1 # HRLT: A high-resolution (1 day, 1 km) and long-term

2 # (1961–2019) gridded dataset for surface temperature

3 # and precipitation across China

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Abstract

Accurate long-term temperature and precipitation estimates at high spatial and temporal resolutions are vital for a wide variety of climatological studies. We have produced a new, publicly available, daily, gridded maximum temperature, minimum temperature, and precipitation dataset for China with a high spatial resolution of 1 km and over a long-term period (1961 to 2019). It has been named the HRLT and the dataset is publicly available at https://doi.org/10.1594/PANGAEA.941329 (Qin and Zhang, 2022). In this study, the daily gridded data were interpolated using comprehensive statistical analyses, which included machine learning methods, the generalized additive model, and thin plate splines. It was based on the 0.5° × 0.5° gridded dataset from the China Meteorological Administration, together with covariates for elevation, aspect, slope, topographic wetness index, latitude, and longitude. The accuracy of the HRLT daily dataset was assessed using observation data from meteorological stations across China. The maximum and minimum temperature estimates were more accurate than the precipitation estimates. For maximum temperature, the mean absolute error (MAE), root mean square error (RMSE), Pearson's correlation coefficient (Cor), coefficient of determination after adjustment (R^2), and Nash-Sutcliffe modeling efficiency (NSE) were 1.07 ℃, 1.62 ℃, 0.99, 0.98, and 0.98, respectively. For minimum temperature, the MAE, RMSE, Cor, R^2, and NSE were 1.08 ℃, 1.53 ℃, 0.99, 0.99, and 0.99, respectively. For precipitation, the MAE, RMSE, Cor, R^2, and NSE were 1.30 mm, 4.78 mm, 0.84, 0.71, and 0.70, respectively. The accuracy of the HRLT was compared to those of the other three existing datasets and its accuracy was either greater than the others, especially for precipitation, or comparable in accuracy, but with higher spatial resolution or over a longer time period. In summary, the HRLT dataset, which has a high spatial resolution, covers a longer period of time and has reliable accuracy.

1 Introduction

Climate change has led to an increase in the frequency and severity of extreme temperature and precipitation events (Myhre et al., 2019), and these events have affected vegetation growth (Xu et al., 2019), especially crop growth (Rao et al., 2015; Li et al., 2019b; Lu et al., 2018; Lobell et al., 2011; Lesk et al., 2016). Thus, long-term and accurate daily maximum temperature, minimum temperature, and precipitation data are important when attempting to reveal the mechanism underlying the effects of extreme climate on plants, predicting disasters (such as drought, frost, and floods), and for agricultural and forestry management. Although the meteorological observation network makes better use of the data from meteorological stations (Merino et al., 2014; Yang et al., 2014), there is a tradeoff between large spatial scale and the high density of stations in the meteorological observation network. Moreover, the installation and maintenance of meteorological stations are challenging in harsh areas (Hartl et al., 2020). Daily and gridded meteorological datasets are also essential inputs for many models related to terrestrial, hydrological, and ecological systems (Iizumi et al., 2017; Wang et al., 2018; Zhang et al., 2018; Lee et al., 2019). High-resolution, long-term, and accurate gridded datasets can help improve the performance of these models.

Researchers have previously used interpolation methods, such as inverse distance weighting, kriging, and regression analysis, to produce gridded meteorological data (Brinckmann et al., 2016; Herrera et al., 2019; Schamm et al., 2014). However, the accuracy of these interpolation results is limited by the density of the meteorological stations. In recent years, artificial intelligence, machine learning methods, such as random forest (Chen et al., 2021; Sekulić et al., 2021); artificial neural networks (Sadeghi et al., 2021), and support vector machines (He et al., 2021) have been gradually

66 and widely applied to meteorological data estimation. Therefore, comprehensive statistical analyses

67 using machine learning and traditional interpolation, such as thin-plate-smoothing splines, are

68 feasible and reliable methods that can be used to estimate meteorological data.

69   At present, only a few research institutes in China are developing meteorological datasets for

70 temperature and precipitation with high spatial and temporal resolutions. Among them, Beijing

71 Normal University has produced meteorological datasets for 1958–2010 with a resolution of 1 km,

72 but the latest data is not available (Li et al., 2014). The China Meteorological Administration is also

73 developing the CMA Land Data Assimilation System product (Shi et al., 2011) and Tsinghua

74 University has published a driving dataset from 1979 to 2018 with a resolution of 0.1° over China

75 (He et al., 2020).

76   We present a new high-resolution daily gridded maximum temperature, minimum temperature,

77 and precipitation dataset for China (HRLT) with a spatial resolution of 1×1 km for the period 1961

78 to 2019. We created the HRLT dataset using comprehensive statistical analyses, which included

79 machine learning, the generalized additive model and thin plate splines. It uses the $0.5° \times 0.5°$

80 gridded dataset from the China Meteorological Administration (CMA) as input data together with

81 other covariates, including elevation, aspect, slope, topographic wetness index (TWI), latitude, and

82 longitude. The dataset was created in three steps: (1) preparation of input data and covariates; (2)

83 the creation of the gridded dataset using comprehensive statistical analyses; and (3) an evaluation

84 of the accuracy of the gridded dataset and accuracy comparison with other three exiting products

85 that use meteorological station data.

2 Data

2.1 The CMA dataset and meteorological stations data

The CMA dataset, which includes the daily surface temperature $0.5° \times 0.5°$ gridded dataset and the daily precipitation $0.5° \times 0.5°$ gridded dataset for China (V2.0) (https://data.cma.cn/, last access: 15 September, 2022), was obtained from the China Meteorological Data Service Centre and was used as the basic input data. The researchers also reported daily precipitation $0.5° \times 0.5°$ gridded dataset during 1961-2010 from CAM dataset (Zhao and Zhu, 2015). The daily dataset of surface climatological data for China (V3.0) (https://data.cma.cn/, last access: 15 September, 2022), which includes 699 meteorological stations, was also obtained from the China Meteorological Data Service Centre and was used to evaluate the new dataset (Fig. 1).

2.2 Topographic data

The basic topographic data, including elevation, flow direction, and flow accumulation with a 30 second (approximately 1 km) resolution, were obtained from the HydroSHEDS database. More detailed information can be found at these links: http://www.worldwildlife.org/hydrosheds (last access: 15 September, 2022) for general information and http://hydrosheds.cr.usgs.gov (last access: 15 September, 2022) for data download and technical information. The "Aspect" and "Slope" option of the Spatial Analyst Tools in ArcGIS10.6 were used to calculate aspect and slope. The specific catchment area (SCA) was calculated based on flow direction and flow accumulation. The TWI is formulated as follow:

$$\text{TWI} = ln(\frac{\text{SCA}}{\text{tan(Slope)}}) \tag{1}$$

where TWI and SCA is topographic wetness index and specific catchment area, respectively.

2.3 Other datasets

We used observed data from meteorological stations (Fig. 1) to evaluate our dataset and the existing three daily datasets, then the accuracy of the existing three daily datasets was compared to that of our dataset, respectively. The China Meteorological Administration Land Data Assimilation System (CLDAS) version 2 dataset was provided by the China Meteorological Data Service Centre (https://data.cma.cn/, last access: 15 September, 2022) for 2017 to 2019 with a 0.0625° (approximately 7.5 km) spatial resolution and a 1 day temporal resolution. The China Meteorological Forcing Dataset (CMFD) (He et al., 2020; Yang and He, 2019) was obtained from the National Tibetan Plateau Third Pole Environment Data Center (https://data.tpdc.ac.cn/ , last access: 15 September, 2022) for 1979 to 2018 with a spatial resolution of 0.1° (approximately 12 km) and a temporal resolution of 1 day. The historical dataset relating to the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP3a) was obtained from the web (https://data.isimip.org/ , last access: 15 September, 2022) for 1961 to 2016 with a spatial resolution of 0.5° (approximately 60 km) and a temporal resolution of 1 day. The daily maximum temperature, minimum temperature, and precipitation data in the CLDAS and ISIMIP3a were used for evaluation and comparison. The daily average temperature and precipitation data from the CMFD was also used for evaluation and comparison.

3 Methods

3.1 The input data and covariates

In this study, the input data (dependent variable) was the daily 0.5° × 0.5° CMA dataset, which includes daily maximum temperature, minimum temperature and precipitation. Other covariates

127 (independent variables) included elevation, aspect, slope, TWI (with a spatial resolution of 1 km),

128 latitude, and longitude.

129 **3.2 The interpolation scheme**

130 As shown in Figure 2, the different combinations of six algorithms, which are the boosted

131 regression trees (BRT), random forests (RF), neural networks (NN), multivariate adaptive

132 regression splines (MAR), support vector machines (SVM) and the generalized additive model

133 (GAM), to predict the input data. Firstly, through k-fold cross validation (k = 10), the input data was

134 randomly divided into 10 sub-training datasets and sub-testing datasets. Each algorithm runs in a

135 loop through all the sub-training sets and calculates the residuals from the sub-testing sets. The

136 residuals obtained in each loop are retained. The residual of each algorithm is assigned a weight of

137 0-1 and summed up, and the ensemble of models that has the lowest residual sum is chosen. After

138 determining the best ensemble of models, surface results were interpolated using the best ensemble

139 of models, input data and covariates. The thin-plate-smoothing splines (TPS) is used to correct

140 residual error from the ensemble of models. Therefore, residuals of the ensemble are calculated from

141 the input data and these values are interpolated using TPS. Surface results from the ensemble add

142 residuals from the thin-plate-smoothing splines to get the surface result of final model. Compare R^2

143 of surface result from the ensemble and final model, and retain the surface result with higher R^2.

144 **3.3 The interpolation methods**

145 The introduction of individual algorithm (method) and the implementations for model training

146 (R packages and functions) of that is as follows. After the model training, the function 'predict' in

147 R package 'raster' used to implemented spatial interpolation for BRT, RF, NN, MAR, SVM and

148 GAM model, and the function 'interpolate' in R package 'raster' used to spatial interpolation for

149 TPS. More details on R packages and functions could refer the web

150 (https://www.rdocumentation.org/ , last access: 15 September, 2022).

3.3.1 The BRT model

152   As a powerful tool for exploratory regression analysis, BRT is a combination of two techniques:

153 decision trees and boosting method (Elith et al., 2008). The BRT can automatically detect the best

154 fit and is robust to missing values and outliers, therefore, BRT now widely used in remote sensing,

155 species distribution and meteorological interpolation (Pouteau et al., 2011; Appelhans et al., 2015;

156 Froeschke and Froeschke, 2011). There are two important parameters in BRT, (1) the tree

157 complexity (TC): this controls the number of splits in each tree. (2) learning rate (LR): this

158 determines the contribution of each tree to the growth model. The smaller value of LR, the more

159 trees will be built. These two parameters together determine the number of trees required for the

160 best prediction in order to find the combination of parameters that leads to the least prediction error.

161 The function 'gbm.step' in R package 'dismo' for the BRT implementation. The tree complexity

162 was set at 5, the learning rate was set at 0.001. In addition, the 'bag.fraction', which specifies the

163 proportion of data to be selected at each step, was set at 0.5 and other parameters are default values

164 in 'gbm.step'.

3.3.2 The RF model

166   Like BRT, the main technology of RF also includes decision trees, however, the way in which

167 the data to build the trees is selected is different (boosting method for BRT, bagging method for RF).

168 For regression analysis, the bagging method, which take a random subset of all data for each new

169 tree that is built, makes the final output based on average of multiple trees (Breiman, 2001). As one

170 of the most accurate algorithms, RF has been used widely for predicting spatio-temporal variables,

171 such as temperature and precipitation (He et al., 2016; Mital et al., 2020; Webb et al., 2016). The

172 function 'randomForest' in R package 'randomForest' for the RF implementation. The importance

173 was set TRUE, and other parameters are default values in 'randomForest'.

174 **3.3.3 The NN model**

175 As a powerful set of tools for solving problems in pattern recognition, data processing, and

176 non-linear control (Bishop, 1994), the NN consists of a large number of nodes and connections and

177 it includes input layer, hidden layer and output layer (Lek and Guégan, 1999). Information from

178 each node in the input layer is fed to the hidden layer. Connections between input layer nodes and

179 hidden layer nodes can all be given specific weights according to their importance. The connection

180 between the hidden layer and the output layer is also weighted, so the output is the result of the

181 weighted sum of the hidden nodes. Information transfer between hidden layer and output layer

182 through transfer function. Since the 1980s, the NN has been used in a number of fields, such as

183 prediction for meteorological variables (Snell et al., 2000; Lek and Guégan, 1999; Tang et al., 2020).

184 The function 'nnet' in R package 'nnet' for the NN implementation. The number of units in the

185 hidden layer (size) was set 10, the transfer function is linear for the output layer (linout was set

186 TRUE), the maximum number of iterations (maxit) was set 10000, and other parameters are default

187 values in 'nnet'.

188 **3.3.4 The MAR model**

189 The MAR is an extension of linear model, which can build multiple linear regression models

190 within the range of predictive variable values by partitioning data (Friedman, 1991; Friedman and

191 Roosen, 1995). The MAR consists of two steps: firstly, it creates a set of so-called basis functions.

192   In this process, the range of predictive variable values is divided into several groups. For each group,

193   separate linear regression was modeled. Secondly, MAR estimates a least square model with its

194   basis function as the independent variable. Overfitting is avoided by iterating to remove the basis

195   functions that contribute least to the model fitting. The MAR works well with a large number of

196   predictor variables, automatically detects interactions between variables and is robust to outliers,

197   therefore, studies has done on downscaling or predicting meteorological data using MAR (Panda et

198   al., 2022; Li et al., 2019a; Zawadzka et al., 2020). The function 'earth' in R package 'earth' for the

199   MAR implementation. Use linear model to estimate standard deviation as a function of the predicted

200   response (varmod.method = 'lm'). The nfold was set 10, the ncross was set 30, and other parameters

201   are default values in 'earth'.

202   **3.3.5 The SVM model**

203   The SVM is also one of the machine learning supervised algorithms and mainly deals with the

204   ideas of classification and regression (Vapnik, 1999; Vapnik, 1991; Brereton and Lloyd, 2010). The

205   SVM is well supported by mathematical theory and can use kernel tricks to efficiently process non-

206   linear data. With the development of SVM, it also has been widely used in the regression and

207   prediction of meteorological variables (Belaid and Mellit, 2016; Chen et al., 2010; Tripathi et al.,

208   2006). In this study, the function 'ksvm' in R package 'kernlab' for the SVM implementation and

209   all parameters are default values in 'ksvm'.

210   **3.3.6 The GAM model**

211   The GAM is an extension of the generalized linear model (GLM). Like GLM, GAM consists

212   of three important components: the probability distribution of the dependent variable, the linear

213   predictor and the link function, however, in GAM, the coefficient of the independent variable in the

214 linear is replaced by a sum of smooth functions (Hastie and Tibshirani, 2017; Liu, 2008). Because

215 the GAM can deal with nonlinear and non-monotone relationships between dependent and

216 independent variables, it has been used to predict and interpolate meteorological data (Hjort et al.,

217 2016; Burnett and Anderson, 2019; Aalto et al., 2013). The function 'gam' in R package 'mgcv' for

218 the GAM implementation and all parameters are default values in 'gam'.

219 **3.3.7 The TPS method**

220 As a traditional interpolation method, the TPS has been widely used to spatially interpolate

221 surface climate data (Gong et al., 2022; Hancock and Hutchinson, 2006; Risk and James, 2022). In

222 this study, it used to correct residual error from the ensemble of models. The function 'Tps' in R

223 package 'fields' for the TPS implementation. The matrix of independent variables consists latitude

224 and longitude, the vector of dependent variables is residual error in the combinations of above

225 algorithms, and other parameters are default values in 'Tps'.

226 **3.4 The interpolation implementation**

227 A complete operation was constructed per day per variable, so there were 64647 operations

228 (21549 days × 3 variables) from January 1, 1961 to December 31, 2019 for maximum temperature,

229 minimum temperature and precipitation. A complete operation for a day per variable requires a

230 Central Processing Unit core, 18 G of operating memory, and 2 hours of time. In order to shorten

231 the running time, we carried out parallel computing on a supercomputer platform. Spatial

232 interpolation work was executed by R version 4.0.2 (R Core Team, 2018) and the R package

233 "machisplin" (Brown, 2019) was referenced to achieve it.

3.5 Evaluation metrics

The mean absolute error (MAE), root mean square error (RMSE), Pearson's correlation coefficient (Cor), coefficient of determination after adjustment (R^2), and Nash-Sutcliffe modeling efficiency (NSE) were used to evaluate the interpolation results. Pearson's correlation coefficient was used to evaluate the correlation between the simulated and observed values and the other metrics are defined separately as follows:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |S_i - O_i| \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (S_i - O_i)^2} \tag{3}$$

$$R^2 = 1 - (1 - \frac{\sum_{i=1}^{n}(S_i - \bar{O})^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2}) \frac{(n-1)}{(n-k-1)} \tag{4}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \tag{5}$$

where S_i and O_i are the model predicted and the experimentally observed values, respectively; $\bar{O}$ is the mean of the observed values; n is the number of observations; and k is the value of the independent variable. High Cor, R^2, and NSE values, and small RMSE and MAE values indicate the strength of agreement between the predicted and observed values.

4 Results and discussion

4.1 Validation of temperature and precipitation

The spatial interpolation results, including daily maximum temperature, minimum temperature, and precipitation, were validated using meteorological station data. The results of the validation

248   showed that the daily maximum and minimum temperatures were highly accurate (Fig. 3 and Table

249   1). The fitting slopes between the simulated and observed values were both close to 1 and the

250   coefficients of determination after adjustment were 0.98 and 0.99, respectively, for daily maximum

251   and minimum temperature (Figs. 3a, b). As shown in Table 1, the MAE was 1.07 °C and 1.08 °C,

252   and the RMSE was 1.62 °C and 1.53 °C for daily maximum and minimum temperatures, respectively.

253   In addition, the Cor and NSE values were close to 1 for both the daily maximum and minimum

254   temperatures. Daily precipitation was less accurate than temperature with an R^2 of 0.71 (Fig. 3c),

255   which was mainly caused by underestimating high daily precipitation. However, most of the points

256   were concentrated in the low daily precipitation section. Furthermore, the MAE and RMSE for daily

257   precipitation were 1.30 mm and 4.78 mm, respectively; the Cor between the simulated and observed

258   daily precipitation was 0.84, and the NSE was 0.70 (Table 1).

259   The interpolation accuracy shows spatial differences (Fig. 4). The R^2 values of the daily

260   maximum and minimum temperatures in southwest China were less than 0.94 and lower than those

261   for other regions (Figs. 4a, c). The mean absolute errors for the daily maximum and minimum

262   temperature ranges at most meteorological stations were less than 1 °C. However, there were some

263   meteorological stations with mean absolute errors of more than 2 °C and these were evenly

264   distributed across China (Figs. 4b, d). The R^2 value for daily precipitation at most meteorological

265   stations was greater than 0.7 and the MAE decreased from south to north across China (Figs. 4e, f).

266   For precipitation where the R^2 map (Fig. 4e) shows a west-east gradient in the scores that is

267   different from the north-south gradient in the MAE map (Fig. 4f). There are fewer meteorological

268   observation stations in the western region than in the eastern region, which may lead to the subtle

269 east-west gradient of the R^2 value for daily precipitation. The obvious north-south gradient for

270 MAE of daily precipitation could be caused by the rainfall frequency (Fig. 4f, Fig. 5), the MAE of

271 monthly precipitation in China from other study showed a similar pattern (Peng et al., 2019).

272 Rainfall frequency above light rainfall, which is defined as a daily rainfall from 0 to 4 mm (Alpert et

273 al., 2002), is strongly correlated with the MAE of daily precipitation (illustration in Fig. 5), so that

274 the MAE of daily precipitation in the southern region with higher rainfall frequency is larger than

275 that in the northern region with lower rainfall frequency.

276   The meteorological stations were divided into the middle and lower reaches of the Yangtze

277 River (MLYR), North China (NC), Northeast China (NEC), Northwest China (NWC), South China

278 (SC), and Southwest China (SWC) (Fig. 1) according to their diverse geographic and climatic

279 conditions and administrative areas (Qin, et al., 2022). The cumulative distribution functions curve

280 trend of difference between the simulated and observed values was always similar for daily

281 maximum temperature, minimum temperature, and precipitation in the six regions, as well as in

282 whole China. The daily maximum and minimum temperatures were all underestimated in the MLYR,

283 NEC, NWC, SC, and SWC (Fig. 6a). The daily minimum temperatures were all underestimated in

284 the MLYR, NC, NWC, SC, and SWC (Fig. 6b). For both daily maximum and minimum

285 temperatures, the lowest average difference between the simulated and observed values occurred in

286 NC and NEC, while the greatest difference occurred in SWC (Figs. 6a,b). Except in the NWC region,

287 the average difference between simulated and observed values for daily precipitation was less than

288 0 mm in the other regions (Fig. 6c). The largest averages difference between simulated and observed

289 for daily precipitation occurred in the SC region, with a value of 0.49 mm (Fig. 6c). Across whole

290   China, the average difference between simulated and observed values for daily maximum

291   temperature, minimum temperature, and precipitation was 0.36 ℃, 0.30 ℃ and 0.12 mm,

292   respectively.

4.2 Temporal and spatial distributions of temperature and precipitation

294   The results showed that detailed spatial changes in temperature and precipitation over time

295   could be obtained (Fig. 7). For example, the increase in annual average values (both maximum

296   temperature and minimum temperature) were obvious over the Tibetan Plateau from 1965 to 2010

297   (Figs. 7a–h, the d1 and h1 subregions). In addition, compared with other years, the annual average

298   daily minimum temperature clearly increased in some areas of NWC (Figs. 7e–h, the h2 and h3

299   subregions) and MLYR (Figs. 7e–h, the h4 subregion) in 2010. The most significant annual

300   precipitation changes occurred in NEC (Figs. 7i–l, the l1 subregion) between 1965 and 2010.

301   The distributions of annual average daily maximum and minimum temperatures and annual

302   precipitation across the six regions of China in 1965, 1980, 1995, and 2010 were analyzed (Fig. 8).

303   Compared with other years, the areas with smaller values for annual average daily maximum

304   temperature (less than 0) and annual average daily minimum temperature (less than −10) in SWC

305   and NWC decreased in 2010 (Figs. 8a1, 8a2, 8b1, 8b2). These areas are mainly distributed on the

306   Qinghai-Tibet Plateau, which has seen a large increase in temperature over the past few decades.

307   The density distribution peak for the annual average daily maximum and minimum temperatures in

308   NEC moved to the right from 1965 to 1995, but moved to the left in 2010 (Figs. 8a3, 8b3). The

309   mean annual average daily minimum temperature in 2010 was higher in the MLYR, NC, and SC

310   than in the other three years (Figs. 8b4–6). There was an increase in mean annual precipitation in

311 the northern part of China over the period 1965–2010 (Figs. 8c2–4). It increased from 335 mm to

312 415 mm across NWC (Fig. 8c2), from 487 mm to 593 mm across NEC (Fig. 8c3), and from 531

313 mm to 654 mm across NC (Fig. 8c4). In the MLYR, there were more areas with annual precipitation

314 of less than 1000 mm, and areas with an annual precipitation of more than 2000 mm increased in

315 1995 and 2010 compared 1965 and 1980 (Fig. 8c5). Similarly, compared with other years, there

316 were more areas with annual precipitation of less than 1000 mm and more than 2000 mm in SC in

317 2010 (Fig. 8c6).

318 **4.3 Accuracy comparison with other products**

319   The performances of the CMFD, CLDAS and ISIMIP3a generated daily temperatures and

320 precipitations were evaluated against observations from all the meteorological stations and

321 compared their performance with that of our dataset (Figs. 9–11; Tables 2–4). The fitting slopes

322 between the simulated and observed daily temperature values were always close to 1 for all datasets

323 (Figs. 9a–c; Figs. 10a–d; Figs. 11a–d). The R^2 for the CMFD daily average temperature was

324 slightly smaller than that for daily minimum temperature in our dataset (Figs. 9b, c), but was equal

325 to our data set for daily maximum temperature (Figs. 9a, c). The Cor and NSE for the CMFD daily

326 average temperature were also similar to our estimated daily maximum and minimum temperatures

327 (Table 2). By contrast, the MAE and RMSE for the CMFD daily average temperature were 1.12 ℃

328 and 1.64 ℃, respectively, which were greater than for our estimated daily maximum and minimum

329 temperatures (Table 2). The MAEs of daily maximum and minimum temperature for our dataset

330 were 1.07 ℃ and 1.08 ℃ respectively; and the RMSEs of daily maximum and minimum

331 temperature for our dataset were 1.63 ℃ and 1.54 ℃, respectively, between 1979 and 2018 (Table

332   2). The R^2, Cor, NSE, MAE, and RMSE for the CLDAS daily maximum temperatures were 0.91,

333   0.95, 0.90, 2.54 °C, and 3.63 °C, respectively. Accuracy clearly improved for our daily maximum

334   temperature, and the corresponding metrics were 0.98, 0.99, 0.98, 1.10 °C, and 1.73 °C (Figs. 10a,

335   b; Table 3). The MAE and RMSE for the CLDAS daily minimum temperature were clearly higher

336   than our estimates for daily minimum temperature, and the R^2, Cor, and NSE for daily minimum

337   temperature in our dataset were higher than those for the CLDAS daily minimum temperature (Figs.

338   10c, d; Table 3), thus indicating that the accuracy of our daily minimum temperature estimates was

339   superior to that of the CLDAS daily minimum temperature product. Compared with the ISIMIP3a,

340   the R^2, Cor, and NSE of daily maximum and minimum temperature in our dataset are always higher

341   and the MAE and RMSE of these are always smaller (Figs. 11 a–d; Table 4).

342   The R^2 value for our estimated daily precipitation clearly improved compared to the other

343   three datasets, especially the ISIMIP3a and CLDAS dataset (Figs. 9d, e; Figs. 10e, f; Figs. 11e, f).

344   The Cor and NSE for the CMFD daily precipitation were obviously smaller than those for our

345   dataset, and the RMSE for CMFD daily precipitation were greater than those for our dataset (Table

346   2). During 2017–2019, the Cor, NSE, MAE, and RMSE for our estimated daily precipitation were

347   0.84, 0.70, 1.42 mm, and 4.93 mm, respectively, and the corresponding values for the CLDAS daily

348   precipitation changed to 0.58, 0.28, 2.36 mm, and 7.67 mm, respectively (Table 3). During 1961–

349   2016, the Cor, NSE, MAE, and RMSE for our estimated daily precipitation were 0.84, 0.70, 1.30

350   mm, and 4.78 mm, respectively, and the corresponding values for the ISIMIP3a daily precipitation

351   changed to 0.48, 0.14, 2.75 mm, and 8.10 mm, respectively (Table 4). Thus, the daily precipitation

352   accuracy of our dataset was generally higher than that of CMFD, CLDAS and ISIMIP3a.

5 Data availability

The HRLT dataset includes daily maximum temperature, minimum temperature, and precipitation at a 1 km spatial resolution across China from January 1961 to December 2019. The datasets are publicly available in NetCDF format at https://doi.org/10.1594/PANGAEA.941329 (Qin and Zhang, 2022).

6 Conclusions

The result of this study is a high-resolution (1 km) daily gridded maximum temperature, minimum temperature and precipitation dataset across China for the long-term (1961–2019) (HRLT). The HRLT dataset shows an overall high correlation with the observations from meteorological stations for daily maximum and minimum temperatures (R^2 was 0.98 and 0.99, respectively; Cor were both 0.99; NSE was 0.98 and 0.99, respectively) and the errors were smaller (MAE was 1.07 ℃ and 1.08 ℃, respectively; RMSE was 1.62 ℃ and 1.53 ℃, respectively). Although the HRLT dataset showed that the daily precipitation accuracy was lower than the daily temperature accuracy (R^2, Cor, NSE, MAE, and RMSE were 0.71, 0.84, 0.70, 1.30 mm, and 4.78 mm, respectively), the daily precipitation data in the HRLT dataset were more accurate and had a finer spatial resolution compared to the other three existing datasets (CMFD, CLDAS and ISIMIP3a). Furthermore, the accuracies for daily maximum and minimum temperatures and precipitation were lower in the southwestern part of China, probably because of the complex topography in that area compared to other areas. Calculation and interpolation by subregions may solve this problem in future studies. The use of satellite data as an input covariate in future studies will further improve the accuracy of the HRLT dataset, especially for precipitation. The HRLT

374 dataset will help identify future extreme climatic events and can be also used to improve process-

375 based models for prediction, adaptation, and mitigation strategies.

Author contributions

377   Rongzhu Qin and Feng Zhang calculated the dataset, analyzed the results, and wrote the

378 manuscript; all other authors reviewed and revised the manuscript.

Competing interests

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

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Table 1 Summary of the accuracies for the HRLT datasets using data from the meteorological stations

Variable	MAE	RMSE	Cor	NSE	N	Period
Maximum temperature (℃)	1.07	1.62	0.99	0.98	14731830	1961–2019
Minimum temperature (℃)	1.08	1.53	0.99	0.99	14730410	1961–2019
Precipitation (mm)	1.30	4.78	0.84	0.70	14730380	1961–2019

MAE, RMSE, Cor, and NSE are the mean absolute error, root mean square error, Pearson's correlation coefficient, and Nash-Sutcliffe modeling efficiency, respectively. N is the number of observations and Period is the beginning to end years of the data.

Table 2 Comparison of accuracies for the HRLT and CMFD datasets using data from the meteorological stations

Variable	Dataset	MAE	RMSE	Cor	NSE	N	Period
Maximum temperature (℃)	HRLT	1.07	1.63	0.99	0.98	9969602	1979–2018
Minimum temperature (℃)	HRLT	1.08	1.54	0.99	0.99	9969602	1979–2018
Average temperature (℃)	CMFD	1.12	1.64	0.99	0.98	9969602	1979–2018
Precipitation (mm)	HRLT	1.30	4.73	0.84	0.71	9968784	1979–2018
	CMFD	1.30	5.85	0.75	0.55	9968784	1979–2018

MAE, RMSE, Cor, and NSE are the mean absolute error, root mean square error, Pearson's correlation coefficient, and Nash-Sutcliffe modeling efficiency, respectively. N is the number of observations and Period is the beginning to end years of the data.

Table 3 Comparison of accuracies for the HRLT and the CLDAS datasets using data from the meteorological stations

Variable	Dataset	MAE	RMSE	Cor	NSE	N	Period
Maximum	HRLT	1.10	1.73	0.99	0.98	686653	2017–2019
temperature (℃)	CLDAS	2.54	3.63	0.95	0.90	686653	2017–2019
Minimum	HRLT	1.14	1.65	0.99	0.98	686653	2017–2019
temperature (℃)	CLDAS	1.58	2.63	0.98	0.95	686653	2017–2019
Precipitation	HRLT	1.42	4.93	0.84	0.70	685936	2017–2019
(mm)	CLDAS	2.36	7.67	0.58	0.28	685936	2017–2019

MAE, RMSE, Cor, and NSE are the mean absolute error, root mean square error, Pearson's correlation coefficient, and Nash-Sutcliffe modeling efficiency, respectively. N is the number of observations and Period is the beginning to end years of the data.

Table 4 Comparison of accuracies for the HRLT and the ISIMP3a datasets using data from the meteorological stations

Variable	Dataset	MAE	RMSE	Cor	NSE	N	Period
Maximum	HRLT	1.06	1.61	0.99	0.98	13973110	1961–2016
temperature (℃)	ISIMP3a	2.47	3.47	0.96	0.91	13973110	1961–2016
Minimum	HRLT	1.07	1.52	0.99	0.99	13971690	1961–2016
temperature (℃)	ISIMP3a	2.63	3.60	0.96	0.92	13971690	1961–2016
Precipitation	HRLT	1.30	4.78	0.84	0.70	13971680	1961–2016
(mm)	ISIMP3a	2.75	8.10	0.48	0.14	13971680	1961–2016

MAE, RMSE, Cor, and NSE are the mean absolute error, root mean square error, Pearson's correlation coefficient, and Nash-Sutcliffe modeling efficiency, respectively. N is the number of observations and Period is the beginning to end years of the data.
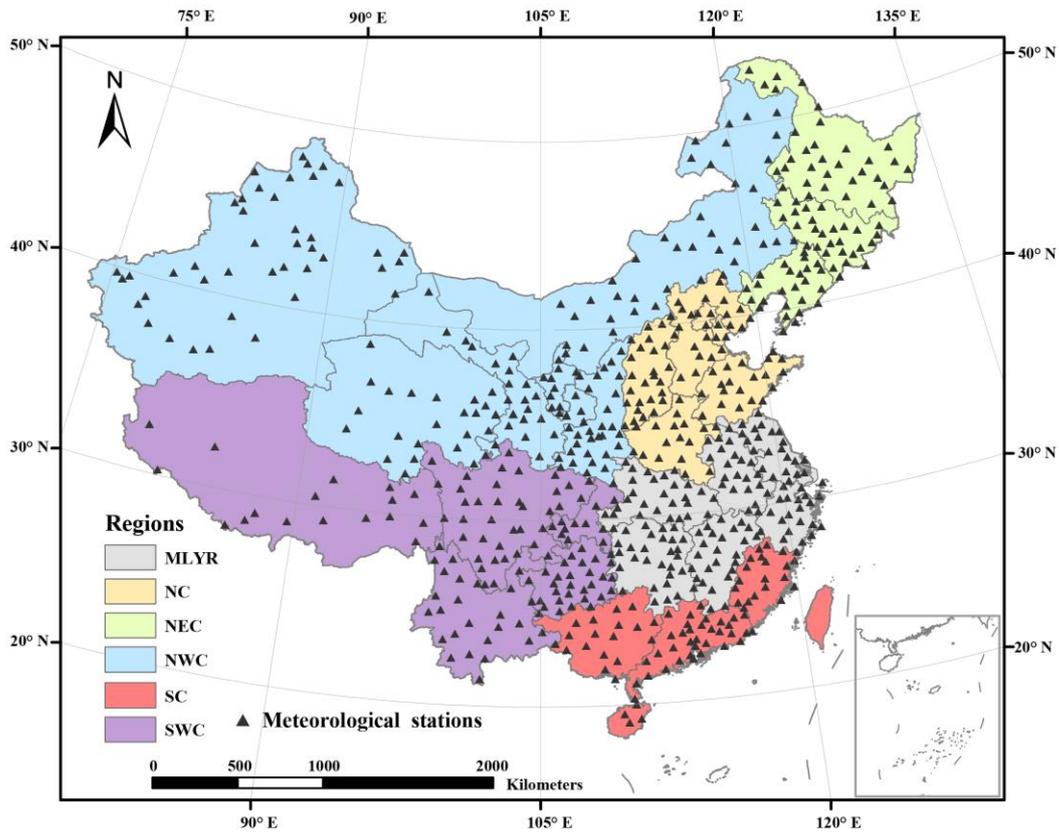
Figure 1. Regions and spatial distribution of the meteorological stations in China. MLYR, NC, NEC, NWC, SC, and SWC are the Middle and Lower reaches of the Yangtze River, North China, Northeast China, Northwest China, South China, and Southwest China, respectively. Note: meteorological stations data were missing for Taiwan Province.
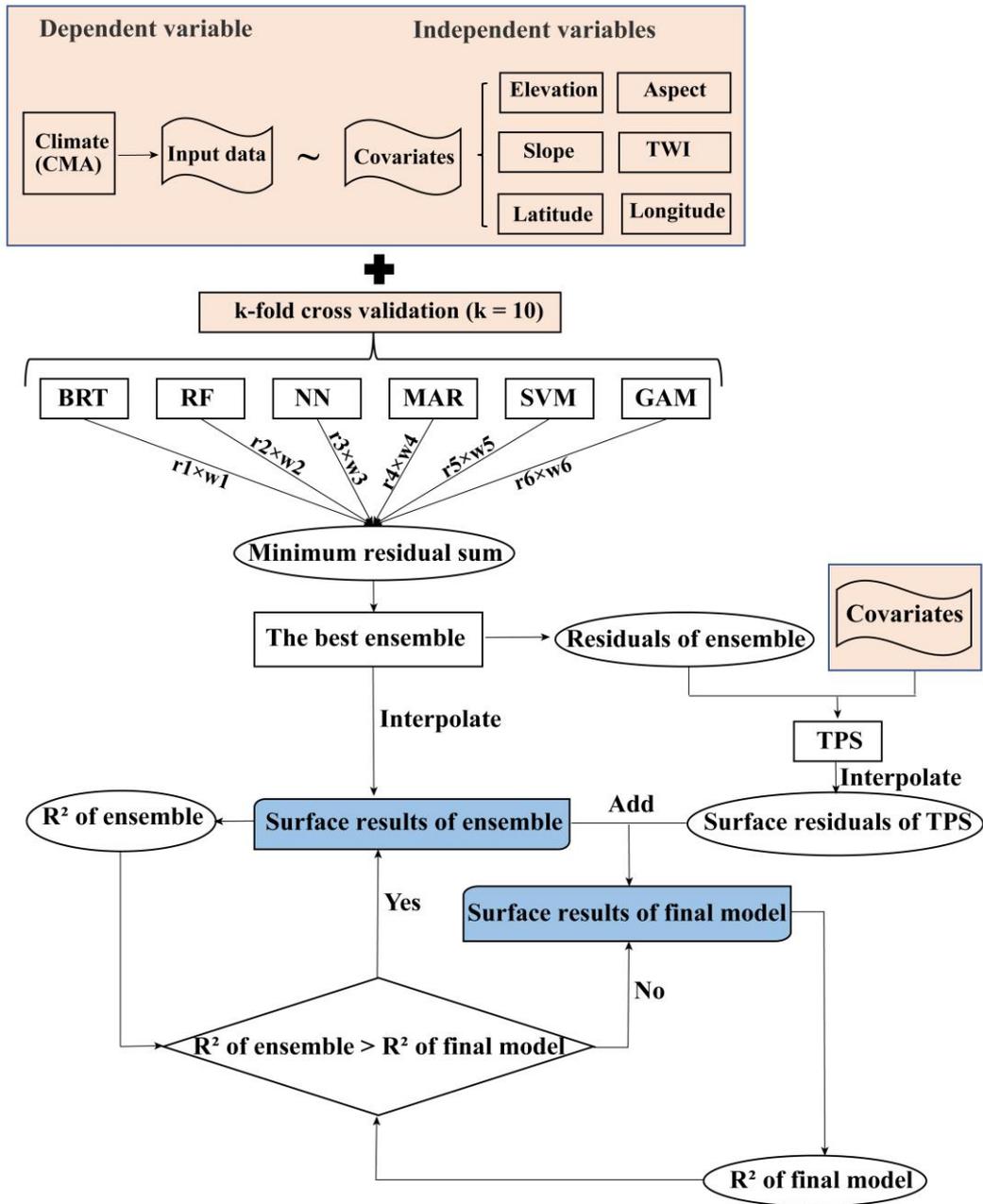
Figure 2. The process of spatial interpolation. The r1 to r6 are the residual error from each algorithm, respectively. The w1 to w6 are the weights of each algorithm, respectively. BRT, RF, NN, MAR, SVR, GAM and TPS are the boosted regression trees, random forests, neural networks, multivariate adaptive regression splines, support vector machines, the generalized additive model and thin-plate-smoothing splines, respectively. R^2 is the coefficient of determination between the estimated and observed values. The TWI is topographic wetness index.
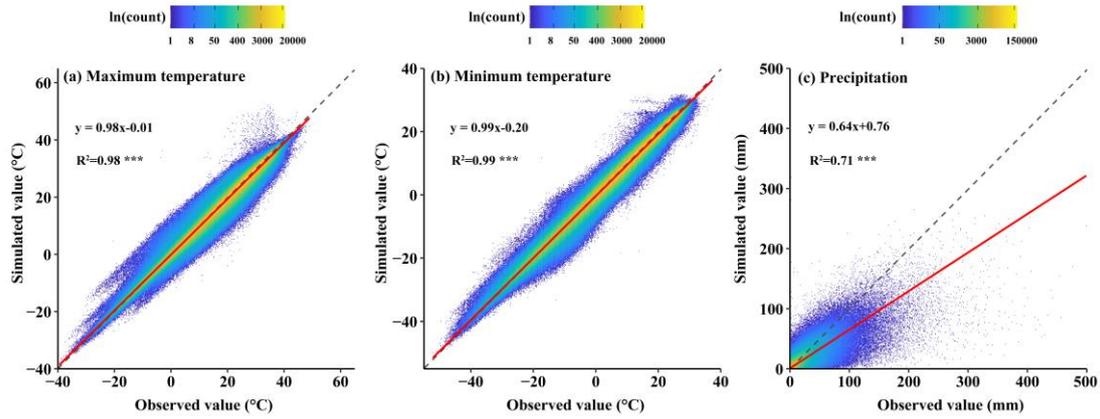
Figure 3. Scatter density plots of daily maximum and minimum temperatures and precipitation between estimated and observed values at meteorological stations were used to test the HRLT dataset. Dashed line is a line with slope 1 and the red line is a fitting between estimated and observed values. R^2 is the coefficient of determination between the estimated and observed values. *** asterisks indicate that the significance of the regression equation between the estimated and observed values was $p < 0.001$.
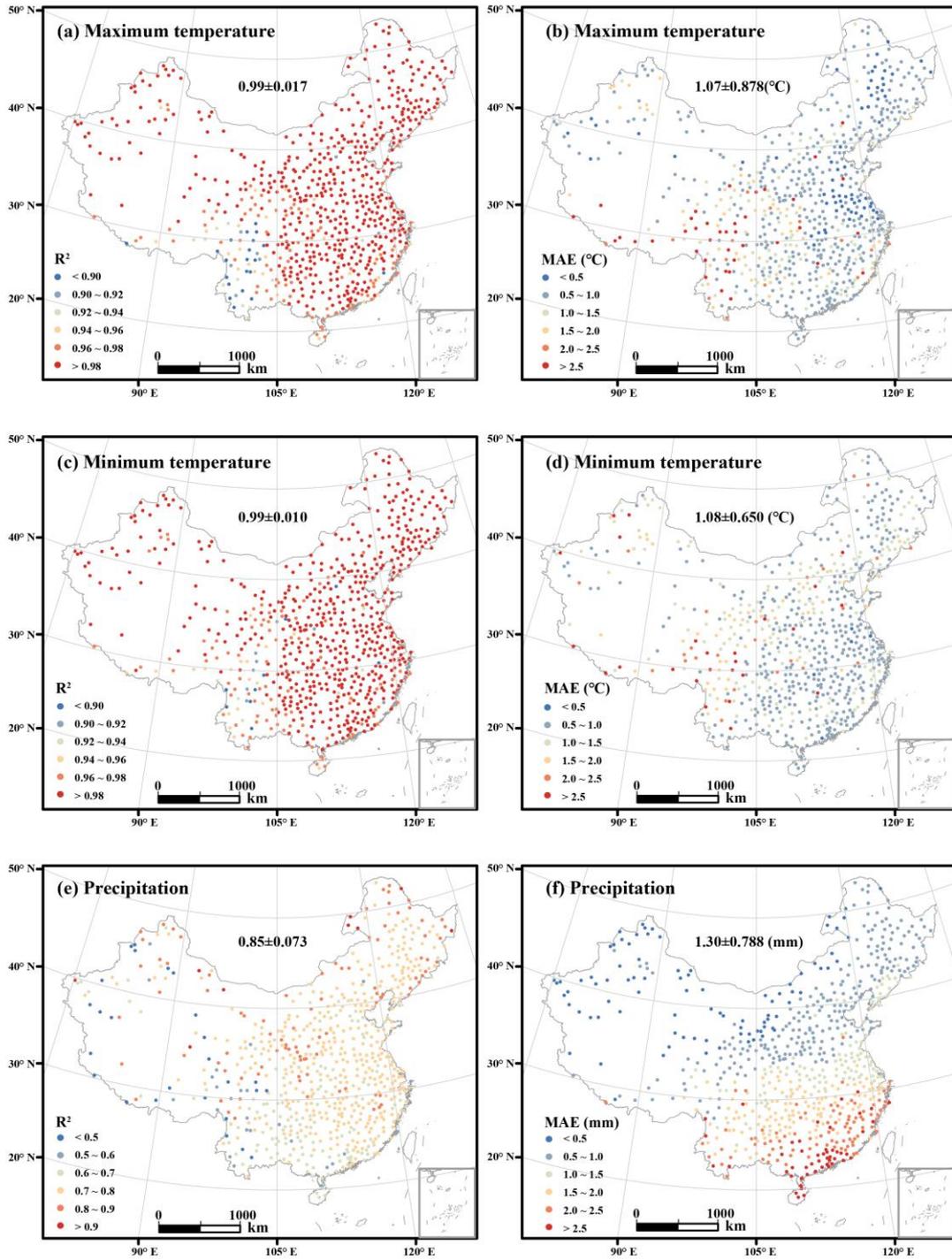
Figure 4. Spatial distribution of R^2 and MAE for daily maximum temperature, minimum temperature, and precipitation between 1961 and 2019. The value before the $\pm$ is the R^2 or MAE mean value and the value after the $\pm$ is the R^2 or MAE standard deviation for all meteorological stations.
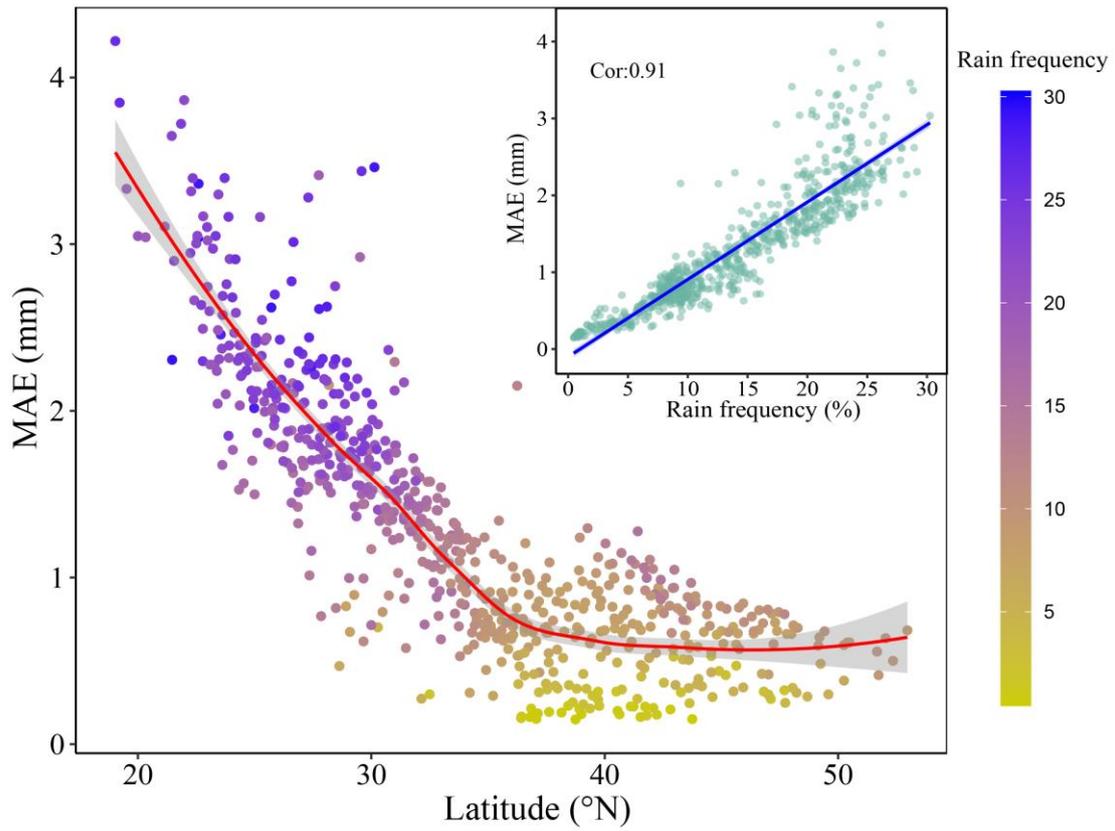
Figure 5. The relationship between latitude and MAE of daily precipitation. Illustration indicates the relationship between rainfall frequency above light rainfall and MAE of daily precipitation. MAE is the mean absolute error, Cor is Pearson's correlation coefficient, Rain frequency is rainfall frequency above light rainfall, which is defined as a daily rainfall from 0 to 4 mm (Alpert et al., 2002)
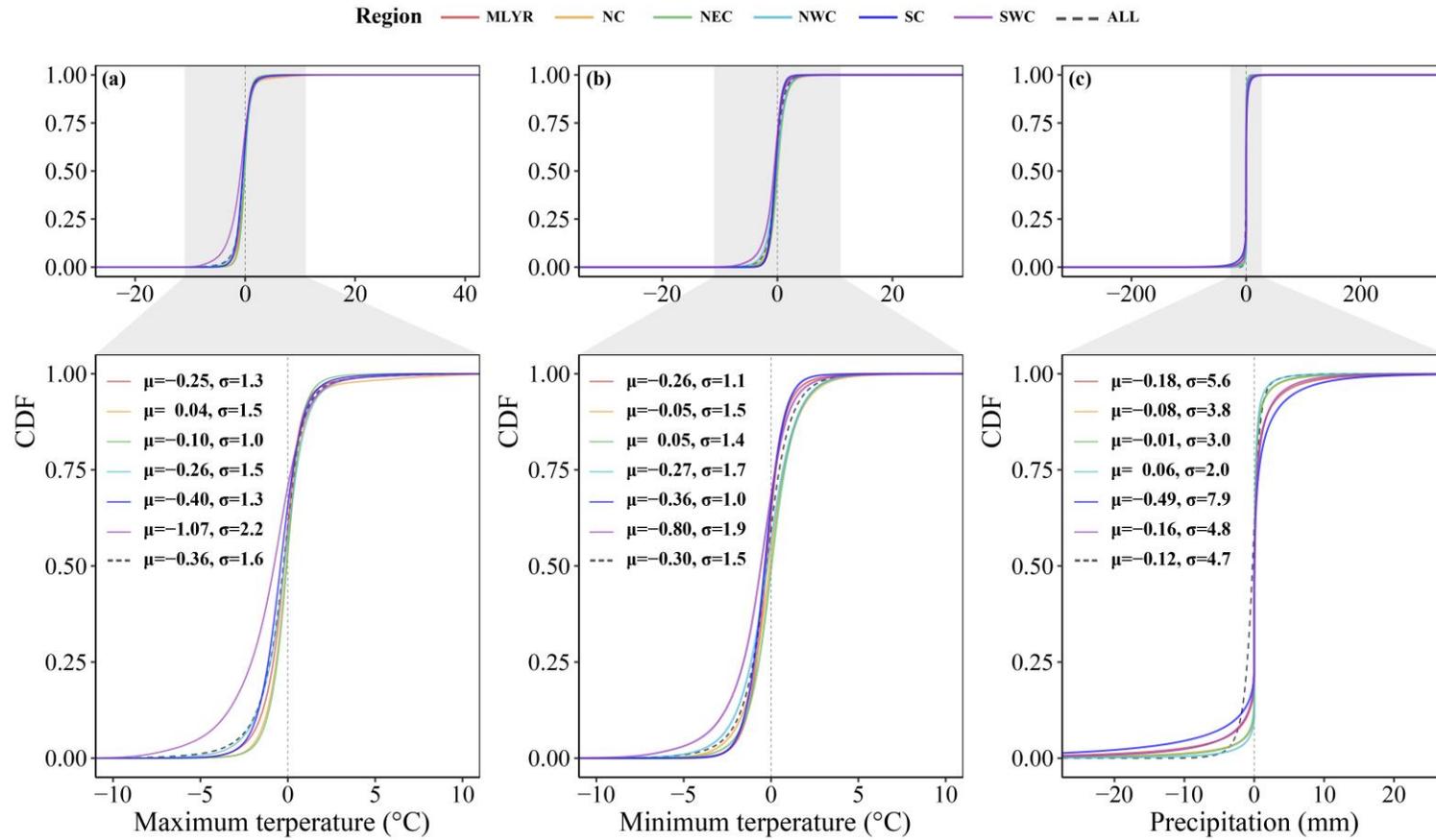
Figure 6. Cumulative distribution functions (CDF) of difference between the estimated and observed values for three variables in all meteorological stations from 1961 to 2020. μ is the mean and σ is the standard deviation. MLYR, NC, NEC, NWC, SC, and SWC are the Middle and Lower reaches of the Yangtze River, North China, Northeast China, Northwest China, South China, and Southwest China, respectively.
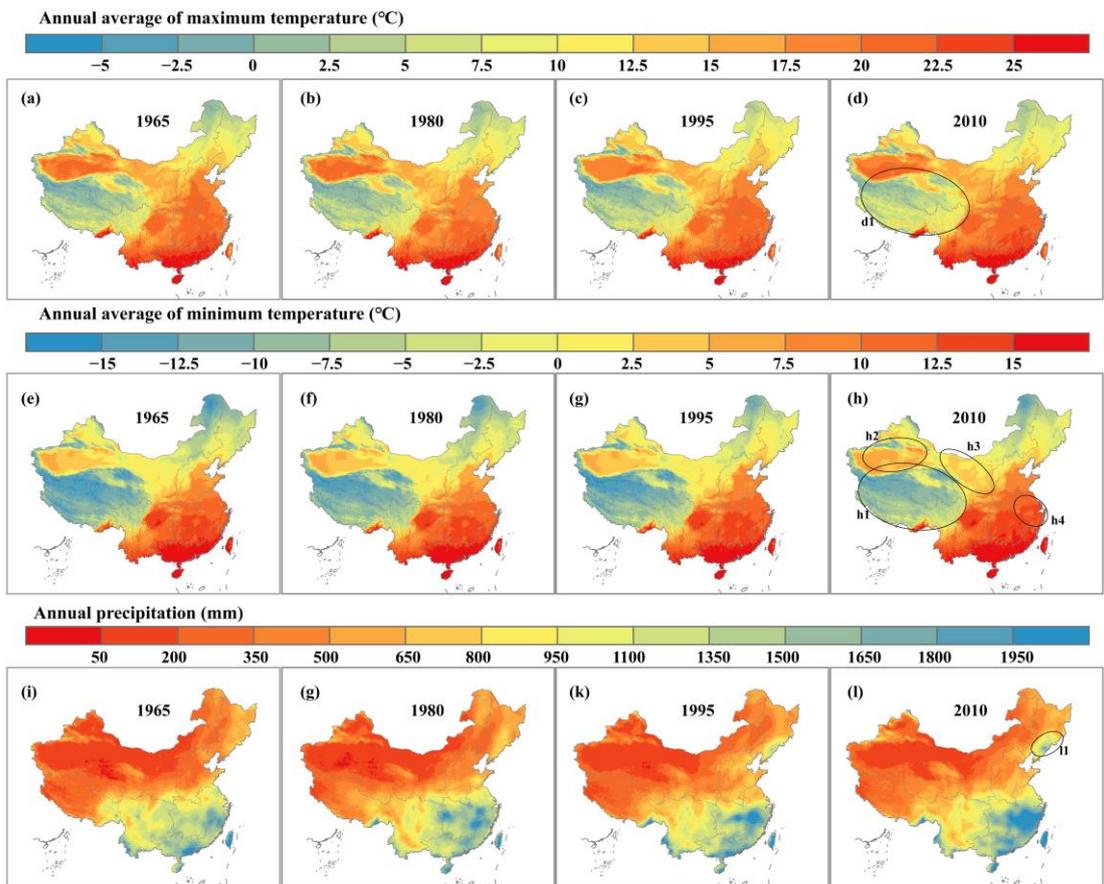
Figure 7. Spatial distributions of annual average values for daily maximum and minimum temperatures, and the spatial distribution of annual precipitation in 1965, 1980, 1990, and 2010. The ellipse regions are where the change is most visible.
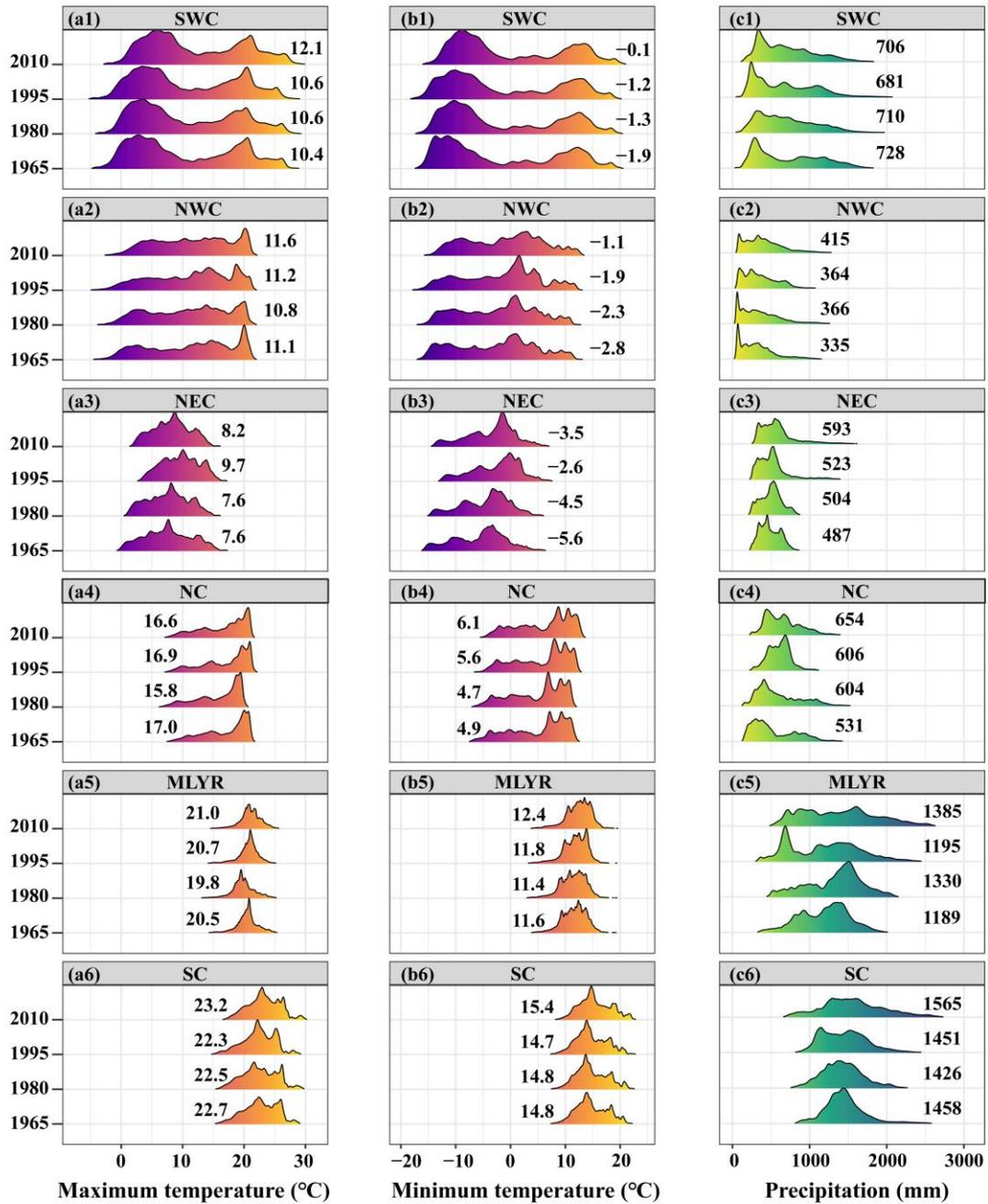
Figure 8. Density distributions of annual average values for daily maximum and minimum temperatures, and annual precipitation across the different regions in 1965, 1980, 1990, and 2010. The value in the illustrations is the mean value.
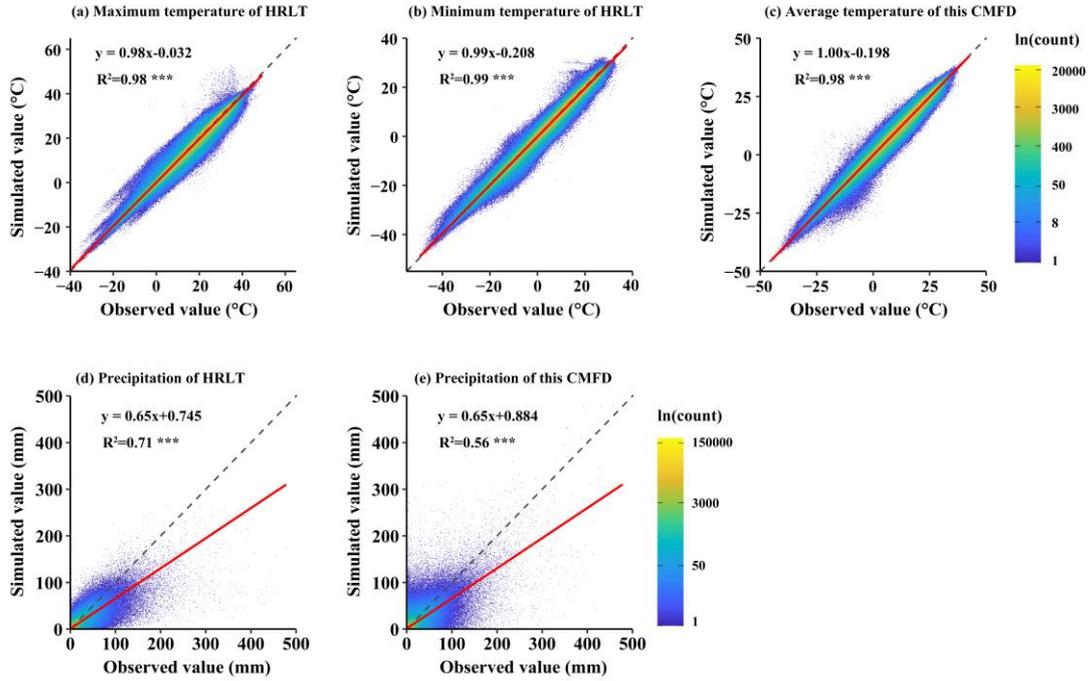
Figure 9. Scatter density plots of daily temperature and precipitation between the estimated and observed values at all meteorological stations (both training sets and testing sets) for the HRLT dataset and the CMFD dataset between 1979 and 2018. The dashed line is a line with slope 1 and the red line is a fitting between the estimated and observed values. R^2 is the coefficient of determination between the estimated and observed values. *** asterisks indicate that the significance of the regression equation between the estimated and observed values was $p < 0.001$.
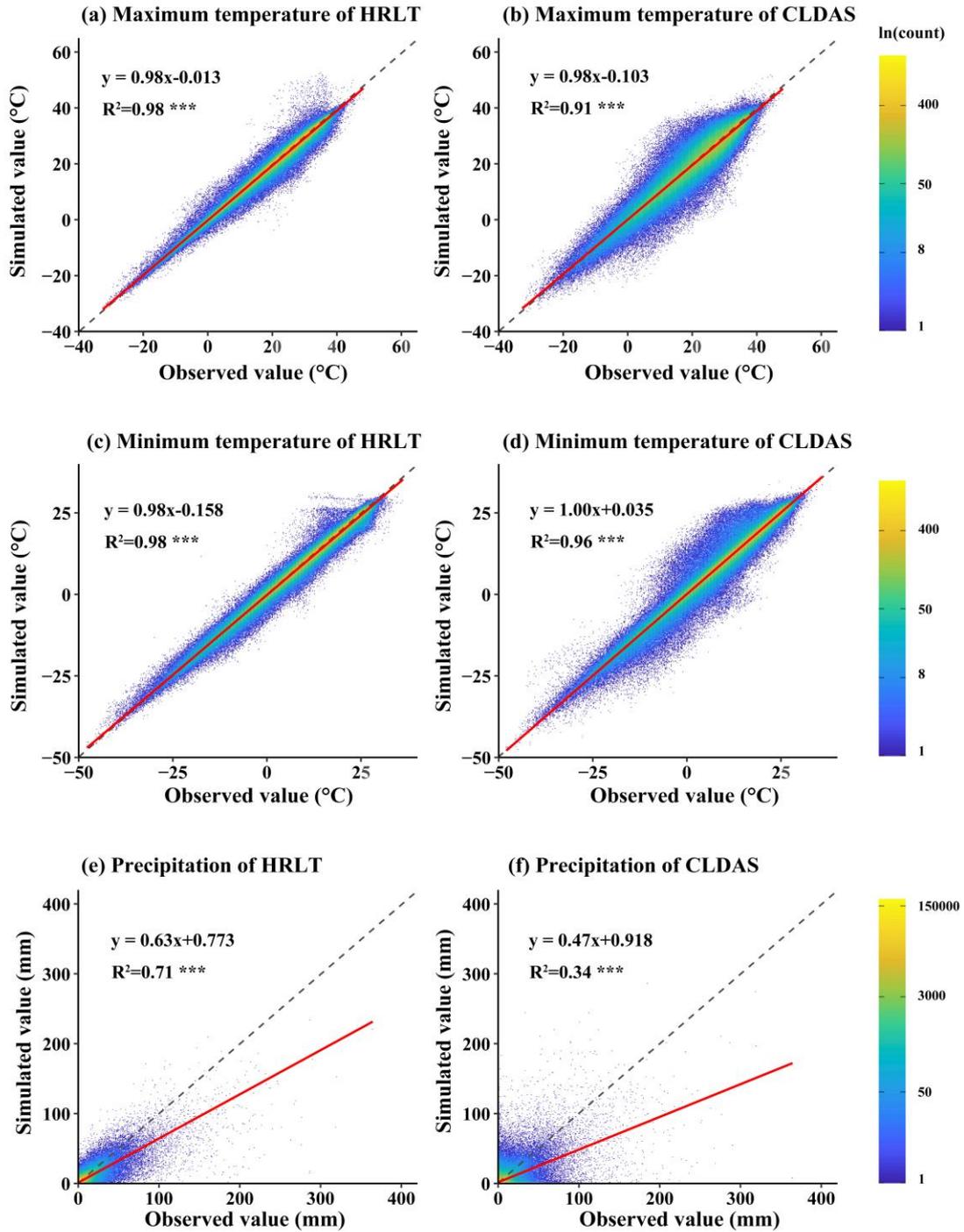
Figure 10. Scatter density plots of daily temperature and precipitation between the estimated and observed values from all meteorological stations (both training sets and testing sets) for our HRLT dataset and the CLDAS dataset between 2017 and 2019. Dashed line is a line with slope 1 and the red line is the fitting between the estimated and observed values. R^2 is the coefficient of determination between the estimated and observed values. *** asterisks indicate that the significance of the regression equation between the estimated and observed values was $p < 0.001$.
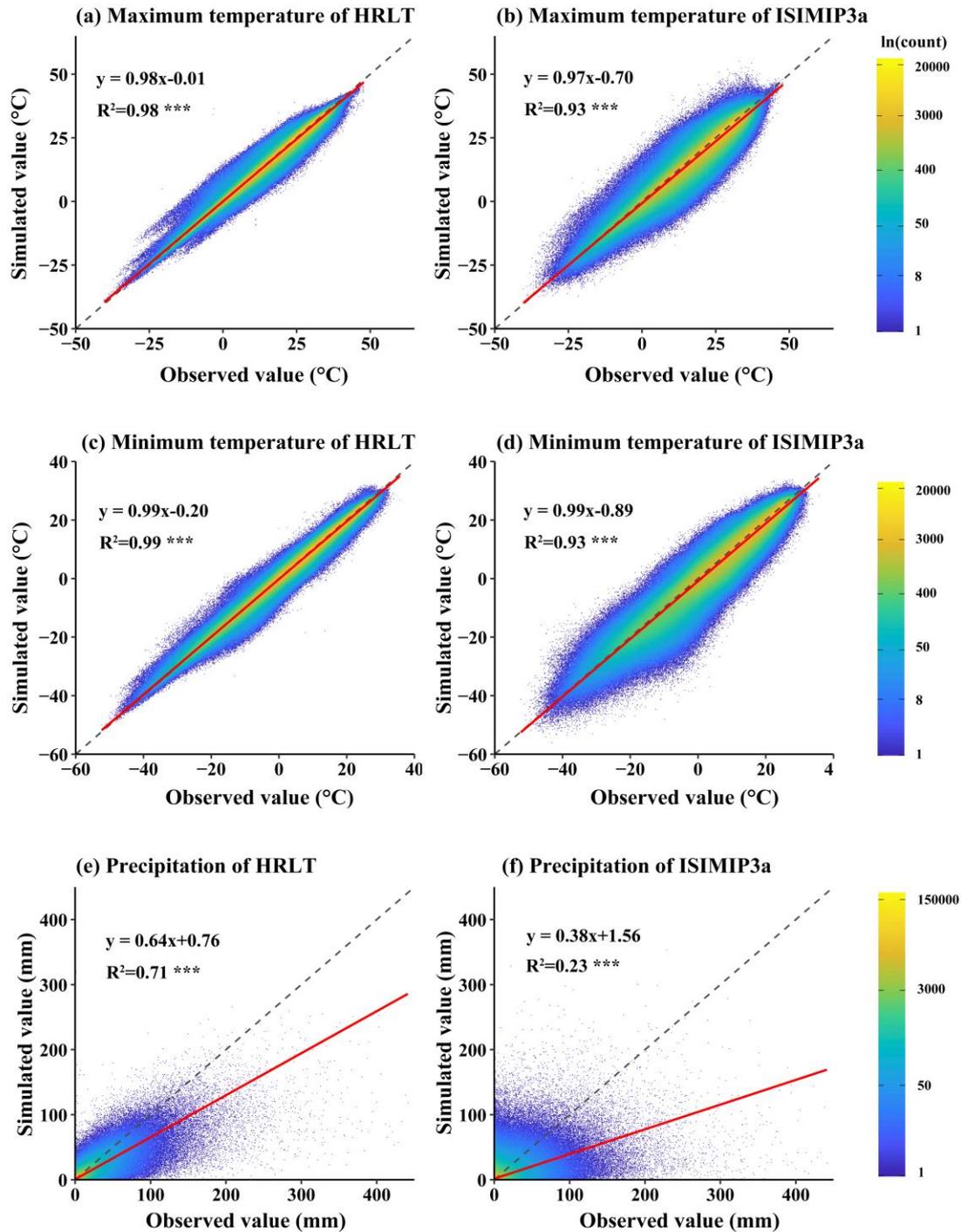
Figure 11. Scatter density plots of daily temperature and precipitation between the estimated and observed values from all meteorological stations (both training sets and testing sets) for our HRLT dataset and the ISIMIP3a dataset between 1961 and 2016. Dashed line is a line with slope 1 and the red line is the fitting between the estimated and observed values. R^2 is the coefficient of determination between the estimated and observed values. *** asterisks indicate that the significance of the regression equation between the estimated and observed values was $p < 0.001$.