Global solar radiation modeling using different machine learning and empirical models in Northeast China

Yue Jia (✉ jiayuescu@163.com)

Hebei University of Water Resources and Electric Engineering

Yongjun Su (✉ 15130800077@163.com)

Hebei university of water resources and electric engineering

Fengchun Wang (✉ wangfengchun813@163.com)

Hebei university of water resources and electric engineering

Pengcheng Li

Hebei university of water resources and electric engineering

Shuyi Huo

Hebei university of water resources and electric engineering

Research Article

Keywords: Global solar radiation, Machine learning models, Empirical models, Sunshine duration

Posted Date: May 17th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-422151/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Global solar radiation modeling using different machine learning and empirical models in Northeast China

Yue Jia ^{a,b}, Yongjun Su ^{a,b} *, Fengchun Wang ^{a,b} *, Pengcheng Li ^{a,b}, Shuyi Huo ^{a,b}

a. Hebei University of Water Resources and Electric Engineering & Remote sensing and

Smart water innovation Center, Cangzhou, 061001, China

b. Hebei University Center for Water Automation and Information Application Technology,

Cangzhou, 061001, China

* Corresponding authors.

Email: 15130800077@163.com(Y. Su); wangfengchun813@163.com (F. Wang)

1 **Abstract:** Reliable global solar radiation (R_s) information is crucial for the design and
2 management of solar energy systems for agricultural and industrial production.
3 However, R_s measurements are unavailable in many regions of the world, which
4 impedes the development and application of solar energy. To accurately estimate R_s ,
5 this study developed a novel machine learning model, called a Gaussian exponential
6 model (GEM), for daily global R_s estimation. The GEM was compared with four other
7 machine learning models and two empirical models to assess its applicability using
8 daily meteorological data from 1997–2016 from four stations in Northeast China. The
9 results showed that the GEM with complete inputs had the best performance. Machine
10 learning models provided better estimates than empirical models when trained by the
11 same input data. Sunshine duration was the most effective factor determining the
12 accuracy of the machine learning models. Overall, the GEM with complete inputs had
13 the highest accuracy and is recommended for modeling daily R_s in Northeast China.
14 **Keywords:** Global solar radiation; Machine learning models; Empirical models;
15 Sunshine duration

Declarations

Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

Availability of data and materials

The data that support the findings of this study are available from [National Meteorological Science Data Center<https://data.CMA.cn/>] but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of [National Meteorological Science Data Center<https://data.CMAcma.cn/>].

Competing interests

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

Funding

The research was funded by the Scientific Research Program of Higher Education in Hebei Province (QN2021227) and the Water Conservancy Research and Extension Project of Hebei Province(2020-64) and the Hebei Province Innovation Ability Promotion Plan, Soft Science Research(20557682D), and the Colleges and Universities in Hebei Province Science and Technology Research(ZD2020348) and

38 the Doctoral Scientific Research Foundation of Hebei University of Water Resources
39 and Electric Engineering(SYBJ1902).

40 **Authors' contributions**

41 YJ analyzed and calculated the data and wrote the manuscript. YS and FW was
42 a major contributor in writing the manuscript and got the data of the manuscript. PL
43 calculated the data and made the tables of the manuscript. SH made the figures for the
44 manuscript. All authors read and approved the final manuscript.

1. Introduction

Solar radiation (R_s) provides the essential energy for life on Earth (Wild et al., 2005) and is the foundation of global climate formation (Antonopoulos et al., 2019). Solar energy is one of the most advantageous energy sources, as it is clean, free, abundant, and inexhaustible (Khatib et al., 2012; Desideri et al., 2013; Jamil and Akhtar, 2017; Zhang et al., 2019). As the global energy demand is gradually increasing, solar energy has attracted increasing attention. The application of solar energy systems depends on the amount and intensity of global R_s ; thus, reliable information on R_s directly affects the development of solar energy (Citakoglu, 2015; Zhang et al., 2019). Furthermore, the level of R_s is directly related to the characteristics of regional climate change and the layout of agricultural production, especially crop production (Bailek et al., 2018; Chen et al., 2019; Fan et al., 2019). The most accurate R_s data can be obtained by measurements (Wu et al., 2019). However, the high requirements and costs of the measuring devices have resulted in few measurements worldwide (Besharat et al., 2013; Oates et al., 2017). China has the largest energy demand in the world. Among the 752 national meteorological stations in China, only 122 stations have measured R_s data (Pan et al., 2013). Thus, using other commonly available climatic data to predict R_s is a feasible alternative.

Various climatic variables, such as precipitation (P), sunshine duration (n), air temperature, and relative humidity (H_r), are effective factors for R_s estimation

65 (Katiyar and Pandey, 2010; Jamil and Akhtar, 2017; Jamil and Siddiqui, 2018; Kaba
66 et al., 2018; Anis et al., 2019). Thus, various types of models have been developed
67 based on these climatic variables, including empirical models (Liu et al., 2009;
68 Citakoglu, 2015; Demircan et al., 2020), machine learning models (Hossain et al.,
69 2017; Fan et al., 2018), and radiative transfer models (Gueymard, 2001; Pawlak et al.,
70 2004). Owing to the acceptable accuracy and low computational costs and input
71 requirements, empirical models are the most widely applied models (Hassan et al.,
72 2016), among which the Hargreaves–Samani (HS) model and Bristow–Campbell (BC)
73 model are two well-known empirical models. Liu et al. (2009) modified the HS and
74 BC models in different regions of China, and found that the accuracy of the models
75 was improved by 4%–7% after correction.

76 Because R_s has a nonlinear relationship with other climatic variables, as indicated by
77 empirical models, machine learning models can improve the accuracy of R_s estimation
78 and prediction (Chen et al., 2011). To date, many machine learning models have been
79 extensively applied to estimate and simulate R_s (Katiyar and Pandey, 2010; Jamil and
80 Akhtar, 2017; Kaba et al., 2018; Feng et al., 2019a), such as the adaptive neuro-fuzzy
81 inference system (ANFIS) (Tabari et al., 2012), M5 model tree (Kisi, 2016), and gene
82 expression programming (Shiri et al., 2014). Bueno et al. (2019) evaluated the
83 performances of neural networks, support vector regression, and Gaussian processes
84 for R_s prediction using satellite data as inputs, and reported that the three machine
85 learning models provided reliable estimates. Zou et al. (2017) compared the ANFIS

model with an improved BC model and Yang's model for R_s estimation, and found that machine learning models showed better results than the BC model and Yang's model. Fan et al. (2019) compared 12 machine learning models and 12 empirical models to estimate R_s . They showed that the ANFIS model, MARS model, and XGBoost model may be promising models in China.

Day of year(DOY) is an important time parameter. Taking DOY as an input parameter can comprehensively reflect the change rule of meteorological factors with time, and further improve the model accuracy(Zhu et al., 2019a). Gaussian exponential model(GEM) is a novel machine learning model that has not been applied to R_s estimation. China consumes a large amount of energy, and a significant amount of energy is used for economic development every year (Liu et al., 2017; Fan et al., 2018). Clean solar energy is of great significance for energy conservation and emission reduction (Jin et al., 2005; Feng et al., 2017a). Northeast China, which is the main industrial production region, accounts for approximately 20% of China's energy consumption (Zheng et al., 2019). Therefore, determining an optimal R_s model for this region can provide scientific information for solar energy applications. However, the performance of different models in this region has not been well documented. Thus, in this paper, DOY was added into the input parameter of machine learning models to estimate R_s . GEM was developed to estimate R_s in Northeast China with different climate data. The main purpose of this study was to examine the applicability of five machine learning models (M5 model tree, support vector machine (SVM), random

forest (RF) model, GEM, and boosted trees (BT) and two empirical models (HS and BC) for R_s prediction in Northeast China.

2. Methods and materials

2.1 Study area and data collection

Northeast China generally consists of three provinces and has a temperate monsoon climate (Feng et al., 2018). In this study, long-term climatic data, including R_s , n , maximum and minimum air temperature ($T_{\max}$ and $T_{\min}$, respectively), H_r , wind speed at 2 m height, and P , during 1997–2016 were collected from four stations located in Northeast China (Fig. 1). Extra-terrestrial solar radiation (R_a) calculated from geographic information and the day of the year (DOY) were also used for modeling. These data were provided and quality examined by the China Meteorological Administration. Figure 2 shows the monthly variations in climatic variables. Table 1 shows the climatic conditions of the study region.

2.2 M5 model tree

Quinlan (1992) first developed the M5 tree (M5T) model, which selects the expected standard deviation after scanning all the possible splits (Wang et al., 1997; Feng et al., 2019b). The procedure that makes up the model is divided into two parts. First, the data are divided into several subsets to create decision trees. The expected error of the subsets can be calculated by the model. The model accuracy can be defined as follows:

$$SDR = SD(Q) - \sum \frac{|Q_i|}{|Q|} SD(Q_i) \quad (1)$$

where SD and SDR are the standard deviations, Q is a set of samples that reach the target value, and Q_i is a subset of Q .

To improve the application efficiency of the model, it is necessary to traverse each node of the initial model tree through the pruning process to merge some subtrees and replace them with leaf nodes (Sattari et al., 2013). The detailed model procedure of the M5T model is described by Quinlan (1992).

2.3 Support vector machine

The SVM was first proposed by Vapnik (1999). This model is considered the best theory for current small-sample statistical estimation and prediction learning (Belaid et al., 2016; Shamshirband et al., 2016). The model replaces traditional experience minimization with structural experience minimization, which can overcome many shortcomings of neural networks (Quej et al., 2017). The SVM function can be expressed as follows:

$$f(x) = \sum_{i=1}^n \alpha_i y_i \kappa(x_i, x_j) + b \quad (2)$$

where $\kappa(x_i, x_j)$ is a higher-dimensional feature vector converted from the input vector x_i and x_j . y_i is the ordinate of the input vector, α_i is the weight of the input vector, and b is the bias.

2.4 Random forest model

The RF model was proposed by Breiman (2001). The model introduces random

attribute selection during model training. The model extracts data based on randomness and difference, which can greatly improve decision accuracy. The procedures of the RF model are described by Buja et al. (2008).

2.5 Gaussian exponential model

The GEM was proposed by Liu et al. (2014). The model is divided into three procedures. First, learning samples are clustered by the k-means algorithm as the most primitive allocation of samples. Second, the parameter estimates of the sample are calculated using the maximum likelihood estimation. Third, learning samples are regrouped according to the maximum posterior probability criterion. The model can be defined as follows:

$$f(n) = H_i \times \exp\left(-\frac{2(n - N_i)}{W_i^2}\right), i = 1, 2, \dots, n \quad (3)$$

where H_i is the peak amplitude, N_i is the peak time position, and W_i is the half-width of the Gaussian wave.

2.6 Boosted trees model

The BT model was first proposed by Friedman (2001). The model is designed to improve the performance of a single model by fitting multiple models while combining them for prediction. The principle of model boosting is to promote a strong combination through the input of weak learners. The BT model is divided into two procedures, namely regression trees and boosting (Elias et al., 2016). The detailed model procedure is described in the study by Friedman (2001).

2.7 Hargreaves–Samani model

The HS model only uses $T_{\max}$ and $T_{\min}$ data as inputs and is widely reported to have acceptable accuracy for R_s estimation. The model is as follows:

$$R_s = [C(T_{\max} - T_{\min})^{0.5}] \times R_a \quad (4)$$

where R_s is the global R_s ($\text{MJ} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$), $T_{\max}$ and $T_{\min}$ are the $T_{\max}$ and $T_{\min}$, respectively ($^{\circ}\text{C}$), C is the empirical coefficient, and R_a is the R_a ($\text{MJ} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$).

2.8 Bristow–Campbell model

Bristow and Campbell (1984) developed the BC model, which only uses R_a and the diurnal temperature range (ΔT) as the input data. The model is defined as follows:

$$R_s = a[1 - \exp(-b\Delta T^c)] \times R_a \quad (5)$$

where ΔT is the ΔT ($^{\circ}\text{C}$) and a , b , and c are empirical coefficients.

2.9 Model training and testing

Five input combinations of meteorological data were used to train the machine learning models. Details of the combinations are presented in Table 2. The dataset was divided into two parts, i.e., 1997–2011 and 2012–2016, for training and testing the machine learning models, respectively. The coefficients of the empirical models were locally calibrated at each station by the least square error method using the training data (data from 1997–2011). The model training/calibration and testing were performed in Matlab 2018a. The parameters of the machine models are presented in Table 3.

2.10 Statistical indicators

The root mean square error (RMSE), relative root mean square error (RRMSE), coefficient of determination (R^2), mean absolute error (MAE), and coefficient of efficiency (E_{ns}) were used to assess the R_s models (Feng et al., 2017b), as follows:

$$RMSE = \sqrt{\frac{1}{m} \sum_{i=1}^m (Y_i - X_i)^2} \times 100\% \quad (6)$$

$$RRMSE = \frac{\sqrt{\frac{1}{m} \sum_{i=1}^m (Y_i - X_i)^2}}{\bar{X}} \times 100\% \quad (7)$$

$$R^2 = \frac{\left[\sum_{i=1}^m (X_i - \bar{X})(Y_i - \bar{Y}) \right]^2}{\sum_{i=1}^m (X_i - \bar{X})^2 \sum_{i=1}^m (Y_i - \bar{Y})^2} \quad (8)$$

$$MAE = \frac{1}{m} \sum_{i=1}^m |X_i - Y_i| \quad (9)$$

$$E_{ns} = 1 - \frac{\sum_{i=1}^m (Y_i - X_i)^2}{\sum_{i=1}^m (X_i - \bar{X})^2} \quad (10)$$

where X_i and Y_i are the trained and estimated values, respectively, and $\bar{X}$ is the average value of X_i .

Owing to the excessive evaluation index, it is very difficult for a single evaluation index to compare different models. Therefore, the global performance indicator (GPI) was introduced to comprehensively evaluate the model simulation results (Despotovic et al., 2015), as follows:

$$GPI_i = \sum_{j=1}^5 \alpha_j (g_j - y_{ij}) \quad (11)$$

where α_j is a coefficient that is equal to 1 for the RMSE, RRMSE, and MAE and equal to -1 for E_{ns} and R^2 ; g_j represents the median of statistical indicator j , and y_{ij}

represents the scaled value of the statistical indicator j . A higher GPI value indicates the better performance of the model.

3. Results and discussion

3.1 Results

3.1.1 Evaluation of the models on a daily basis

The statistical performance of the models at the four stations is presented in Table 4.

At Harbin station, the BT1 model showed the highest accuracy under input scenario 1 with RMSE, RRMSE, R^2 , E_{ns} , and MAE values of $2.893 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, 36.1%, 0.569, 0.563, and $3.742 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, respectively. Under input scenario 2, the BT2 model showed the highest accuracy with RMSE, RRMSE, R^2 , E_{ns} , and MAE values of $3.068 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, 22.6%, 0.842, 0.828, and $2.305 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, respectively. Under input scenario 3, the five machine learning models had higher accuracies than the models under input scenarios 1 and 2, with an RMSE value of less than $2.900 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, RRMSE value of less than 21.4%, R^2 value of greater than 0.952, E_{ns} value of greater than 0.931, and MAE of less than $2.237 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$. This indicated that introducing climatic variables into the model training greatly improved the model performance.

Among the models under input scenario 3, the BT3 model had the highest accuracy with RMSE, RRMSE, R^2 , E_{ns} , and MAE values of $1.944 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, 15.4%, 0.952, 0.931, and $1.456 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, respectively. The BT4 model showed the highest accuracy under input scenario 4 with RMSE, RRMSE, R^2 , E_{ns} , and MAE values of

225 2.033 MJ·m⁻²·d⁻¹, 15.0%, 0.948, 0.925, and 1.525 MJ·m⁻²·d⁻¹, respectively. Under
226 input scenario 5, the GEM5 showed the highest accuracy with RMSE, RRMSE, R^2 ,
227 E_{ns} , and MAE values of 1.719 MJ·m⁻²·d⁻¹, 12.7%, 0.964, 0.946, and 1.283 MJ·m⁻²·d⁻¹,
228 respectively.

229 At Jilin station, the BT1 model showed the highest accuracy under input scenario 1
230 with RMSE, RRMSE, R^2 , E_{ns} , and MAE values of 5.393 MJ·m⁻²·d⁻¹, 43.6%, 0.503,
231 0.501, and 4.030 MJ·m⁻²·d⁻¹, respectively. Under input scenario 2, the BT2 model
232 showed the highest accuracy with RMSE, RRMSE, R^2 , E_{ns} , and MAE values of 3.157
233 MJ·m⁻²·d⁻¹, 23.2%, 0.835, 0.829, and 2.211 MJ·m⁻²·d⁻¹, respectively. Under input
234 scenario 3, the BT3 model had the highest accuracy with RMSE, RRMSE, R^2 , E_{ns} ,
235 and MAE values of 1.513 MJ·m⁻²·d⁻¹, 11.1%, 0.961, 0.961, and 1.013 MJ·m⁻²·d⁻¹,
236 respectively. Under input scenario 4, the BT4 model showed the highest accuracy. The
237 five machine learning models under input scenario 5 showed the highest accuracies
238 among the models under different input scenarios. The GEM5 showed the highest
239 accuracy with RMSE, RRMSE, R^2 , E_{ns} , and MAE values of 1.245 MJ·m⁻²·d⁻¹, 9.1%,
240 0.974, 0.973, and 0.844 MJ·m⁻²·d⁻¹, respectively.

241 At Shenyang station, the BT1 model showed the highest accuracy under input
242 scenario 1 with RMSE, RRMSE, R^2 , E_{ns} , and MAE values of 5.355 MJ·m⁻²·d⁻¹, 37.7%,
243 0.503, 0.489, and 4.265 MJ·m⁻²·d⁻¹, respectively. Under input scenario 2, the BT2
244 model showed the highest accuracy with RMSE, RRMSE, R^2 , E_{ns} , and MAE values of

245 $3.227 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, 22.7%, 0.822, 0.814, and $2.412 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, respectively. Under
 246 input scenario 3, all the machine learning models had higher accuracies than the
 247 models under input scenarios 1 and 2, with an RMSE value of less than 2.619
 248 $\text{MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, RRMSE of less than 18.4%, R^2 of over 0.882, E_{ns} of over 0.878, and
 249 MAE of less than $1.836 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$. The BT3 model had the highest accuracy with
 250 RMSE, RRMSE, R^2 , E_{ns} , and MAE values of $1.876 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, 13.2%, 0.940, 0.937,
 251 and $1.299 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, respectively. The BT4 model showed the highest accuracy
 252 under input scenario 4 with RMSE, RRMSE, R^2 , E_{ns} , and MAE values of 2.010
 253 $\text{MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, 14.1%, 0.930, 0.928, and $1.407 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, respectively. Under input
 254 scenario 5, the GEM5 showed the highest accuracy with RMSE, RRMSE, R^2 , E_{ns} , and
 255 MAE values of $1.658 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, 11.7%, 0.953, 0.951, and $1.147 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$,
 256 respectively.

257 At Yanji station, the BT1 model showed the highest accuracy under input scenario 1
 258 with RMSE, RRMSE, R^2 , E_{ns} , and MAE values of $5.030 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, 36.6%, 0.484,
 259 0.476, and $3.973 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, respectively. Under input scenario 2, the BT2 model
 260 showed the highest accuracy with RMSE, RRMSE, R^2 , E_{ns} , and MAE values of 2.809
 261 $\text{MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, 20.4%, 0.849, 0.837, and $2.194 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, respectively. Under input
 262 scenario 3, the five models had higher accuracies than the models under input
 263 scenarios 1 and 2, with an RMSE of less than $1.746 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, RRMSE of less than
 264 12.7%, R^2 of over 0.946, E_{ns} of over 0.937, and MAE of less than $1.322 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$.
 265 The BT3 model had the highest accuracy with RMSE, RRMSE, R^2 , E_{ns} , and MAE

266 values of $1.226 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, 8.9%, 0.973, 0.969, and $0.943 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, respectively.

267 The BT4 model showed the highest accuracy under input scenario 4 with RMSE,
268 RRMSE, R^2 , E_{ns} , and MAE values of $1.259 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, 9.2%, 0.971, 0.967, and 0.970
269 $\text{MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, respectively. Under input scenario 5, the GEM5 showed the highest
270 accuracy with RMSE, RRMSE, R^2 , E_{ns} , and MAE values of $1.045 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, 7.6%,
271 0.981, 0.977, and $0.801 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, respectively.

272 As for the empirical models, the HS and BC models showed lower accuracies
273 compared with those of the machine learning models with the same inputs (input
274 scenario 3), with an RMSE of $3.885\text{--}4.557 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, R^2 of 0.634–0.707, RRMSE of
275 28.3%–32.2%, E_{ns} of 0.630–0.696, and MAE of $3.069\text{--}3.526 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$. The
276 accuracy of the machine learning models considering n was significantly higher than
277 that of the models without n input, with the RMSE reduced by 44.3%–79.9%,
278 RRMSE reduced by 44.2%–91.2%, MAE reduced by 40.2%–80.6%, R^2 increased by
279 67.7%–95.6%, and E_{ns} increased by 67.4%–124.9%.

280 The Boxplots of the statistical indicators of daily R_s for different models in the study
281 area are presented in Fig. 3. Under input scenario 1, the five machine learning models
282 showed low prediction accuracies for the whole region, with average RMSE, RRMSE,
283 MAE, and E_{ns} values of $4.668\text{--}9.627 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, 38.8%–69.9%, $4.002\text{--}7.579$
284 $\text{MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, and 0.220–0.507, respectively. The BT1 model showed the highest
285 accuracy among the five models. Under input scenario 2, the BT2 model was the best

286 model with average RMSE, RRMSE, MAE, and E_{ns} values of $3.065 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$,
 287 22.2%, $2.281 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, and 0.827, respectively. The five models under input
 288 scenario 3 showed higher prediction accuracies than the models under input scenarios
 289 1 and 2, which did not consider climatic variables as inputs. The BT3 model showed
 290 the best results with average RMSE, RRMSE, MAE, and E_{ns} values of 1.639
 291 $\text{MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, 12.2%, $1.178 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, and 0.950, respectively. Under input scenario 4,
 292 the BT4 model showed the highest accuracy with average RMSE, RRMSE, MAE,
 293 and E_{ns} values of $1.711 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, 12.4%, $1.243 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, and 0.945, respectively.
 294 Under input scenario 5, the GEM5 showed the highest accuracy with average RMSE,
 295 RRMSE, MAE, and E_{ns} values of $1.417 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, 10.26%, $1.019 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, and
 296 0.962, respectively. The HS and BC models showed much lower prediction accuracies
 297 compared with those of the machine learning models, with average RMSE, RRMSE,
 298 MAE, and E_{ns} values of $4.306 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$ and $4.174 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, 31.23% and 30.26%,
 299 $3.341 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$ and $3.218 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, and 0.658 and 0.679, respectively.

300 The GPI values of the different models at the four stations are presented in Fig. 4. The
 301 SVM1, M5T1, GEM1, RF1, and BT1 models under input scenario 1 showed the
 302 lowest prediction accuracies compared with those of models under other input
 303 scenarios, with average GPI values of -3.915, -3.101, -2.883, -3.357, and -2.163,
 304 respectively. Under input scenario 2, the BT2 model showed the highest overall
 305 accuracy, followed by the GEM2, SVM2, RF2, and M5T2 models with average GPI
 306 values of -0.569, -0.852, -1.131, -1.478, and -1.599, respectively. Under input

scenario 3, the BT3 model showed the highest accuracy, followed by the GEM3, SVM3, RF3, and M5T3 models with average GPI values of 0.485, 0.399, 0.193, 0.034, and -0.040, respectively. The BT4 model was the best model under input scenario 4, followed by the GEM4, RF4, M5T4, and SVM4 models with average GPI values of 0.434, 0.375, 0.033, 0.019, and -0.211, respectively. Under input scenario 5, the GEM5 and BT5 models showed much higher accuracies with average GPI values of 0.641 and 0.560, respectively. The accuracies of the HS and BC models were higher than those of the M5T1, SVM1, GEM1, RF1, and BT1 models without climatic inputs, with average GPI values of -1.745 and -1.622, respectively. Relatively good estimates and high accuracies could be obtained from models with at least the DOY, R_a , and n as inputs, including models under input scenarios 3, 4, and 5. These results further confirm that n is the most important variable for estimating R_s .

3.1.2 Evaluation of the models on a monthly basis

The accuracy index of monthly R_s of different models in different stations is presented in Table.5. As shown in Table.5, in Harbin station, the BT1 model showed the highest accuracy under input scenario1, with RMSE of $0.878 \text{ MJ m}^{-2} \text{ d}^{-1}$, RRMSE of 13.5%, R^2 of 0.984, E_{ns} of 0.943, MAE of $0.803 \text{ MJ m}^{-2} \text{ d}^{-1}$. Under input scenario2, the BT2 model showed the highest accuracy, followed by the GEM2 model, with RMSE of 0.692 and $0.814 \text{ MJ m}^{-2} \text{ d}^{-1}$, RRMSE of 11.1% and 11%, R^2 of 0.997 and 0.996, E_{ns} of 0.953 and 0.937, MAE of 0.702 and $1.371 \text{ MJ m}^{-2} \text{ d}^{-1}$. Under input scenario3, the five models had higher accuracy than the models under input scenario1

328 and scenario2, with RMSE less than $0.825 \text{ MJ m}^{-2} \text{ d}^{-1}$, RRMSE less than 8.5%, R^2
 329 over than 0.999, E_{ns} over than 0.972, MAE less than $0.621 \text{ MJ m}^{-2} \text{ d}^{-1}$. BT3 model had
 330 the highest accuracy with RMSE of $0.601 \text{ MJ m}^{-2} \text{ d}^{-1}$, RRMSE of 7.5%, R^2 of 1.000,
 331 E_{ns} of 0.984, MAE of $0.467 \text{ MJ m}^{-2} \text{ d}^{-1}$. BT4 model showed the best precision under
 332 input scenario4, with RMSE of $0.506 \text{ MJ m}^{-2} \text{ d}^{-1}$, RRMSE of 7.2%, R^2 of 0.999, E_{ns} of
 333 0.987, MAE of $0.463 \text{ MJ m}^{-2} \text{ d}^{-1}$. Under input scenario5, GEM5 model and BT5
 334 model showed much higher accuracy among the five models, with RMSE of 0.575
 335 and $0.456 \text{ MJ m}^{-2} \text{ d}^{-1}$, RRMSE of 7.0% and 7.1%, R^2 of 1.000 and 1.000, E_{ns} of 0.989
 336 and 0.988, MAE of 0.499 and $0.411 \text{ MJ m}^{-2} \text{ d}^{-1}$. HS model and BC model showed
 337 much poorer prediction accuracy with RMSE of 1.186 and $1.193 \text{ MJ m}^{-2} \text{ d}^{-1}$, with
 338 RRMSE of 8.8% and 8.8%, R^2 of 0.977 and 0.976, MAE of 0.955 and 0.951 MJ m^{-2}
 339 d^{-1} , E_{ns} of 0.951 and 0.950, respectively.

340 In Jilin station, the BT1 model showed the highest accuracy under input scenario1,
 341 with RMSE of $0.932 \text{ MJ m}^{-2} \text{ d}^{-1}$, RRMSE of 6.6%, R^2 of 0.971, E_{ns} of 0.964, MAE of
 342 $0.750 \text{ MJ m}^{-2} \text{ d}^{-1}$. Under input scenario2, the BT2 model had the best precision, with
 343 RMSE of $0.525 \text{ MJ m}^{-2} \text{ d}^{-1}$, RRMSE of 2.4%, R^2 of 0.907, E_{ns} of 0.926, MAE of
 344 $0.261 \text{ MJ m}^{-2} \text{ d}^{-1}$. Under input scenario3, the BT3 model had the highest accuracy
 345 with RMSE of $0.256 \text{ MJ m}^{-2} \text{ d}^{-1}$, RRMSE of 1.9%, R^2 of 0.998, E_{ns} of 0.998, MAE of
 346 $0.176 \text{ MJ m}^{-2} \text{ d}^{-1}$. Under input scenario4, the BT4 model showed the best precision,
 347 with RMSE of $0.341 \text{ MJ m}^{-2} \text{ d}^{-1}$, RRMSE of 2.8%, R^2 of 0.998, E_{ns} of 0.994, MAE of
 348 $0.301 \text{ MJ m}^{-2} \text{ d}^{-1}$. The five models under the input scenario5 showed the highest

349 accuracy among the models under other inputs. GEM5 model showed the highest
350 accuracy, followed by the BT5 model, with RMSE of 0.197 and 0.242 MJ m⁻² d⁻¹,
351 RRMSE of 1.5% and 1.8%, R² of 0.999 and 0.998, E_{ns} of 0.999 and 0.998, MAE of
352 0.137 and 0.159 MJ m⁻² d⁻¹. HS model and BC model showed much poorer prediction
353 accuracy with RMSE of 0.672 and 0.643 MJ m⁻² d⁻¹, with RRMSE of 5.4% and 4.7%,
354 R² of 0.872 and 0.991, MAE of 0.520 and 0.559 MJ m⁻² d⁻¹, E_{ns} of 0.971 and 0.984,
355 respectively.

356 In Shenyang station, under input scenario1, BT1 model showed the highest
357 accuracy, followed by GEM1 model, with RMSE of 0.932 and 0.962 MJ m⁻² d⁻¹,
358 RRMSE of 6.6% and 6.8%, R² of 0.971 and 0.979, E_{ns} of 0.964 and 0.962, MAE of
359 0.750 and 0.788 MJ m⁻² d⁻¹. Under input scenario2, BT2 model showed the best
360 precision, with RMSE of 0.579 MJ m⁻² d⁻¹, RRMSE of 4.7%, R² of 0.986, E_{ns} of 0.984,
361 MAE of 0.496 MJ m⁻² d⁻¹. Under input scenario3, the five models had higher accuracy
362 than the models under input scenario1 and scenario2, with RMSE less than 0.617 MJ
363 m⁻² d⁻¹, RRMSE less than 4.3%, R² over than 0.995, E_{ns} over than 0.984, MAE less
364 than 0.513 MJ m⁻² d⁻¹. GEM3 model and BT3 model showed higher accuracy with
365 RMSE of 0.347 and 0.340 MJ m⁻² d⁻¹, RRMSE of 2.4% and 2.4%, R² of 0.999 and
366 0.999, E_{ns} of 0.995 and 0.995, MAE of 0.268 and 0.276 MJ m⁻² d⁻¹. BT4 model,
367 GEM4 model and SVM4 model showed better precision under input scenario4, with
368 RMSE of 0.341, 0.320 and 0.398 MJ m⁻² d⁻¹, RRMSE of 2.8%, 3.0% and 3.0%, R² of
369 0.998, 0.998 and 0.996, E_{ns} of 0.994, 0.995 and 0.993, MAE of 0.301, 0.293 and

0.309 MJ m⁻² d⁻¹, respectively. Under input scenario5, GEM5 model showed the highest accuracy, followed by BT5 model, with RMSE of 0.313 and 0.351 MJ m⁻² d⁻¹, RRMSE of 2.2% and 2.5%, R² of 0.999 and 0.998, E_{ns} of 0.996 and 0.995, MAE of 0.256 and 0.273 MJ m⁻² d⁻¹, respectively. HS model and BC model showed much poorer prediction accuracy with RMSE of 0.856 and 0.962 MJ m⁻² d⁻¹, with RRMSE of 6.0% and 6.8%, R² of 0.939 and 0.926, MAE of 0.680 and 0.790 MJ m⁻² d⁻¹, E_{ns} of 0.970 and 0.962, respectively.

In Yanji station, the BT1 model showed the highest accuracy under input scenario1, with RMSE of 0.795 MJ m⁻² d⁻¹, RRMSE of 8.1%, R² of 0.991, E_{ns} of 0.977, MAE of 0.627 MJ m⁻² d⁻¹. Under input scenario2, the BT2 model showed the highest accuracy, with RMSE of 0.661 MJ m⁻² d⁻¹, RRMSE of 4.8%, R² of 0.998, E_{ns} of 0.979, MAE of 0.603 MJ m⁻² d⁻¹. Under input scenario3, the five models had higher accuracy than the models under input scenario1 and scenario2, with RMSE less than 0.694 MJ m⁻² d⁻¹, RRMSE less than 5.4%, R² over than 0.998, E_{ns} over than 0.974, MAE less than 0.649 MJ m⁻² d⁻¹. BT3 model had the highest accuracy with RMSE of 0.455 MJ m⁻² d⁻¹, RRMSE of 3.6%, R² of 0.999, E_{ns} of 0.991, MAE of 0.408 MJ m⁻² d⁻¹. BT4 model showed the best precision under input scenario4, with RMSE of 0.454 MJ m⁻² d⁻¹, RRMSE of 3.3%, R² of 0.999, E_{ns} of 0.992, MAE of 0.409 MJ m⁻² d⁻¹. Under input scenario5, the GEM5 model showed the highest accuracy, followed by the BT5 model, with RMSE of 0.463 and 0.447 MJ m⁻² d⁻¹, RRMSE of 3.0% and 3.3%, R² of 1.000 and 0.999, E_{ns} of 0.992 and 0.992, MAE of 0.384 and 0.407 MJ m⁻² d⁻¹. HS model and

391 BC model showed much poorer prediction accuracy with RMSE of 1.305 and 1.239
392 MJ m⁻² d⁻¹, with RRMSE of 9.5% and 9.0%, R² of 0.979 and 0.984, MAE of 1.133
393 and 1.092 MJ m⁻² d⁻¹, E_{ns} of 0.917 and 0.926, respectively.

394 The Boxplots of the statistical indicators of monthly R_s for different models in the
395 study area are presented in Fig.5. Under input scenario1, the five models showed
396 lower prediction accuracy in the whole studied area, with RMSE of 0.824-1.308 MJ
397 m⁻² d⁻¹, with RRMSE of 8.0%-10.3%, MAE of 0.636-1.077 MJ m⁻² d⁻¹, E_{ns} of
398 0.898-0.944. BT1 model showed the highest accuracy among the five models. Under
399 input scenario2, the BT2 model was the best model with RMSE of 0.614 MJ m⁻² d⁻¹,
400 with RRMSE of 5.7%, MAE of 0.515 MJ m⁻² d⁻¹, E_{ns} of 0.961. The five models under
401 the input scenario3 showed higher prediction accuracy than the models under the
402 input scenario1-2. The BT3 model showed the best precision, followed by the GEM3
403 model, with RMSE of 0.413 and 0.433 MJ m⁻² d⁻¹, with RRMSE of 3.85% and 3.8%,
404 MAE of 0.331 and 0.365 MJ m⁻² d⁻¹, E_{ns} of 0.992 and 0.989. Under input scenario4,
405 the BT4 model showed the highest accuracy with RMSE of 0.387 MJ m⁻² d⁻¹, with
406 RRMSE of 3.8%, MAE of 0.334 MJ m⁻² d⁻¹, E_{ns} of 0.993. Under input scenario5, the
407 BT5 model and GEM5 model showed higher accuracy, with RMSE of 0.374 and
408 0.387 MJ m⁻² d⁻¹, with RRMSE of 3.7% and 3.8%, MAE of 0.312 and 0.319 MJ m⁻²
409 d⁻¹, E_{ns} of 0.993 and 0.994. HS model and BC model showed much poorer prediction
410 accuracy with RMSE of 1.005 and 1.009 MJ m⁻² d⁻¹, with RRMSE of 7.3% and 7.4%,
411 MAE of 0.822 and 0.848 MJ m⁻² d⁻¹, E_{ns} of 0.952 and 0.955, respectively.

412 GPI of monthly R_s of different models in the whole studied area is presented in
 413 Fig.6. As shown in Fig.6, SVM1, MET1, RF1, GEM1 and BT1 models under input
 414 scenario1 showed the lowest prediction accuracy, with average GPI of -2.957, -2.406,
 415 -1.979, -1.553 and -1.034 respectively. Under input scenario2, the BT2 model showed
 416 the highest accuracy, followed by the GEM2 model, SVM2 model, RF2 model, M5T2
 417 model, with average GPI of -0.182, -0.648, -0.965, -1.172 and -1.381 respectively.
 418 Under input scenario3, the BT3 model showed the best precision, followed by the
 419 GEM3 model, SVM3 model, RF3 model, M5T3 model, with average GPI of 0.730,
 420 0.654, 0.450, 0.112 and 0.076. The BT4 model was the best model under input
 421 scenario4, followed by the GEM4 model, SVM4 model, RF4 model, M5T4 model,
 422 with average GPI of 0.755, 0.686, 0.403, 0.120 and 0.077. Under input scenario5, the
 423 GEM5 model showed the best precision, followed by the BT5 model, SVM5 model,
 424 RF5 model, M5T5 model, with average GPI of 0.855, 0.809, 0.566, 0.166 and 0.121.
 425 The accuracy of HS and BC models was high than M5T1, SVM1 and RF1 models,
 426 with average GPI of -1.734 and -1.742 respectively. Machine learning models with
 427 complete data inputs had the highest precision. Meanwhile, the models which
 428 considered n , $T_{\max}$ and $T_{\min}$, n and P showed similar precision compared the models as
 429 for seven-inputs. The models only considered DOY and Ra showed the lowest
 430 prediction accuracy, with GPI of -4.114--0.588. The accuracy of the monthly R_s
 431 models which considered DOY, Ra, $T_{\max}$ and $T_{\min}$ were higher than the models for two
 432 inputs, with GPI increased by 17.5%-29.4%. The increase in accuracy was not

significant. In the calculation of monthly R_s , sunshine duration were the most significant variables in the studied area.

3.2 Discussion

Machine learning models generally had a higher accuracy than the HS and BC models when climatic variables were included as inputs. The machine learning models that considered only the DOY and R_a showed the lowest accuracies at the four stations, especially the SVM1 and RF1 models. Fan et al. (2019) showed that in China, the SVM and RF models had worse rankings, which agrees with our conclusion. The GEM and BT models had higher accuracies than other machine learning models when the same inputs were applied. The BT model was found to be the best model under input scenarios 1, 2, 3, and 4. It is an information-theoretical discriminative predictor which can boost an information-theoretical discriminative predictor (Israeli et al., 2019). Persson et al. (2017) analyzed the accuracy of the BT model for R_s estimation in Japan, and reported that the BT model had the highest accuracy with an RMSE of between $0.100 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$ and $0.137 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$. However, under the full climatic input scenario (input scenario 5), the GEM provided the best estimates. Through the statistical analysis of big data, the GEM estimation could be obtained by comprehensively analyzing the relationship between the measured data and the model access data (Lesser et al., 2011). This may be the reason for the high accuracy of the GEM. Although the BT model and GEM showed alternate rankings under different input scenarios, the differences were small.

To further confirm the reliability of GEM for R_s estimation, the Taylor diagrams of different models at four stations were analyzed. The standard deviation and correlation coefficient of the statistical indicators by the models over the stations are listed in Fig.5. It was clear that GEM5 models at different stations have the lowest standard deviation, the lowest mean square error and the highest correlation coefficient with the standard values. These results further confirmed the performance of GEM5 at different stations in Northeast China.

The results of this study showed that the models with complete inputs had the highest accuracy. This indicated that the effect of each meteorological factor on R_s estimation was positive. However, the models with $T_{\max}$ and $T_{\min}$ as inputs showed lower accuracy, especially the HS and BC models. The models considering n (input scenarios 3, 4, and 5) showed a much higher accuracy, which revealed that n is the most important factor affecting R_s estimation in Northeast China. Mecibah et al. (2014) investigated the performance of different R_s models and found that the accuracy of models with n was much higher than that of models with air temperature. The same conclusion was also reported by Zhang et al. (2018) because the magnitude of n directly affects the R_s reaching the surface of the earth.

4. Conclusions

Five machine models with five groups of input parameters and two empirical models were evaluated for R_s prediction using meteorological data from four stations in Northeast China. The GEM with full climatic data as inputs showed the highest

accuracy with RMSE, RRMSE, MAE, and E_{ns} values of $1.416 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, 10.27%, $1.018 \text{ MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, and 0.962, respectively. The BT model showed a worse performance with full climatic data as inputs, but showed better performance under other input scenarios compared with that of the GEM. n is the most influential factor affecting R_s estimation by machine learning models.

Overall, the GEM5 is recommended for estimating R_s in Northeast China when all the meteorological variables are available. The BT3 model is recommended when only n and air temperature data are accessible. The BT4 model and GEM4 are recommended only when sunshine data and P data are available.

Acknowledgments

We wish to thank the China Meteorological Administration for providing the data for this study. This study was supported by the Scientific Research Program of Higher Education in Hebei Province (QN2021227) and the Water Conservancy Research and Extension Project of Hebei Province(2020-64) and the Hebei Province Innovation Ability Promotion Plan, Soft Science Research(20557682D) and the Colleges and Universities in Hebei Province Science and Technology Research(ZD2020348) and the Doctoral Scientific Research Foundation of Hebei University of Water Resources and Electric Engineering(SYBJ1902)

References

Allen, R., 1995. Evaluation of Procedures of Estimating Mean Monthly Solar Radiation from Air

495 Temperature, FAO, Rome, Italy.

496 Anis, M. S., Jamil, B., Ansari, M.A., Bellos, E., 2019. Generalized models for estimation of global
497 solar radiation based on sunshine duration and detailed comparison with the existing: A case study
498 for India. *Sustainable Energy Technologies and Assessments*, 31, 179-198.

499 Annandale, J., Jovanovic, N., Benade, N., Allen, R., 2002. Software for missing data error analysis of
500 Penman-Monteith reference evapotranspiration. *Irrigation Science* 21(2), 57–67.

501 Antonopoulos, V. Z., Papamichail, D. M., Aschonitis, V. G., Antonopoulos, A. V., 2019. Solar radiation
502 estimation methods using ANN and empirical models. *Computers and Electronics in Agriculture*
503 160, 160–167.

504 Bailek. N., Bouchouicha, K., Al-Mostafa, Z., El-Shimy, M., Aoun, N., Slimani, A., Al-Shehri, S., 2018.
505 A new empirical model for forecasting the diffuse solar radiation over Sahara in the Algerian Big
506 South. *Renewable Energy* 117, 530–537.

507 Belaid, A., Mellit, A., Prediction of daily and mean monthly global solar radiation using support vector
508 machine in an arid climate, *Energy Convers Manag* 118, 105–118.

509 Breiman, L., 2001. Random forests. *Machine Learning* 45, 5–32.

510 Besharat, F., Dehghan, A. A., Faghih, A. R., 2013. Empirical models for estimating global solar
511 radiation: A review and case study. *Renewable and Sustainable Energy Reviews* 21, 798–821.

512 Bristow, K. L., Campbell, G. S., 1984. On the relationship between incoming solar radiation and daily
513 maximum and minimum temperature. *Agricultural and Forest Meteorology* 31(2), 159–166.

514 Bueno, C. L., Mateo., C. C., Justo., J. S., Sanz., S. S., 2019. Machine learning regressors for solar
515 radiation estimation from satellite data. *Solar Energy* 183, 768–775.

516 Buja, A., Swayne, D. F., Littman, M. L., Dean, N., Hofmann, H., Chen, L., 2008. Data visualization
 517 with multidimensional scaling. *Journal of Computational and Graphical Statistics* 17(2), 444–472.
 518 Chen, J.L., Liu, H.B., Wu, W., Xie, D.T., 2011. Estimation of monthly solar radiation from measured
 519 temperatures using support vector machines – a case study. *Renew. Energy* 36, 413–420
 520 Chen, Q. Y., Ding, Q., Liu, X. H., 2019. Establishment and validation of a solar radiation model for a
 521 living wall system. *Energy & Buildings* 195, 105–115.
 522 Chukwujindu, N. S., 2017. A comprehensive review of empirical models for estimating global solar
 523 radiation in Africa. *Renew Sustain Energy Rev* 78, 955–95.
 524 Citakoglu, H., 2015. Comparison of artificial intelligence techniques via empirical equations for
 525 prediction of solar radiation. *Computers and Electronics in Agriculture* 118, 28–37.
 526 Desideri, U., Zepparelli, F., Morettini, V., Garroni, E., 2013. Comparative analysis of concentrating
 527 solar power and photovoltaic technologies: technical and environmental evaluations. *Appl Energy*
 528 102, 765–784.
 529 Demircan, C., Bayrakçı, H.C., Keçebaş, A., 2020. Machine learning-based improvement of empiric
 530 models for an accurate estimating process of global solar radiation. *Sustainable Energy*
 531 *Technologies and Assessments*, 37, 100574.
 532 Elias, C. L., Calapez, A. R., Almeida, S. F. P., Chessman, B., Simoes, N., Feio, M. J., 2016. Predicting
 533 reference conditions for river bioassessment by incorporating boosted trees in the environmental
 534 filters method. *Ecological Indicators* 69, 239–251.
 535 Emamgolizadeh, S., Bateni, S.M., Shahsavani, D., Ashrafi, T., Gorbani, H., 2015. Estimation of soil
 536 cation exchange capacity using genetic expression programming (GEP) and multivariate adaptive

537 regression splines (MARS). *Journal of Hydrology*. 529 (3), 1590–1600.

538 Fan, J., Wang, X., Wu, L., Zhou, H., Zhang, F., Yu, X., Lu, X., Xiang, Y., 2018. Comparison of support
539 vector machine and extreme gradient Boosting for predicting daily global solar radiation using
540 temperature and precipitation in humid subtropical climates: a case study in China. *Energy*
541 *Convers Manag* 164, 102–111.

542 Fan, J. L., Wu, L. F., Zhang, F. C., Cai, H. J., Zeng, W. Z., Wang, X. K., Zou, H. Y., 2019. Empirical
543 and machine learning models for predicting daily global solar radiation from sunshine duration: A
544 review and case study in China. *Renewable and Sustainable Energy Reviews* 100, 186–212.

545 Feng, Y., Cui N. B., Gong D. Z., Zhang Q. W, Zhao L., 2017a. Evaluation of random forests and
546 generalized regression neural networks for daily reference evapotranspiration modeling,
547 *Agricultural Water Management* 193, 163–173.

548 Feng, Y., Jia, Y., Cui, N., Zhao, L., Li, C., Gong, D., 2017b. Calibration of Hargreaves model for
549 reference evapotranspiration estimation in Sichuan basin of southwest China. *Agriculture Water*
550 *Management* 181, 1–9.

551 Feng, Y., Jia, Y., Zhang, Q., Gong, D., Cui, N., 2018. National-scale assessment of pan evaporation
552 models across different climatic zones of China. *Journal of Hydrology* 564, 314–328.

553 Feng, Y., Cui, N., Chen, Y., Gong, D., Hu, X. 2019a. Development of data-driven models for prediction
554 of daily global horizontal irradiance in northwest China. *Journal of Cleaner Production* 223, 136–
555 146.

556 Feng, Y., Cui, N., Hao, W., Gao, L. and Gong, D., 2019b. Estimation of soil temperature from
557 meteorological data using different machine learning models. *Geoderma* 338, 67–77.

558 Friedman, J. H., 2001. Greedy Function Approximation: A Gradient Boosting Machine. *Annals of*
559 *Statistics* 29(5), 1189–1232.

560 Gueymard, C. A., 2001. Parameterized transmittance model for direct beam and circumsolar spectral
561 irradiance. *Sol Energy* 71, 325–346.

562 Hargreaves, G. H., Samani, Z. A., 1982. Estimating potential evapotranspiration. *Journal of the*
563 *Irrigation & Drainage Division*, 108(3), 225–230.

564 Hassan, G. E., Youssef, M. E., Mohamed, Z. E., Ali, M. A., and Hanafy, A. A., 2016. New
565 temperature-based models for predicting global solar radiation. *Applied Energy* 179, 437–450.

566 Hossain, M., Mekhilef, S., Olatomiwa, L., Danesh, M., Shamshirband, S., 2017. Application of
567 Extreme Learning Machine for short term output power forecasting of three grid-connected PV
568 systems. *Journal of Cleaner Production* 167, 395–405.

569 Israeli, A., Rokach, L., Shabtai, A., 2019. Constraint learning-based gradient boosting trees. *Expert*
570 *Systems With Applications* 128, 287–300.

571 Jamil, B., Akhtar, N., 2017. Estimation of diffuse solar radiation in the humid-subtropical climatic
572 region of India: Comparison of diffuse fraction and diffusion coefficient models. *Energy* 131,
573 149–164.

574 Jamil, B., Siddiqui, A.T., 2018. Estimation of monthly mean diffuse solar radiation over India:
575 performance of two variable models under different climatic zones. *Sustainable Energy*
576 *Technologies and Assessments*, 25, 161-180.

577 Jahani, B., Dinpashoh, Y., Nafchi, A.R., 2017. Evaluation and development of empirical models for
578 estimating daily solar radiation. *Renew Sustain Energy Rev* 73, 878–91.

579 Jin, Z., Ye, Z. W., Gang Y., 2005. General formula for estimation of monthly average daily global solar
580 radiation in China. *Energy Conversion and Management* 46(2), 257–268.

581 Kaba, K., Sarıgül, S., Avcı, M., Kandırmaz, M., 2018. Estimation of daily global solar radiation using
582 deep learning model. *Energy* 162, 126–135.

583 Katiyar, A. K., Pandey, C. K., 2010. Simple correlation for estimating the global solar radiation on
584 horizontal surfaces in India. *Energy* 35(12), 5043–5048.

585 Khatib, T., Mohamed, A., Sopian, K., 2012. A review of solar energy modeling techniques. *Renew*
586 *Sustain Energy Rev* 16, 2864–2869.

587 Kisi, O., Sanikhani, H., Zounemat-Kermani, M., Niazi, F., 2015. Long-term monthly
588 evapotranspiration modeling by several data-driven methods without climatic data. *Computers and*
589 *Electronics in Agriculture*. 115, 66–77.

590 Kisi, O., 2016. Modeling reference evapotranspiration using three different heuristic regression
591 approaches. *Agric. Water Manage.* 169, 162–172.

592 Lesser, B., Mucke, M., Gansterer, W. W., 2011. Effects of Reduced Precision on Floating-Point SVM
593 Classification Accuracy. *Procedia Computer Science* 4, 508–517.

594 Liu, X., Mei, X., Li, Y., Wang, Q., Jensen, J. R., Zhang, Y., Porter, J. R., 2009. Evaluation of
595 temperature-based global solar radiation models in China. *Agric For Meteorol* 149, 1433–1446.

596 Liu, C., Zheng, D., Zhao, L., Liu, C., 2014. Gaussian fitting for carotid and radial artery pressure
597 waveforms: Comparison between normal subjects and heart failure patients. *Bio-Medical*
598 *Materials and Engineering* 24, 271–277.

599 Liu., Y, Zhou., Y, Wang., D, Wan., Y, Li., Y, Zhu., Y, 2017. Classification of solar radiation zones and

600 general models for estimating the daily global solar radiation on horizontal surfaces in China,
 601 Energy Convers Manag 154, 167–179.

602 Mecibah, S. M., Boukelia, E. T., Tahtah, R., Gairaa, K., 2014. Introducing the best model for estimation
 603 the monthly mean daily global solar radiation on a horizontal surface (Case study:Algeria).
 604 Renewable & Sustainable Energy Reviews 36, 194–202.

605 Oates, M. J., Ruiz-Canales, A., Ferrández-Villena, M., FernándezLópez, A., 2017. A low cost sunlight
 606 analyser and data logger measuring radiation. Computers and Electronics in Agriculture 143, 38–
 607 48.

608 Pawlak, D. T., Clothiaux, E. E., Modest, M. F., Cole, J.N.S., 2004. Full-spectrum correlated-k
 609 distribution for shortwave atmospheric radiative transfer. Journal of the Atmospheric Sciences 61,
 610 2588–2601.

611 Pan, T., Wu, S. H., Dai, E. F., Liu, Y.J., 2013. Estimating the daily global solar radiation spatial
 612 distribution from diurnal temperature ranges over the Tibetan Plateau in China. Appl Energy 107,
 613 384–393.

614 Persson, G., Bacher, P., Shiga, T., Madsen, H., 2017. Multi-site solar power forecasting using gradient
 615 boosted regression trees. Solar Energy 120, 423–436.

616 Qiu R J, Wang Y K, Wang D, Qiu W J, Wu J C, Tao W Y, 2020. Water temperature forecasting based on
 617 modified artificial neural network methods: Two cases of the Yangtze River. Science of the Total
 618 Environment, 737, 1-12.

619 Quej, V. H., Almorox, J., Arnaldo, J. A., Saito, L., 2017. ANFIS, SVM and ANN soft-computing
 620 techniques to estimate daily global solar radiation in a warm sub-humid environment. Journal of

621 Atmospheric and Solar-terrestrial Physics 155, 62–70.

622 Quinlan, J. R., 1992. Learning with continuous classes, in Proceedings of the 5th Australian Joint
623 Conference on Artificial Intelligence, 343–348.

624 Sattari, M. T., Pal, M., Apaydin, H., et al, 2013. M5 model tree application in Daily River flow
625 forecasting in Sohu Stream, Turkey. Water Resources, 40(3), 233–242.

626 Shamshirband, S., Mohammadi, K., Tong, C. W., Zamani, M., Motamedi, S., Ch, S., 2016. A hybrid
627 SVM-FFA method for prediction of monthly mean global solar radiation. Theoretical and Applied
628 Climatology 125, 53–65.

629 Shiri, J., Nazemi, A.H., Sadraddini, A.A., Landaras, G., Kisi, O., Fard, A.F., Marti, P., 2014.
630 Comparison of heuristic and empirical approaches for estimating reference evapotranspiration
631 from limited inputs in Iran. Computers and Electronics in Agriculture. 108, 230–241.

632 Tabari, H., Kisi, O., Ezani, A., Talaei, P.H., 2012. SVM, ANFIS, regression and climate based models
633 for reference evapotranspiration modeling using limited climatic data in a semi-arid highland
634 environment. Journal of Hydrology. 44, 78–89.

635 Tian, H., Zhao, Y. Q., Luo, M., He Q. Q., Han, Y., Zeng, Z. L., 2020. Estimating PM2.5 from
636 multisource data: A comparison of different machine learning models in the Pearl River Delta of
637 China. 2021, 35: 100740.

638 Vapnik, V., 1999. The nature of statistical learning theory[M]. New York: Springer-Verlag.

639 Wang, Y., Witten, I. H., 1997. Inducing model trees for continuous classes, In Proceedings of the ninth
640 European conference on machine learning, 128–137.

641 Wang, L., Kisi, O., Zounemat-Kermani, M., Salazar, G.A., Zhu, Z., Gong, W., 2016. Solar radiation

642 prediction using different techniques: model evaluation and comparison. *Renew. Sust. Energy Rev.*
 643 61, 384–397.

644 Wild, M., Gilgen, H., Roesch, A., Ohmura, A., Long, C. N., Dutton, E. G., Forgan, B., Kallis, A.,
 645 Russak, V., Tsvetkov, A., 2005. From dimming to brightening: decadal changes in solar radiation at
 646 Earth's surface. *Sci* 308(5723), 847–850.

647 Wu., L., Huang., G., Fan., J., Zhanga., X., Wang., W., Zeng., W., 2019. Potential of kernel-based nonlinear
 648 extension of Arps decline model and gradient boosting with categorical features support for
 649 predicting daily global solar radiation in humid regions, *Energy Convers Manag* 183, 280–295.

650 Yu, H. H., Chen, Y. G., Hassan, S. G., Li, D. L., 2016. Prediction of the temperature in a Chinese solar
 651 greenhouse based on LSSVM optimized by improved PSO. *Computers and Electronics in*
 652 *Agriculture* 155, 257–282.

653 Zhang, Q. W., Cui, N. B., Feng, Y., Jia, Y., Li, Z., Gong, D. Z., 2018. Comparative Analysis of Global
 654 Solar Radiation Models in Different Regions of China. *Advances in Meteorology* 2018, 1–21.

655 Zhang, H. X., Cheng, L. L., Ding, T., Cheung, K. W., Wang, M. M., Wei, Z. N., Guo, Q. S., 2019.
 656 Estimation and validation of daily global solar radiation by day of the year-based models for
 657 different climates in China. *Renewable Energy* 135, 984–1003.

658 Zheng, M. G., Hu, S. Y., Liu, X. W., Wang, W., Yin, X. C., Zheng, L., Wang, L., Lou, Y. H., 2019.
 659 Levels and distribution of synthetic musks in farmland soils from the Three Northeast Provinces
 660 of China. *Ecotoxicology and Environmental Safety* 172, 303–307.

661 Zhu, S.L., Heddarn, S., Nyarko, E.K., Hadzima-Nyarko, M., Piccolroaz, S., Wu, S.Q., 2019a.
 662 Modelling daily water temperature for rivers: comparison between adaptive neurofuzzy inference

663 systems and artificial neural networks models. Environmental Sciences and Pollution Research. 26,
664 402–420.

665 Zhu, S.L., Nyarko, E.K., Hadzima-Nyarko, M., Heddam, S., Wu, S.Q., 2019b. Assessing the
666 performance of a suite of machine learning models for daily river water temperature prediction.
667 PeerJ 7, e7065.

668 Zou, L., Wang, L., Xia, L., Lin, A., Hu, B., Zhu, H., 2017. Prediction and comparison of solar radiation
669 using improved empirical models and adaptive neuro-fuzzy inference systems. Renew Energy 106,
670 343–353.

671

672 Table 1 Climatic conditions of the four stations in this study.

Station	Longitude (°E)	Latitude (°N)	Variable	Max	Min	Average	S _x	C _v
Harbin	126.8	45.8	U_2 (m·s ⁻¹)	7.6	0.0	1.9	0.9	0.5
			T_{ave} (°C)	30.9	-30.9	5.3	15.1	2.8
			n (h)	14.9	0.0	6.3	4.0	0.6
			H_r (%)	100	20	60	20	20
			P (mm·d ⁻¹)	146.6	0.0	1.4	5.4	3.7
			R_s (MJ·m ⁻² ·d ⁻¹)	33.3	0.0	13.0	7.2	0.6
Jilin	125.2	43.9	U_2 (m·s ⁻¹)	10.5	0.0	2.4	1.2	0.5
			T_{ave} (°C)	30.4	-30.1	6.5	14.2	2.2
			n (h)	14.3	0.0	7.1	3.8	0.5
			H_r (%)	100	10	60	20	30
			P (mm·d ⁻¹)	122.0	0.0	1.6	6.1	3.8
			R_s (MJ·m ⁻² ·d ⁻¹)	39.6	0.0	13.5	7.4	0.5
Shenyang	123.5	41.7	U_2 (m·s ⁻¹)	9.0	0.0	2.0	1.0	0.5
			T_{ave} (°C)	30.5	-26.8	8.6	13.3	1.5
			n (h)	13.9	0.0	6.5	3.9	0.6
			H_r (%)	100	10	60	20	30
			P (mm·d ⁻¹)	145.7	0.0	1.9	7.6	4.0
			R_s (MJ·m ⁻² ·d ⁻¹)	33.4	0.0	13.5	7.0	0.5
Yanji	129.5	42.9	U_2 (m·s ⁻¹)	10.0	0.0	1.9	1.3	0.7
			T_{ave} (°C)	29.7	-23.7	6.0	12.8	2.1
			n (h)	14.0	0.0	6.3	3.7	0.6
			H_r (%)	100	10	60	20	30
			P (mm·d ⁻¹)	124.6	0.0	1.5	5.5	3.6
			R_s (MJ·m ⁻² ·d ⁻¹)	32.6	0.0	13.2	6.9	0.5

673 Max, Min, Average, S_x, and C_v denote the maximum, minimum, mean, standard deviation, and
674 variation coefficient of each meteorological variable, respectively.

Table 2 Input combinations for training the machine learning models in this study.

Input scenario	Model ID	Models M5T	Model ID	Models SVM	Model ID	Models GEM	Model ID	Models RF	Model ID	Models BT	Inputs
1	A	M5T1	E	SVM1	K	GEM1	P	RF1	U	BT1	DOY, R_a
2	B	M5T2	G	SVM2	L	GEM2	Q	RF2	V	BT2	DOY, R_a , $T_{\max}$, $T_{\min}$
3	C	M5T3	H	SVM3	M	GEM3	R	RF3	W	BT3	DOY, R_a , $T_{\max}$, $T_{\min}$, n
4	D	M5T4	I	SVM4	N	GEM4	S	RF4	X	BT4	DOY, R_a , n , $\ln(P+1)$
5	E	M5T5	J	SVM5	O	GEM5	T	RF5	Y	BT5	DOY, R_a , $T_{\max}$, $T_{\min}$, n , H_r , $\ln(P+1)$

676 Table 3 Parameters applied for different machine learning models in this study.

Model	Key parameters
M5T model	Minimum leaf size = 10, Minimum parent size = 20
SVM	Kernel function type = Gaussian function, Gamma = 30, Cost = 40
RF model	Maximum depth of the tree = 3, Number of trees = 500
GEM	Kernel function type = Gaussian function, Gamma = 2, Cost = 10
BT model	Size of regressions trees = 6, Number of iterations = 200

Table 4 Statistical performances of daily R_s of different models at the four stations. The best model in each station is marked in bold.

Station	Indicators	M5T1	M5T2	M5T3	M5T4	M5T5	SVM1	SVM2	SVM3	SVM4	SVM5	GEM1	GEM2	GEM3	GEM4	GEM5	RF1	RF2	RF3	RF4	RF5	BT1	BT2	BT3	BT4	BT5	HS	BC
Harbin	RMSE ($\text{MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$)	5.207	4.132	2.900	2.809	2.824	5.749	3.791	2.518	2.497	2.406	5.049	3.398	2.149	2.161	1.719	5.404	4.044	2.813	2.766	2.700	2.893	3.068	1.944	2.033	1.797	4.229	4.127
	RRMSE (%)	38.4	30.5	21.4	20.7	20.8	41.4	27.9	18.6	18.4	17.7	37.2	25.0	15.8	15.9	12.7	39.8	29.8	20.7	20.4	19.9	36.1	22.6	15.4	15.0	13.2	31.2	30.4
	R^2	0.516	0.705	0.904	0.914	0.911	0.424	0.746	0.919	0.923	0.929	0.541	0.803	0.941	0.942	0.964	0.483	0.721	0.913	0.919	0.924	0.569	0.842	0.952	0.948	0.960	0.689	0.705
	E_{ns}	0.505	0.688	0.847	0.856	0.854	0.397	0.738	0.884	0.886	0.894	0.535	0.789	0.916	0.915	0.946	0.467	0.702	0.856	0.860	0.867	0.563	0.828	0.931	0.925	0.941	0.674	0.689
	MAE ($\text{MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$)	4.015	3.096	2.237	2.164	2.187	4.718	2.791	1.892	1.869	1.798	3.886	2.524	1.604	1.632	1.283	4.110	3.067	2.178	2.149	2.108	3.742	2.305	1.456	1.525	1.353	3.270	3.187
Jilin	RMSE ($\text{MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$)	5.543	4.465	2.049	1.982	1.962	19.887	3.937	1.839	1.830	1.760	5.550	3.471	1.610	1.538	1.245	6.020	4.105	1.947	1.972	1.869	5.393	3.157	1.513	1.543	1.410	4.377	4.207
	RRMSE (%)	40.7	32.8	15.1	14.6	14.4	146.1	28.9	13.5	13.4	12.9	40.8	25.5	11.8	11.3	9.1	44.2	30.2	14.3	14.5	13.7	43.6	23.2	11.1	11.3	10.4	32.2	30.9
	R^2	0.474	0.661	0.929	0.934	0.933	0.147	0.734	0.942	0.943	0.947	0.473	0.795	0.956	0.960	0.974	0.384	0.712	0.935	0.934	0.941	0.503	0.835	0.961	0.959	0.966	0.672	0.696
	E_{ns}	0.472	0.658	0.928	0.933	0.934	0.105	0.734	0.942	0.943	0.947	0.471	0.793	0.956	0.959	0.973	0.378	0.711	0.935	0.933	0.940	0.501	0.829	0.961	0.959	0.966	0.671	0.696
	MAE ($\text{MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$)	4.125	3.062	1.427	1.377	1.358	15.663	2.714	1.249	1.256	1.183	4.147	2.403	1.077	1.067	0.844	4.462	2.888	1.337	1.392	1.271	4.030	2.211	1.013	1.072	0.945	3.248	3.069
Shenyang	RMSE ($\text{MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$)	5.697	4.407	2.619	2.539	2.484	5.994	3.983	2.274	2.387	2.119	5.586	3.565	2.019	2.088	1.658	5.919	4.283	2.465	2.526	2.347	5.355	3.227	1.876	2.010	1.754	4.557	4.479
	RRMSE (%)	40.1	31.0	18.4	17.9	17.5	42.2	28.0	16.0	16.8	15.5	39.3	25.1	14.2	14.7	11.7	41.6	30.1	17.3	17.8	16.5	37.7	22.7	13.2	14.1	14.1	32.1	31.5
	R^2	0.440	0.656	0.882	0.890	0.894	0.389	0.717	0.909	0.901	0.916	0.457	0.776	0.929	0.925	0.953	0.392	0.676	0.897	0.891	0.908	0.503	0.822	0.940	0.930	0.947	0.634	0.648
	E_{ns}	0.421	0.654	0.878	0.885	0.890	0.359	0.717	0.908	0.898	0.914	0.444	0.773	0.927	0.922	0.951	0.375	0.673	0.892	0.886	0.902	0.489	0.814	0.937	0.928	0.945	0.630	0.642
	MAE ($\text{MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$)	4.557	3.284	1.836	1.797	1.764	4.741	2.912	1.566	1.642	1.436	4.466	2.637	1.394	1.481	1.147	4.644	3.234	1.778	1.799	1.703	4.265	2.412	1.299	1.407	1.206	3.526	3.483
Yanji	RMSE ($\text{MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$)	5.402	3.849	1.746	1.675	1.743	6.879	3.454	1.509	3.521	1.434	5.209	3.118	1.274	1.319	1.045	5.571	3.767	1.686	1.671	1.682	5.030	2.809	1.226	1.259	1.149	4.063	3.885
	RRMSE (%)	39.3	28.0	12.7	12.2	12.7	50.0	25.1	11.0	25.6	10.4	37.9	22.7	9.3	9.6	7.6	40.5	27.4	12.3	12.2	12.2	36.6	20.4	8.9	9.2	8.4	29.6	28.3
	R^2	0.406	0.716	0.946	0.952	0.947	0.430	0.961	0.953	0.762	0.963	0.445	0.812	0.971	0.969	0.981	0.376	0.727	0.952	0.952	0.957	0.484	0.849	0.973	0.971	0.977	0.677	0.707
	E_{ns}	0.396	0.693	0.937	0.942	0.937	0.021	0.753	0.959	0.744	0.958	0.439	0.799	0.966	0.964	0.977	0.358	0.706	0.941	0.942	0.941	0.476	0.837	0.969	0.967	0.973	0.659	0.688
	MAE ($\text{MJ}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$)	4.296	2.980	1.322	1.297	1.332	5.197	2.628	1.169	2.655	1.101	4.138	2.431	0.977	1.018	0.801	4.347	2.962	1.306	1.300	1.316	3.973	2.194	0.943	0.970	0.877	3.320	3.132

Table 5 Statistical performances of monthly R_s of different models at the four stations. The best model in each station is marked in bold.

Stations	Evaluation index	M5T1	M5T2	M5T3	M5T4	M5T5	SVM1	SVM2	SVM3	SVM4	SVM5	GEM1	GEM2	GEM3	GEM4	GEM5	RF1	RF2	RF3	RF4	RF5	BT1	BT2	BT3	BT4	BT5	HS	BC
Harbin	RMSE	1.155	1.145	0.825	0.802	0.790	1.941	0.848	0.593	0.592	0.593	0.885	0.814	0.655	0.594	0.575	1.16	1.175	0.783	0.802	0.739	0.878	0.692	0.601	0.506	0.456	1.186	1.193
	RRMSE	13.5	13.4	8.5	8.3	8.2	14.3	13.3	8.3	8.6	8.3	12.5	11.0	7.5	7.8	7.0	12.6	14.7	8.2	8.3	7.8	13.5	11.1	7.5	7.2	7.1	8.8	8.8
	R^2	0.972	0.991	0.999	0.999	0.999	0.947	0.992	0.999	0.999	0.999	0.984	0.996	0.999	0.999	1	0.971	0.988	0.999	0.999	0.999	0.984	0.997	1	0.999	1	0.977	0.976
	E_{NS}	0.953	0.954	0.984	0.987	0.989	0.868	0.925	0.972	0.968	0.988	0.923	0.937	0.973	0.985	0.989	0.935	0.952	0.989	0.987	0.994	0.943	0.953	0.984	0.987	0.988	0.951	0.95
	MAE	1.523	1.502	0.545	0.525	0.513	1.586	1.552	0.621	0.664	0.616	1.494	1.371	0.568	0.548	0.499	1.236	1.113	0.608	0.627	0.603	0.803	0.702	0.467	0.463	0.411	0.955	0.951
Jilin	RMSE	0.495	0.542	0.41	0.359	0.407	1.078	0.772	0.307	0.317	0.312	0.692	0.648	0.264	0.221	0.197	0.685	0.547	0.394	0.36	0.377	0.69	0.525	0.256	0.245	0.242	0.672	0.643
	RRMSE	5.6	4.0	3.0	2.6	3.0	7.9	3.5	2.3	2.3	2.3	5.6	2.6	1.9	1.6	1.5	5.0	3.3	2.9	2.6	2.8	3.6	2.4	1.9	1.8	1.8	5.4	4.7
	R^2	0.984	0.983	0.995	0.996	0.994	0.956	0.984	0.997	0.997	0.999	0.844	0.897	0.998	0.998	0.999	0.918	0.976	0.995	0.996	0.995	0.954	0.907	0.998	0.998	0.998	0.872	0.991
	E_{NS}	0.871	0.989	0.994	0.995	0.997	0.856	0.892	0.996	0.996	0.996	0.891	0.915	0.997	0.998	0.999	0.902	0.973	0.994	0.995	0.997	0.891	0.926	0.998	0.998	0.998	0.971	0.984
	MAE	0.593	0.417	0.321	0.26	0.304	0.743	0.363	0.217	0.218	0.211	0.381	0.276	0.189	0.149	0.137	0.526	0.390	0.279	0.246	0.249	0.364	0.261	0.176	0.164	0.159	0.520	0.559
Shenyang	RMSE	1.225	0.828	0.606	0.633	0.612	1.415	0.705	0.376	0.398	0.318	0.962	0.687	0.347	0.32	0.313	1.227	0.919	0.617	0.629	0.614	0.932	0.579	0.340	0.341	0.351	0.856	0.962
	RRMSE	8.6	6.4	4.3	4.5	4.3	10.0	5.9	3.1	3.0	2.9	6.8	4.7	2.4	3.0	2.2	8.6	6.4	4.3	4.6	4.5	6.6	4.7	2.4	2.8	2.5	6.0	6.8
	R^2	0.981	0.987	0.995	0.995	0.996	0.953	0.973	0.997	0.996	0.998	0.979	0.986	0.999	0.998	0.999	0.972	0.988	0.996	0.994	0.996	0.971	0.986	0.999	0.998	0.998	0.939	0.926
	E_{NS}	0.938	0.964	0.985	0.983	0.985	0.917	0.993	0.994	0.993	0.996	0.962	0.984	0.995	0.995	0.996	0.938	0.964	0.984	0.983	0.983	0.964	0.984	0.995	0.994	0.995	0.970	0.962
	MAE	0.996	0.625	0.477	0.497	0.478	1.079	0.497	0.305	0.309	0.305	0.788	0.390	0.268	0.293	0.256	1.005	0.785	0.513	0.51	0.512	0.750	0.496	0.276	0.301	0.273	0.680	0.790
Yanji	RMSE	1.215	1.149	0.694	0.695	0.693	0.800	0.745	0.552	0.607	0.506	0.989	0.786	0.467	0.475	0.463	0.976	0.787	0.536	0.523	0.533	0.795	0.661	0.455	0.454	0.447	1.305	1.239
	RRMSE	10.7	8.4	5.1	5.2	5.3	8.8	7.4	4.0	4.8	4.1	9.0	6.7	3.4	3.6	3.0	9.1	7.9	5.4	5.3	5.4	8.1	4.8	3.6	3.3	3.3	9.5	9.0
	R^2	0.915	0.992	0.998	0.998	0.999	0.951	0.974	0.998	0.998	0.998	0.992	0.977	0.999	0.999	1	0.978	0.993	0.998	0.998	0.999	0.991	0.998	0.999	0.999	0.999	0.979	0.984
	E_{NS}	0.929	0.936	0.977	0.979	0.980	0.949	0.973	0.985	0.989	0.989	0.947	0.97	0.989	0.988	0.992	0.934	0.943	0.974	0.975	0.976	0.977	0.979	0.991	0.992	0.992	0.917	0.926
	MAE	1.198	1.039	0.649	0.648	0.642	0.701	0.608	0.514	0.526	0.522	0.804	0.713	0.436	0.438	0.384	0.864	0.78	0.523	0.533	0.528	0.627	0.603	0.408	0.409	0.407	1.133	1.092

Fig. 1 The geographical distribution of the stations in Northeast China.

Fig.2 Monthly variations of meteorological variables at the four stations in Northeast China.

Fig.3 Boxplots of the statistical indicators of daily R_s for different models.

Fig.4 GPI values of daily R_s of different models at the four stations in Northeast China.

Fig.5 Boxplots of the statistical indicators monthly R_s for different models.

Fig.6 GPI values of monthly R_s of different models at the four stations in Northeast China.

Fig.7 Taylor diagrams of daily R_s of different machine learning models at different stations.

Fig.7 Taylor diagrams of monthly R_s of different machine learning models at different stations.