

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

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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 from Zenodo at  
52 <https://zenodo.org/record/6895533> and the National Tibetan Plateau Data Center (TPDC) of China at  
53 <https://data.tpdac.cn/disallow/036e67b7-7a3a-4229-956f-40b8cd11871d> (Zhang et al., 2022a).

54



## 55 **1 Introduction**

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

66  
67 The thermal stress that human beings actually perceive is not only related to air temperature, but also  
68 jointly influenced by other environmental variables such as humidity, wind, and/or direct sunlight (Mistry,  
69 2020; Djongyang et al., 2010). These variables alter the heat balance that maintains the core temperature  
70 of human bodies by influencing the heat exchange (e.g., radiation, convection, conduction, and  
71 evaporation) between humans and the surrounding environment (Periard et al., 2021; Stolwijk, 1975).  
72 High atmospheric humidity can exacerbate the thermal stress on human bodies by reducing evaporation  
73 from the skin through sweating when the air temperature is high (Li et al., 2018; Rogers et al., 2021; Luo  
74 and Lau, 2021). Furthermore, abnormal weather with a combination of extremely high air temperature,  
75 humidity, and/or wind can reduce labor capacity and human performance (Roghanchi and Kocsis, 2018;  
76 Lazaro and Momayez, 2020; Enander and Hygge, 1990), leading to temperature-related discomfort,  
77 stress, morbidity, and even death (Di Napoli et al., 2018; Kuchcik, 2021; Nastos and Matzarakis, 2011),  
78 particularly during heatwaves. For example, in the summer of 2017, 2018, and 2019, there were 1489,  
79 1700, and 161 heatwave-related deaths, respectively, in the United Kingdom (Rustemeyer and Howells,  
80 2021). Additionally, vulnerable groups including children, the elderly, chronic patients, and poor  
81 communities are at higher risk of being affected by thermal stress (Patz et al., 2005; Wang et al., 2019),  
82 which is likely to be further exacerbated as global population aging and climate warming (United Nations,  
83 2017).

84

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

100

101 Although extensive studies have been conducted to generate high-resolution land surface temperature  
102 (LST) [such as the Land Surface Temperature in China (LSTC; (Zhao et al., 2020) and the global  
103 seamless land surface temperature dataset (Zhang et al., 2022b; Hong et al., 2022)], or near surface air  
104 temperatures (SAT) products [such as ERA5 (ECMWF, 2017), TerraClimate (Abatzoglou et al., 2018),  
105 and GPRChinaTemp1km (He et al., 2021)], human thermal stress datasets were generally produced at  
106 low-resolution levels, such as ERA5-HEAT (Di Napoli et al., 2020), HDI\_0p25\_1970\_2018 (hereafter,  
107 HDI) (Mistry, 2020), and HiTiSEA (Yan et al., 2021). ERA5-HEAT was derived from ERA5 and  
108 includes two global hourly human thermal stress indices (UTCI and mean radiant temperature (MRT))  
109 from January 1979 to the present (Di Napoli et al., 2020). The HDI dataset was generated using 3-hourly  
110 climate variables of the global land data assimilation system (GLDAS), and it contains ten daily indices  
111 with a spatial resolution of  $0.25^{\circ} \times 0.25^{\circ}$ , covering  $90^{\circ}\text{N}$ – $60^{\circ}\text{S}$  from 1970 to 2018 (Mistry, 2020).  
112 HiTiSEA contains ten daily human thermal stress indices from 1981 to 2017, with a spatial resolution of

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

117

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

133

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

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

148

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

160

## 161 **2 Data**

### 162 **2.1 Meteorological data**

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

## 168 2.2 Covariates

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

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

200

## 201 **3 Methodology**

### 202 **3.1 Calculation of human thermal indices**

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

$$208 \quad E_s = 6.112 \times \exp^{(17.67 \times T / (T + 243.5))} \quad (1)$$

$$209 \quad E_a = \frac{RH}{100} \times E_s \quad (2)$$

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

212

### 213 **3.2 Prediction of human thermal indices using LGBM**

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

223

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

231

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

236

### 237 3.3 Accuracy assessment

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

$$245 \quad MAE = \frac{1}{N} \times \sum_{i=1}^N |y_i - \hat{y}| \quad (3)$$

$$246 \quad RMSE = \sqrt{\frac{1}{N} \times \sum_{i=1}^N (y_i - \hat{y})^2} \quad (4)$$

$$248 \quad R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y})^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (5)$$

$$249 \quad Bias = \frac{1}{N} \times \sum_{i=1}^N (y_i - \hat{y}) \quad (6)$$

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

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

252

## 253 **4 Results**

### 254 **4.1 Evaluation of the predicted human thermal indices**

#### 255 **4.1.1 Overall accuracy**

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

267

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



279 with complex topography, such as arid Northwest China, mountainous Northeast and South China,  
280 and the Hengduan Mountains. These differences are related to the uneven distribution of weather  
281 stations, i.e., dense in plains and coarse in complex terrain areas. The *Bias* values range from  $-0.3^{\circ}$   
282  $C$  to  $0.3^{\circ}C$  (Figure 7). Positive *Bias* values tend to distribute in northern China while negative  
283 values are mainly located in the south. This spatial variability is likely caused by the generally lower  
284 temperatures in the north and higher temperatures in the south. In particular, the extremely small  
285 values in the north and the extremely large values in the south may be overestimated and  
286 underestimated to some extent, respectively, due to limited samples of extremely small and large  
287 values (compared with the rest of the samples) when training the machine learning model. The  
288 overestimation and underestimation issues caused by limited training samples of extreme values are  
289 quite common in machine learning (Wu et al., 2022; Li et al., 2020; Uddin et al., 2022; Cho et al.,  
290 2020).

291

#### 292 **4.1.2 Annual and monthly accuracies**

293 The annual accuracies regarding *RMSE*, *MAE*, and *Bias* of the 12 human thermal indices during 2003–  
294 2020 are shown in Figure 8. *RMSEs* and *MAEs* of all indices in nearly all years are less than  $1.0^{\circ}C$   
295 (Figures 8a-b). Yearly *RMSE* (*MAE*) of ET fluctuates around  $0.3^{\circ}C$  ( $0.2^{\circ}C$ ) during 2003–2020. *RMSEs*  
296 (*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.  
297 *Biases* vary between  $-0.04^{\circ}C$  and  $0.04^{\circ}C$  across all years. This temporal variability of the *Bias* is related  
298 to the yearly climate variations, and is characterized by a marginal overestimation of lower temperatures  
299 that mainly appeared in early periods (e.g., 2003–2005) and the underestimation of higher temperatures  
300 mostly in recent periods (e.g., 2016–2019). Under climatic warming over the past decades, the lower  
301 temperatures tended to appear in early periods while relatively higher temperatures more likely occurred  
302 in more recent periods. Extremely small values of temperature in earlier periods and the large values in  
303 the later periods may be slightly overestimated (i.e., with positive *Bias* values) and underestimated (i.e.,  
304 with negative *Bias* values), respectively, thereby characterizing the temporal variations of the *Bias*.  
305 Moreover, Figure S1 displays the monthly *RMSEs*, *MAEs*, and *Biases* of all human thermal indices. For  
306 *RMSE*, all the indices in 12 months are lower than  $1.4^{\circ}C$ , and their *MAEs* are less than  $1^{\circ}C$ . HI and HMI  
307 have relatively higher *RMSE* and *MAE* values in summer than in other seasons; whereas, other indices

308 tend to have larger errors in winter than in summer. Additionally, the magnitude of *Bias* is smaller than  
309 0.03 °C for all the indices in 12 months.

310

### 311 **4.1.3 Accuracies in major urban agglomerations**

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

324

## 325 **4.2 Spatial variations of the human thermal indices**

326 The abovementioned assessments show that our model based on LGBM can yield high-accuracy  
327 predictions at both national and local scales. Therefore, this model is employed to generate a high-  
328 resolution human thermal index collection at a monthly scale over China (HiTIC-Monthly) during 2003–  
329 2020. By taking monthly ET in 2020 as an example, we examined the monthly evolution of spatial  
330 patterns of the HiTIC-Monthly dataset in this subsection.

331

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

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

343

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

349

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

357

### 358 **4.3 Temporal changes in the human thermal indices**

359 The yearly evolutions of the annual mean human thermal indices during 2003–2020 are displayed in  
360 Figure 11. Despite the interannual fluctuation in the time series, all indices exhibit upward trends except  
361 for NET and WCT, of which the decreasing trends are mainly affected by the recovering wind speed in  
362 the recent decade (Zeng et al., 2019). The fastest warming appears in HMI (0.303 °C/decade), and the  
363 slowest is in ET (0.111 °C/decade). These warming trends are stronger than the rising rate of global mean  
364 near surface temperature (IPCC, 2021), demonstrating China as one of the severest hotspots suffering

365 from dramatic climate warming under global change. The detailed spatial variations regarding the trends  
366 of the human thermal indices across China are further depicted in Figure 12. Most parts of China  
367 experience are seen with increases in nearly all the indices during 2003–2020. These increases are  
368 especially more profound in North China, Southwest China, TP, and parts of Northwest China. The  
369 possible reasons for the prominent warming trends in North China are explained as follows. The  
370 urbanization process has been prevailing in this area, with rapid growth in the economy and population.  
371 This process is accompanied by dramatic increases in impervious surfaces and decreases in green spaces.  
372 These changes lead to warmer surface and near surface air temperature, known as urban heat islands  
373 (UHI), thus increasing thermal stress in this region. The urbanization effects on local heat stress have  
374 also been reported by (Luo and Lau, 2021). Moreover, North China has a large amount of croplands with  
375 prominent irrigation activities, which may increase air humidity near the surface and exacerbate the  
376 combined effects of temperature and humidity, leading to increased heat stress (Kang and Eltahir, 2018).  
377 In addition, this area has experienced a weakening of surface wind speed (Zhang et al., 2021), which also  
378 exacerbates thermal stress, especially in NET and WCT.

379

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

386

387 The temporal trends of the human thermal indices in different seasons were also examined (Figure 13).  
388 The fastest warming tendency is observed in the spring season. The rising trends of spring HMI, HI, MDI,  
389  $AT_{in}$ , and  $AT_{out}$  exceed  $0.4\text{ }^{\circ}\text{C}/\text{decade}$ , and the trends of other indices (except ET and NET) are larger  
390 than  $0.3\text{ }^{\circ}\text{C}/\text{decade}$  (Figure S2). Summer also has been experiencing significant increasing trends in all  
391 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,  
392 MDI, DI, sWBGT,  $AT_{in}$ , and  $AT_{out}$  exceed  $0.3\text{ }^{\circ}\text{C}/\text{decade}$  (Figure S3). Differing from spring and summer,  
393 the human thermal indices (except WCT and NET) in the autumn season show slightly cooling trends

394 (Figure S4). Autumn WCT and NET have significantly strong decreasing trends, i.e., -0.349 and -  
395 0.507 °C/decade, respectively. Similar strong cooling trends of WCT and NET appear in winter, i.e., -  
396 0.661 and -0.453 °C/decade, respectively, while other indices experience marginal long-term changes  
397 (Figure S5).

398

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

405

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

412

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

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

418

## 419 **5 Discussion**

### 420 **5.1 Comparison with existing human thermal index datasets**

421 We compared our HITIC-Monthly with two existing datasets, i.e., HDI (Mistry, 2020) and HiTiSEA (Yan

422 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.  
423 We derived monthly mean  $AT_{in}$  in July 2018 from HDI and HiTiSEA and compared them with HITIC-  
424 Monthly over the mainland of China, with a particular highlight in the four largest UAs, including  
425 Beijing-Tianjin-Hebei (BTH), YRD, middle Yangtze River Valley (mYRV) and Pearl River Delta (PRD)  
426 (Figure 14). The summer of 2018 was selected because it was included in all three datasets and frequent  
427 heat events occurred in this summer (Zhou et al., 2020). Generally, the three datasets depict similar spatial  
428 patterns. However, our HiTIC-Monthly dataset obviously provides more detailed and clearer spatial  
429 information on human thermal stress than the other two. Additionally, the observed  $AT_{in}$  values at  
430 individual weather stations are also compared (Figure 14). It can be seen that HDI and HiTiSEA  
431 overestimate  $AT_{in}$ , and such overestimation is especially severe for HDI, while our dataset is in good  
432 agreement with the observed  $AT_{in}$  at individual weather stations. Therefore, our predicted temperature  
433 can describe the spatial variations in the city areas well, thereby providing fundamental support for fine-  
434 scale climate studies, such as urban climate research.

## 435 **5.2 Limitations and future works**

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

444

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

451 prediction accuracy of the human thermal indices.

452

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

460

## 461 **6 Data availability**

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

476

## 477 **7 Conclusions**

478 A long-term and high-resolution dataset of multiple human thermal indices is of great significance for  
479 monitoring detailed spatiotemporal changes of human thermal stress in different climate regions across  
480 China and assessing the health risks of people exposed to extreme heat at a fine scale. However, the  
481 current datasets of human thermal indices (e.g., HDI and HiTiSEA) only have coarse spatial resolutions  
482 ( $> 0.1^\circ$ ). In this study, we generated a dataset of monthly human thermal index collection with a high  
483 spatial resolution of 1 km over the mainland of China (HiTIC-Monthly). In this collection, 12 human  
484 thermal indices from 2003 to 2020 were predicted, including SAT,  $AT_{in}$ ,  $AT_{out}$ , DI, ET, HI, HMI, MDI,  
485 NET, sWBGT, WBT, and WCT.

486

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

498

## 499 **Author contribution**

500 H.Z.: Data curation, Formal analysis, Investigation, Methodology, Writing – original draft preparation;

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508 Investigation, Writing – review & editing; X.W.: Investigation, Writing – review & editing.  
509

## 510 **Competing interests**

511 The authors declare that they have no conflict of interest.  
512

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520

## 521 **References**

- 522 Abatzoglou, J. T., Dobrowski, S. Z., Parks, S. A., and Hegewisch, K. C.: TerraClimate, a high-resolution  
523 global dataset of monthly climate and climatic water balance from 1958-2015, *Sci Data*, 5, 170191,  
524 <https://doi.org/10.1038/sdata.2017.191>, 2018.
- 525 Arias, P., Bellouin, N., Coppola, E., Jones, R., Krinner, G., Marotzke, J., Naik, V., Palmer, M., Plattner,  
526 G.-K., and Rogelj, J.: *Climate Change 2021: The Physical Science Basis. Contribution of Working*  
527 *Group14 I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change;*  
528 *Technical Summary, 2021.*
- 529 Blazejczyk, K.: New climatological-and-physiological model of the human heat balance outdoor  
530 (MENEX) and its applications in bioclimatological studies in different scales, *Zeszyty IgiPZ PAN*,  
531 28, 27-58, 1994.
- 532 Bolton, D.: The computation of equivalent potential temperature, *Monthly weather review*, 108, 1046-  
533 1053, 1980.
- 534 Brake, R. and Bates, G.: A valid method for comparing rational and empirical heat stress indices, *The*  
535 *Annals of Occupational Hygiene*, 46, 165-174, <https://doi.org/10.1093/annhyg/mef030>, 2002.

536 Brimicombe, C., Di Napoli, C., Cornforth, R., Pappenberger, F., Petty, C., and Cloke, H. L.: Borderless  
537 Heat Hazards With Bordered Impacts, *Earth's Future*, 9, <https://doi.org/10.1029/2021ef002064>,  
538 2021.

539 Budhathoki, N. K. and Zander, K. K.: Socio-Economic Impact of and Adaptation to Extreme Heat and  
540 Cold of Farmers in the Food Bowl of Nepal, *International Journal of Environmental Research and  
541 Public Health*, 16, <https://doi.org/10.3390/ijerph16091578>, 2019.

542 Candido, C., Blanco, A. C., Medina, J., Gubatanga, E., Santos, A., Ana, R. S., and Reyes, R. B.:  
543 Improving the consistency of multi-temporal land cover mapping of Laguna lake watershed using  
544 light gradient boosting machine (LightGBM) approach, change detection analysis, and Markov  
545 chain, *Remote Sensing Applications: Society and Environment*, 23,  
546 <https://doi.org/10.1016/j.rsase.2021.100565>, 2021.

547 Cho, D., Yoo, C., Im, J., and Cha, D. H.: Comparative Assessment of Various Machine Learning-Based  
548 Bias Correction Methods for Numerical Weather Prediction Model Forecasts of Extreme Air  
549 Temperatures in Urban Areas, *Earth and Space Science*, 7, <https://doi.org/10.1029/2019ea000740>,  
550 2020.

551 Di Napoli, C., Pappenberger, F., and Cloke, H. L.: Assessing heat-related health risk in Europe via the  
552 Universal Thermal Climate Index (UTCI), *International Journal of Biometeorology*, 62, 1155-1165,  
553 <https://doi.org/10.1007/s00484-018-1518-2>, 2018.

554 Di Napoli, C., Barnard, C., Prudhomme, C., Cloke, H. L., and Pappenberger, F.: ERA5-HEAT: A global  
555 gridded historical dataset of human thermal comfort indices from climate reanalysis, *Geoscience  
556 Data Journal*, 8, 2-10, <https://doi.org/10.1002/gdj3.102>, 2020.

557 Djongyang, N., Tchinda, R., and Njomo, D.: Thermal comfort: A review paper, *Renewable and  
558 Sustainable Energy Reviews*, 14, 2626-2640, <https://doi.org/10.1016/j.rser.2010.07.040>, 2010.

559 ECMWF: Copernicus Climate Change Service (C3S): ERA5: Fifth generation of ECMWF atmospheric  
560 reanalyses of the global climate. Copernicus Climate Change Service Climate Data Store (CDS),  
561 2017.

562 Enander, A. E. and Hygge, S.: Thermal stress and human performance, *Scand J Work Environ Health*, 16  
563 Suppl 1, 44-50, <https://doi.org/10.5271/sjweh.1823>, 1990.

564 Epstein, Y. and Moran, D. S.: Thermal comfort and the heat stress indices, *Ind Health*, 44, 388-398,  
565 <https://doi.org/10.2486/indhealth.44.388>, 2006.

566 Fan, J., Ma, X., Wu, L., Zhang, F., Yu, X., and Zeng, W.: Light Gradient Boosting Machine: An efficient  
567 soft computing model for estimating daily reference evapotranspiration with local and external  
568 meteorological data, *Agricultural Water Management*, 225,  
569 <https://doi.org/10.1016/j.agwat.2019.105758>, 2019.

570 Fang, C.: China's New Urbanization Developmental Paths, Blueprints and Patterns/Chuanglin Fang,  
571 Danlin Yu, 2016.

572 Fanger, P. O.: Thermal comfort. Analysis and applications in environmental engineering, *Thermal  
573 comfort. Analysis and applications in environmental engineering.*, 1970.

574 Gagge, A. and Nishi, Y.: Physical indices of the thermal environment, *ASHRAE J.:(United States)*, 18,  
575 1976.

576 Gagge, A., Stolwijk, J. A., and Nishi, Y.: An effective temperature scale based on a simple model of  
577 human physiological regulatory response, *Memoirs of the Faculty of Engineering, Hokkaido  
578 University*, 13, 21-36, 1972.

579 Gaughan, A. E., Stevens, F. R., Linard, C., Jia, P., and Tatem, A. J.: High resolution population

580 distribution maps for Southeast Asia in 2010 and 2015, *PLoS One*, 8, e55882,  
581 <https://doi.org/10.1371/journal.pone.0055882>, 2013.

582 Gong, P., Li, X., Wang, J., Bai, Y., Chen, B., Hu, T., Liu, X., Xu, B., Yang, J., Zhang, W., and Zhou, Y.:  
583 Annual maps of global artificial impervious area (GAIA) between 1985 and 2018, *Remote Sensing*  
584 of Environment, 236, <https://doi.org/10.1016/j.rse.2019.111510>, 2020.

585 Haines, A. and Ebi, K.: The Imperative for Climate Action to Protect Health, *The New England Journal*  
586 of Medicine, 380, 263-273, <https://doi.org/10.1056/NEJMra1807873>, 2019.

587 He, Q., Wang, M., Liu, K., Li, K., and Jiang, Z.: GPRChinaTemp1km: a high-resolution monthly air  
588 temperature dataset for China (1951–2020) based on machine learning, *Earth System Science Data*  
589 Discussions, 1-29, 2021.

590 Hong, F., Zhan, W., Götsche, F.-M., Liu, Z., Dong, P., Fu, H., Huang, F., and Zhang, X.: A global dataset  
591 of spatiotemporally seamless daily mean land surface temperatures: generation, validation, and  
592 analysis, *Earth System Science Data*, 14, 3091-3113, <https://doi.org/10.5194/essd-14-3091-2022>,  
593 2022.

594 Höpfe, P.: The physiological equivalent temperature—a universal index for the biometeorological  
595 assessment of the thermal environment, *International journal of Biometeorology*, 43, 71-75, 1999.

596 Houghton, F. C. and Yaglou, C. P.: Determining equal comfortlines, *ASHVE Trans.*, 29, 165-176, 1923.

597 IPCC: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth  
598 Assessment Report of the Intergovernmental Panel on Climate Change, 2021.

599 Kang, S. and Eltahir, E. A. B.: North China Plain threatened by deadly heatwaves due to climate change  
600 and irrigation, *Nature Communications*, 9, 2894, <https://doi.org/10.1038/s41467-018-05252-y>,  
601 2018.

602 Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., Ye, Q., and Liu, T.-Y.: Lightgbm: A highly  
603 efficient gradient boosting decision tree, *Advances in neural information processing systems*, 30,  
604 2017.

605 Krzysztof, B., Pavol, N., Oleh, S., Agnieszka, H., Olesya, S., Anna, B., and Katarina, M.: Influence of  
606 geographical factors on thermal stress in northern Carpathians, *International Journal of*  
607 *Biometeorology*, 65, 1553-1566, <https://doi.org/10.1007/s00484-020-02011-x>, 2021.

608 Kuchcik, M.: Mortality and thermal environment (UTCI) in Poland-long-term, multi-city study,  
609 *International Journal of Biometeorology* 65, 1529-1541, <https://doi.org/10.1007/s00484-020-01995-w>, 2021.

611 Lazaro, P. and Momayez, M.: Heat Stress in Hot Underground Mines: a Brief Literature Review, *Mining,*  
612 *Metallurgy & Exploration*, 38, 497-508, <https://doi.org/10.1007/s42461-020-00324-4>, 2020.

613 Li, J., Chen, Y. D., Gan, T. Y., and Lau, N.-C.: Elevated increases in human-perceived temperature under  
614 climate warming, *Nature Climate Change*, 8, 43-47, <https://doi.org/10.1038/s41558-017-0036-2>,  
615 2018.

616 Li, Q., Liu, X., Zhang, H., Thomas C, P., and David R, E.: Detecting and adjusting temporal  
617 inhomogeneity in Chinese mean surface air temperature data, *Advances in Atmospheric Sciences*,  
618 21, 260-268, <https://doi.org/10.1007/bf02915712>, 2004.

619 Li, W., Hao, X., Wang, L., Li, Y., Li, J., Li, H., and Han, T.: Detection and Attribution of Changes in  
620 Thermal Discomfort over China during 1961–2014 and Future Projections, *Advances in*  
621 *Atmospheric Sciences*, 39, 456-470, <https://doi.org/10.1007/s00376-021-1168-x>, 2022.

622 Li, Y., Li, M., Li, C., and Liu, Z.: Forest aboveground biomass estimation using Landsat 8 and Sentinel-  
623 1A data with machine learning algorithms, *Sci Rep*, 10, 9952, <https://doi.org/10.1038/s41598-020->

624 [67024-3](#), 2020.

625 Liu, X., Guo, J., Zhang, A., Zhou, J., Chu, Z., Zhou, Y., and Ren, G.: Urbanization Effects on Observed  
626 Surface Air Temperature Trends in North China, *Journal of Climate*, 21, 1333-1348,  
627 <https://doi.org/10.1175/2007jcli1348.1>, 2008.

628 Los, H., Mendes, G. S., Cordeiro, D., Grosso, N., Costa, H., Benevides, P., and Caetano, M.: Evaluation  
629 of Xgboost and Lgbm Performance in Tree Species Classification with Sentinel-2 Data, 2021 IEEE  
630 International Geoscience and Remote Sensing Symposium IGARSS,  
631 <https://doi.org/10.1109/igarss47720.2021.9553031>, 2021.

632 Luo, M. and Lau, N.-C.: Characteristics of summer heat stress in China during 1979–2014: climatology  
633 and long-term trends, *Climate Dynamics*, 53, 5375-5388, <https://doi.org/10.1007/s00382-019-04871-5>, 2019.

635 Luo, M. and Lau, N. C.: Increasing Human-Perceived Heat Stress Risks Exacerbated by Urbanization in  
636 China: A Comparative Study Based on Multiple Metrics, *Earth's Future*, 9,  
637 <https://doi.org/10.1029/2020ef001848>, 2021.

638 Luo, M., Lau, N. C., Liu, Z., Wu, S., and Wang, X.: An Observational Investigation of Spatiotemporally  
639 Contiguous Heatwaves in China From a 3D Perspective, *Geophysical Research Letters*, 49,  
640 <https://doi.org/10.1029/2022gl097714>, 2022.

641 Masterton, J. M., Richardson, F. A., and atmosphérique, C. S. d. l. e.: Humidex: A Method of Quantifying  
642 Human Discomfort Due to Excessive Heat and Humidity, *Service de l'environnement*  
643 *atmosphérique*.1979.

644 McCarty, D. A., Kim, H. W., and Lee, H. K.: Evaluation of Light Gradient Boosted Machine Learning  
645 Technique in Large Scale Land Use and Land Cover Classification, *Environments*, 7,  
646 <https://doi.org/10.3390/environments7100084>, 2020.

647 Mistry, M. N.: A High Spatiotemporal Resolution Global Gridded Dataset of Historical Human  
648 Discomfort Indices, *Atmosphere*, 11, <https://doi.org/10.3390/atmos11080835>, 2020.

649 Moda, H. M., Filho, W. L., and Minhas, A.: Impacts of Climate Change on Outdoor Workers and their  
650 Safety: Some Research Priorities, *International Journal of Environmental Research and Public*  
651 *Health*, 16, <https://doi.org/10.3390/ijerph16183458>, 2019.

652 Moran, D., Shapiro, Y., Epstein, Y., Matthew, W., and Pandolf, K.: A modified discomfort index (MDI)  
653 as an alternative to the wet bulb globe temperature (WBGT), *Environmental Ergonomics VIII*,  
654 Hodgdon JA, Heaney JH, Buono MJ (Eds.), 77-80, 1998.

655 Nastos, P. T. and Matzarakis, A.: The effect of air temperature and human thermal indices on mortality  
656 in Athens, Greece, *Theoretical and Applied Climatology*, 108, 591-599,  
657 <https://doi.org/10.1007/s00704-011-0555-0>, 2011.

658 NWS: Meteorological Conversions and Calculations: Heat Index Calculator, 2011.

659 Oszcewski, R. and Bluestein, M.: The New Wind Chill Equivalent Temperature Chart, *Bulletin of the*  
660 *American Meteorological Society*, 86, 1453-1458, <https://doi.org/10.1175/bams-86-10-1453>, 2005.

661 Patz, J. A., Campbell-Lendrum, D., Holloway, T., and Foley, J. A.: Impact of regional climate change on  
662 human health, *Nature*, 438, 310-317, <https://doi.org/10.1038/nature04188>, 2005.

663 Peng, S., Ding, Y., Liu, W., and Li, Z.: 1 km monthly temperature and precipitation dataset for China  
664 from 1901 to 2017, *Earth System Science Data*, 11, 1931-1946, <https://doi.org/10.5194/essd-11-1931-2019>, 2019.

666 Periard, J. D., Eijvogels, T. M. H., and Daanen, H. A. M.: Exercise under heat stress: thermoregulation,  
667 hydration, performance implications, and mitigation strategies, *Physiol Rev*, 101, 1873-1979,

668 <https://doi.org/10.1152/physrev.00038.2020>, 2021.

669 Rahman, M. A., Franceschi, E., Pattnaik, N., Moser-Reischl, A., Hartmann, C., Paeth, H., Pretzsch, H.,  
670 Rotzer, T., and Pauleit, S.: Spatial and temporal changes of outdoor thermal stress: influence of  
671 urban land cover types, *Sci Rep*, 12, 671, <https://doi.org/10.1038/s41598-021-04669-8>, 2022.

672 Raymond, C., Matthews, T., and Horton, R. M.: The emergence of heat and humidity too severe for  
673 human tolerance, *Science Advances*, 6, eaaw1838, <https://doi.org/10.1126/sciadv.aaw1838>, 2020.

674 Ren, Z., Fu, Y., Dong, Y., Zhang, P., and He, X.: Rapid urbanization and climate change significantly  
675 contribute to worsening urban human thermal comfort: A national 183-city, 26-year study in China,  
676 *Urban Climate*, 43, <https://doi.org/10.1016/j.uclim.2022.101154>, 2022.

677 Rice, J. A.: *Mathematical statistics and data analysis*, Cengage Learning, 2006.

678 Rogers, C. D. W., Ting, M., Li, C., Kornhuber, K., Coffel, E. D., Horton, R. M., Raymond, C., and Singh,  
679 D.: Recent Increases in Exposure to Extreme Humid-Heat Events Disproportionately Affect  
680 Populated Regions, *Geophysical Research Letters*, 48, <https://doi.org/10.1029/2021gl094183>, 2021.

681 Roghanchi, P. and Kocsis, K. C.: Challenges in Selecting an Appropriate Heat Stress Index to Protect  
682 Workers in Hot and Humid Underground Mines, *Saf Health Work*, 9, 10-16,  
683 <https://doi.org/10.1016/j.shaw.2017.04.002>, 2018.

684 Rothfusz, L. P. and Headquarters, N. S. R.: *The heat index equation (or, more than you ever wanted to  
685 know about heat index)*, Fort Worth, Texas: National Oceanic and Atmospheric Administration,  
686 National Weather Service, Office of Meteorology, 9023, 1990.

687 Rustemeyer, N. and Howells, M.: Excess Mortality in England during the 2019 Summer Heatwaves,  
688 *Climate*, 9, <https://doi.org/10.3390/cli9010014>, 2021.

689 Schwingshackl, C., Sillmann, J., Vicedo-Cabrera, A. M., Sandstad, M., and Aunan, K.: Heat Stress  
690 Indicators in CMIP6: Estimating Future Trends and Exceedances of Impact-Relevant Thresholds,  
691 *Earth's Future*, 9, <https://doi.org/10.1029/2020ef001885>, 2021.

692 Sohar, E., Adar, R., and Kaly, J.: Comparison of the environmental heat load in various parts of Israel,  
693 *ISRAEL JOURNAL OF EXPERIMENTAL MEDICINE*, 10, 111-&, 1963.

694 Staiger, H., Laschewski, G., and Matzarakis, A.: Selection of Appropriate Thermal Indices for  
695 Applications in Human Biometeorological Studies, *Atmosphere*, 10,  
696 <https://doi.org/10.3390/atmos10010018>, 2019.

697 Steadman, R. G.: The assessment of sultriness. Part I: A temperature-humidity index based on human  
698 physiology and clothing science, *Journal of Applied Meteorology and Climatology*, 18, 861-873,  
699 1979.

700 Steadman, R. G.: A universal scale of apparent temperature, *Journal of Applied Meteorology and  
701 Climatology*, 23, 1674-1687, 1984.

702 Stolwijk, J.: Heat exchangers between body and environment, *Bibliotheca Radiologica*, 144-150, 1975.

703 Stull, R.: Wet-Bulb Temperature from Relative Humidity and Air Temperature, *Journal of Applied  
704 Meteorology and Climatology*, 50, 2267-2269, <https://doi.org/10.1175/jamc-d-11-0143.1>, 2011.

705 Su, H., Wang, A., Zhang, T., Qin, T., Du, X., and Yan, X.-H.: Super-resolution of subsurface temperature  
706 field from remote sensing observations based on machine learning, *International Journal of Applied  
707 Earth Observation and Geoinformation*, 102, <https://doi.org/10.1016/j.jag.2021.102440>, 2021.

708 Su, Y.: Prediction of air quality based on Gradient Boosting Machine Method, 2020 International  
709 Conference on Big Data and Informatization Education (ICBDIE),  
710 <https://doi.org/10.1109/icbdie50010.2020.00099>, 2020.

711 Sulla-Menashe, D. and Friedl, M.: MCD12Q1 MODIS/Terra+ Aqua Land Cover Type Yearly L3 Global

712 500m SIN Grid V006, NASA EOSDIS Land Processes DAAC: Sioux Falls, SD, USA,  
713 <https://doi.org/10.5067/MODIS/MCD12Q1.006>, 2019.

714 Sun, Q., Miao, C., Hanel, M., Borthwick, A. G. L., Duan, Q., Ji, D., and Li, H.: Global heat stress on  
715 health, wildfires, and agricultural crops under different levels of climate warming, *Environment*  
716 *International*, 128, 125-136, <https://doi.org/10.1016/j.envint.2019.04.025>, 2019.

717 Szer, I., Lipecki, T., Szer, J., and Czarnocki, K.: Using meteorological data to estimate heat stress of  
718 construction workers on scaffolds for improved safety standards, *Automation in Construction*, 134,  
719 <https://doi.org/10.1016/j.autcon.2021.104079>, 2022.

720 Tamiminia, H., Salehi, B., Mahdianpari, M., Beier, C. M., Johnson, L., and Phoenix, D. B.: A Comparison  
721 of Random Forest and Light Gradient Boosting Machine for Forest above-Ground Biomass  
722 Estimation Using a Combination of Landsat, Alos Palsar, and Airborne Lidar Data, *The*  
723 *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*,  
724 XLIV-M-3-2021, 163-168, <https://doi.org/10.5194/isprs-archives-XLIV-M-3-2021-163-2021>,  
725 2021.

726 Tian, H., Zhao, Y., Luo, M., He, Q., Han, Y., and Zeng, Z.: Estimating PM<sub>2.5</sub> from multisource data: A  
727 comparison of different machine learning models in the Pearl River Delta of China, *Urban Climate*,  
728 35, <https://doi.org/10.1016/j.uclim.2020.100740>, 2021.

729 Tian, P., Lu, H., Li, D., and Guan, Y.: Quantifying the effects of meteorological change between  
730 neighboring days on human thermal comfort in China, *Theoretical and Applied Climatology*, 147,  
731 1345-1357, <https://doi.org/10.1007/s00704-021-03908-2>, 2022.

732 Tong, S., Prior, J., McGregor, G., Shi, X., and Kinney, P.: Urban heat: an increasing threat to global health,  
733 *BMJ*, 375, n2467, <https://doi.org/10.1136/bmj.n2467>, 2021.

734 Tuholske, C., Caylor, K., Funk, C., Verdin, A., Sweeney, S., Grace, K., Peterson, P., and Evans, T.: Global  
735 urban population exposure to extreme heat, *Proc Natl Acad Sci U S A*, 118,  
736 <https://doi.org/10.1073/pnas.2024792118>, 2021.

737 Uddin, M. G., Nash, S., Mahammad Diganta, M. T., Rahman, A., and Olbert, A. I.: Robust machine  
738 learning algorithms for predicting coastal water quality index, *J Environ Manage*, 321, 115923,  
739 <https://doi.org/10.1016/j.jenvman.2022.115923>, 2022.

740 United Nations: World population prospects, Multimedia Library, 2017.

741 Varentsov, M., Shartova, N., Grischenko, M., and Konstantinov, P.: Spatial Patterns of Human Thermal  
742 Comfort Conditions in Russia: Present Climate and Trends, *Weather, Climate, and Society*, 12, 629-  
743 642, <https://doi.org/10.1175/wcas-d-19-0138.1>, 2020.

744 Wang, C., Zhan, W., Liu, Z., Li, J., Li, L., Fu, P., Huang, F., Lai, J., Chen, J., Hong, F., and Jiang, S.:  
745 Satellite-based mapping of the Universal Thermal Climate Index over the Yangtze River Delta  
746 urban agglomeration, *Journal of Cleaner Production*, 277,  
747 <https://doi.org/10.1016/j.jclepro.2020.123830>, 2020.

748 Wang, F., Duan, K., and Zou, L.: Urbanization Effects on Human-Perceived Temperature Changes in the  
749 North China Plain, *Sustainability*, 11, <https://doi.org/10.3390/su11123413>, 2019.

750 Wang, P., Luo, M., Liao, W., Xu, Y., Wu, S., Tong, X., Tian, H., Xu, F., and Han, Y.: Urbanization  
751 contribution to human perceived temperature changes in major urban agglomerations of China,  
752 *Urban Climate*, 38, <https://doi.org/10.1016/j.uclim.2021.100910>, 2021.

753 Wu, J., Fang, H., Qin, W., Wang, L., Song, Y., Su, X., and Zhang, Y.: Constructing High-Resolution (10  
754 km) Daily Diffuse Solar Radiation Dataset across China during 1982–2020 through Ensemble  
755 Model, *Remote Sensing*, 14, <https://doi.org/10.3390/rs14153695>, 2022.



756 Xu, W., Li, Q., Wang, X. L., Yang, S., Cao, L., and Feng, Y.: Homogenization of Chinese daily surface  
757 air temperatures and analysis of trends in the extreme temperature indices, *Journal of Geophysical*  
758 *Research: Atmospheres*, 118, 9708-9720, <https://doi.org/10.1002/jgrd.50791>, 2013.

759 Yaglou, C. and Minaed, D.: Control of heat casualties at military training centers, *Arch. Indust. Health*,  
760 16, 302-316, 1957.

761 Yamazaki, D., Ikeshima, D., Tawatari, R., Yamaguchi, T., O'Loughlin, F., Neal, J. C., Sampson, C. C.,  
762 Kanae, S., and Bates, P. D.: A high-accuracy map of global terrain elevations, *Geophysical Research*  
763 *Letters*, 44, 5844-5853, <https://doi.org/10.1002/2017gl072874>, 2017.

764 Yan, Y., Xu, Y., and Yue, S.: A high-spatial-resolution dataset of human thermal stress indices over South  
765 and East Asia, *Sci Data*, 8, 229, <https://doi.org/10.1038/s41597-021-01010-w>, 2021.

766 Yan, Y. Y.: Human Thermal Climates in China, *Physical Geography*, 26, 163-176,  
767 <https://doi.org/10.2747/0272-3646.26.3.163>, 2013.

768 Zeng, Z., Gui, K., Wang, Z., Luo, M., Geng, H., Ge, E., An, J., Song, X., Ning, G., Zhai, S., and Liu, H.:  
769 Estimating hourly surface PM<sub>2.5</sub> concentrations across China from high-density meteorological  
770 observations by machine learning, *Atmospheric Research*, 254,  
771 <https://doi.org/10.1016/j.atmosres.2021.105516>, 2021.

772 Zeng, Z., Ziegler, A. D., Searchinger, T., Yang, L., Chen, A., Ju, K., Piao, S., Li, L. Z. X., Ciais, P., Chen,  
773 D., Liu, J., Azorin-Molina, C., Chappell, A., Medvigy, D., and Wood, E. F.: A reversal in global  
774 terrestrial stilling and its implications for wind energy production, *Nature Climate Change*, 9, 979-  
775 985, <https://doi.org/10.1038/s41558-019-0622-6>, 2019.

776 Zhang, G., Azorin-Molina, C., Chen, D., McVicar, T. R., Guijarro, J. A., Kong, F., Minola, L., Deng, K.,  
777 and Shi, P.: Uneven Warming Likely Contributed to Declining Near-Surface Wind Speeds in  
778 Northern China Between 1961 and 2016, *Journal of Geophysical Research: Atmospheres*, 126,  
779 <https://doi.org/10.1029/2020jd033637>, 2021.

780 Zhang, H., Luo, M., Zhao, Y., Lin, L., Ge, E., Yang, Y., Ning, G., Zeng, Z., Gui, K., Li, J., Chen, T. O.,  
781 Li, X., Wu, S., Wang, P., and Wang, X.: HiTIC-Monthly: A Monthly High Spatial Resolution (1 km)  
782 Human Thermal Index Collection over China during 2003–2020 (1.0), Zenodo [dataset],  
783 <https://doi.org/10.5281/zenodo.6895533>, 2022a.

784 Zhang, T., Zhou, Y., Zhu, Z., Li, X., and Asrar, G. R.: A global seamless 1 km resolution daily land surface  
785 temperature dataset (2003–2020), *Earth System Science Data*, 14, 651-664,  
786 <https://doi.org/10.5194/essd-14-651-2022>, 2022b.

787 Zhao, B., Mao, K., Cai, Y., Shi, J., Li, Z., Qin, Z., Meng, X., Shen, X., and Guo, Z.: A combined Terra  
788 and Aqua MODIS land surface temperature and meteorological station data product for China from  
789 2003 to 2017, *Earth System Science Data*, 12, 2555-2577, [https://doi.org/10.5194/essd-12-2555-](https://doi.org/10.5194/essd-12-2555-2020)  
790 [2020](https://doi.org/10.5194/essd-12-2555-2020), 2020.

791 Zhao, C., Liu, B., Piao, S., Wang, X., Lobell, D. B., Huang, Y., Huang, M., Yao, Y., Bassu, S., Ciais, P.,  
792 Durand, J. L., Elliott, J., Ewert, F., Janssens, I. A., Li, T., Lin, E., Liu, Q., Martre, P., Muller, C.,  
793 Peng, S., Penuelas, J., Ruane, A. C., Wallach, D., Wang, T., Wu, D., Liu, Z., Zhu, Y., Zhu, Z., and  
794 Asseng, S.: Temperature increase reduces global yields of major crops in four independent estimates,  
795 *Proc Natl Acad Sci U S A*, 114, 9326-9331, <https://doi.org/10.1073/pnas.1701762114>, 2017.

796 Zhao, Y. and Zhu, Z.: ASI: An artificial surface Index for Landsat 8 imagery, *International Journal of*  
797 *Applied Earth Observation and Geoinformation*, 107, <https://doi.org/10.1016/j.jag.2022.102703>,  
798 2022.

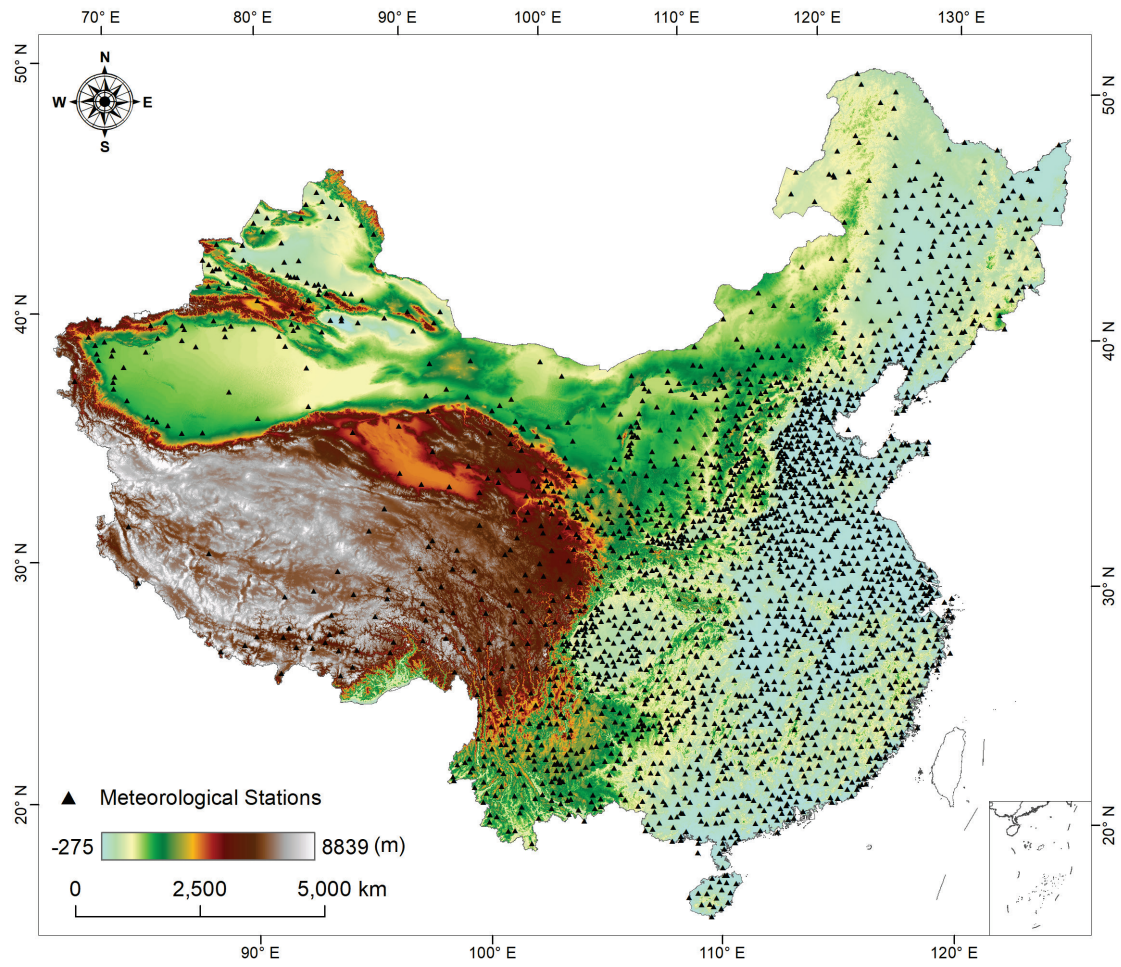
799 Zhou, C., Chen, D., Wang, K., Dai, A., and Qi, D.: Conditional Attribution of the 2018 Summer Extreme

800 Heat over Northeast China: Roles of Urbanization, Global Warming, and Warming-Induced  
801 Circulation Changes, *Bulletin of the American Meteorological Society*, 101, S71-S76,  
802 <https://doi.org/10.1175/bams-d-19-0197.1>, 2020.

803



804 **Figures**

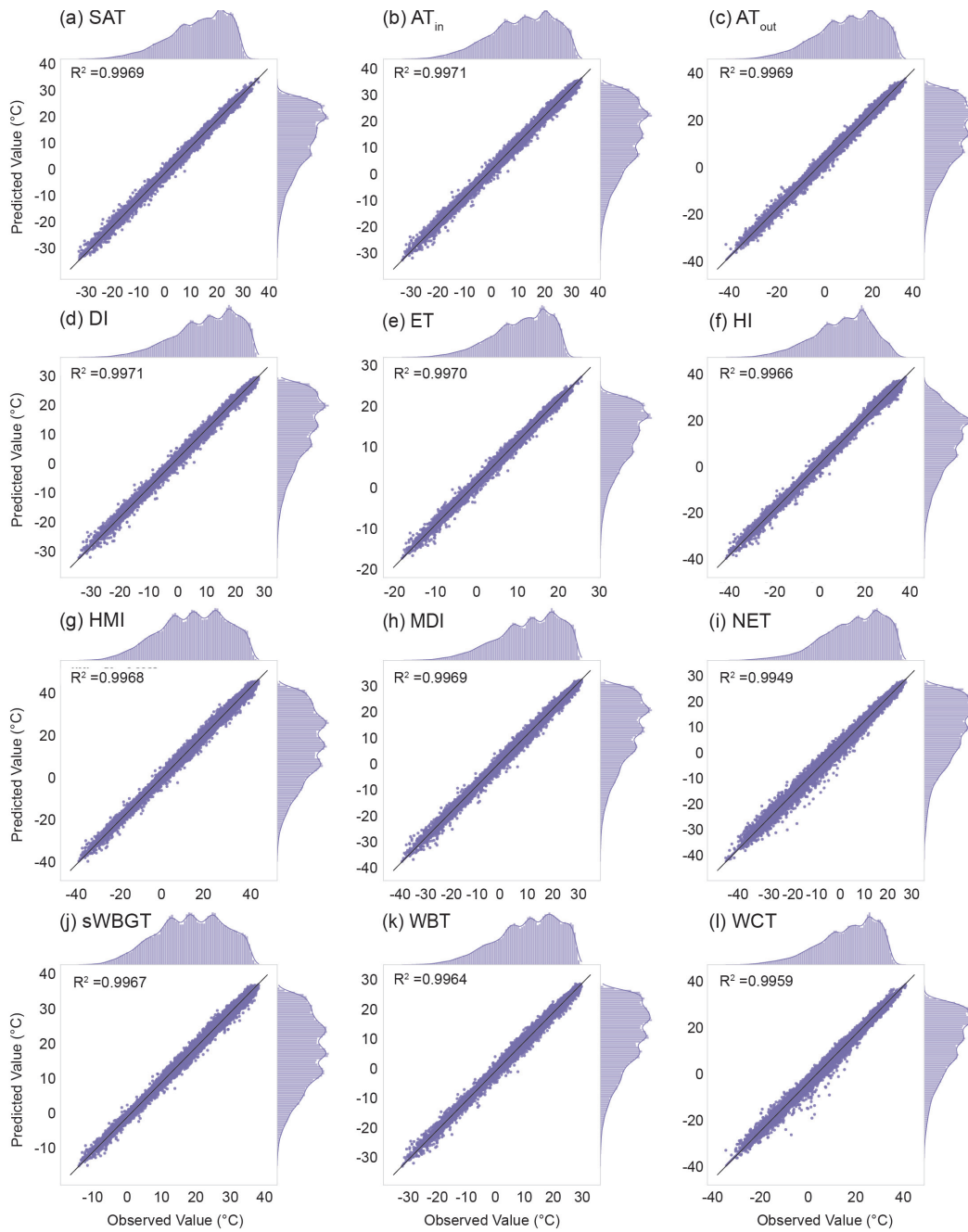


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806 **Figure 1. Spatial distribution of meteorological stations in the mainland of China, with color shadings**

807 **indicating the elevation in meters.**

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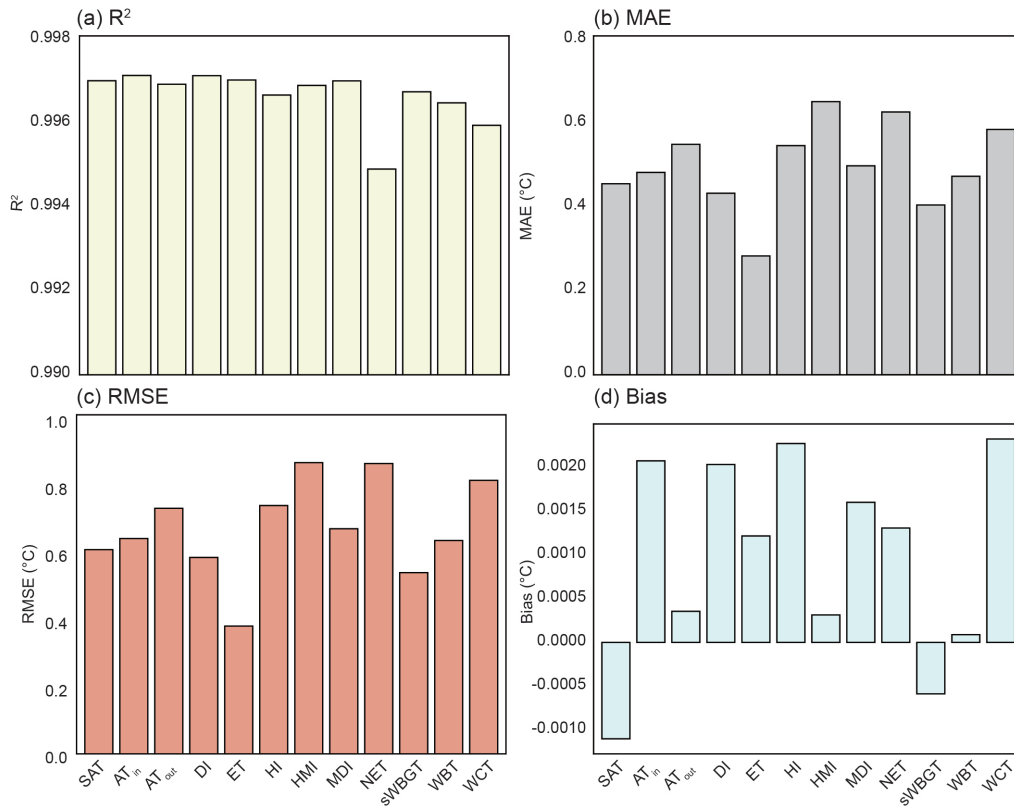
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**Figure 2. Scatter plots of predictions versus observations of the 12 human thermal indices over the mainland of China during 2003–2020. (a) SAT, (b)  $AT_{in}$ , (c)  $AT_{out}$ , (d) DI, (e) ET, (f) HI, (g) HMI, (h) MDI, (i) NET, (j) sWBGT, (k)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



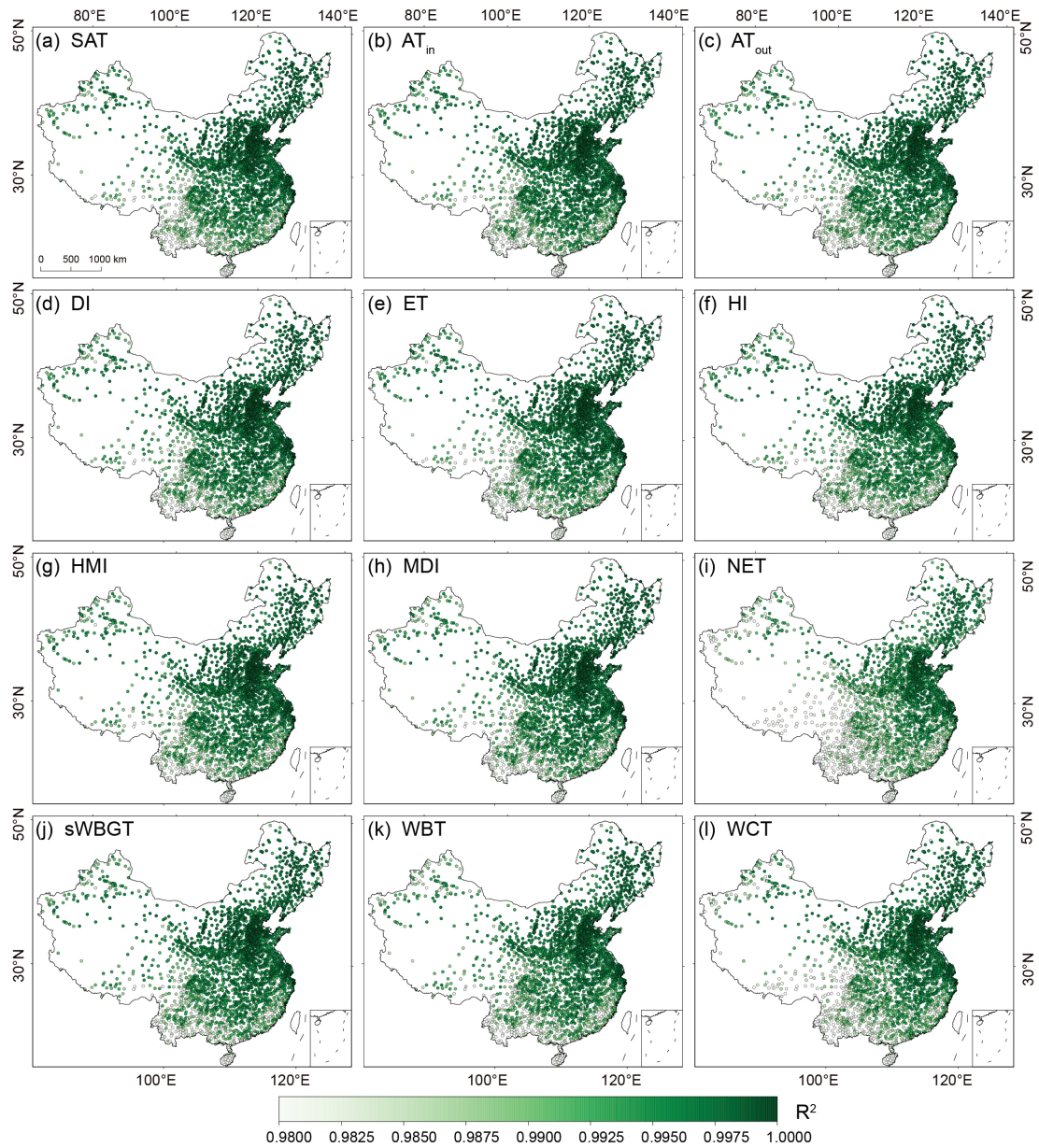
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**Figure 3. Overall prediction accuracies of the 12 human thermal indices over the mainland of China during 2003–2020. (a)  $R^2$ , (b) MAE, (c) RMSE, (d) Bias.**

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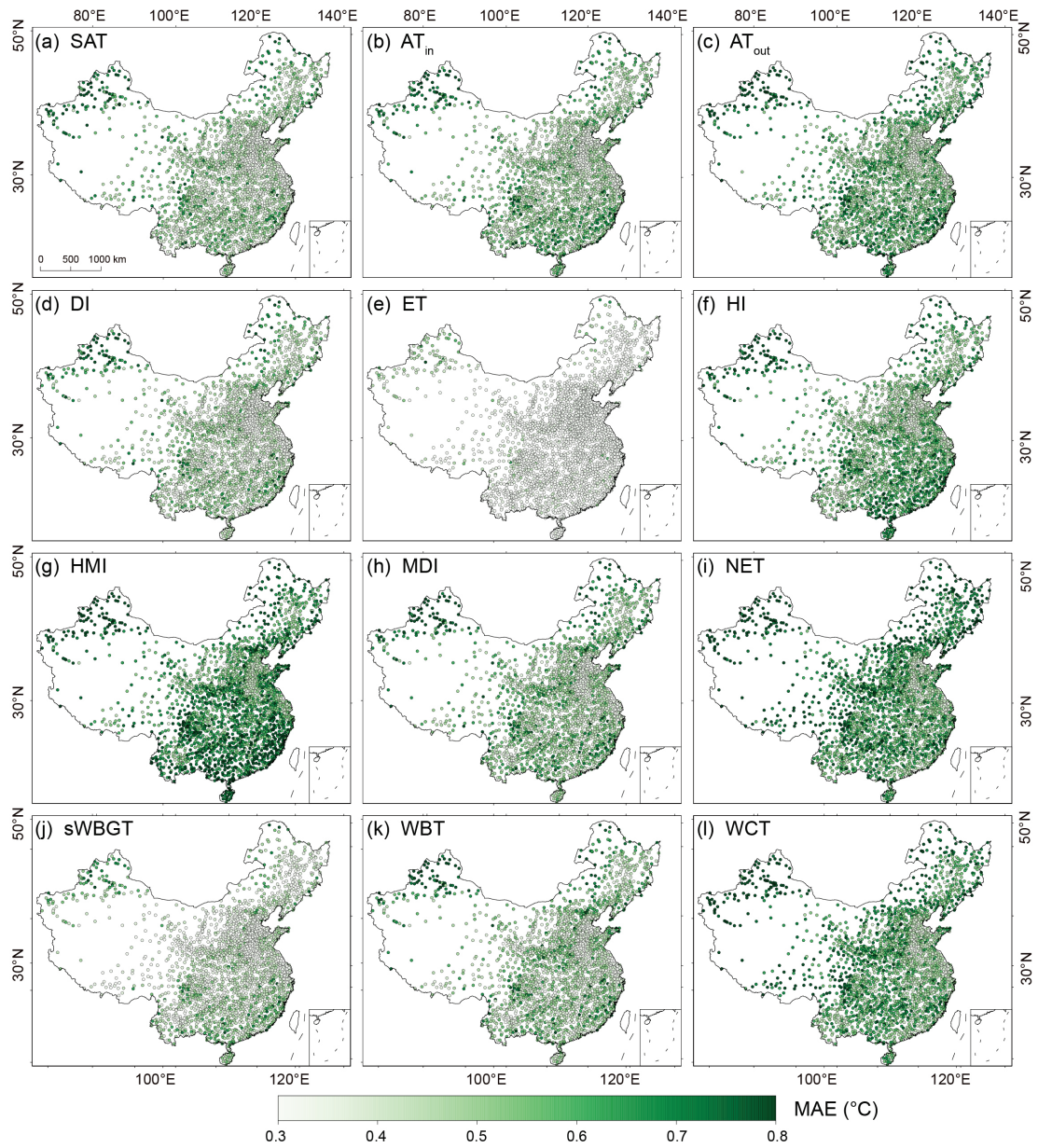


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819 **Figure 4. Spatial distribution of  $R^2$  of the 12 human thermal index predictions at individual meteorological**  
 820 **stations over the mainland of China during 2003–2020.**

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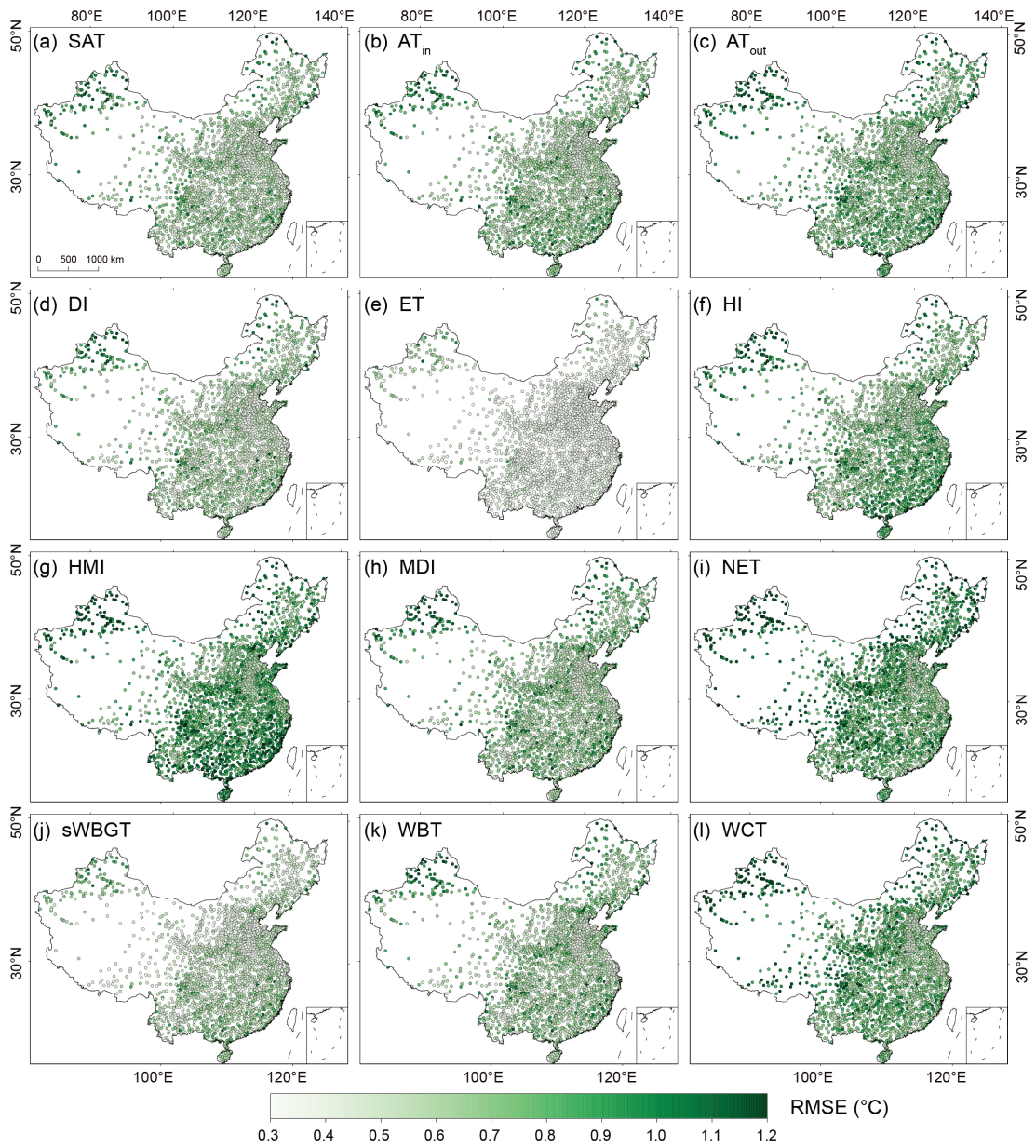




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823 **Figure 5. As Figure 4 but for MAE.**

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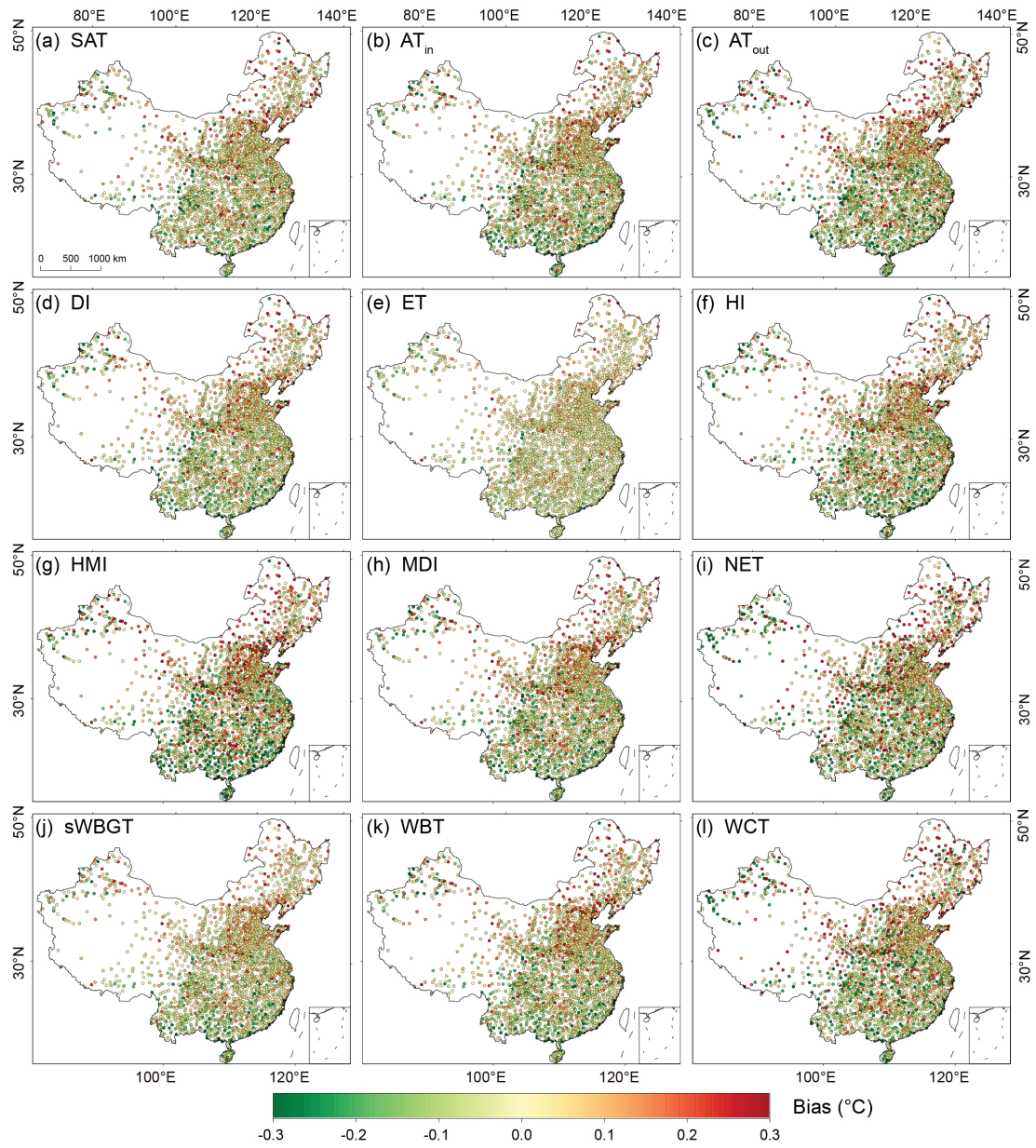


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Figure 6. As Figure 4 but for *RMSE*.

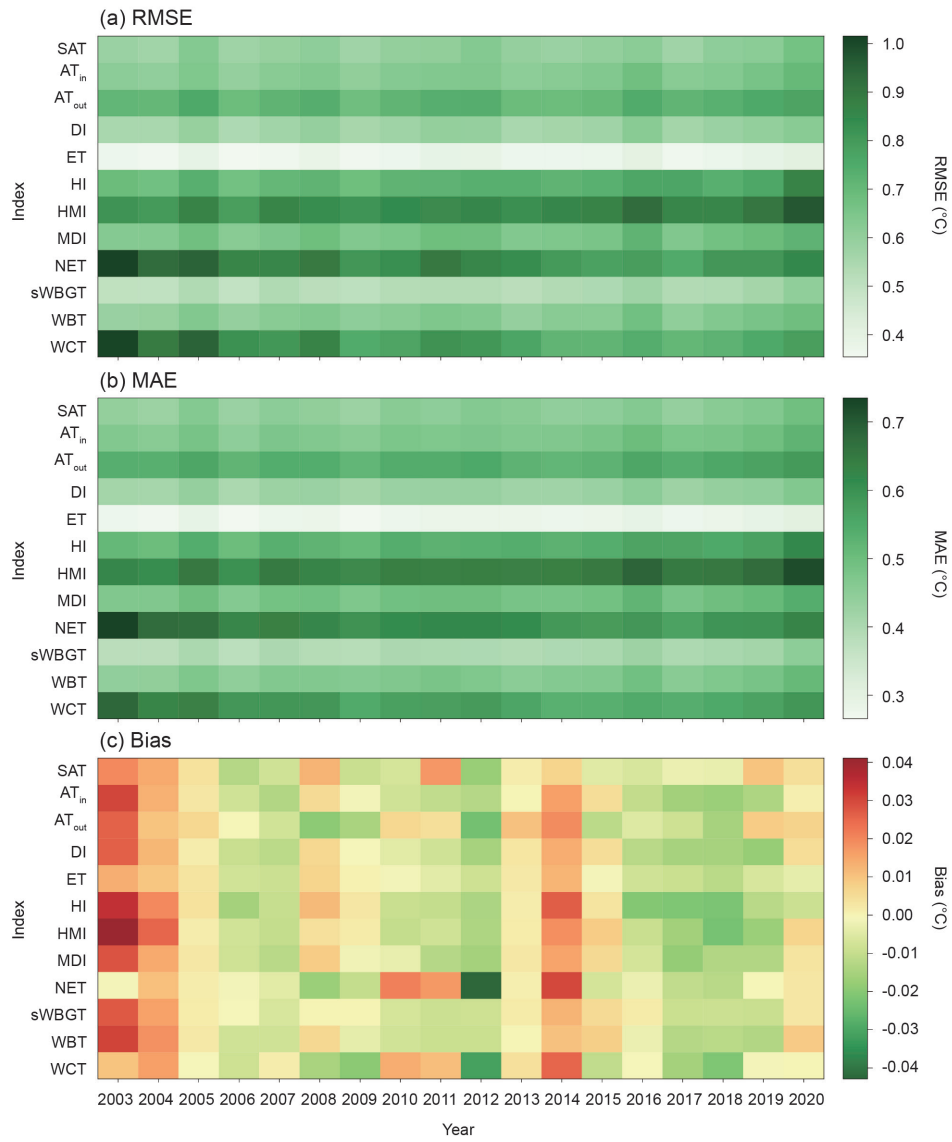
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829 **Figure 7. As Figure 4 but for *Bias*.**

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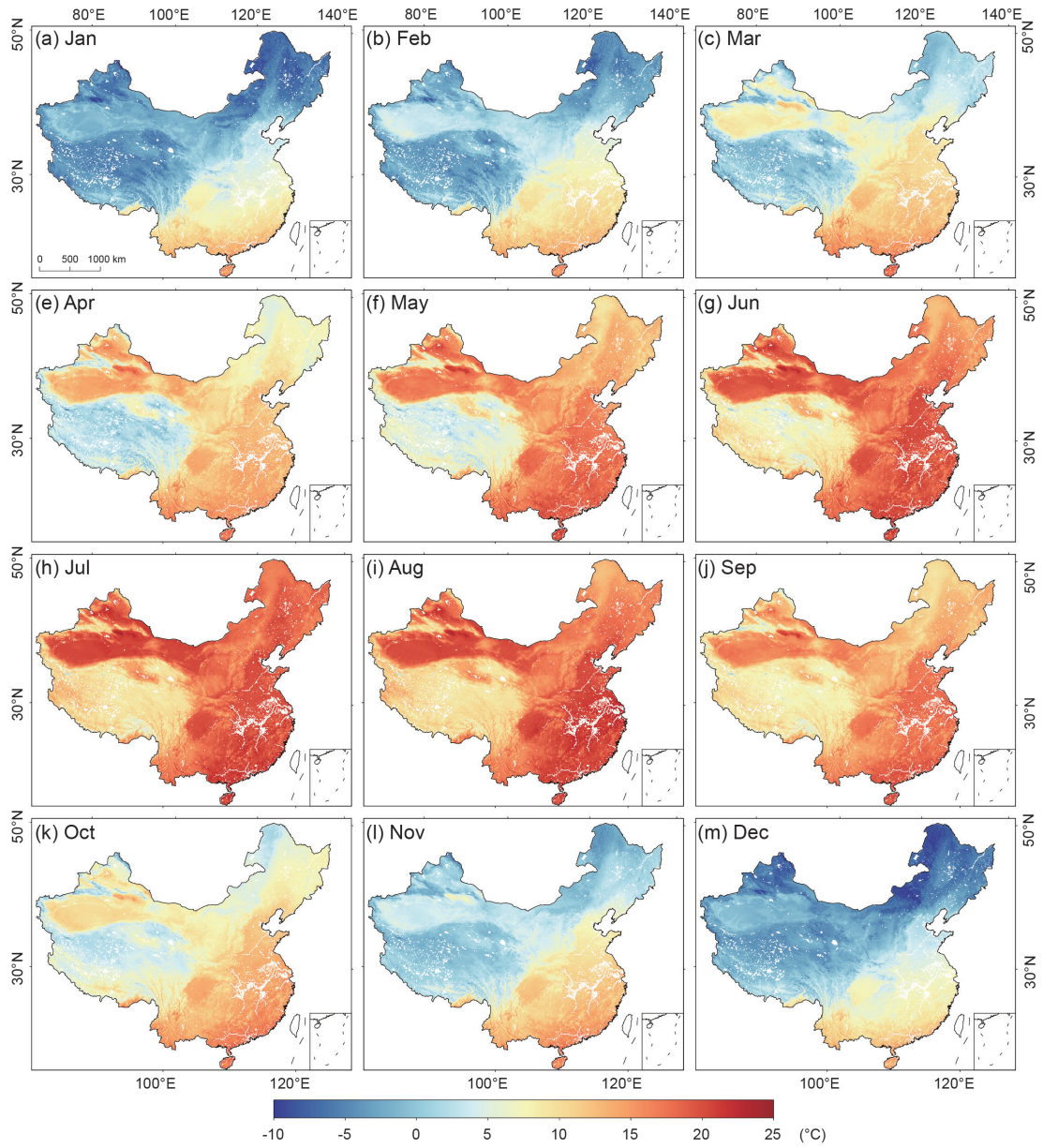
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832 **Figure 8. Annual prediction accuracies of the 12 human thermal indices over the mainland of China during**

833 **2003–2020: (a) *RMSE*, (b) *MAE*, (c) *Bias*.**

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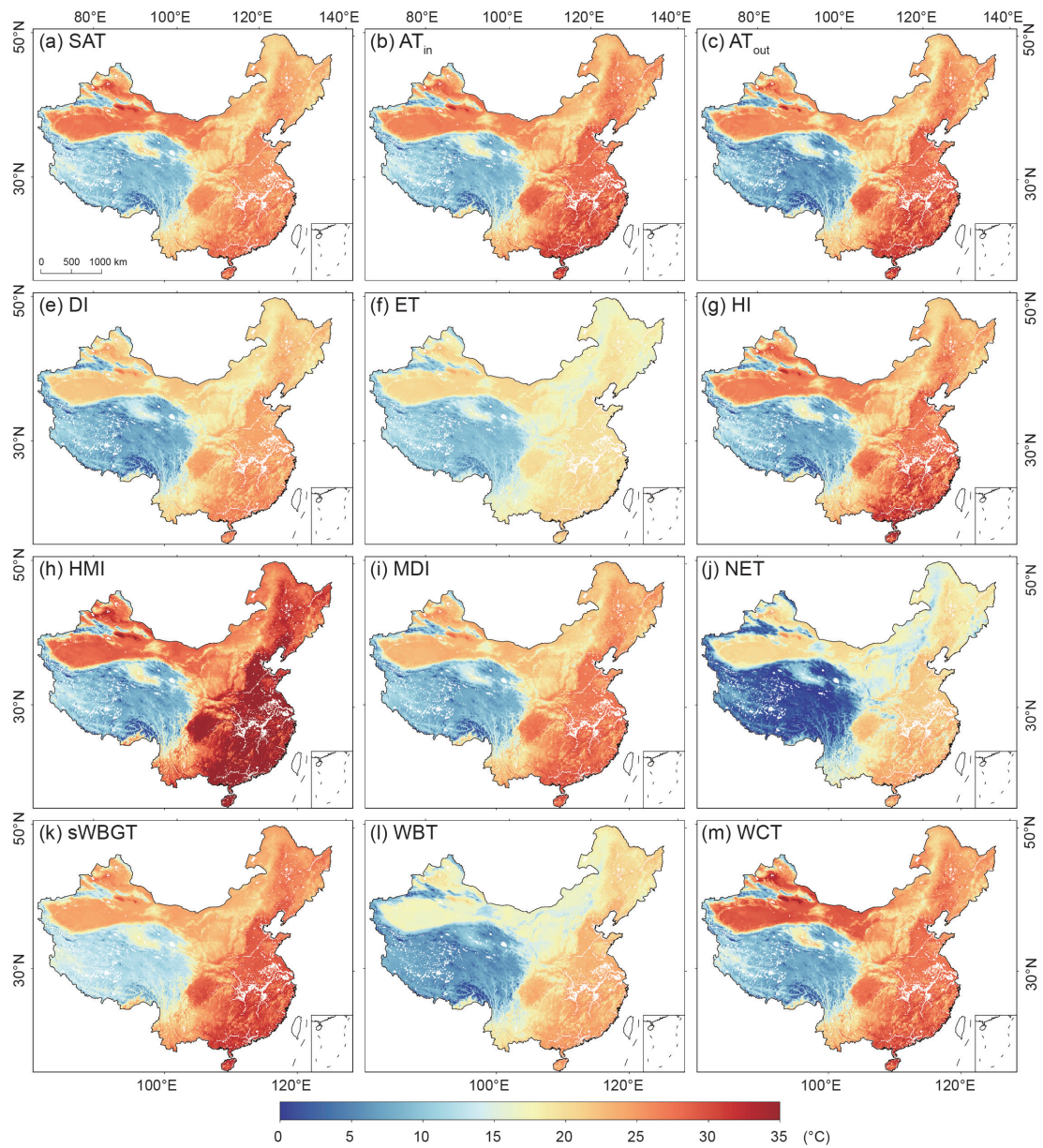


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**Figure 9. Spatial distributions of the monthly mean ET over the mainland of China in 2020.**

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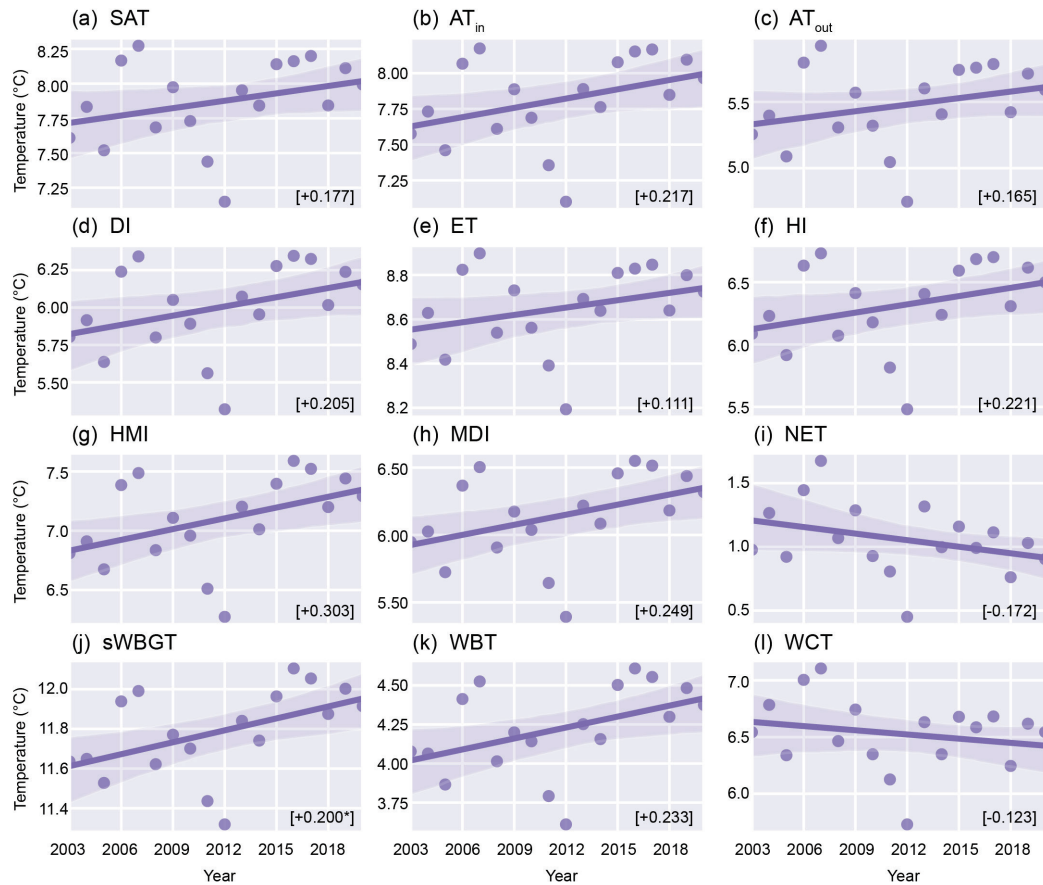


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839 **Figure 10. Spatial distributions of the 12 human thermal indices over the mainland of China in July 2020.**

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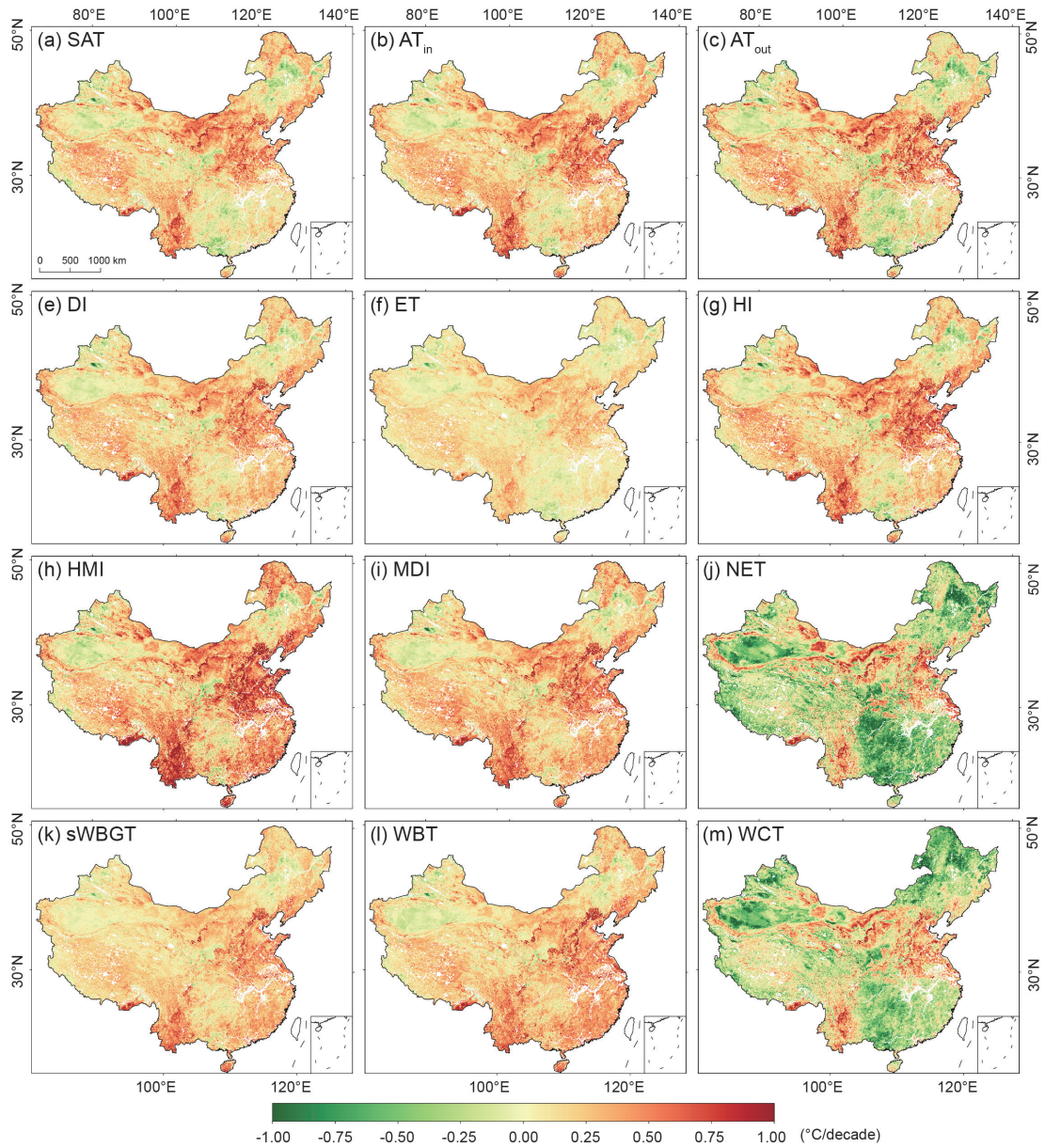
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**Figure 11. Temporal changes of the 12 annually-averaged human thermal indices over the mainland of China during 2003–2020. The line illustrates the linear trend, the number in the square bracket means the corresponding trend per decade, and the asterisk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

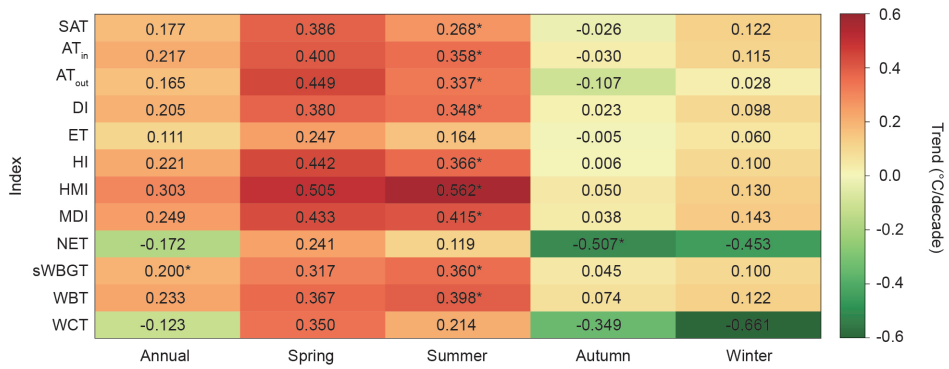




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849 **Figure 12. Spatial distributions of the linear trends (unit: °C per decade) in the 12 annually-averaged human**  
 850 **thermal indices over the mainland of China during 2003–2020.**

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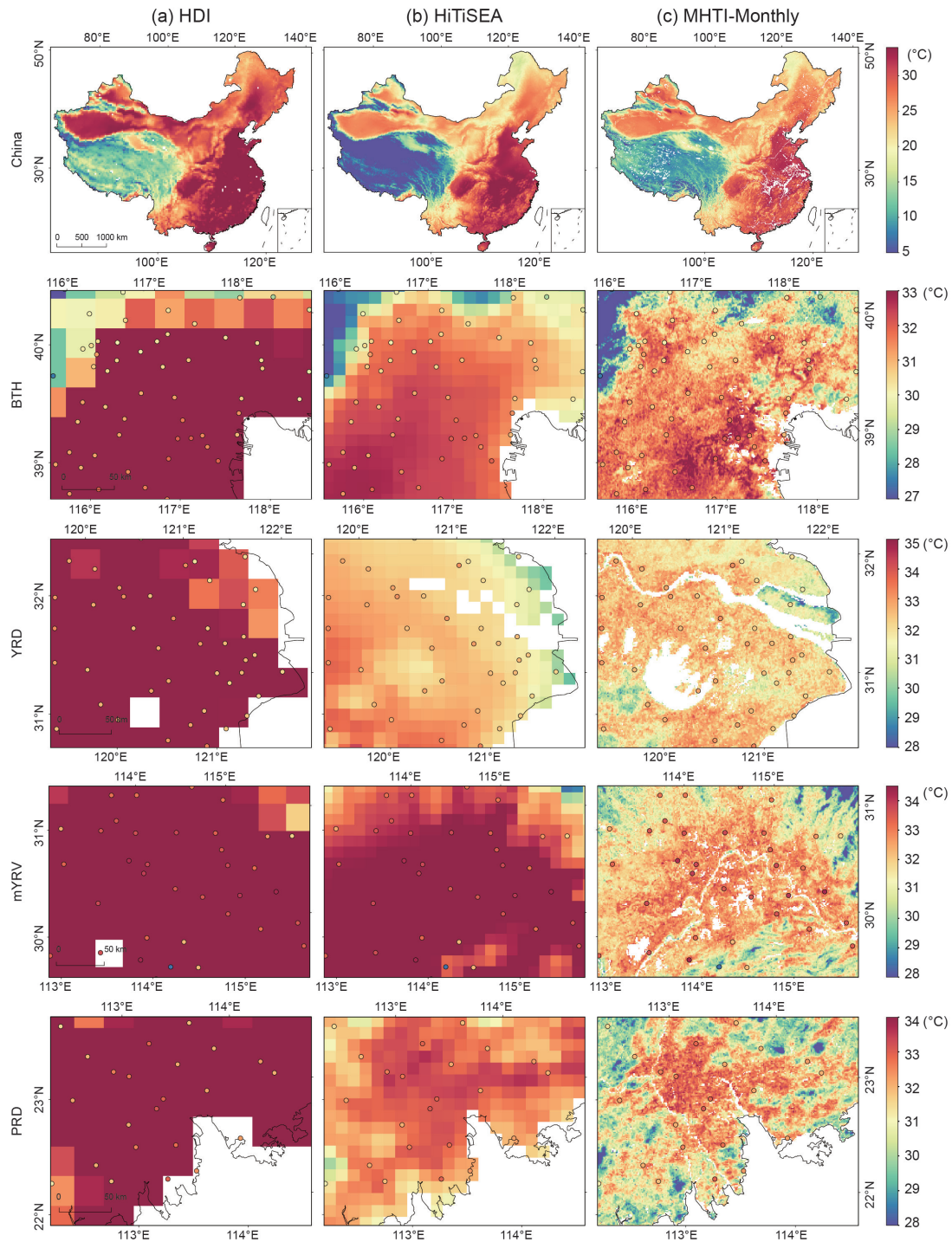
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**Figure 13. Temporal trends of the 12 annually- and seasonally-averaged human thermal indices over the mainland of China during 2003–2020. The number means linear trend per decade. The asterisk indicates that the trends are significant at the 0.05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

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858 **Figure 14. Comparison of the spatial patterns among HDI\_0p25\_1970\_2018 (HDI), HiTiSEA, and HiTiC-**

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

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

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

862

863 **Tables**864 **Table 1. Grided datasets used in this study.**

<b>Category</b>	<b>Dataset</b>	<b>Spatial Resolution</b>	<b>Temporal Resolution</b>	<b>Variables</b>	<b>Data Source</b>
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	/

865

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

Abbreviation	Human thermal index	Computation model	Reference
AT <sub>in</sub>	Apparent Temperature (indoors)	$AT_{in} = -1.3 + 0.92 \times SAT + 2.2 \times E_a$	Steadman (1979)
AT <sub>out</sub>	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)

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

870



871 **Table 3. Overall prediction accuracies of the 12 human thermal indices over the mainland of China during**  
 872 **2003–2020.**

<b>Indices</b>	<b><math>R^2</math></b>	<b><math>RMSE</math> (°C)</b>	<b><math>MAE</math> (°C)</b>	<b><math>Bias</math> (°C)</b>
SAT	0.9969	0.603	0.451	-0.001
AT <sub>in</sub>	0.9971	0.635	0.478	0.002
AT <sub>out</sub>	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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874 **Table 4. Comparisons of the four thermal index datasets.**

	<b>ERA5-HEAT</b>	<b>HDI</b>	<b>HiTiSEA</b>	<b>HiTIC- Monthly</b>
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 <sub>in</sub> , AT <sub>out</sub> , DI, ET, HI, HMI, MDI, NET, sWBGT, WBT, WCT

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