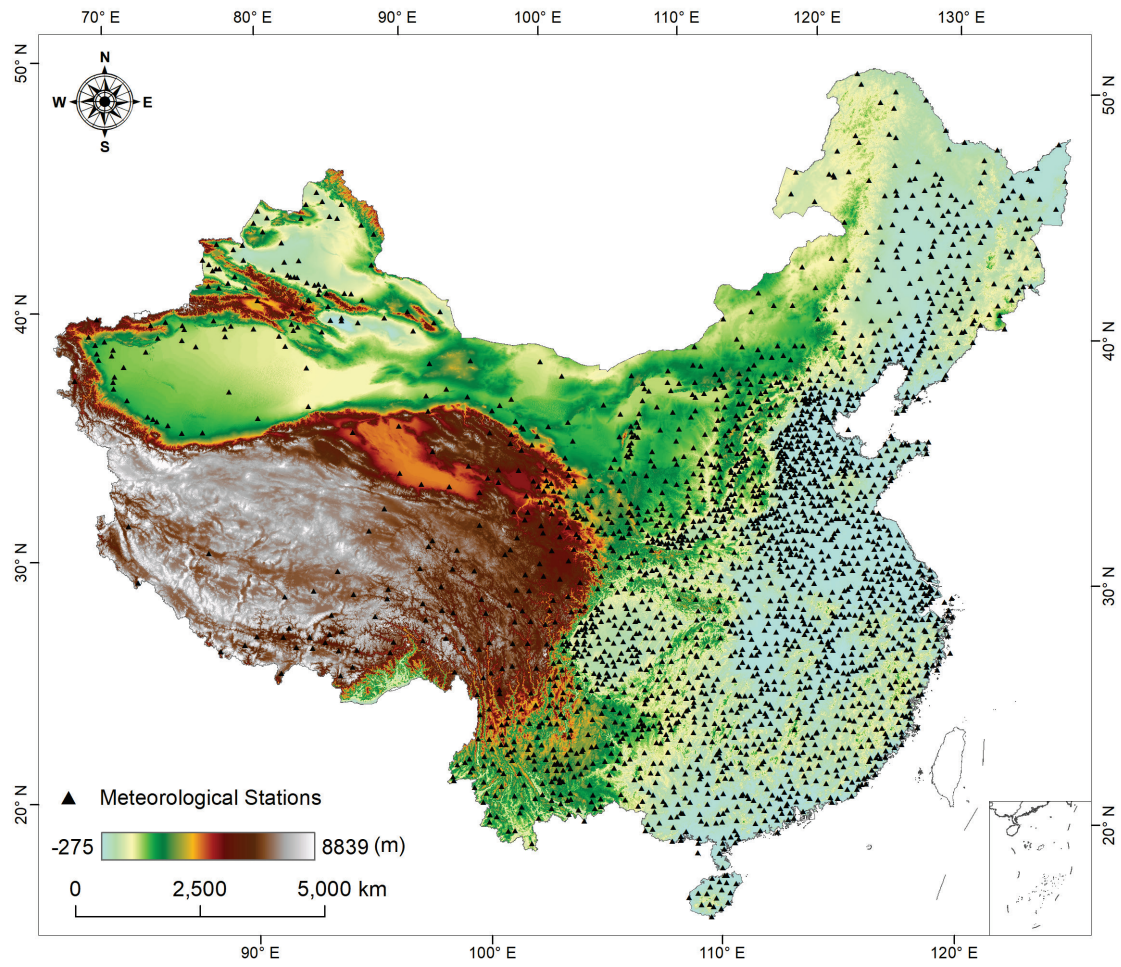
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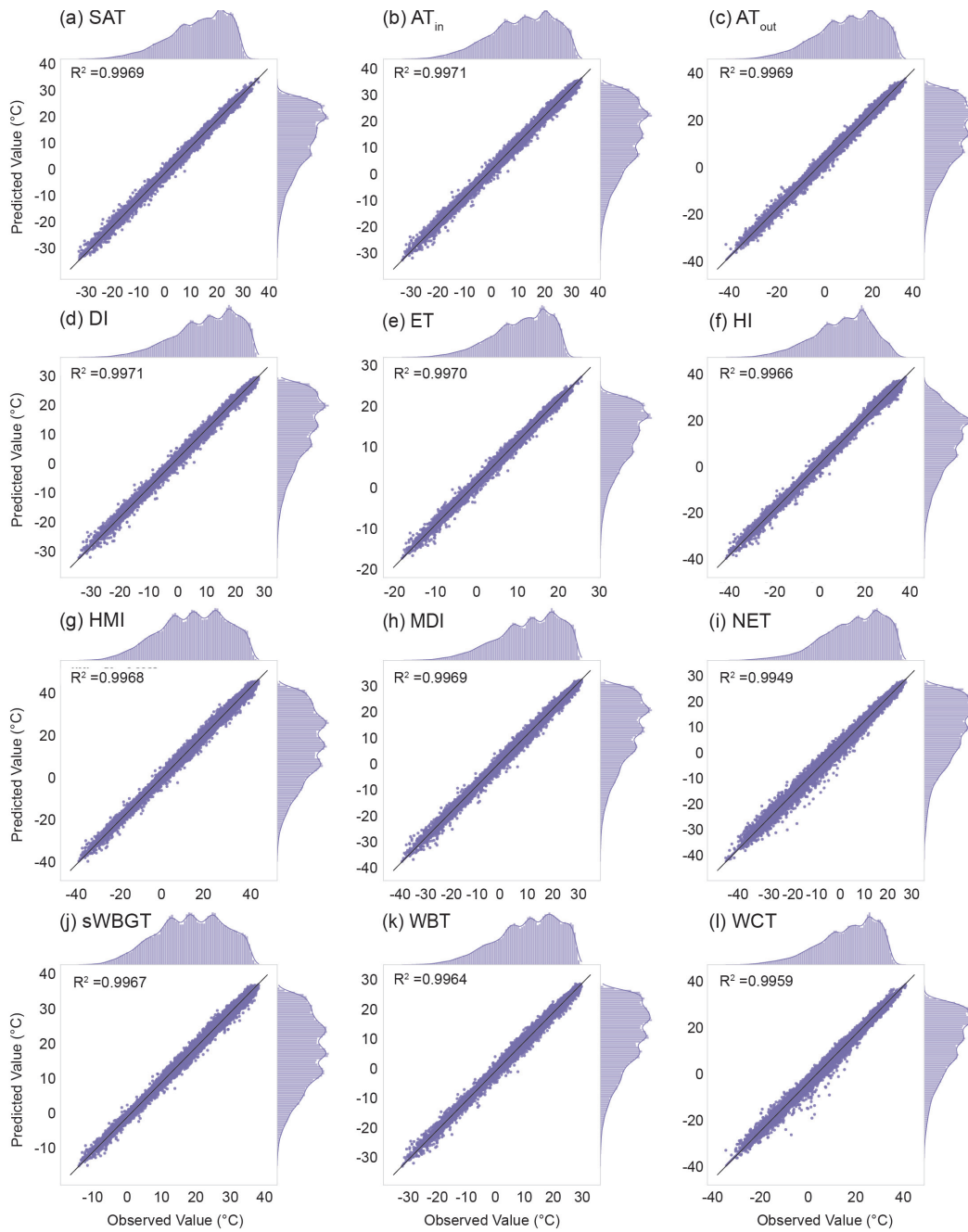
773 **Figures**



774

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

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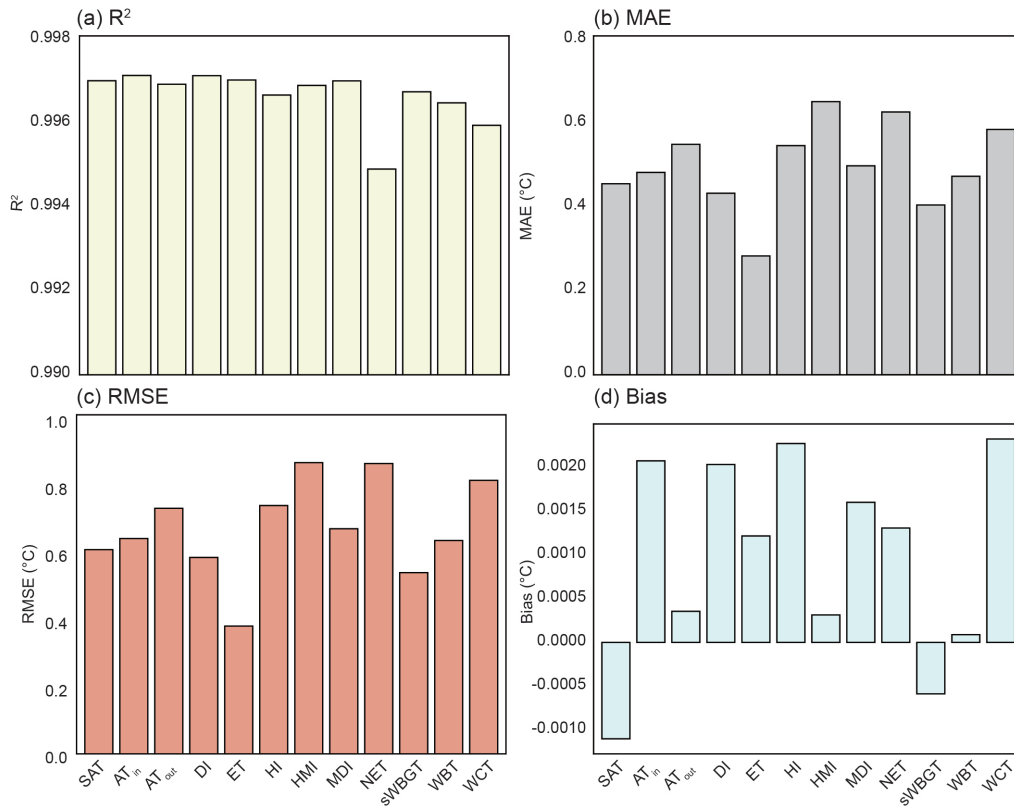
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Figure 2. Scatter plots of predictions versus observations of the 12 human thermal indices over the mainland of China during 2003–2020. (a) SAT, (b) AT_{in} , (c) AT_{out} , (d) DI, (e) ET, (f) HI, (g) HMI, (h) MDI, (i) NET, (j) sWBGT, (k) WBT, and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



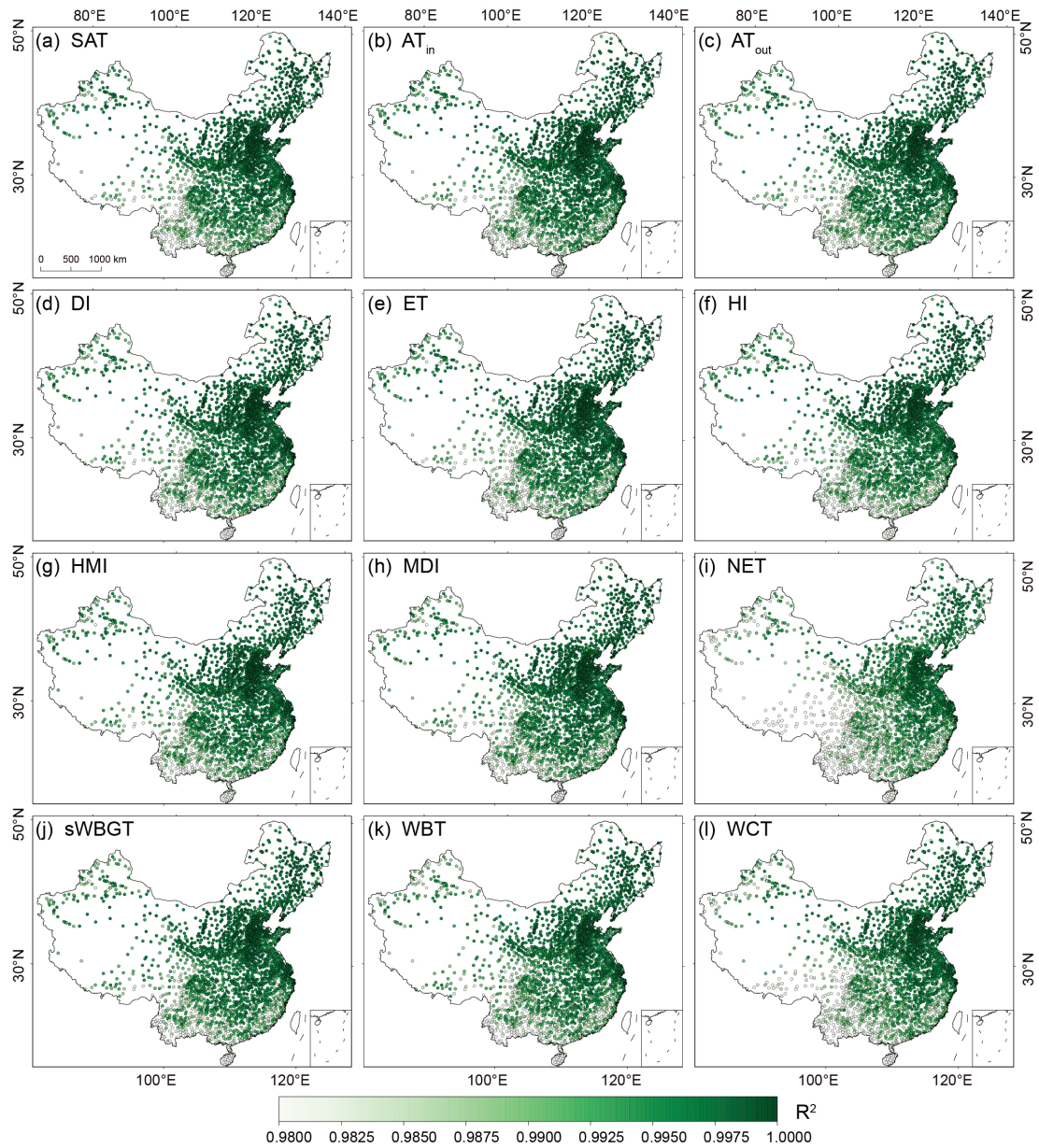
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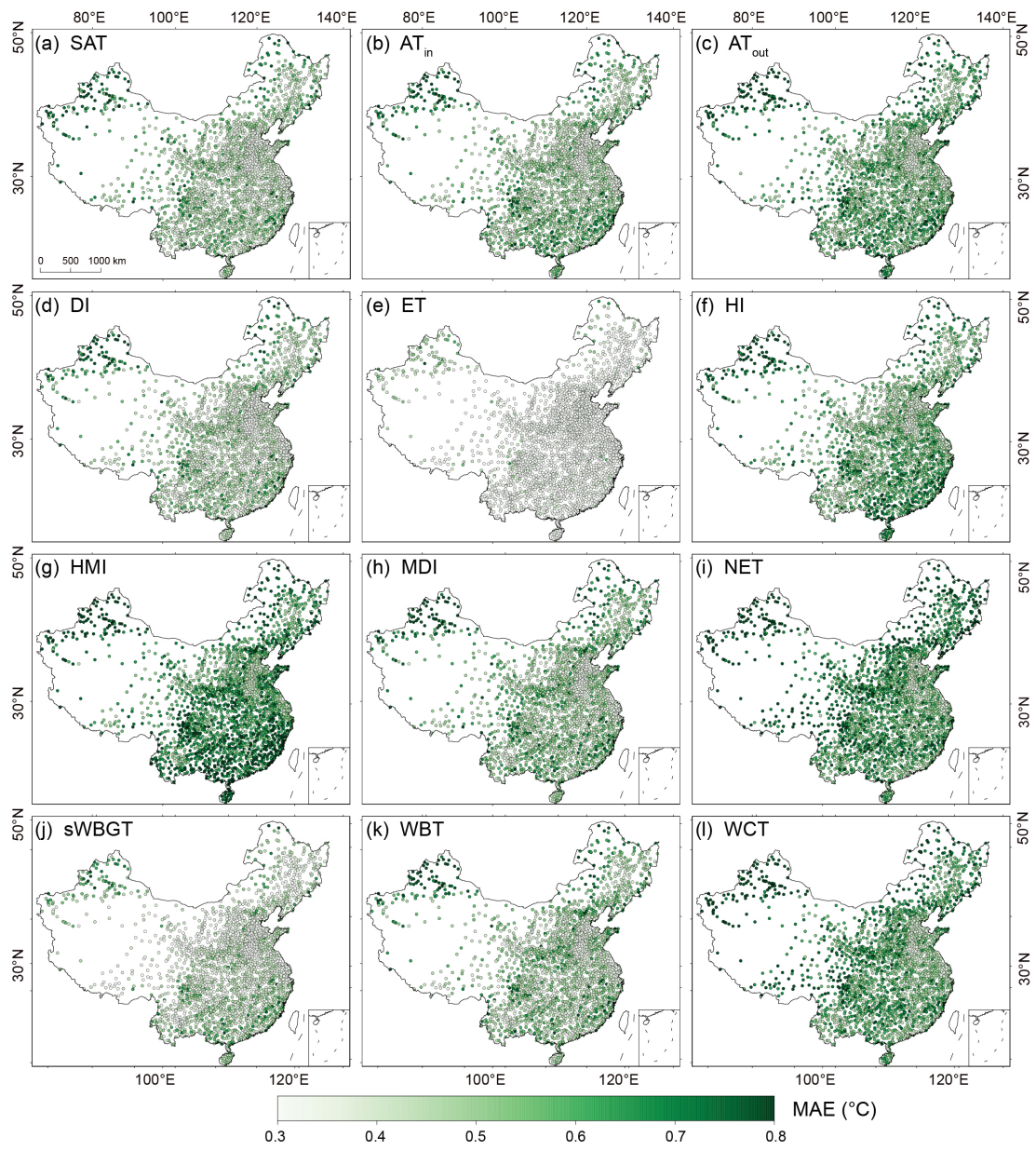
Figure 3. Overall prediction accuracies of the 12 human thermal indices over the mainland of China during 2003–2020. (a) R^2 , (b) MAE, (c) RMSE, (d) Bias.



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

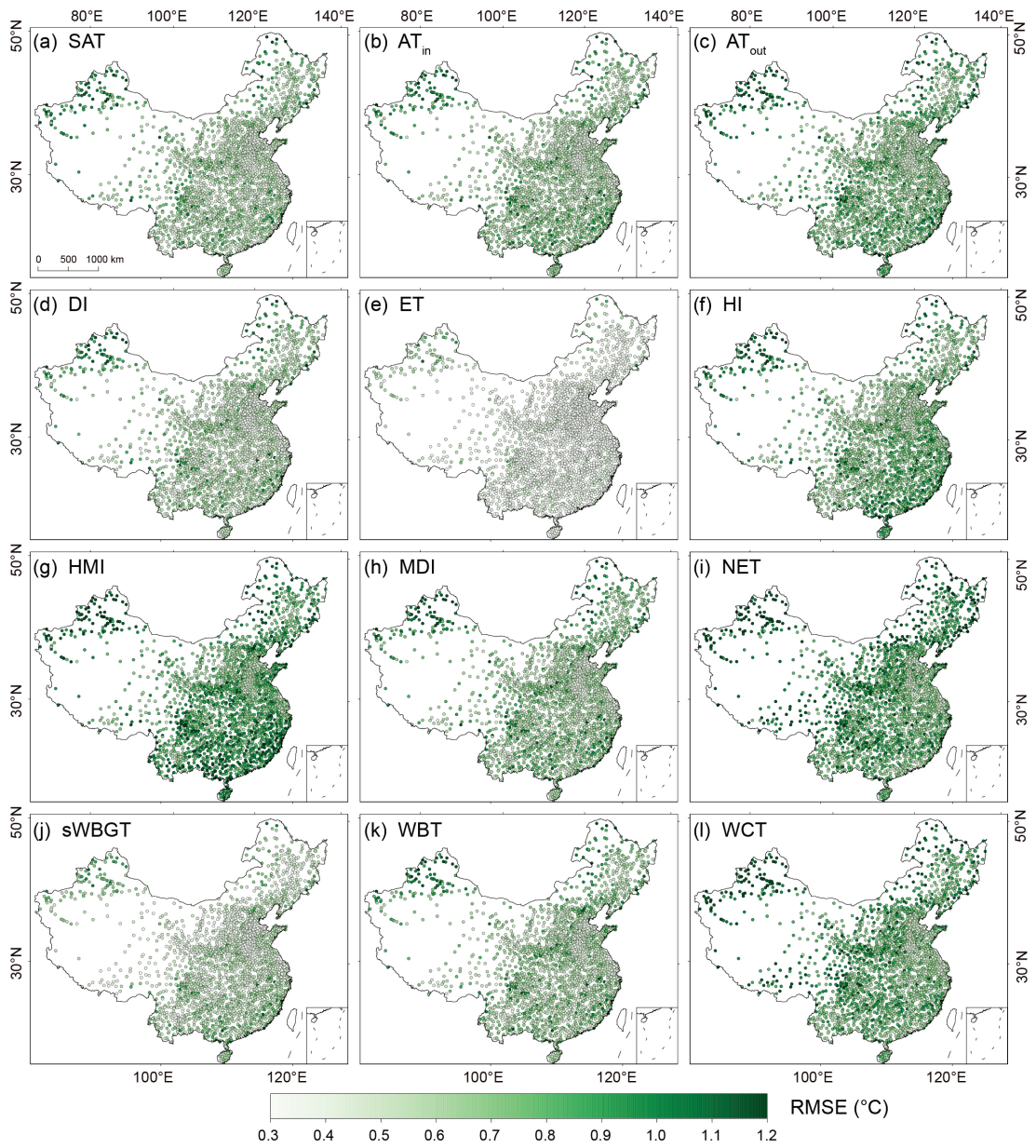
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792 **Figure 5. As Figure 4 but for MAE.**

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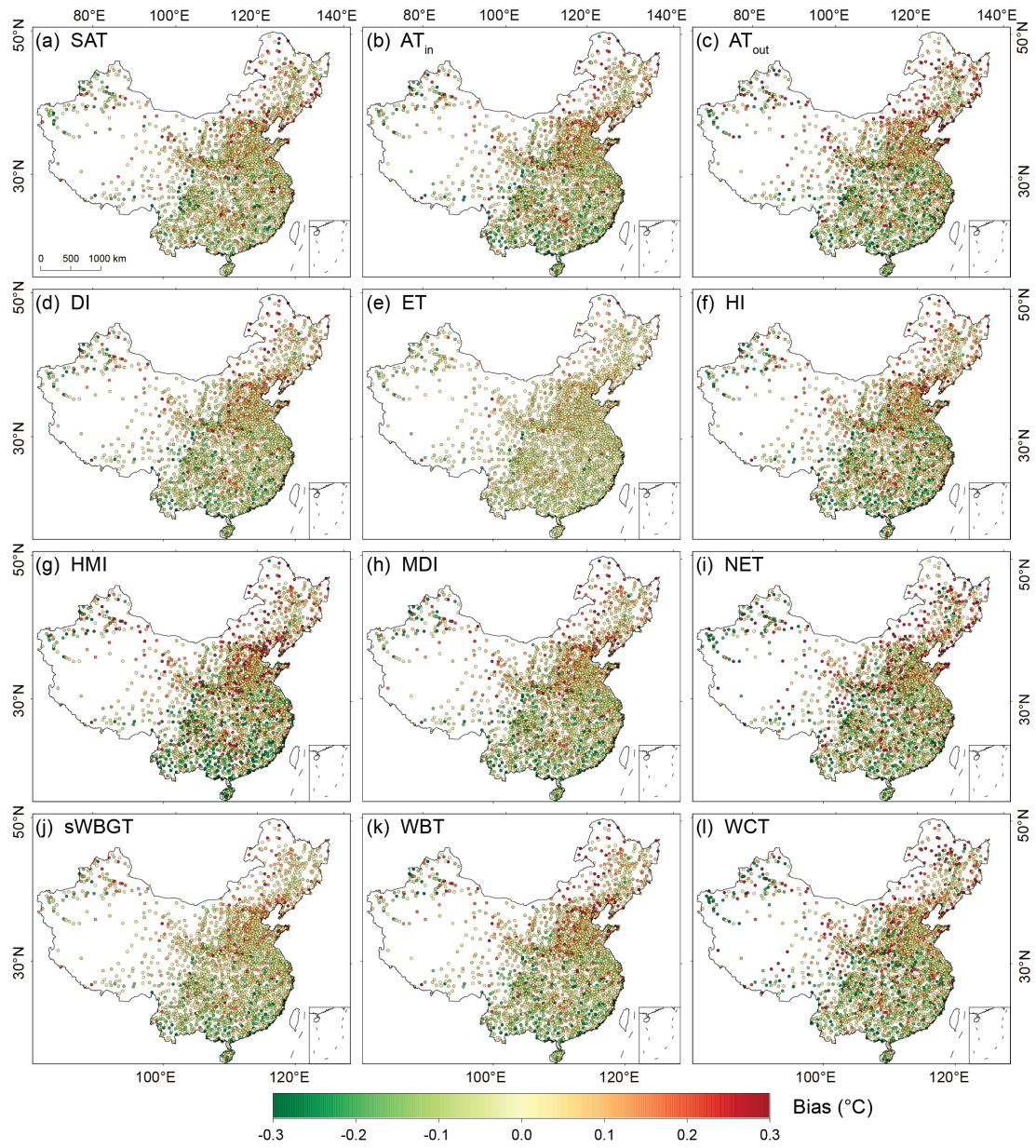


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Figure 6. As Figure 4 but for *RMSE*.

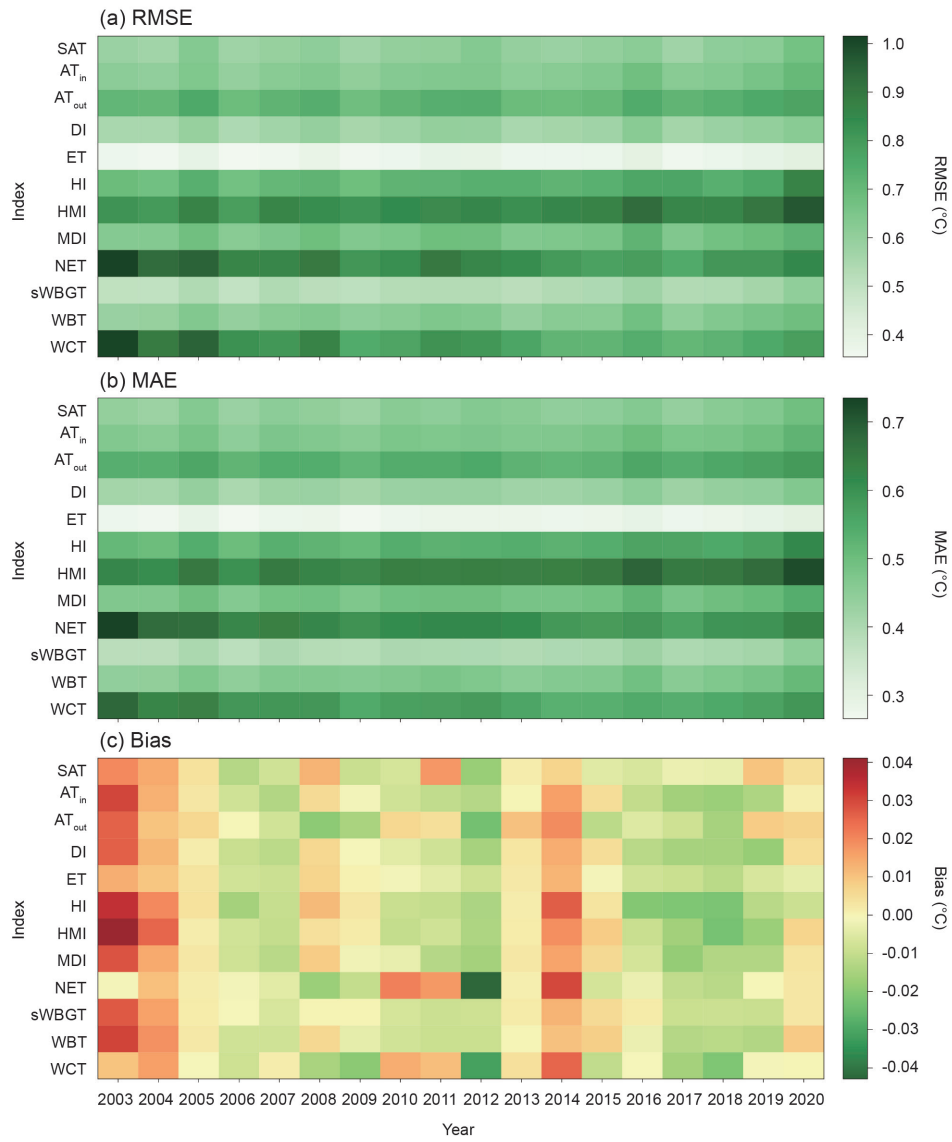
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798 **Figure 7. As Figure 4 but for Bias.**

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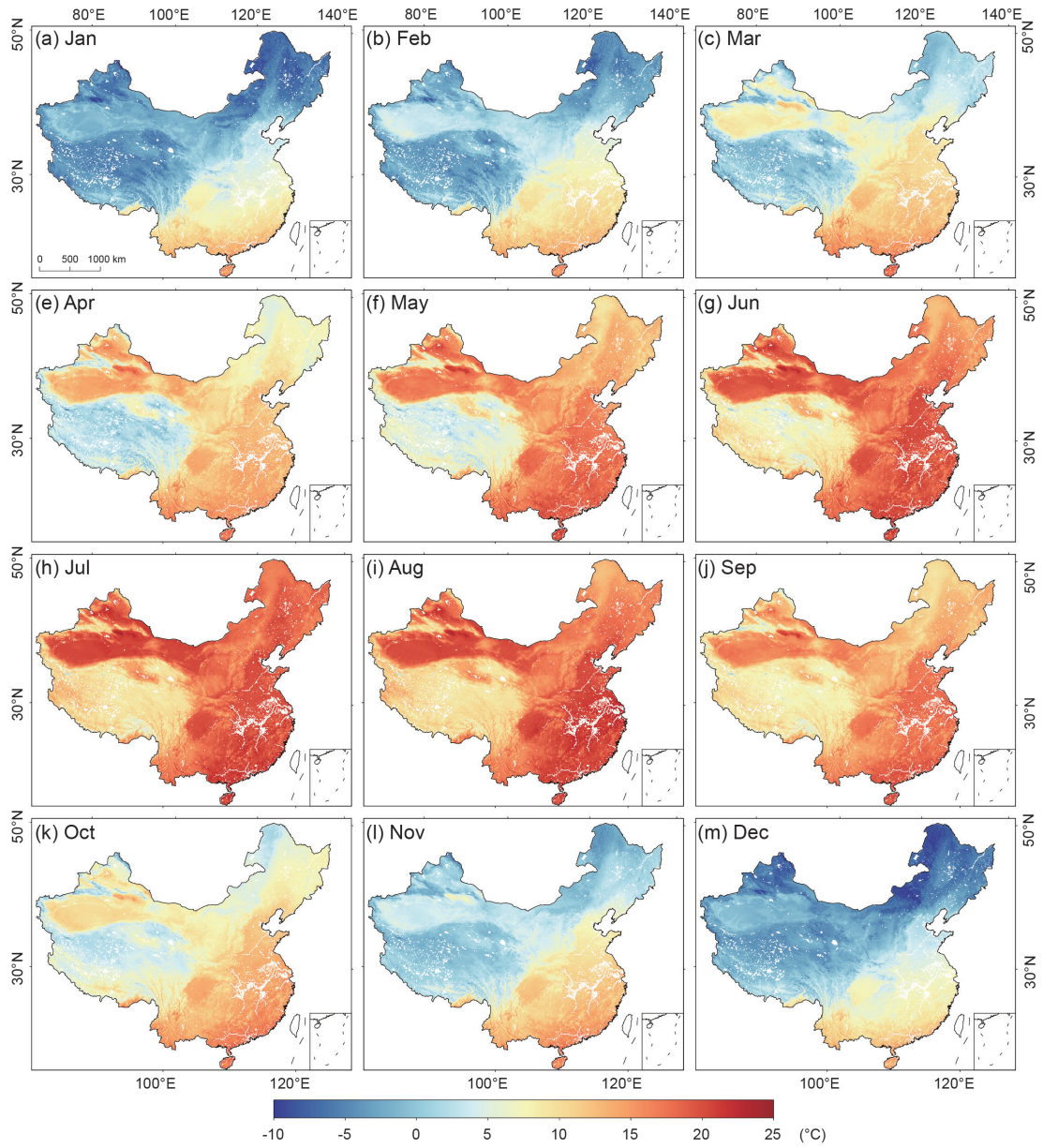


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801 **Figure 8. Annual prediction accuracies of the 12 human thermal indices over the mainland of China during**

802 **2003–2020: (a) RMSE, (b) MAE, (c) Bias.**

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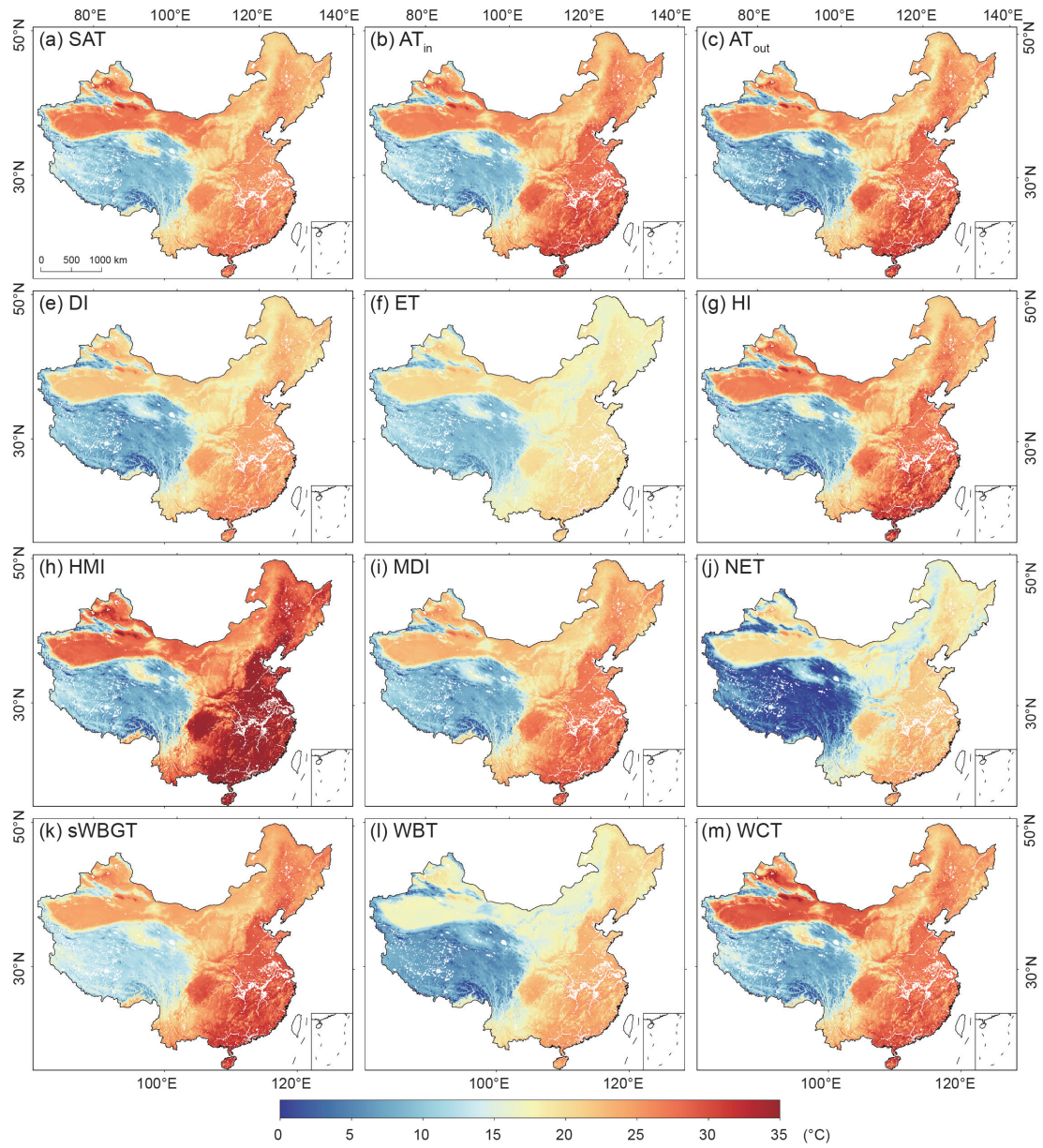


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Figure 9. Spatial distributions of the monthly mean ET over the mainland of China in 2020.

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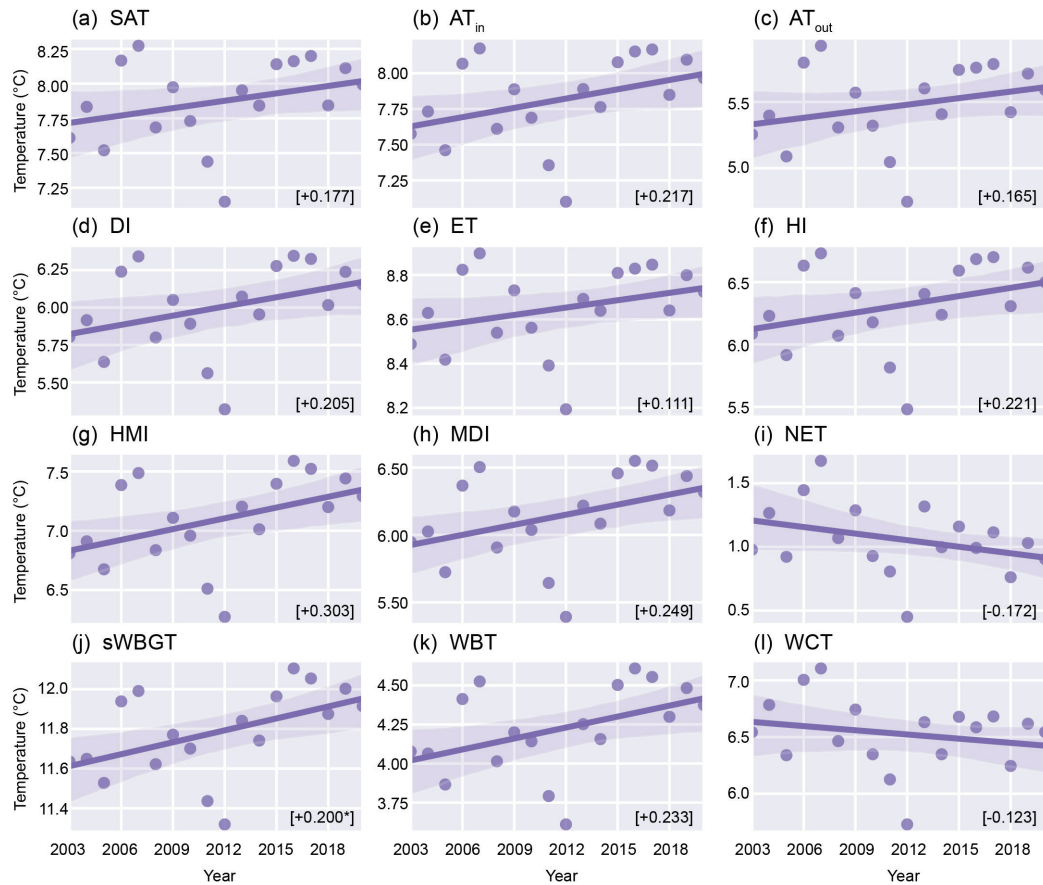


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808 **Figure 10. Spatial distributions of the 12 human thermal indices over the mainland of China in July 2020.**

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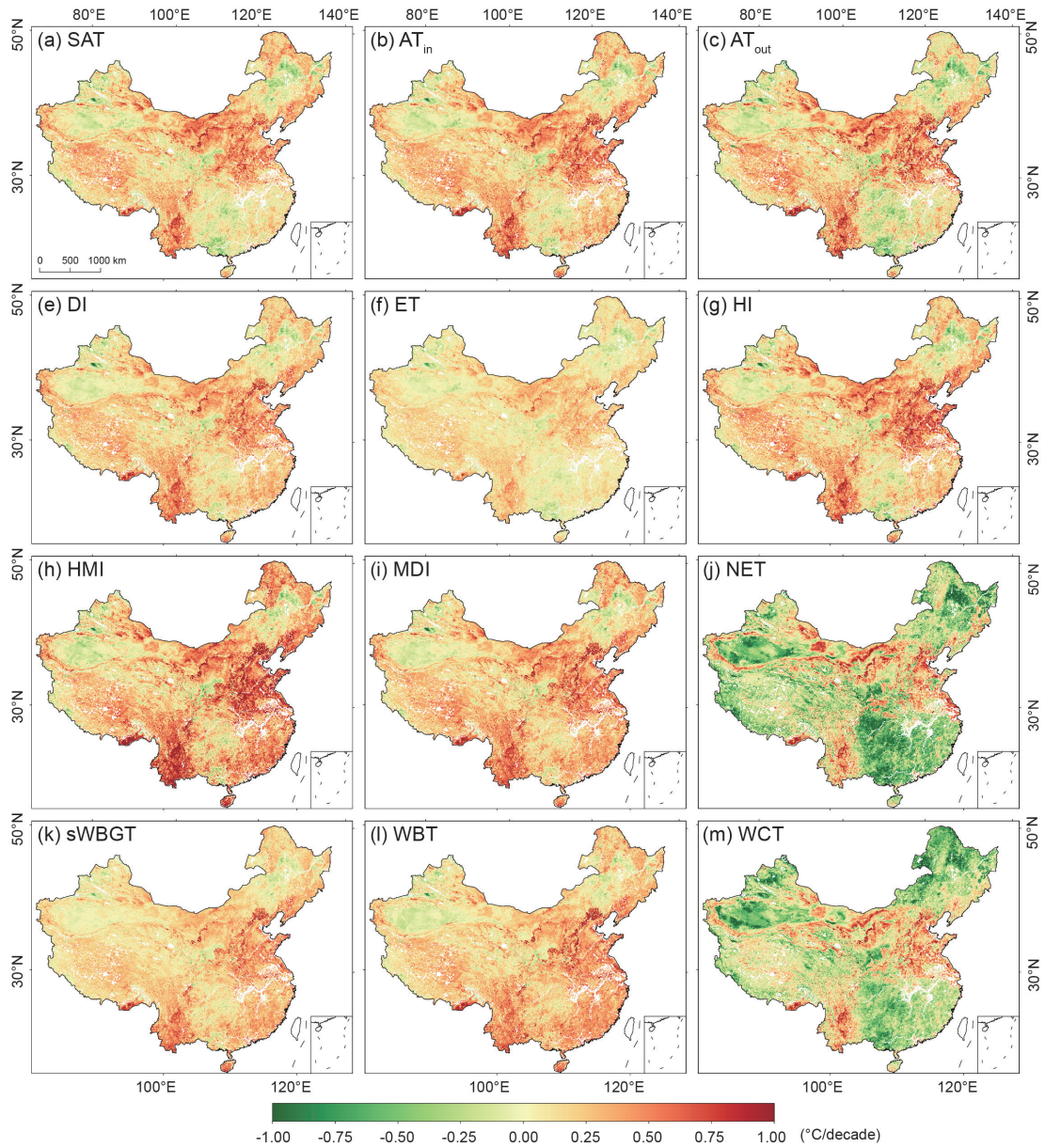
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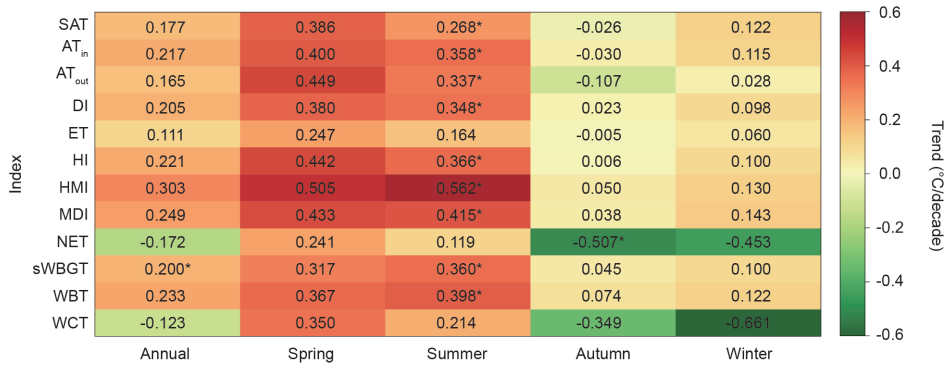
Figure 11. Temporal changes of the 12 annually-averaged human thermal indices over the mainland of China during 2003–2020. The line illustrates the linear trend, the number in the square bracket means the corresponding trend per decade, and the asterisk next to the number indicates that the trends are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



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

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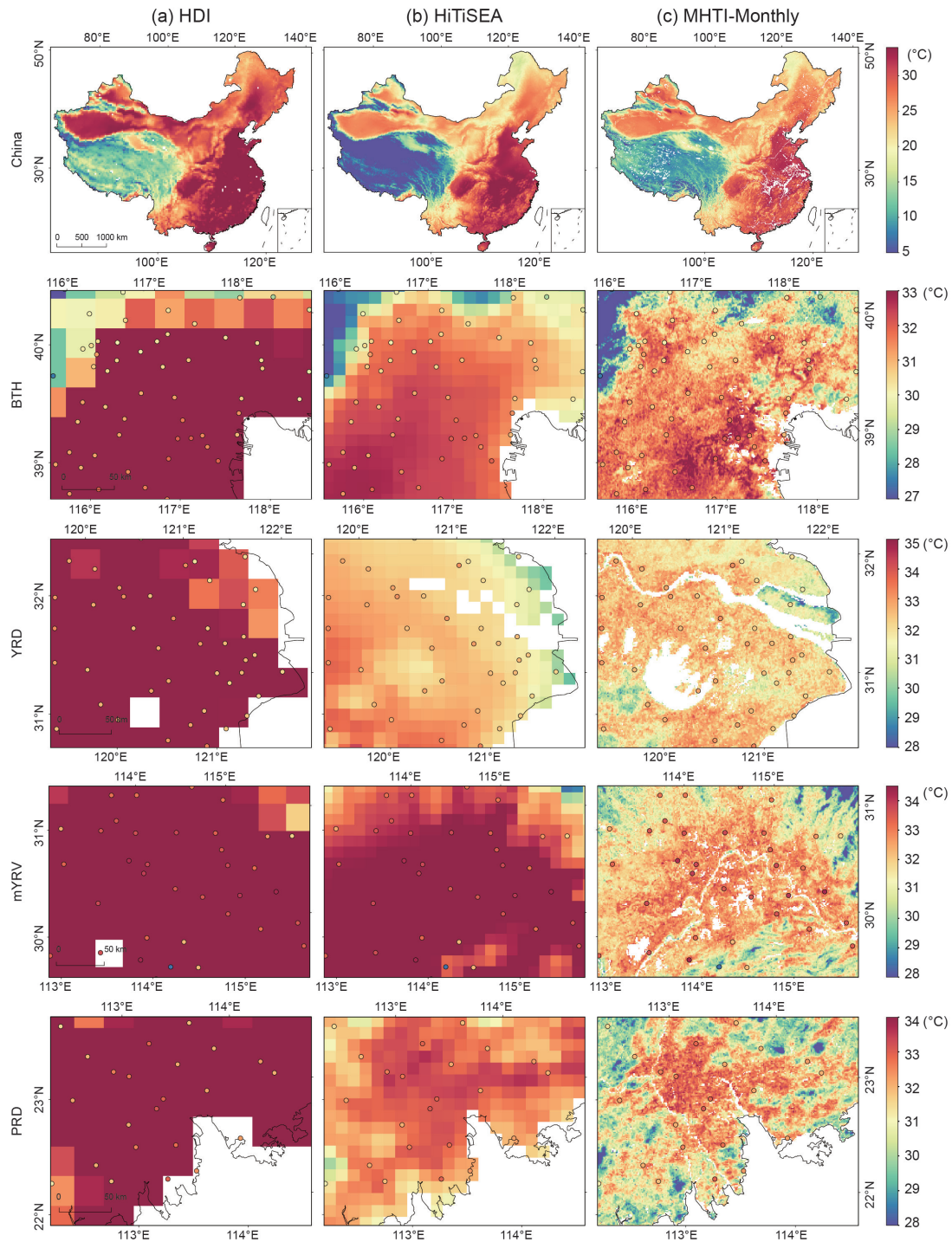
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Figure 13. Temporal trends of the 12 annually- and seasonally-averaged human thermal indices over the mainland of China during 2003–2020. The number means linear trend per decade. The asterisk indicates that the trends are significant at the 0.05 level.

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827 **Figure 14. Comparison of the spatial patterns among HDI_0p25_1970_2018 (HDI), HiTiSEA, and HiTiC-**

828 **Monthly for AT_{in} over the mainland of China and its four largest UAs in July 2018: Beijing-Tianjin-Hebei**

829 **(BTH), Yangtze River Delta (YRD), middle Yangtze River Valley (mYRV) and Pearl River Delta (PRD).**

830 **Colored circles indicate the observed AT_{in} values at individual meteorological stations.**

831

832 **Tables**833 **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	/

834

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)	$AT_{out} = -2.7 + 1.04 \times SAT + 2 \times E_a - 0.65 \times V$	Steadman (1984)
DI	Discomfort Index	$DI = 0.5 \times WBT + 0.5 \times SAT$	Sohar et al. (1963)
ET	Effective Temperature	$ET = SAT - 0.4 \times (SAT - 10) \times (1 - 0.001 \times RH)$	Gagge et al. (1972)
HI	Heat Index*	$HI^* = -8.784695 + 1.61139411 \times SAT - 2.338549 \times RH$ $- 0.14611605 \times SAT \times RH$ $- 1.2308094 \times 10^{-2} \times SAT^2$ $- 1.6424828 \times 10^{-2} \times RH^2$ $+ 2.211732 \times 10^{-3} \times SAT^2 \times RH$ $+ 7.2546 \times 10^{-4} \times SAT \times RH^2$ $+ 3.582 \times 10^{-6} \times SAT^2 \times RH^2$	Rothfus 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	$NET = 37 - \frac{37 - SAT}{0.68 - 0.0014 \times RH + \frac{1}{1.76 + 1.4 \times V^{0.75}}}$ $- 0.29 \times SAT \times (1 - 0.01 \times RH)$	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)

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

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

Indices	R^2	$RMSE$ ($^{\circ}C$)	MAE ($^{\circ}C$)	$Bias$ ($^{\circ}C$)
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

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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

Supporting Information for

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

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Figures

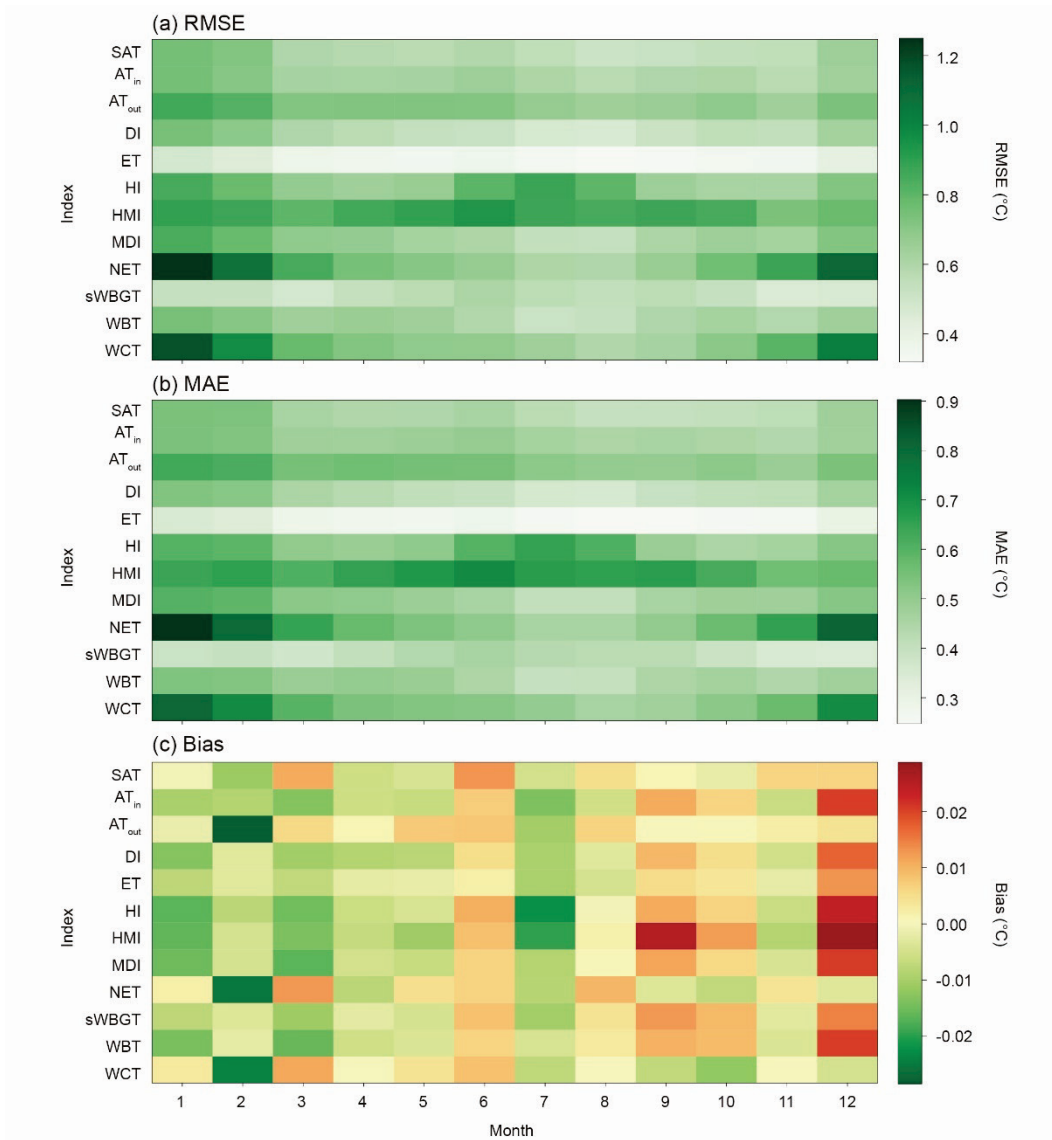


Figure S1. Monthly prediction accuracies of the 12 human thermal indices over the mainland of China during 2003–2020.

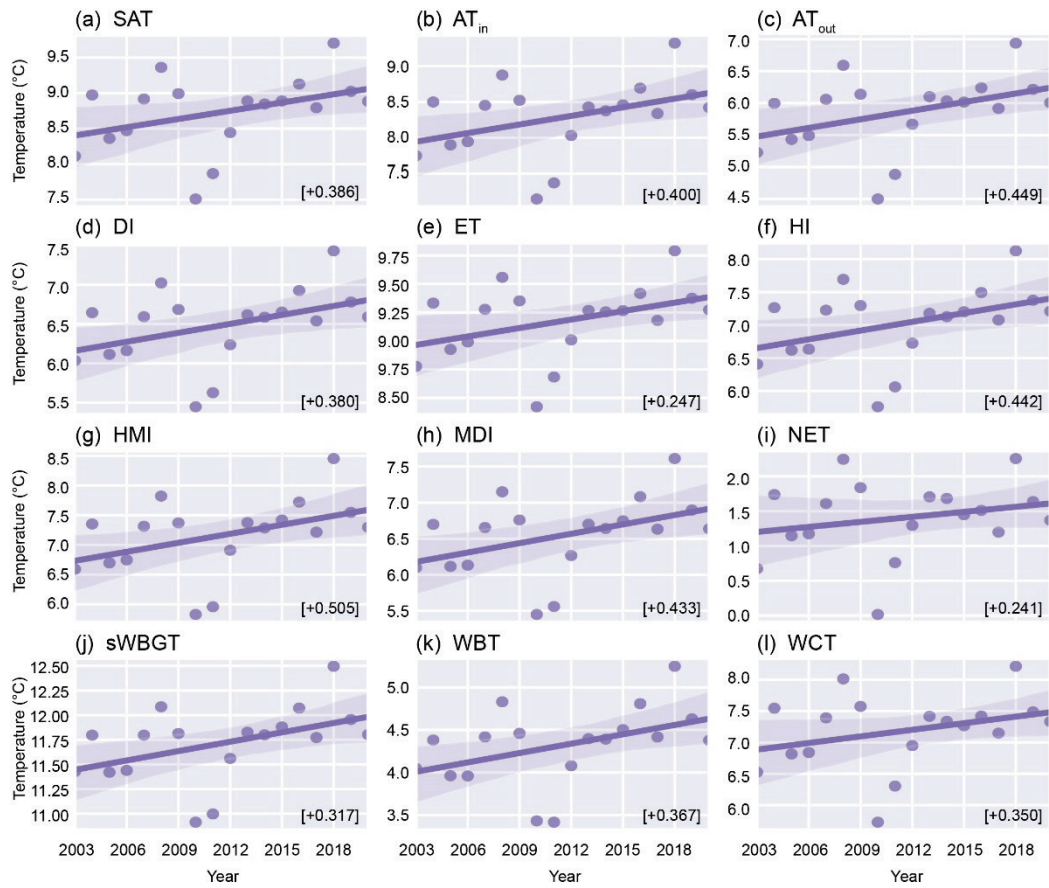


Figure S2. Temporal changes of the national average of spring mean human thermal indices over the mainland of China during 2003–2020. The straight line illustrates the linear trend, and the number in the square bracket means the corresponding trend per decade. The asterisk next to the number indicates that the trend is significant at the 0.05 level.

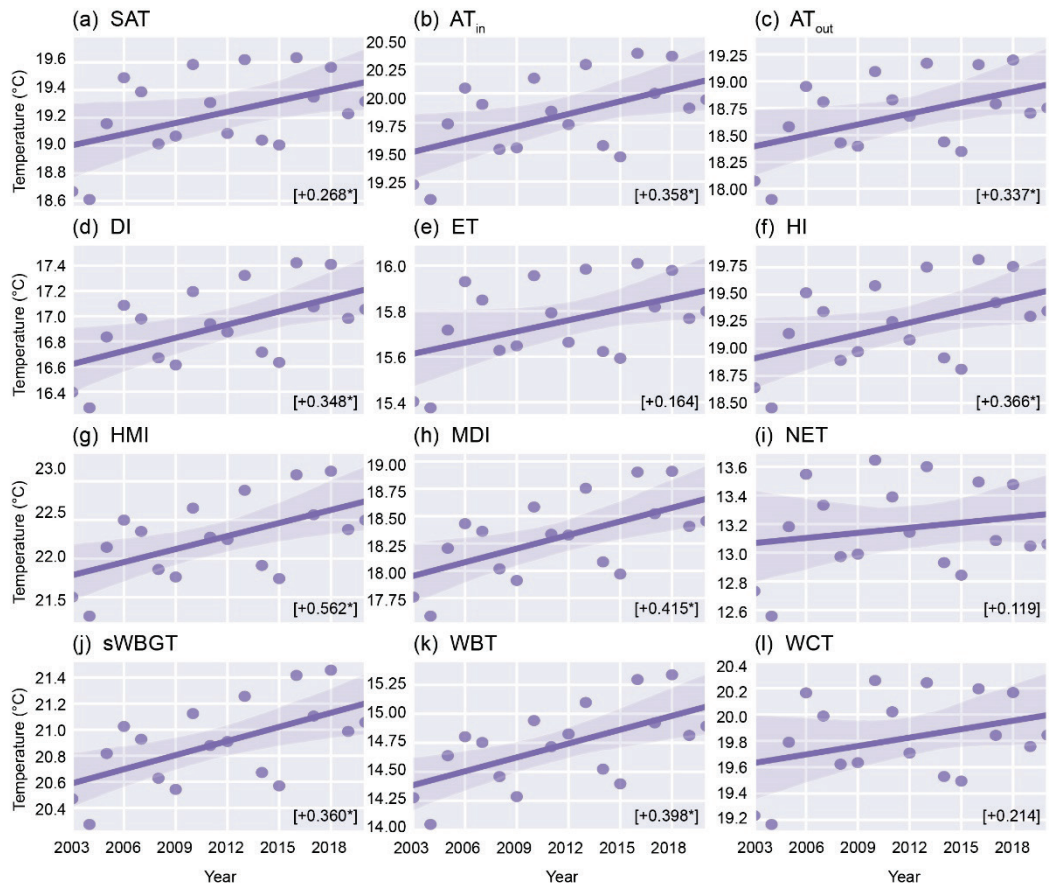


Figure S3. As Figure S2 but for summer mean.

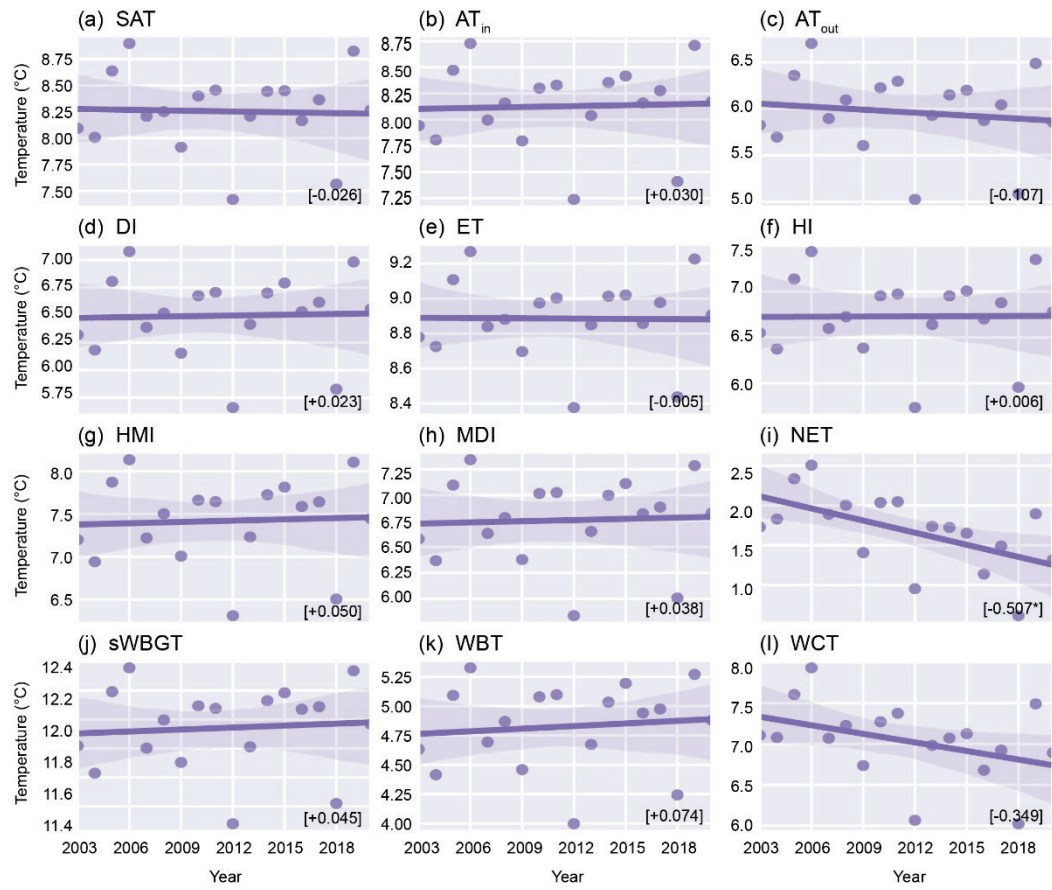


Figure S4. As Figure S2 but for autumn mean.

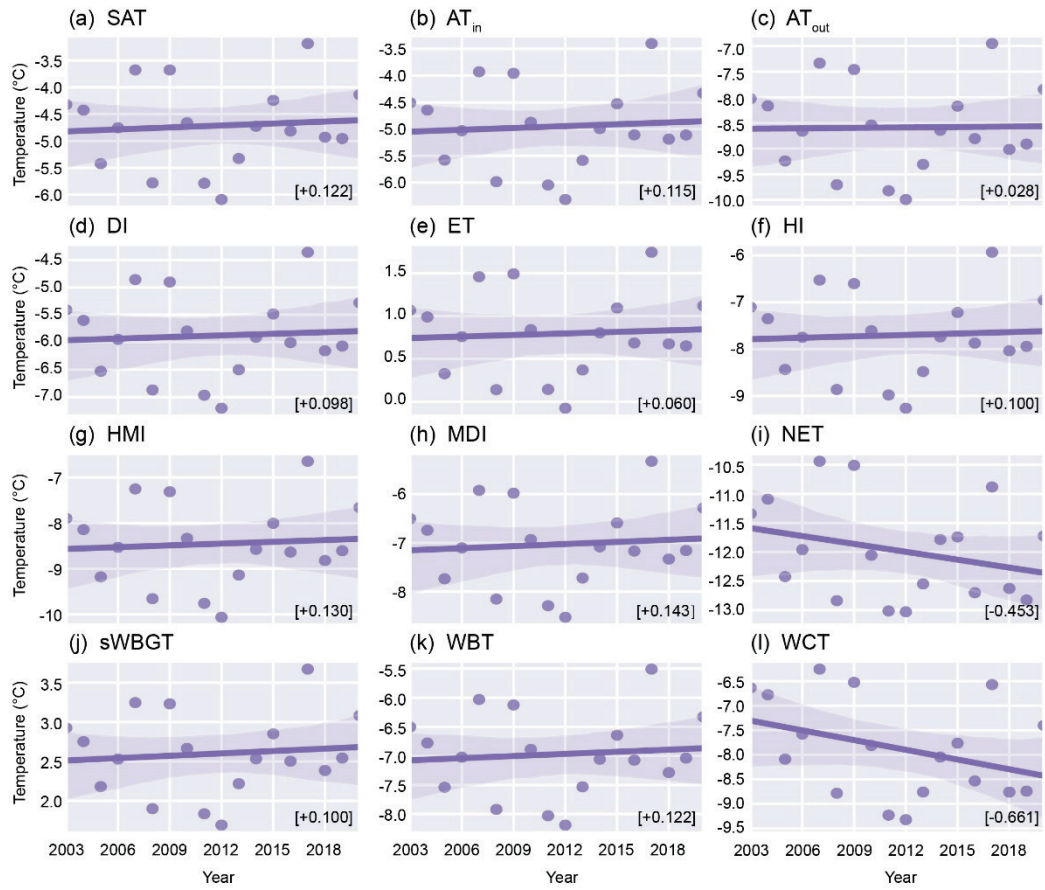


Figure S5. As Figure S2 but for winter mean.

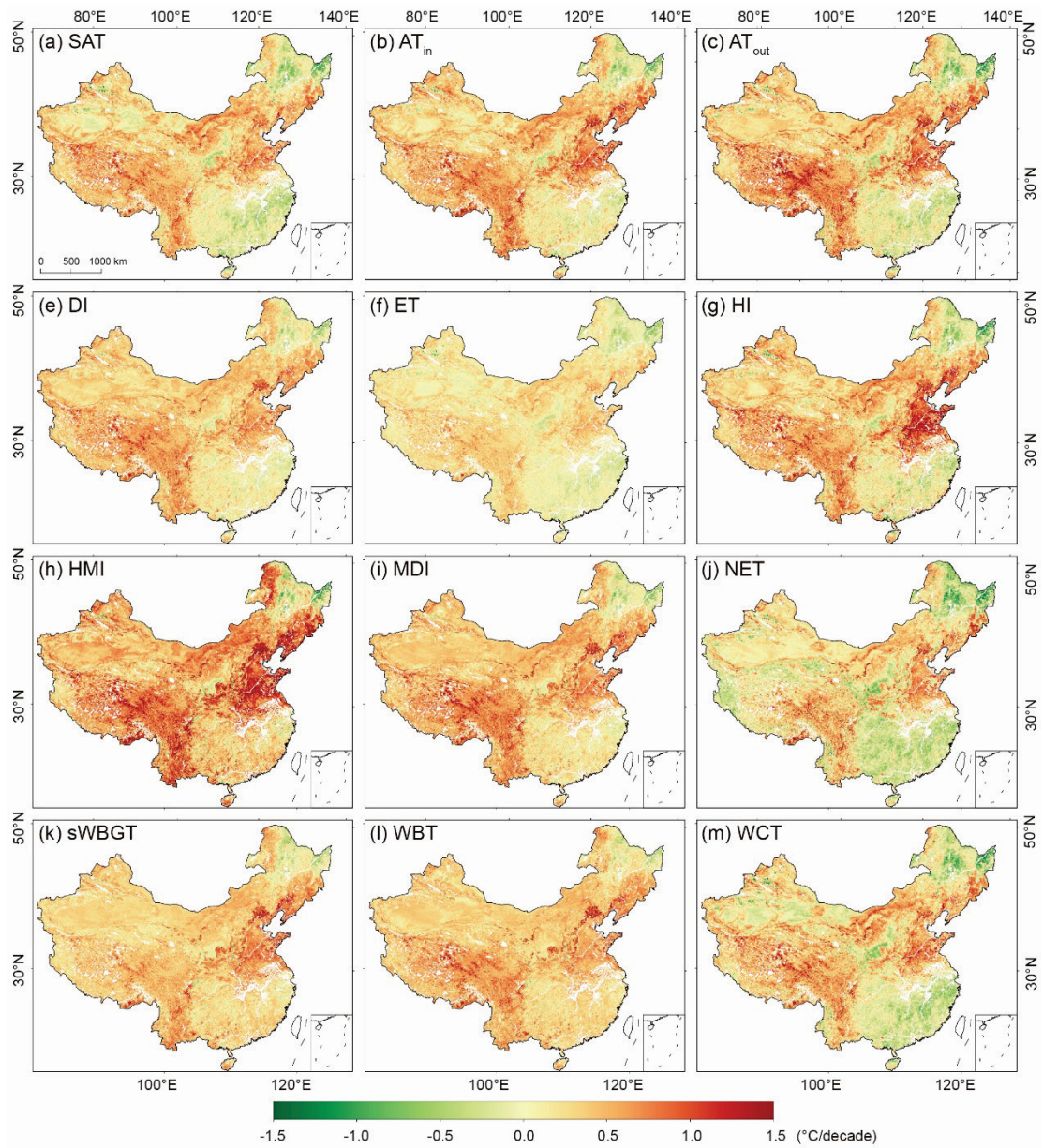


Figure S6. Spatial distributions of the trends (unit: °C/decade) of summer mean human thermal indices over the mainland of China during 2003–2020.

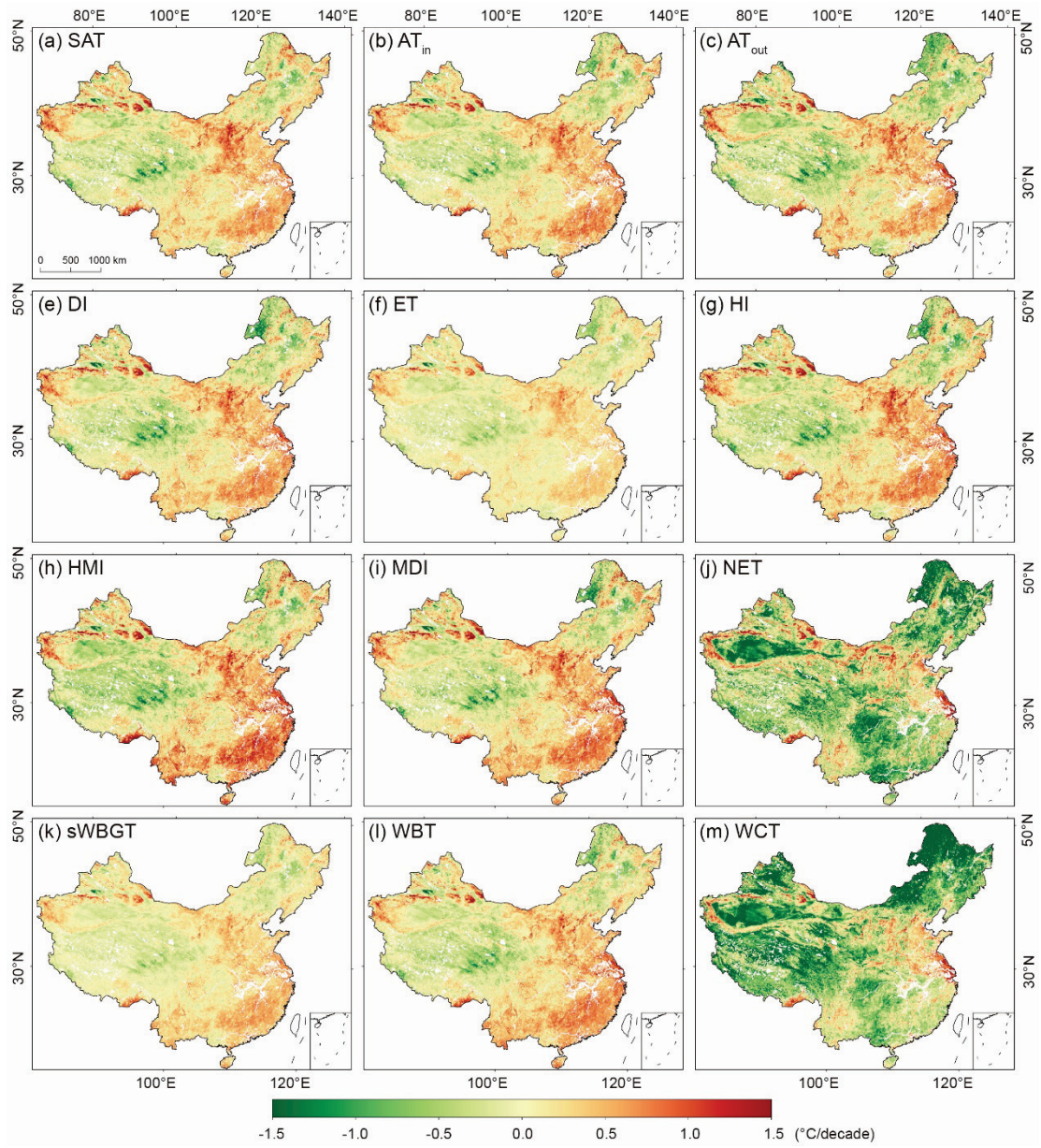


Figure S7. As Figure S6 but for winter mean.

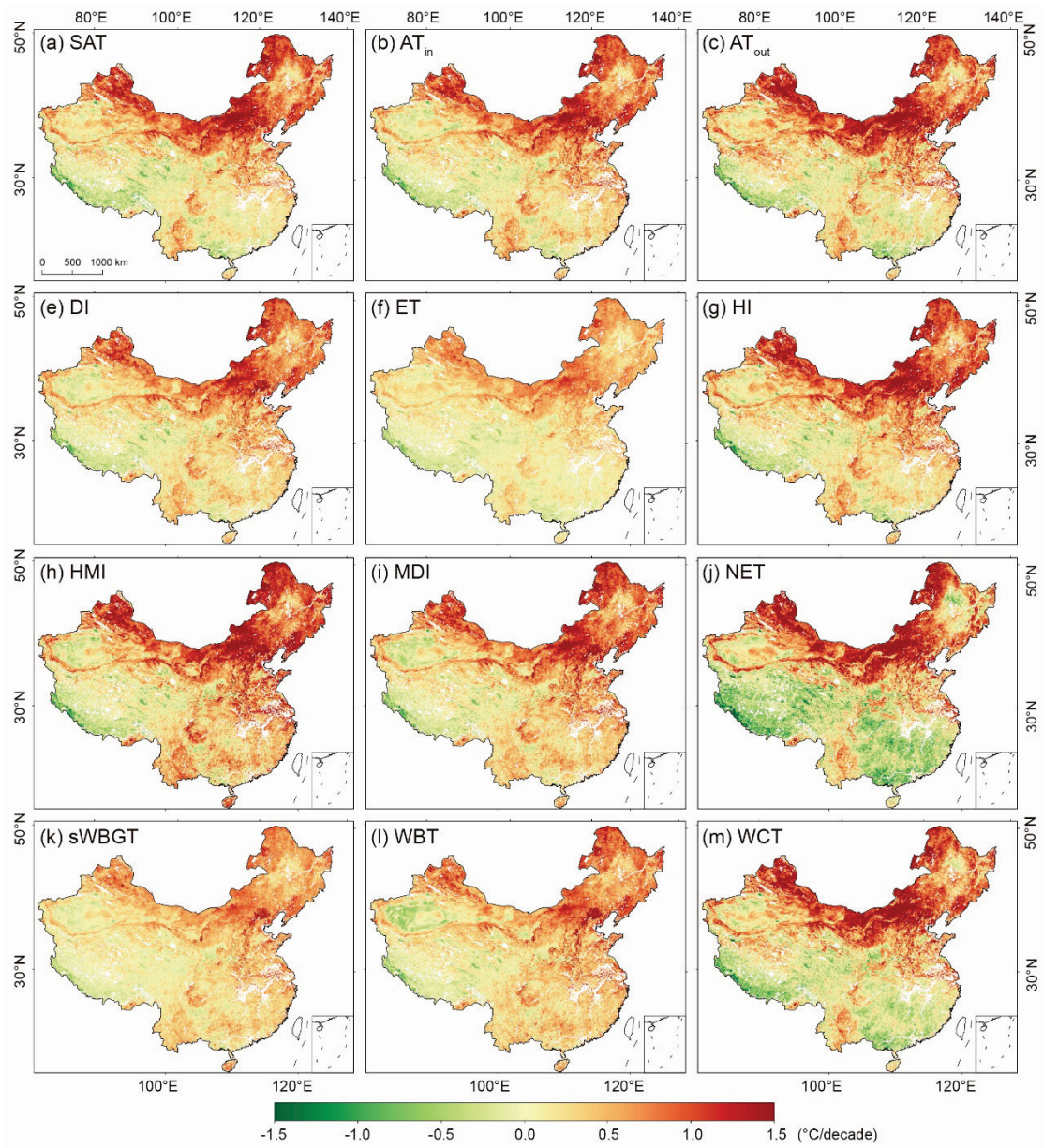


Figure S8. As Figure S6 but for spring mean.

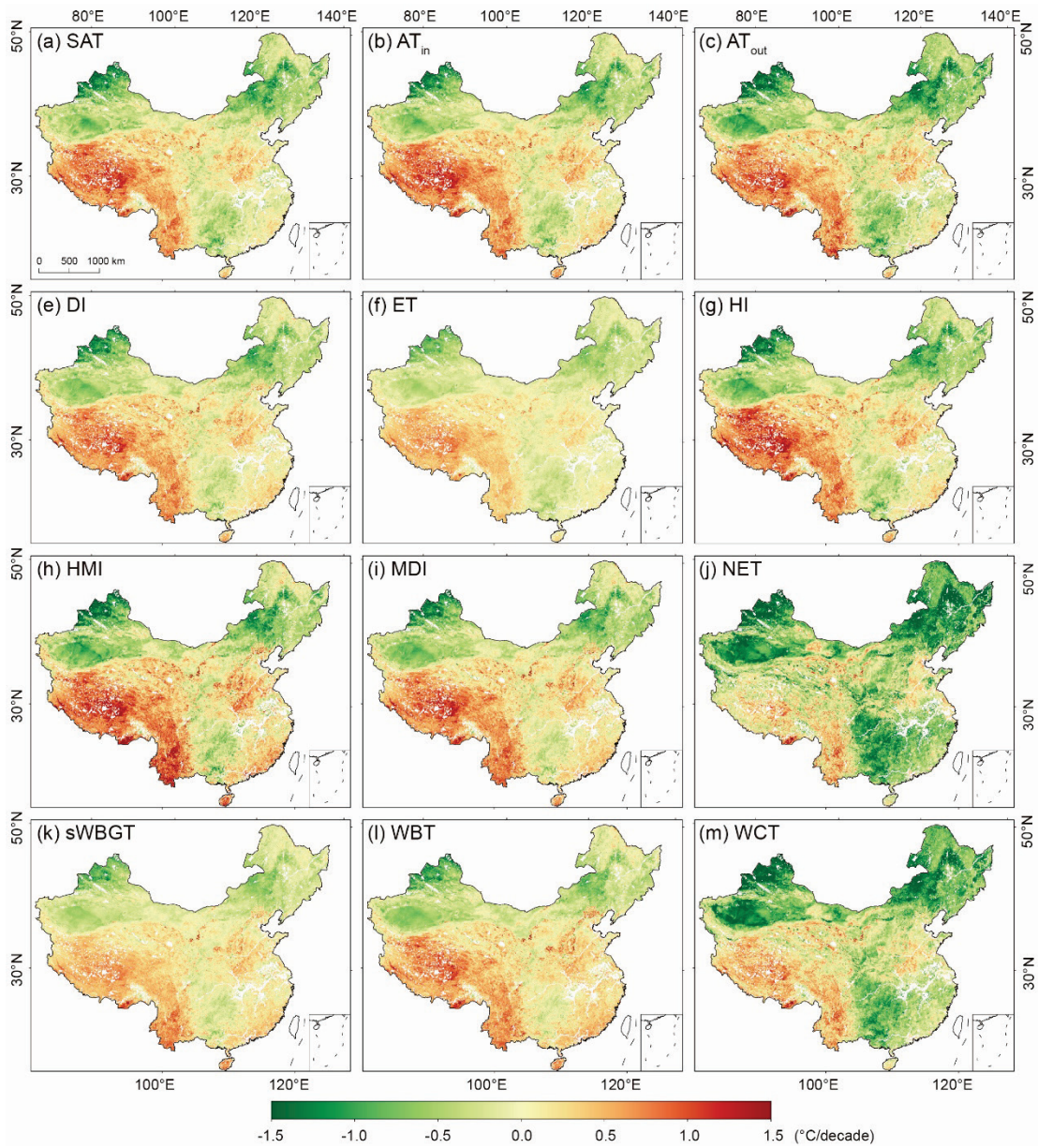


Figure S9. As Figure S6 but for autumn mean.

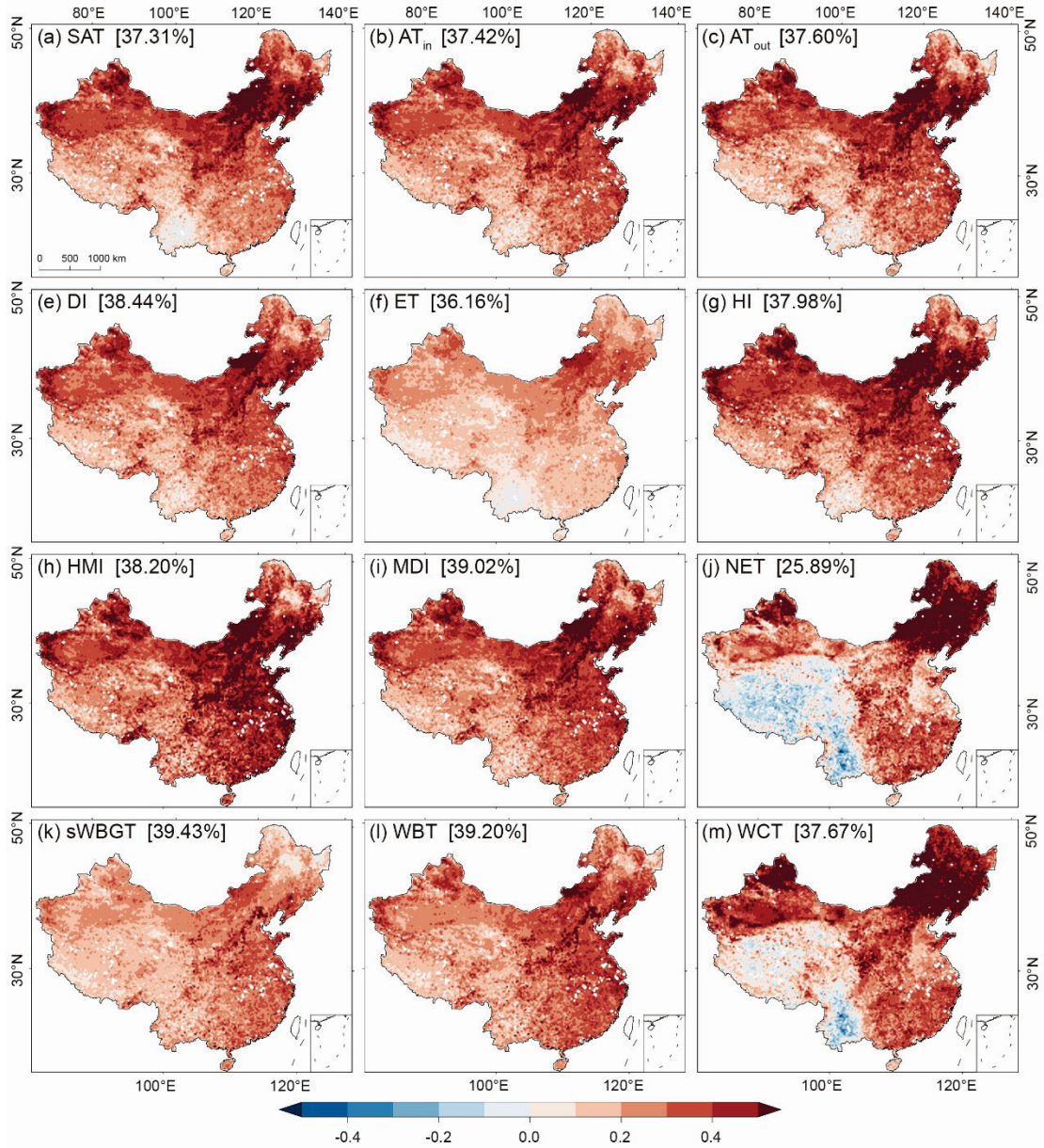


Figure S10. Spatial distributions of the first empirical orthogonal function (EOF1) mode of the 12 human thermal indices over the mainland of China. The number in square brackets represents the percentage of the variance explained by the corresponding EOF mode.



Figure S11. 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.

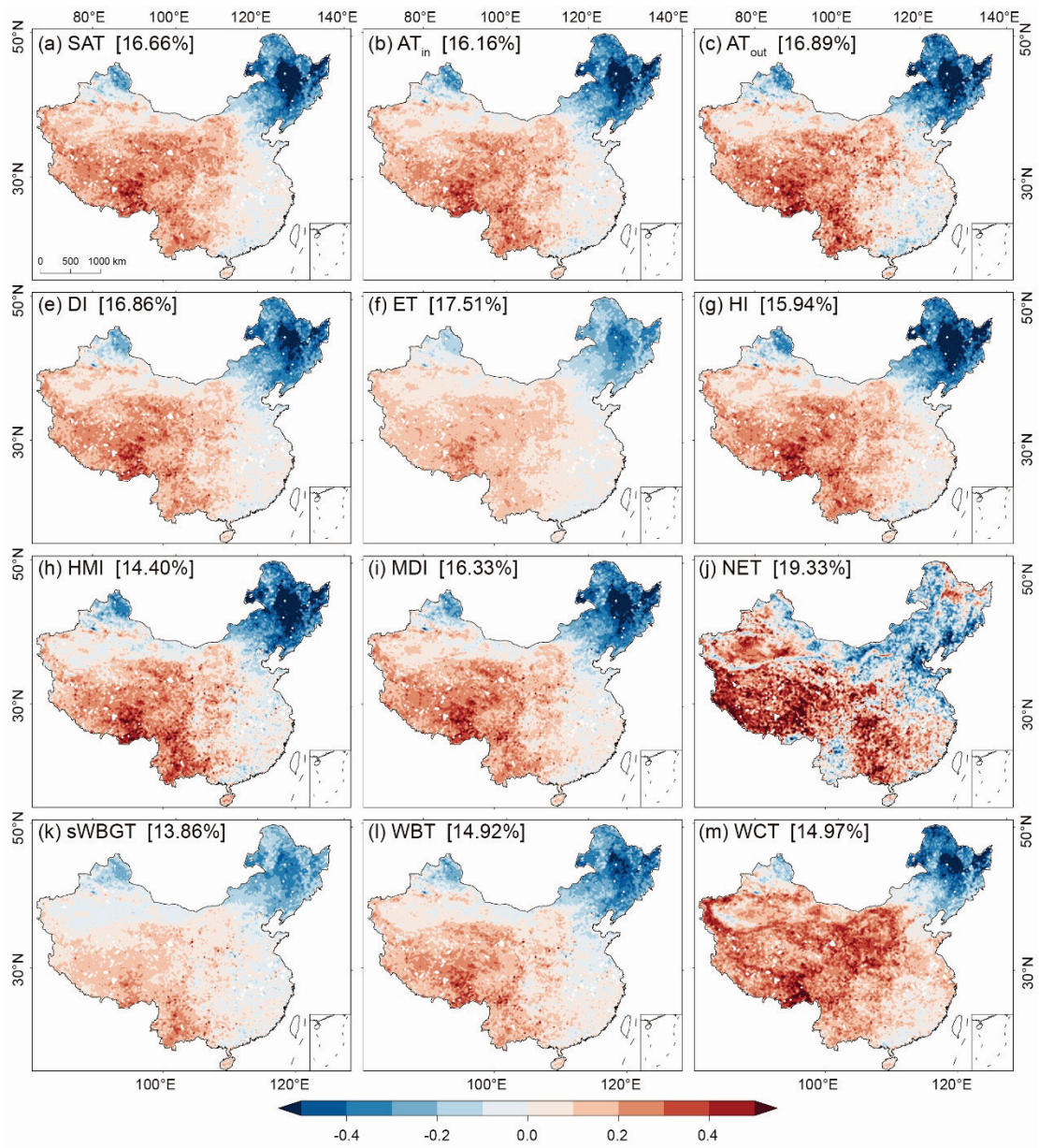


Figure S12. As Figure S10 but for the second EOF (EOF2).

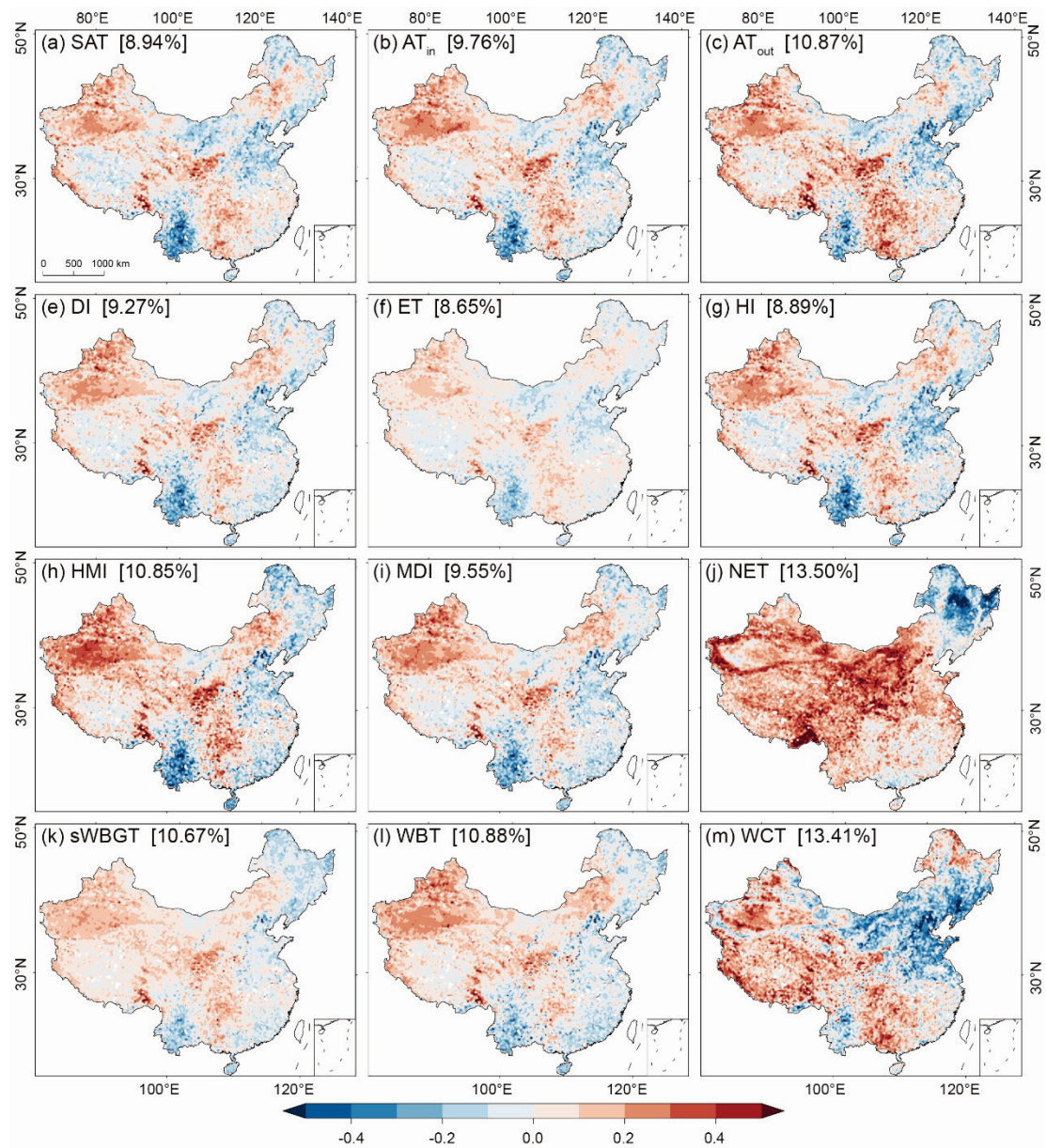


Figure S13. As Figure S10 but for the third EOF (EOF3).

Tables

Table S1. R^2 of the 12 predicted human thermal indices in the 20 major urban agglomerations (UAs) of the mainland of China during 2003–2020.

UAs	SAT	AT _{in}	AT _{out}	DI	ET	HI	HMI	MDI	NET	sWBGT	WBT	WCT
Beibu Gulf	0.9874	0.9884	0.9881	0.9886	0.9880	0.9851	0.9881	0.9883	0.9862	0.9871	0.9866	0.9872
Beijing-Tianjin-Hebei	0.9979	0.9979	0.9978	0.9977	0.9979	0.9974	0.9974	0.9975	0.9964	0.9972	0.9966	0.9974
Central Guizhou	0.9930	0.9931	0.9927	0.9929	0.9928	0.9928	0.9927	0.9926	0.9871	0.9923	0.9912	0.9899
Central Henan	0.9972	0.9973	0.9973	0.9973	0.9972	0.9967	0.9970	0.9971	0.9946	0.9968	0.9960	0.9957
Central Shanxi	0.9973	0.9974	0.9974	0.9973	0.9973	0.9972	0.9973	0.9971	0.9943	0.9971	0.9965	0.9955
Central Yunnan	0.9892	0.9912	0.9898	0.9912	0.9899	0.9904	0.9913	0.9915	0.9837	0.9913	0.9904	0.9876
Chengdu-Chongqing	0.9929	0.9936	0.9932	0.9931	0.9929	0.9921	0.9932	0.9926	0.9884	0.9931	0.9910	0.9897
Guanzhong	0.9959	0.9959	0.9958	0.9957	0.9958	0.9955	0.9957	0.9952	0.9925	0.9954	0.9943	0.9939
Harbin-Changchun	0.9983	0.9984	0.9983	0.9983	0.9983	0.9983	0.9983	0.9983	0.9961	0.9981	0.9980	0.9973
Hu-Bao-E-Yu	0.9977	0.9978	0.9976	0.9977	0.9976	0.9978	0.9977	0.9975	0.9942	0.9975	0.9968	0.9955
Jiang-Huai	0.9966	0.9970	0.9968	0.9968	0.9968	0.9955	0.9966	0.9967	0.9953	0.9964	0.9960	0.9962
Lanzhou-Xining	0.9964	0.9969	0.9968	0.9969	0.9968	0.9970	0.9969	0.9970	0.9939	0.9969	0.9966	0.9952
Mid-southern Liaoning	0.9974	0.9973	0.9971	0.9973	0.9975	0.9971	0.9969	0.9971	0.9949	0.9966	0.9966	0.9967
Middle Reaches of Yangtze River	0.9957	0.9959	0.9956	0.9958	0.9957	0.9943	0.9956	0.9955	0.9933	0.9955	0.9946	0.9946
Ningxia Yellow River	0.9974	0.9978	0.9975	0.9980	0.9978	0.9978	0.9978	0.9978	0.9948	0.9978	0.9972	0.9967
North Tianshan Mountain	0.9955	0.9949	0.9941	0.9942	0.9952	0.9947	0.9943	0.9938	0.9903	0.9938	0.9924	0.9905
Pearl River Delta	0.9893	0.9901	0.9907	0.9904	0.9899	0.9855	0.9893	0.9902	0.9896	0.9888	0.9889	0.9906
Shandong Peninsula	0.9975	0.9976	0.9973	0.9975	0.9976	0.9970	0.9972	0.9973	0.9960	0.9969	0.9965	0.9970

West Coast of Taiwan Strait	0.9925	0.9922	0.9928	0.9923	0.9923	0.9897	0.9916	0.9917	0.9904	0.9911	0.9905	0.9920
Yangtze River Delta	0.9972	0.9974	0.9971	0.9974	0.9972	0.9960	0.9972	0.9972	0.9961	0.9970	0.9966	0.9969

Table S2. RMSE (°C) of the 12 predicted human thermal indices in the 20 major urban agglomerations (UAs) of the mainland of China during 2003–2020.

UAs	SAT	AT_{in}	AT_{out}	DI	ET	HI	HMI	MDI	NET	sWBGT	WBT	WCT
Beibu Gulf	0.626	0.713	0.786	0.587	0.382	0.908	1.031	0.671	0.757	0.672	0.634	0.725
Beijing-Tianjin-Hebei	0.513	0.548	0.618	0.515	0.315	0.640	0.781	0.607	0.699	0.494	0.612	0.649
Central Guizhou	0.574	0.633	0.707	0.564	0.369	0.646	0.864	0.645	0.887	0.545	0.610	0.776
Central Henan	0.492	0.532	0.595	0.475	0.309	0.622	0.747	0.557	0.748	0.471	0.567	0.704
Central Shanxi	0.525	0.549	0.601	0.518	0.334	0.607	0.703	0.598	0.782	0.442	0.567	0.776
Central Yunnan	0.487	0.485	0.592	0.432	0.296	0.509	0.651	0.481	0.717	0.399	0.456	0.621
Chengdu-Chongqing	0.607	0.646	0.730	0.574	0.380	0.738	0.898	0.663	0.832	0.558	0.633	0.813
Guanzhong	0.581	0.630	0.705	0.582	0.370	0.690	0.837	0.685	0.826	0.528	0.656	0.813
Harbin-Changchun	0.590	0.591	0.661	0.563	0.371	0.650	0.749	0.642	0.991	0.463	0.591	0.855
Hu-Bao-E-Yu	0.589	0.566	0.664	0.545	0.371	0.631	0.703	0.619	0.967	0.434	0.587	0.952
Jiang-Huai	0.511	0.549	0.613	0.487	0.313	0.721	0.788	0.557	0.686	0.502	0.536	0.626
Lanzhou-Xining	0.553	0.532	0.591	0.502	0.332	0.574	0.655	0.554	0.729	0.392	0.505	0.723
Mid-southern Liaoning	0.604	0.650	0.746	0.604	0.374	0.717	0.891	0.699	0.932	0.560	0.670	0.806
Middle Reaches of Yangtze River	0.547	0.606	0.686	0.526	0.345	0.773	0.857	0.610	0.765	0.534	0.584	0.702
Ningxia Yellow River	0.541	0.509	0.612	0.449	0.313	0.552	0.627	0.527	0.786	0.373	0.501	0.706
North Tianshan Mountain	0.981	1.025	1.183	1.009	0.635	1.136	1.277	1.135	1.405	0.783	1.034	1.531
Pearl River Delta	0.557	0.660	0.683	0.537	0.346	0.922	0.988	0.614	0.648	0.635	0.585	0.615
Shandong Peninsula	0.498	0.533	0.627	0.490	0.303	0.630	0.764	0.569	0.709	0.486	0.571	0.640
West Coast of Taiwan Strait	0.551	0.652	0.679	0.542	0.346	0.833	0.956	0.634	0.696	0.612	0.599	0.650
Yangtze River Delta	0.453	0.505	0.575	0.436	0.288	0.668	0.706	0.504	0.617	0.451	0.487	0.554

Table S3. MAE (°C) of the 12 predicted human thermal indices in the 20 major urban agglomerations (UAs) of the mainland of China during 2003–2020.

UAs	SAT	AT_{in}	AT_{out}	DI	ET	HI	HMI	MDI	NET	sWBGT	WBT	WCT
Beibu Gulf	0.489	0.550	0.605	0.448	0.296	0.687	0.775	0.506	0.583	0.506	0.481	0.567
Beijing-Tianjin-Hebei	0.389	0.418	0.473	0.384	0.239	0.478	0.587	0.454	0.528	0.369	0.457	0.496
Central Guizhou	0.437	0.493	0.533	0.431	0.283	0.491	0.665	0.489	0.645	0.419	0.460	0.570
Central Henan	0.376	0.403	0.458	0.359	0.236	0.460	0.555	0.419	0.542	0.351	0.424	0.516
Central Shanxi	0.402	0.417	0.472	0.386	0.250	0.454	0.537	0.447	0.588	0.336	0.429	0.554
Central Yunnan	0.377	0.380	0.459	0.332	0.230	0.395	0.505	0.371	0.545	0.308	0.349	0.475
Chengdu-Chongqing	0.455	0.488	0.545	0.425	0.286	0.545	0.680	0.490	0.602	0.424	0.470	0.582
Guanzhong	0.439	0.472	0.530	0.432	0.279	0.513	0.634	0.507	0.611	0.397	0.494	0.596
Harbin-Changchun	0.435	0.442	0.494	0.415	0.276	0.485	0.556	0.475	0.666	0.341	0.438	0.569
Hu-Bao-E-Yu	0.458	0.434	0.517	0.407	0.281	0.485	0.538	0.466	0.689	0.332	0.448	0.629
Jiang-Huai	0.387	0.421	0.480	0.370	0.240	0.528	0.598	0.424	0.536	0.379	0.409	0.488
Lanzhou-Xining	0.432	0.408	0.462	0.386	0.261	0.446	0.503	0.429	0.571	0.302	0.393	0.553
Mid-southern Liaoning	0.465	0.495	0.577	0.458	0.286	0.541	0.671	0.530	0.692	0.423	0.512	0.610
Middle Reaches of Yangtze River	0.418	0.464	0.521	0.397	0.263	0.575	0.651	0.459	0.567	0.406	0.440	0.529
Ningxia Yellow River	0.422	0.400	0.486	0.343	0.242	0.423	0.483	0.409	0.592	0.291	0.372	0.535
North Tianshan Mountain	0.715	0.772	0.861	0.743	0.460	0.838	0.988	0.843	0.963	0.602	0.783	0.977
Pearl River Delta	0.428	0.492	0.522	0.399	0.261	0.663	0.715	0.455	0.495	0.459	0.427	0.470
Shandong Peninsula	0.379	0.408	0.477	0.372	0.234	0.475	0.577	0.432	0.522	0.364	0.433	0.482
West Coast of Taiwan Strait	0.427	0.509	0.530	0.425	0.269	0.623	0.748	0.492	0.530	0.474	0.464	0.501
Yangtze River Delta	0.346	0.378	0.438	0.324	0.217	0.476	0.525	0.373	0.470	0.331	0.360	0.425

Table S4. Bias (°C) of the 12 predicted human thermal indices in the 20 major urban agglomerations of the mainland of China during 2003–2020.

UAs	SAT	AT_{in}	AT_{out}	DI	ET	HI	HMI	MDI	NET	sWBGT	WBT	WCT
Beibu Gulf	-0.072	-0.089	-0.121	-0.079	-0.037	-0.094	-0.147	-0.082	-0.096	-0.098	-0.108	-0.106
Beijing-Tianjin-Hebei	0.052	0.073	0.073	0.069	0.034	0.080	0.119	0.086	0.024	0.096	0.059	0.079
Central Guizhou	0.008	-0.004	-0.020	-0.018	0.005	-0.008	-0.023	-0.029	-0.008	-0.037	0.010	-0.024
Central Henan	0.009	0.023	-0.009	0.026	0.005	0.024	0.051	0.035	-0.015	0.040	-0.020	0.037
Central Shanxi	0.037	0.027	0.031	0.031	0.016	0.036	0.047	0.034	0.041	0.037	0.038	0.028
Central Yunnan	-0.008	-0.019	-0.057	-0.018	-0.007	-0.011	-0.041	-0.023	-0.039	-0.029	-0.055	-0.020
Chengdu-Chongqing	-0.063	-0.053	-0.075	-0.054	-0.029	-0.056	-0.082	-0.071	-0.064	-0.063	-0.064	-0.043
Guanzhong	0.002	0.014	-0.009	0.012	0.013	0.015	0.022	0.017	0.001	0.013	0.022	0.014
Harbin-Changchun	0.008	0.011	0.014	0.009	0.001	0.010	0.028	0.011	0.007	0.012	0.006	0.017
Hu-Bao-E-Yu	0.027	0.007	0.051	0.003	0.003	0.008	0.022	0.011	0.021	0.012	0.003	0.014
Jiang-Huai	0.020	-0.022	-0.016	-0.035	-0.015	-0.020	-0.030	-0.029	-0.012	-0.035	-0.014	-0.023
Lanzhou-Xining	0.018	0.035	0.040	0.043	0.020	0.040	0.053	0.038	0.069	0.044	0.048	0.031
Mid-southern Liaoning	0.078	0.086	0.104	0.079	0.043	0.090	0.123	0.091	0.111	0.085	0.103	0.084
Middle Reaches of Yangtze River	-0.019	-0.028	-0.030	-0.023	-0.016	-0.028	-0.030	-0.030	-0.022	-0.029	-0.027	-0.017
Ningxia Yellow River	0.028	-0.017	0.006	-0.001	-0.001	-0.007	-0.003	0.000	0.003	0.025	0.056	-0.006
North Tianshan Mountain	-0.108	0.015	-0.004	-0.003	-0.017	-0.029	0.064	-0.014	-0.096	0.016	-0.145	0.048
Pearl River Delta	-0.089	-0.105	-0.083	-0.085	-0.061	-0.154	-0.160	-0.099	-0.065	-0.102	-0.069	-0.095
Shandong Peninsula	0.039	0.042	0.072	0.033	0.019	0.051	0.058	0.039	0.070	0.046	0.048	0.038
West Coast of Taiwan Strait	-0.029	-0.058	-0.040	-0.047	-0.023	-0.056	-0.091	-0.056	-0.039	-0.057	-0.036	-0.052
Yangtze River Delta	0.000	-0.020	-0.021	-0.021	-0.011	-0.024	-0.022	-0.023	-0.019	-0.018	-0.024	-0.020