A robust error correction method for numerical weather prediction wind speed based on Bayesian optimization, Variational Mode Decomposition, Principal Component Analysis, and Random Forest: VMD-PCA-RF (version 1.0.0)

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Abstract. Accurate wind speed prediction is crucial for the safe and efficient utilization of wind resources. However, current single-value deterministic numerical weather prediction methods employed by wind farms do not adequately meet the actual needs of power grid dispatching. In this study, we propose a new hybrid forecasting method for correcting 10-meter wind speed predictions made by the Weather Research and Forecasting (WRF) model. Our approach incorporates Variational Mode Decomposition (VMD), Principal Component Analysis (PCA), and five artificial intelligence algorithms: Deep Belief Network (DBN), Multilayer Perceptron (MLP), Random Forest (RF), eXtreme Gradient Boosting (XGBoost), light Gradient Boosting Machine (lightGBM), and the Bayesian Optimization Algorithm (BOA). We first predict wind speeds using the WRF model, with initial and lateral boundary conditions from the Global Forecast System (GFS). We first construct WRF-predicted wind speeds using the Global Forecast System (GFS) model output based on prediction results. We then perform two sets of experiments with different input factors and apply BOA optimization to tune the four artificial intelligence models, ultimately building the final models. Furthermore, we compare the aforementioned five optimal artificial intelligence models suitable for five provinces in southern China in the wintertime: VMD-PCA-RF in December 2021 and VMD-PCA-lightGBM in January 2022. We find that the VMD-PCA-RF evaluation indices exhibit relative stability over nearly a year:

correlation coefficient (R) is above 0.6, Forecasting Accuracy (FA) is above 85 %, mean absolute error

(MAE) is below 0.6 m s^{-1}, root mean square error (RMSE) is below 0.8 m s^{-1}, relative mean absolute

error (rMAE) is below 60 %, and relative root mean square error (rRMSE) is below 75 %. Thus, for its

promising performance and excellent year-round robustness, we recommend adopting the proposed

VMD-PCA-RF method for improved wind speed prediction in models.

1 Introduction

Sustainable energy plays a vital role in reducing carbon footprint and increasing system reliability

(Hanifi et al., 2020). As renewable energy sources have a negligible carbon footprint, they have

become the preferred choice for many industries in the power sector (Dhiman and Deb, 2020). Among

these sources, wind energy is a crucial low-carbon energy technology with the potential to become a

sustainable energy source (Tascikaraoglu and Uzunoglu, 2014). In 2022, the global wind power

capacity reached 906 GW, with a 9 % year-on-year increase due to a newly installed capacity of 77.6

GW. The global onshore wind market increased by 68.8 GW while facing a 5 % growth decline

compared to the previous year. Such change is attributed to a slowdown in China and the U.S., the

world's two largest wind markets that account for over two-thirds of the world's onshore wind farm

installations (Joyce and Feng, 2023). The instability and unpredictability of wind power generation can

lead to instability in the power system. In addition, the decline of the wind energy market also makes it

more challenging to improve the accuracy of wind speed forecasts. An accurate wind speed prediction

method is needed to reduce the instability risk of power system and the economic loss of wind power

enterprises (Huang et al., 2019). Therefore, accurate and stable wind speed prediction (WSP) is very

important for the safe and stable operation of the power grid system and for improving the utilization

rate of wind energy and economic development (Guo et al., 2021; Xiong et al., 2022; Tang et al.,

2021).

Current WSP algorithms are primarily categorized into physical algorithms (Zhao et al., 2016),

statistical algorithms (Wang and Hu, 2015; Barthelmie et al., 1993), machine learning (ML) algorithms

(Huang et al., 2019; Salcedo-Sanz et al., 2011; Ma et al., 2020), and hybrid algorithms (Deng et al.,

2020; Xu et al., 2021; Zhao et al., 2019; Xiong et al., 2022; Tang et al., 2021). Physical methods, such

as numerical weather prediction (NWP), are commonly used in wind speed forecasting. NWP, which

accounts for atmospheric processes and physical laws, solves discrete mass, momentum, and energy conservation equations along with other fundamental physical principles, establishing itself as a widely adopted and reliable physical method. Currently, the High-resolution Limited Area Model (HIRLAM) (Služenikina and Männik, 2016), the European Center for Medium-Range Weather Forecast (ECMWF) model, the fifth-generation mesoscale model (MM5) (Salcedo-Sanz et al., 2009), and the Weather Research and Forecasting Model (WRF) (Skamarock et al., 2021) are extensively utilized for wind speed prediction. However, NWP modeling faces challenges due to the selection of parameterization schemes, such as model microphysics and systematic errors, which exhibit temporal and spatial differences and uncertainties. These uncertainties hinder the accuracy of NWP models in wind speed prediction, making it difficult to meet the rising demands of the grid system (Zhao et al., 2019; Xu et al., 2021).

Studies have demonstrated that enhancing the accuracy of numerical weather prediction (NWP) models and correcting prediction errors can effectively minimize the errors associated with wind speed prediction. These research endeavors have typically sought to optimize the physical and dynamic parameters of the NWP model (Cheng et al., 2013), refine the model structure (Jiménez and Dudhia, 2012), or improve the accuracy of model inputs through preprocessing and denoising techniques (Xu et al., 2015). Additionally, improving initial field error through methods, such as target observation and data assimilation (Williams et al., 2013), can also minimize wind speed errors predicted by NWP models.

Physical methods are generally more appropriate for long-term wind speed prediction, such as those 48-72 hours in advance, while their practical application in short-term forecasting is limited (Zhao et al., 2019; Deng et al., 2020; James et al., 2018). In contrast, statistical methods utilize historical data to establish a relationship between input and output variables and are therefore well-suited for short-term wind speed prediction. They are usually time series models, such as Autoregressive Moving Average (ARMA) (Erdem and Shi, 2011) and Autoregressive Integrated Moving Average (ARIMA) (Wang and Hu, 2015). Whereas filtering models (Cassola and Burlando, 2012; Chen and Yu, 2014), machine learning models (Hu et al., 2013), and hybrid models (Huang et al., 2019) have been gradually developed to further improve wind speed prediction accuracy.

88   With purely statistical models becoming less suitable for wind speed predictions beyond 6 hours,

89   the use of a combination of physical and statistical methods has gained growing interest (Zjavka, 2015;

90   Xu et al., 2021). The error correction model improves the accuracy of the NWP model by training on

91   the relationship between the NWP predictor variables and the observed correlation variables (Sun et al.,

92   2019). However, traditional error prediction models rely solely on historical wind speed sequences as

93   input factors (Deng et al., 2020; Guo et al., 2021) and do not incorporate the characteristic

94   meteorological factors forecasted by the WRF model. Studies have shown that considering all relevant

95   historical meteorological factors can lead to more accurate predictions compared to only taking into

96   account historical wind speed (Zhang et al., 2019c). Therefore, it is crucial to include meteorological

97   characteristic factors as input in the prediction model.

98   For an error prediction model, wind speed is the most important input factor. Traditionally, the

99   error prediction model uses historical wind speed data as input, without any feature selection. Feature

100   selection methods, such as filtering methods, are commonly used in time series analysis. Currently,

101   empirical mode decomposition (EMD) (Liu et al., 2018; Guo et al., 2012), ensemble empirical mode

102   decomposition (EEMD) (Wang et al., 2017), wavelet decomposition (WD) (Zhang et al., 2019b),

103   variational mode decomposition (VMD) (Hu et al., 2021; Zhang et al., 2019a), and other filtering

104   methods are used to select key features in the wind speed data. As mentioned above, studies have

105   shown that these feature selection methods can effectively extract the hidden features in the wind speed

106   series to improve wind speed prediction accuracy. However, despite the effectiveness of wind speed

107   filtering methods in wind speed prediction, only a few studies have applied these methods to the

108   correction of wind speed errors in NWP forecasting (Xu et al., 2021; Li et al., 2022).

109   In addition, traditional error correction methods generally adopt linear regression (Dong et al.,

110   2013), multiple linear regression (Liu et al., 2016), machine learning (Salcedo-Sanz et al., 2011), and

111   deep learning algorithms (Zhang et al., 2019c). However, the efficacy of machine learning and deep

112   learning algorithms is highly dependent on the selection of model parameters (Guo et al., 2021; Xiong

113   et al., 2022). The Bayesian optimization algorithm (Li and Shi, 2010; Guo et al., 2021) is considered a

114   relatively advanced algorithm for optimizing model parameters and has been widely used in MATLAB

115   and Python packages.

116   In this study, we investigate a multi-step wind speed forecasting model that combines NWP

117   simulation and an error correction strategy. We present two sets of experiments divided into three steps:

118   (1) we use the first group of experiments to extract hidden features from various meteorological

119   elements forecasted by NWP; The second group of experiments mainly focuses on the wind speed

120   forecast of NWP, and the VMD-PCA algorithm is used to extract the hidden features in the forecasted

121   wind speed; each set of experimental input factors is matched with the actual 10-meter wind speed data

122   of 410 stations in time and space; (2) we employ four advanced machine learning algorithms optimized

123   by the BOA algorithm, and DBN deep learning algorithm to train the two groups of experiments and

124   perform 5-fold cross-validation; and (3) we analyze six distinct wind speed error indicators to compare

125   and identify the most suitable wind speed error correction schemes for the five southern provinces

126   (Yunnan, Guizhou, Guangxi, Guangdong, Hainan) in winter and throughout most of the year. The

127   remainder of this paper is organized into sections discussing the effects of the BOA-VMD-PCA

128   approach, the interpretability of RF feature importance, and the stability analysis of the proposed

129   models.

130   **2 Data and methods**

131   **2.1 Data**

132   The observed data comes from the China Meteorological Administration land data assimilation

133   system (CLDAS-V2.0) real-time product data set. According to the description of the documents on the

134   official website (https://data.cma.cn/data/cdcdetail/dataCode/NAFP_CLDAS2.0_RT.html), the dataset

135   is constructed through the integration of multiple sources, including ground and satellite data, and is

136   refined using advanced techniques such as multi-grid variational assimilation, physical inversion, and

137   terrain correction. This dataset exhibits superior quality in comparison to other products, offering

138   higher spatial and temporal resolutions. The target observation data includes 2-m air temperature, 2-m

139   specific humidity, 10-meter wind speed, surface pressure, and precipitation. These data are processed

140   by the China Meteorological Public Service Center to equivalent latitude and longitude grid scale,

141   covering a geographical range of 15-32.97°N and 94-120.97°E. The spatial resolution of the grid is

142   0.03° × 0.03° (3km by 3km) and the temporal resolution is 1 hour. China Meteorological Public

143   Service Center applied the nearest neighbor interpolation for precipitation and bilinear interpolation for

144   the other four meteorological elements with downscaling from 3km to 410 sites. We select the

145   10-meter wind speed data of 410 sites, as illustrated in Fig. 1.

146

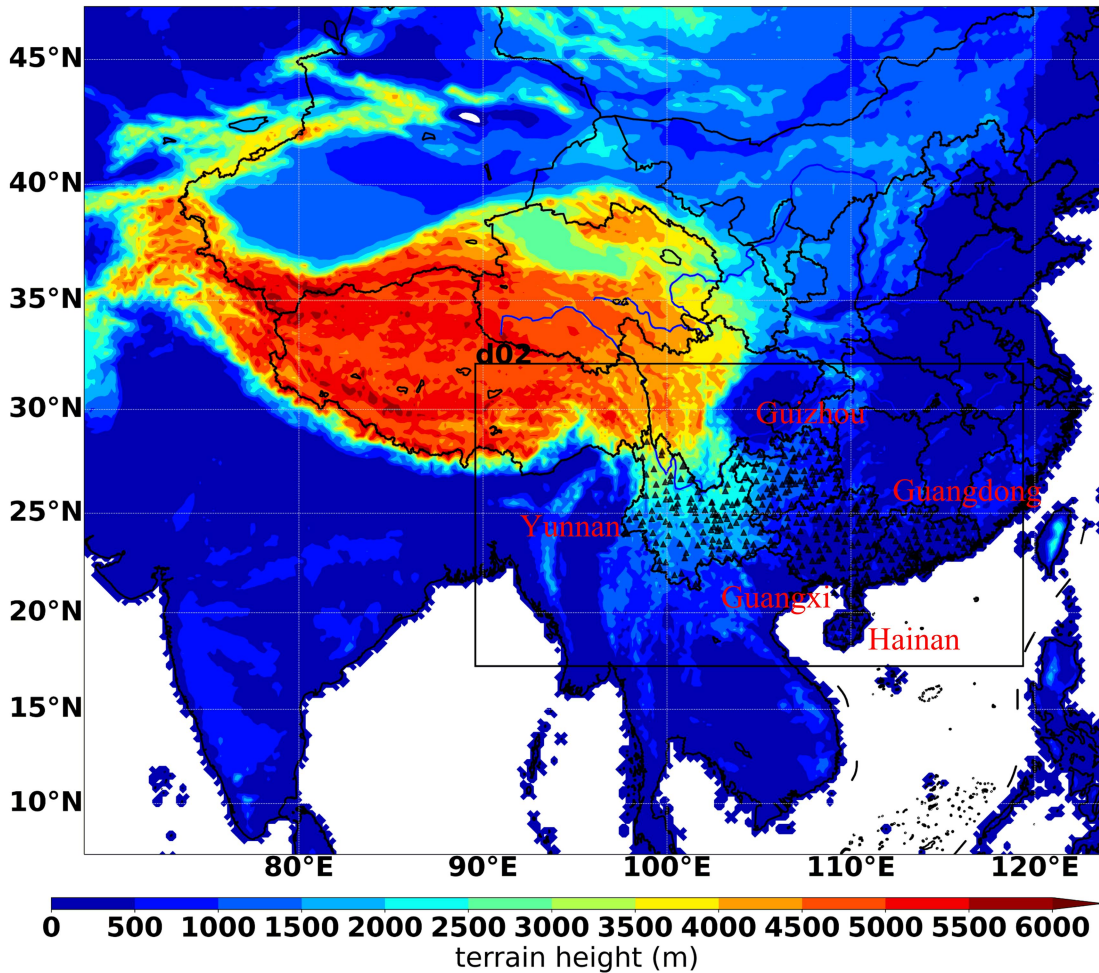



Figure 1. WRF model simulation area elevation diagram. (d02 represents the nested area of the second layer of the WRF model, and the black triangles represent the meteorological sites).

149

2.2 Methods

2.2.1 WRF simulation

    The WRF 4.2 model (Skamarock et al., 2021), developed by the National Center for Atmospheric Research (NCAR), represents a new generation of mesoscale numerical models with numerous applications in research forecasting. We use the WRF model with forcing from the 0.25° × 0.25° GFS model developed by the National Centers for Environmental Prediction (NCEP). We use the first 90 hours of the daily GFS forecast initialized at 06:00 UTC, with 3-h output, to provide initial and boundary conditions for a daily 42-h WRF forecast, analyzing the 18-42 h forecast and discarding the

first 18 h as spin up. ~~When forecasting meteorological elements, the WRF model normally uses the GFS data developed by the National Centers for Environmental Prediction (NCEP). We use the WRF model in combination with daily GFS data resolution of 0.25° × 0.25°. The GFS data used by us is released at 06:00 UTC with forecasting every 3 hours for a total duration of 90 hours. We selected the 24-h forecasting data from the WRF-resulted file after a spin-up time of 18 hours. The GFS data as the initial field and lateral boundary conditions for the WRF model.~~ Surface static data, such as terrain, soil data, and vegetation coverage, are derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite with a resolution of 15 seconds (approximately 500 meters). Incorporating a two-layer grid nesting configuration, the forecast area is illustrated in Fig. 1. The WRF configuration process is detailed in Table 1. Given that the time scale of the meteorological station data in the study area is 1 hour, the forecast data time interval of the WRF model is also set to 1 hour. As a widely used numerical weather forecast model, the WRF model is suitable for weather studies from a few meters to several thousand kilometers. Therefore, this paper uses the WRF model to predict 10-meter wind speed as the input factor for the error correction model.

Table 1. WRF configuration scheme

Model (Version)	WRF (V4.2)	
Domains	D1	D2
Horizontal grid points	600*500	967*535
Δx (km)	9	3
Vertical layers	58	
Longwave radiation	RRTMG (Iacono et al., 2008)	
Shortwave radiation	RRTMG (Iacono et al., 2008)	
Land surface	Noah LSM (Chen et al., 1997)	
Surface layer	MYJ (Janjić, 1994)	
Microphysics	Thompson (Thompson et al., 2008)	
Boundary layer	MYJ (Janjić, 1994)	
Cumulus	Tiedtke (Tiedtke, 1989; Zhang et al., 2011)	

2.2.2 Variational mode decomposition

As a new filtering method, VMD is robust in feature selection. The VMD algorithm decomposes a time series signal into several intrinsic mode functions (Isham et al., 2018). The sum of the modes equals the original signal, and the sum of the bandwidths is the smallest. The analysis signal is

179   calculated using the Hilbert transform to estimate the modal bandwidth. The optimization model is

180   described as

181
$$\left\{ \min_{\{u_k\},\{\omega_k\}} \left\{ \sum_{k=1}^{K} \| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) u_k(t) \right] e^{-j\omega_k t} \Big|_2^2 \right\} \quad s.t. \quad \sum_{k=1}^{K} u_k = v \right. \tag{1.1}$$

182   where K is the total number of modes, u_k is the decomposed K-th mode, w_k is the corresponding

183   center frequency, and v is the time-series signal, representing the wind speed sequence predicted by the

184   WRF model in this study.

185   The above-constrained problem can be transformed into an unconstrained problem using the

186   Lagrangian function:

187
$$L\left(\{u_k\},\{\omega_k\},\lambda\right) = \omega_k^{n+1} = \frac{\int_0^{\infty} \omega \left| \hat{u}_k(\omega) \right|^2 d\omega}{\int_0^{\infty} \left| \hat{u}_k(\omega) \right|^2 d\omega} \sum_{k=1}^{K} \| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) u_k(t) \right.$$

188

189
$$\times] e^{-j\omega_k t} \|_2^2 + \| v(t) - \sum_{k=1}^{K} u_k(t) \|_2^2 + \left\langle \lambda(t), v(t) - \sum_{k=1}^{K} u_k(t) \right\rangle \tag{1.2}$$

190   where α is the penalty parameter and $\lambda(t)$ is the Lagrange multiplier.

191   Then we update u_k, w_k, and λ using the alternating direction method of the multiplier:

192
$$\hat{u}_k^{n+1}(\omega) = \frac{\hat{v}(\omega) - \sum_{i \neq k} \hat{u}_i(\omega) + \frac{\hat{\lambda}(\omega)}{2}}{1 + 2\alpha\left(\omega - \omega_k\right)^2} \tag{1.3}$$

193
$$\omega_k^{n+1} = \frac{\int_0^{\infty} \omega \left| \hat{u}_k(\omega) \right|^2 d\omega}{\int_0^{\infty} \left| \hat{u}_k(\omega) \right|^2 d\omega} \tag{1.4}$$

194
$$\hat{\lambda}^{n+1}(\omega) = \hat{\lambda}^n(\omega) + \tau \left[\hat{v}(\omega) - \sum_{k=1}^{K} \hat{u}_k^{n+1}(\omega) \right] \tag{1.5}$$

195   where τ is the update parameter.

196   When the accuracy (left side of the following expression) meets the following condition, u_k, w_k

197   and λ would stop updating:

198
$$\sum_{k=1}^{K} \frac{\| \hat{u}_k^{n+1} - \hat{u}_k^n \|_2^2}{\| \hat{u}_k^n \|_2^2} < \varepsilon \tag{1.6}$$

199   where ε is the tolerance of the convergence criterion.

200   The VMD algorithm is implemented to decompose the wind speed signal predicted by the WRF

201   model. When using multiple sub-signals instead of the original signal, more features of the wind speed

202 can be obtained. Therefore, it is beneficial to improve the prediction accuracy when using the

203 sub-signal as input to the error correction model (Xu et al., 2021; Li et al., 2022).

2.2.3 Principal Component Analysis

205 Subsequences obtained by VMD usually have several illusory components. Using PCA to extract

206 the principal components of subsequences increases the number of features input to the model and

207 reduces the dimension of the data decomposed by VMD. When principal components (PCs) are used as

208 the input of the error prediction algorithm, the PCs fully reflect the characteristics of the subsequence

209 and reduce the model complexity. The PCs y_k, k=1, 2, …, K of the subsequence matrix U and the

210 cumulative contribution rate η_n of the first n principal components are expressed as:

$$y_k = c_k' U \tag{1.7}$$

$$\eta_n = \frac{\sum_{k=1}^{n} \lambda_k}{\sum_{k=1}^{K} \lambda_k} \tag{1.8}$$

213 where c_k is the corresponding characteristic unit vector, with k=1, 2, …, K; λ_k is the characteristic

214 root, with $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_K$.

2.2.4 Evaluation indicators

216 There are many commonly used predictive effect evaluation indicators. This article uses the

217 following evaluation indicators: correlation coefficient (R), root mean square error (RMSE), mean

218 absolute error (MAE), relative root mean square error (rRMSE), relative mean absolute error (rMAE),

219 Forecasting Accuracy (FA). Six error indicators are used to evaluate the correction results of short-term

220 wind speed forecasts of wind farms. The formula for calculating the error index is as follows:

$$R = \frac{\sum_{i}^{n}\left(y_i - \overline{y}\right)\left(\hat{y}_i - \overline{\hat{y}}\right)}{\sqrt{\sum_{i=1}^{n}\left(y_i - \overline{y}\right)^2}\sqrt{\sum_{i=1}^{n}\left(\hat{y}_i - \overline{\hat{y}}\right)^2}} \tag{1.9}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2} \tag{1.10}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |\hat{y}_i - y_i| \tag{1.11}$$

223

$$rRMSE = \left[\sqrt{\frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2} \Big/ \left(\frac{1}{n} \sum_{i=1}^{n} y_i \right) \right] \times 100\% \tag{1.12}$$

224

$$rMAE = \left(\frac{1}{n} \sum_{i=1}^{n} |\hat{y}_i - y_i| \Big/ \left(\frac{1}{n} \sum_{i=1}^{n} y_i \right) \right) \times 100\% \tag{1.13}$$

225

$$FA = N_r / N_f \tag{1.14}$$

226

227 Among them, n represents the number of samples, $\hat{y}_i$ represents the i-th predicted value, y_i

228 represents the i-th actual value; N_r represents the number of wind speed absolute errors not greater than

229 1 m s^{-1}, and N_f represents the number of research samples.

230

231 **2.2.5 Proposed hybrid forecasting algorithms**

232   This study used five machine learning algorithms to conduct ten experiments following two main

233 paths. The first path involves increasing the meteorological variables possibly related to wind speed in

234 the forecast field. The correlation between the WRF-predicted 10-m wind speed and the observed wind

235 speed is the highest. The purpose of the second experimental path is using the VMD-PCA algorithm to

236 dig out the hidden wind speed characteristics of the 10-meter forecast wind speed, reduce the input of

237 other meteorological factors such as WD$_{10}$ and D$_2$, and further prove that the VMD-PCA algorithm is

238 effective before correcting the WRF-predicted wind speed. The overarching goal is to achieve accurate

239 correction of the forecast field wind speed. The flowchart of the artificial intelligence models used to

240 correct the WRF predicted wind speed for the two main experimental paths is illustrated in Fig. 2 and

241 comprises the following three steps:

242   Step 1. Data fusion, cleaning, and standardization: As depicted in Fig. 2, this paper proposes two

243 distinct experimental paths, with the primary difference being the selection of input variables. In

244 Experiment 1, as shown in Fig. 2, 12 sets of data are selected from the WRF forecast field, including

245 altitude (HGT), 10-meter wind speed (WS$_{10}$), latitude (LAT), longitude (LON), surface pressure (PRS),

246 relative humidity (RH), 10-meter meridional wind (V$_{10}$), 10-meter zonal wind (U$_{10}$), 2-meter

247 temperature (T$_2$), 2-meter dew point temperature (D$_2$), 10-meter wind direction (WD$_{10}$), and hourly

248 precipitation (PRE). Experiment 2 derives 8 sets of data by reducing the selected WRF field forecast

249   data to include only altitude, 10-meter wind speed, latitude, longitude, surface pressure, relative

250   humidity, 2-meter temperature, and hourly precipitation. The focus is on unearthing hidden

251   characteristic information of forecast wind speed. In this experiment, the wind speed is decomposed

252   into 9 Intrinsic Mode Functions (IMFk, k=0, 1, 2, …, 8) using VMD. Subsequently, a low-dimensional

253   wind speed vector is extracted from the 9 IMF components via PCA dimensionality reduction (pca0,

254   pca1, pca2), and all data are concatenated to construct the input factors for the model in Experiment 2.

255   The time points in the dataset where missing values are located are eliminated. Experiment 1

256   (Experiment 2) standardizes 12 sets of meteorological elements (8 sets of meteorological elements in

257   Fig. 3, 9 IMF components, and three PCA vectors in Fig. 4) and wind speed observation data,

258   respectively. Standardization addresses the issue of varying meteorological factor values during

259   training, which may result in different contributions. In this paper, the 24-hour forecast data correspond

260   to the observation data of the subsequent 24 hours. The dataset spans from 00:00 on December 1, 2021,

261   to 23:00 on February 28, 2022, totaling 2160 hours and encompassing 410 weather stations.

262   Consequently, the original dataset comprises 2160*410 samples, with each sample containing 12

263   meteorological features in Experiment 1 and 20 input features in Experiment 2. While similar past

264   studies for wind speed correction from NWP models usually use several years for training and at least

265   one year for testing whereas our periods are shorter, the size of our data set is sufficient. For example,

266   Sun et al. 2019 used a data set that contained 1827 days, from January 2012 to December 2016, using

267   143 grid points with a resolution of 0.5°*0.5° predicted by ECMWF, followed by 24 features for each

268   sample, with a training set size of 1827*143*24 for each prediction time. Meanwhile, the size of our

269   training set is about 2160*410*12. Therefore, even though it only took us a month to train, for this

270   project, we trained millions of data; Second, the training data we used here was obtained through daily

271   operational runs of numerical weather forecasting, so it would have taken several years to get an equal

272   amount of training data.

273   Step 2. BOA optimization of AI models and cross-validation: In this study, the dataset is

274   partitioned into training, validation, and test sets in accordance with the time series. February 2022

275   serves as the training and validation sets, while December 2021 and January 2022 constitute the test set.

276   The training and validation sets are divided based on five-fold cross-validation. Both experiments

277   employ five machine learning algorithms (DBN, MLP, RF, XGBoost, and LightGBM) to construct

278   distinct machine learning models. Concurrently, this paper utilizes the BOA algorithm to tune the

279   parameters of all models, except for DBN, resulting in the optimal hyperparameters for each model.

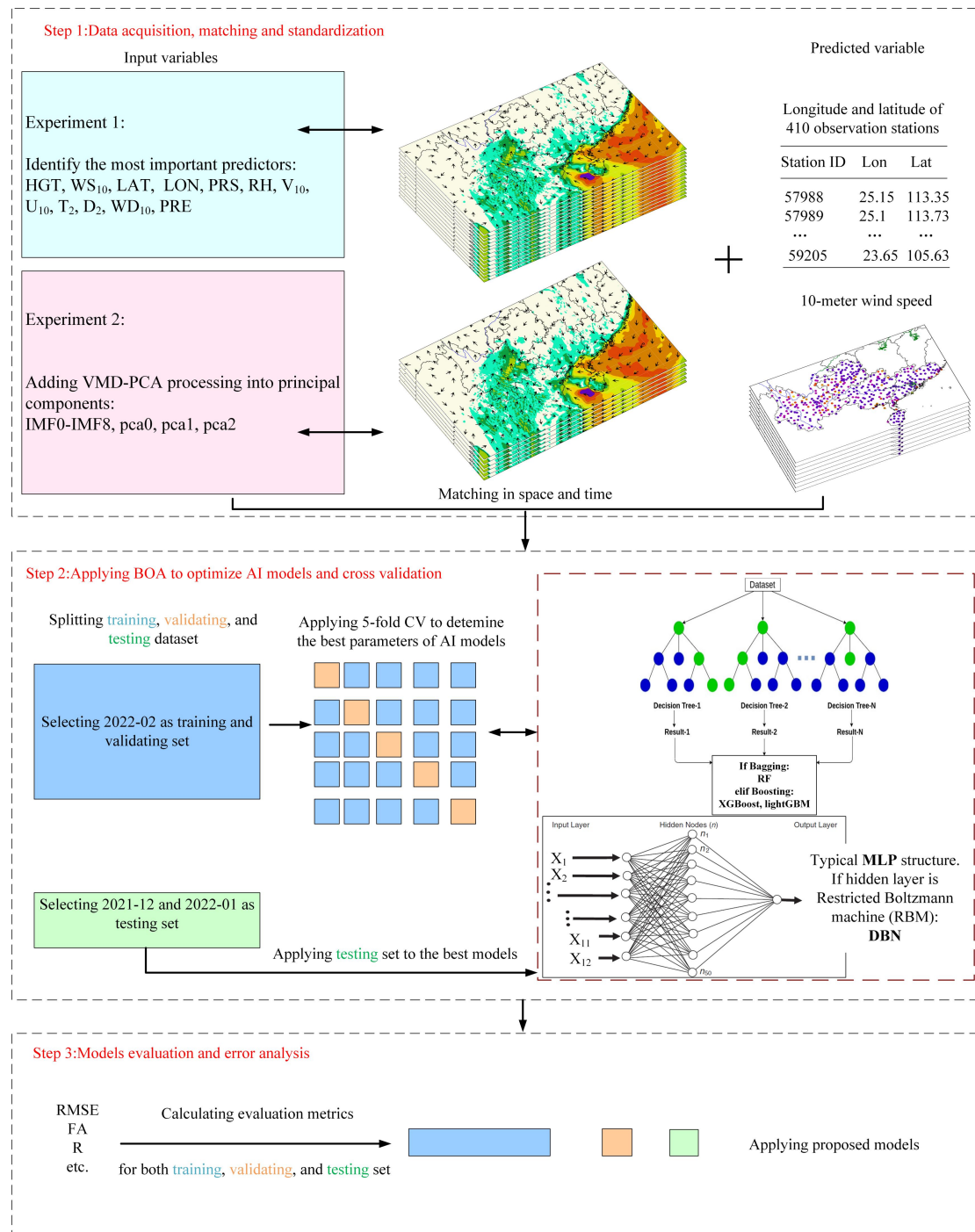
280   Step 3. Model evaluation and error analysis: The trained machine learning models are applied to

281   the test set to obtain the revised wind speed data, and ultimately, the accuracy of all models is assessed

282   through the wind speed evaluation index. The ultimate goal here is to identify the best wind speed

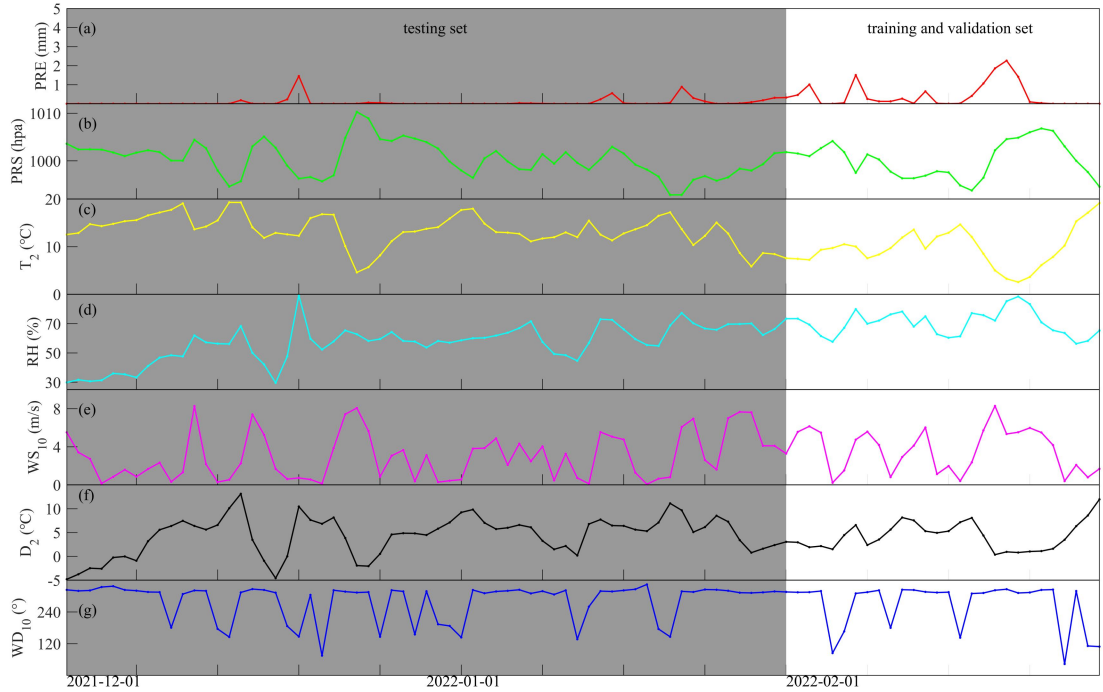
283   correction model suitable for the entire year. Accordingly, the generalization of all models is evaluated

284   across other seasonal months of the year, culminating in the selection of the best model.

285

 Figure 2. Flowchart of the AI model used to correct WRF-predicted wind speeds in the two main

287 **experimental pathways.**

288

289

290 **Figure 3. Daily average hourly rainfall (a), surface pressure (b), 2-meter temperature (c), 2-meter relative**

291 **humidity (d), 10-meter wind speed (e), 2-meter dew point temperature (f), and 10-meter wind direction (g)**

292 **which are located at Guangdong Lechang Station from December 1, 2021, to February 28, 2022. (February**

293 **2022 represents the training and verification sets, and December 2021 to January 2022 represents the**

294 **testing set).**

295

296

3 Results

3.1 Experiment 1 evaluation

In Experiment 1, the BOA optimization algorithm was applied to five AI models to correct the 10-meter wind speed forecasted by WRF. There were 12 meteorological element features to establish five different AI models (see Table S1 for the hyper-parameters of the five AI models). The training, validation, and testing results for 10-meter wind speed are shown in Figs. S1-5 in the supplementary material. It is clear from Table 2 that all models, except the DBN model, can fit the training set data well. The DBN model exhibits the weakest performance on both the training and validation sets. Alternatively, the LightGBM and XGBoost models demonstrate superior prediction performance on the training set compared to the validation set. The scatters of the training sets of these two models accumulate on the 1:1 diagonal, indicating slight overfitting. As shown in Figs. S1-5d, f, considering different evaluation indices, the revision effects of the five models in two months demonstrate that RMSE in January 2022 is generally lower than in December 2021; FA in January 2022 is generally higher than in December 2021; R in January 2022 is generally lower than in December 2021. Overall, the prediction performance of the five models in January 2022 surpassed that in December 2021. Furthermore, the LightGBM and RF models exhibited the best performance among the five models in the two-month test sets, while the DBN model had the least effective correction effect.

As illustrated in Fig. 5a, b, WS_{10} showed the strongest positive correlation with WS_{obs}, with the highest R of 0.51, which was consistent with the highest variable importance value of 31 % (23 %) in experiment 1 (experiment 2). In addition to WS_{10}, experiment 1 (experiment 2) also had another three dominant variables namely, LAT, HGT, and LON, with importance values of 16 % (14 %), 15 % (15 %), and 15 % (13 %), respectively. Meanwhile, in experiment 2, IMF0 and pca0 generated by the VMD-PCA algorithm have a good importance value of 9 % and 4 %, and the R values of them with WS_{obs} are as high as 0.47 and 0.45.

326   Concerning the importance of RF characteristics (Fig. 5a, c), it is indisputable that the 10 m wind

327   speed predicted by WRF plays a dominant role in correcting the actual wind speed. The ones following

328   are latitude, longitude, and topographic height, which represent spatial geographic information, and the

329   actual wind speed is closely related to geographic information. Subsequently, relative humidity is of

330   lesser importance. The distribution of the humidity field typically correlates with the movement of the

331   atmosphere, which is also closely related to wind speed. Certain meteorological elements, such as

332   rainfall, 2 m dew-point temperature, and 2 m temperature, contribute less importance.

333   **Table 2. Table of evaluation indices of wind speed error trained and verified by 10 models in February 2022**

Model	training set			validation set		
	R	RMSE$(\mathrm{m\ s^{-1}})$	FA	R	RMSE$(\mathrm{m\ s^{-1}})$	FA
VMD-PCA-lightGBM	0.96	0.33	0.99	0.88	0.53	0.94
VMD-PCA-XGBoost	0.96	0.31	1.00	0.87	0.54	0.94
VMD-PCA-RF	0.89	0.52	0.94	0.86	0.57	0.93
VMD-PCA-DBN	0.74	0.75	0.87	0.74	0.75	0.87
VMD-PCA-MLP	0.84	0.60	0.91	0.81	0.66	0.90
lightGBM	0.93	0.41	0.98	0.88	0.54	0.94
XGBoost	0.96	0.31	0.99	0.87	0.56	0.93
RF	0.89	0.52	0.94	0.86	0.57	0.93
DBN	0.76	0.73	0.88	0.76	0.73	0.88
MLP	0.85	0.59	0.92	0.83	0.62	0.91

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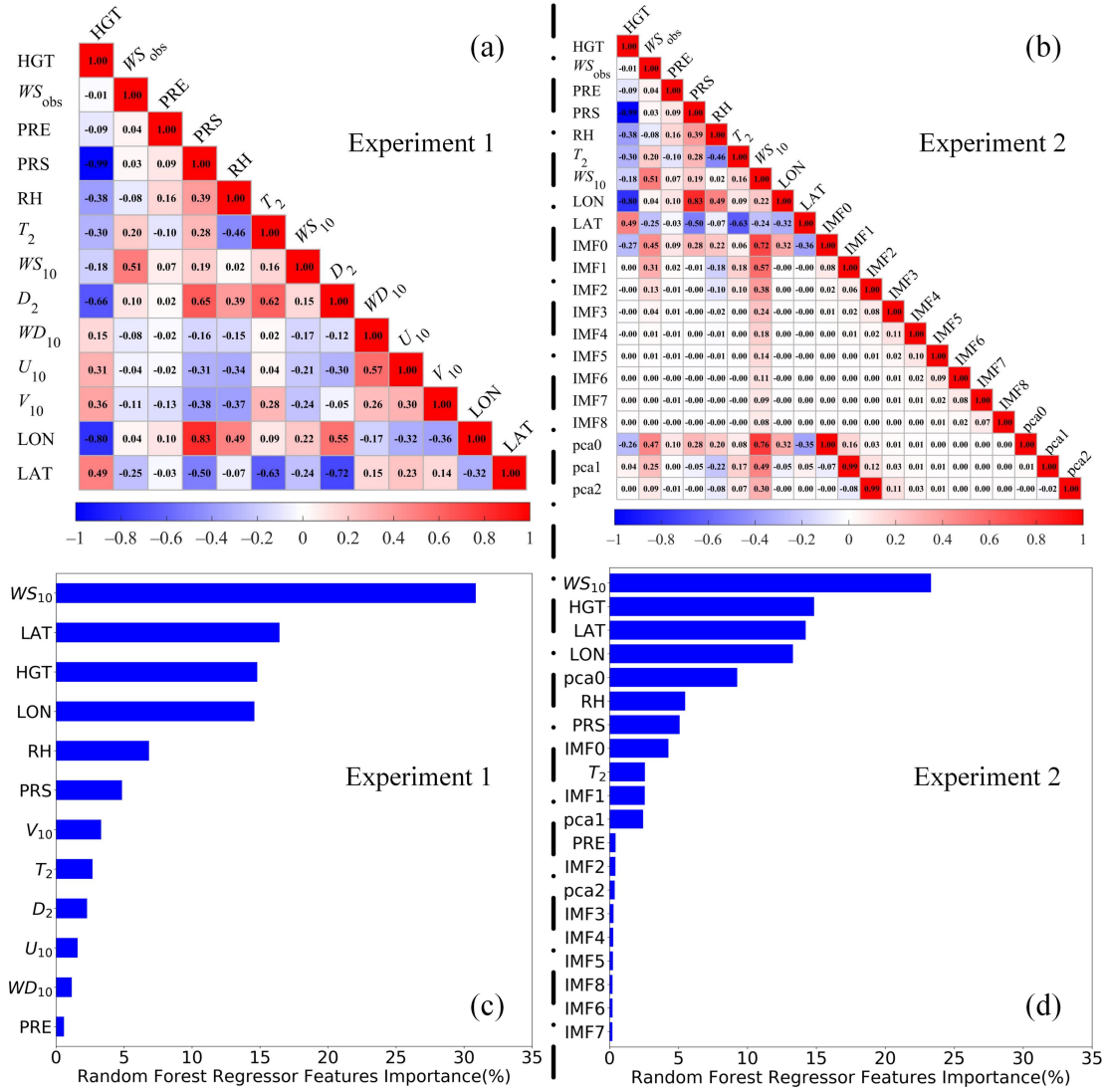
Figure 5. Schematic diagram of correlation coefficients (represented the WS_{10} and input variables) and feature importance (calculated by the scikit-learn python package) for two sets of experiments. (a) and (c) represent experiment 1, and (b) and (d) represent experiment 2.

3.2 Experiment 2 evaluation

Experiment 2 builds upon Experiment 1, concentrating on the predicted 10-meter wind speed by the WRF model. We use the VMD algorithm to decompose the predicted wind speed into 9 components and use the PCA algorithm to extract the main 3 principal components. In the RF feature importance analysis (Fig. 5b, d), it is evident that the VMD algorithm can decompose IMF0 and IMF1, with contributions surpassing those of 2-meter temperature and precipitation, respectively. The importance of the pca0 component, after PCA principal component extraction, reaches up to 8%. What

347   is particularly interesting is that in the correlation analysis, the correlation values between the IMF0

348   and pca0 components and the actual wind speed are 0.50 and 0.51, which are second only to the

349   forecasted wind speed.

350   From the indices (RMSE, FA, R) of the training set and validation set shown in Table 2, in

351   comparison to the above five artificial intelligence methods, the training results of VMD-PCA-DBN

352   are relatively inferior. VMD-PCA-lightGBM and VMD-PCA-XGBoost models still train the processed

353   data effectively. According to the scatter density figure (Fig. 6a, Fig. 7a), the scatters are relatively

354   concentrated on the 1:1 line. From the indicators (RMSE, FA, R) of the testing set shown in Figs.

355   S6-8d, f and Figs. 6-7d, f, the test results of the five models in Experiment 2 in December 2021 and

356   January 2022 show that the error indices of RMSE and FA of each model exhibit a minimal difference

357   in two months. Nonetheless, disregarding the R results, the performance of the five models in

358   December 2021 is inferior to that in January 2022. The diurnal variation scatter plot of two months is

359   tested. As is shown in Figs. S6-8d, f and Figs. 6-7d, f, the red scatters represent the nighttime wind

360   speed, which is more concentrated on the 1:1 line. In contrast, the blue scatters represent the afternoon

361   wind speed, which is slightly away from the 1:1 line. This suggests that the correction effect of the five

362   models (VMD-PCA-lightGBM, VMD-PCA-XGBoost, VMD-PCA-RF, VMD-PCA-DBN, and

363   VMD-PCA-MLP) exhibits a noticeable diurnal variation.

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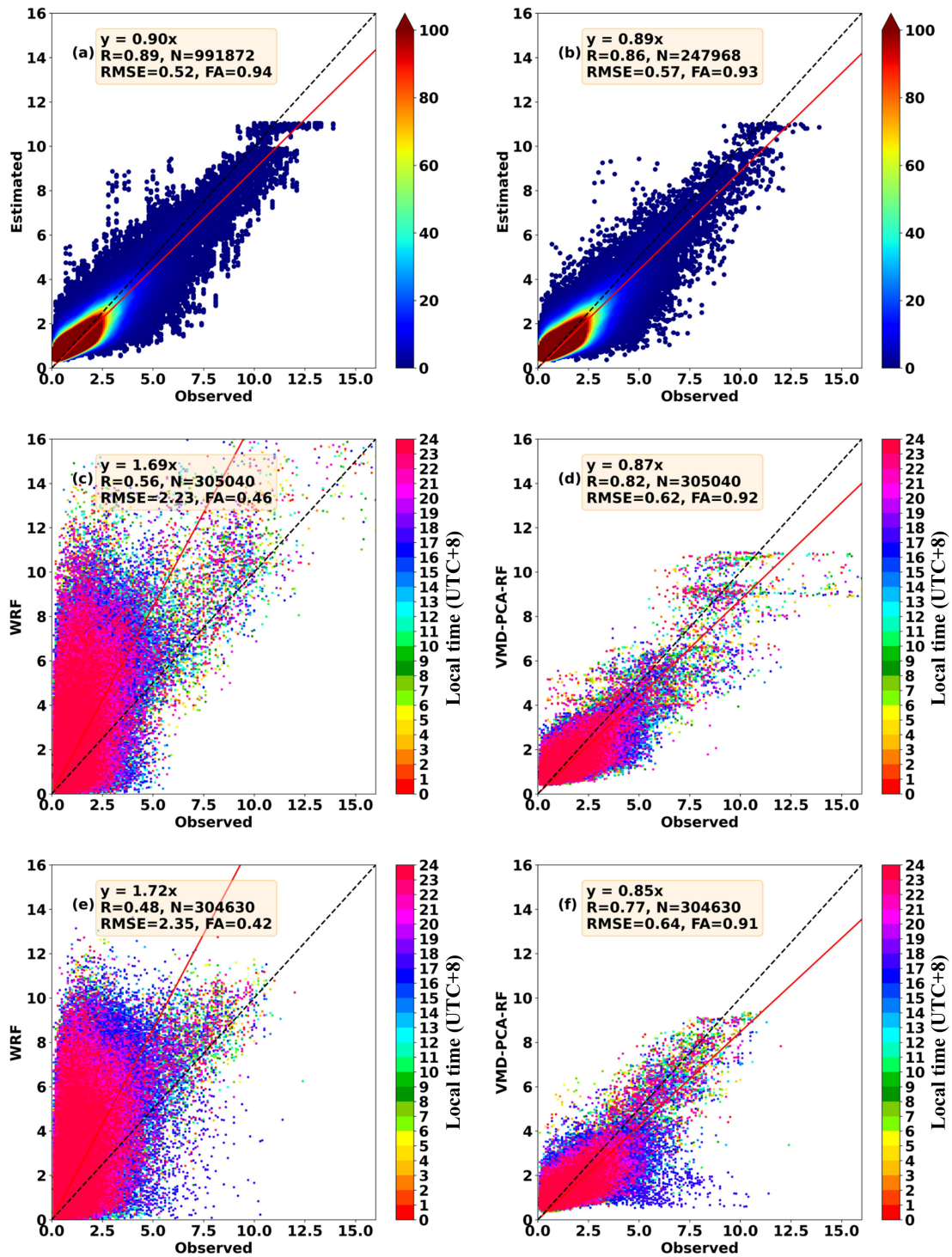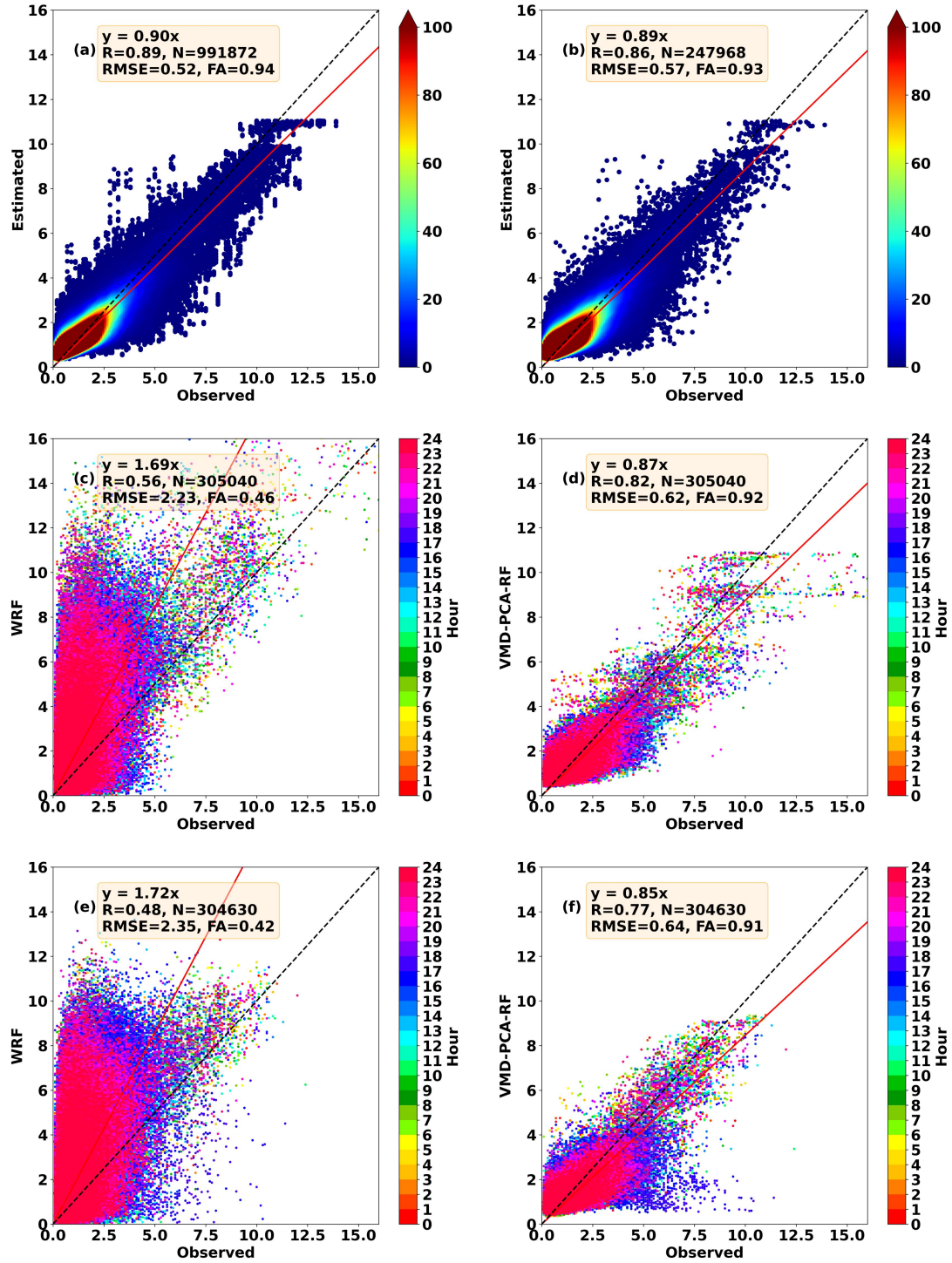
Figure 6. The scatter density map compared with the actual 10-meter wind speed: (a) 10-fold cross-validation training set of VMD-PCA-RF model in February 2022, (b) 10-fold cross-validation validation set of VMD-PCA-RF model in February 2022. The 24-hour scatter map compared with the actual 10-meter wind speed: (c) WRF forecasts in December 2021, (d) VMD-PCA-RF model forecasts in December 2021, (e) WRF forecasts in January 2022, and (f) VMD-PCA-RF model forecasts in January 2022. (The time is UTC + 08:00.)

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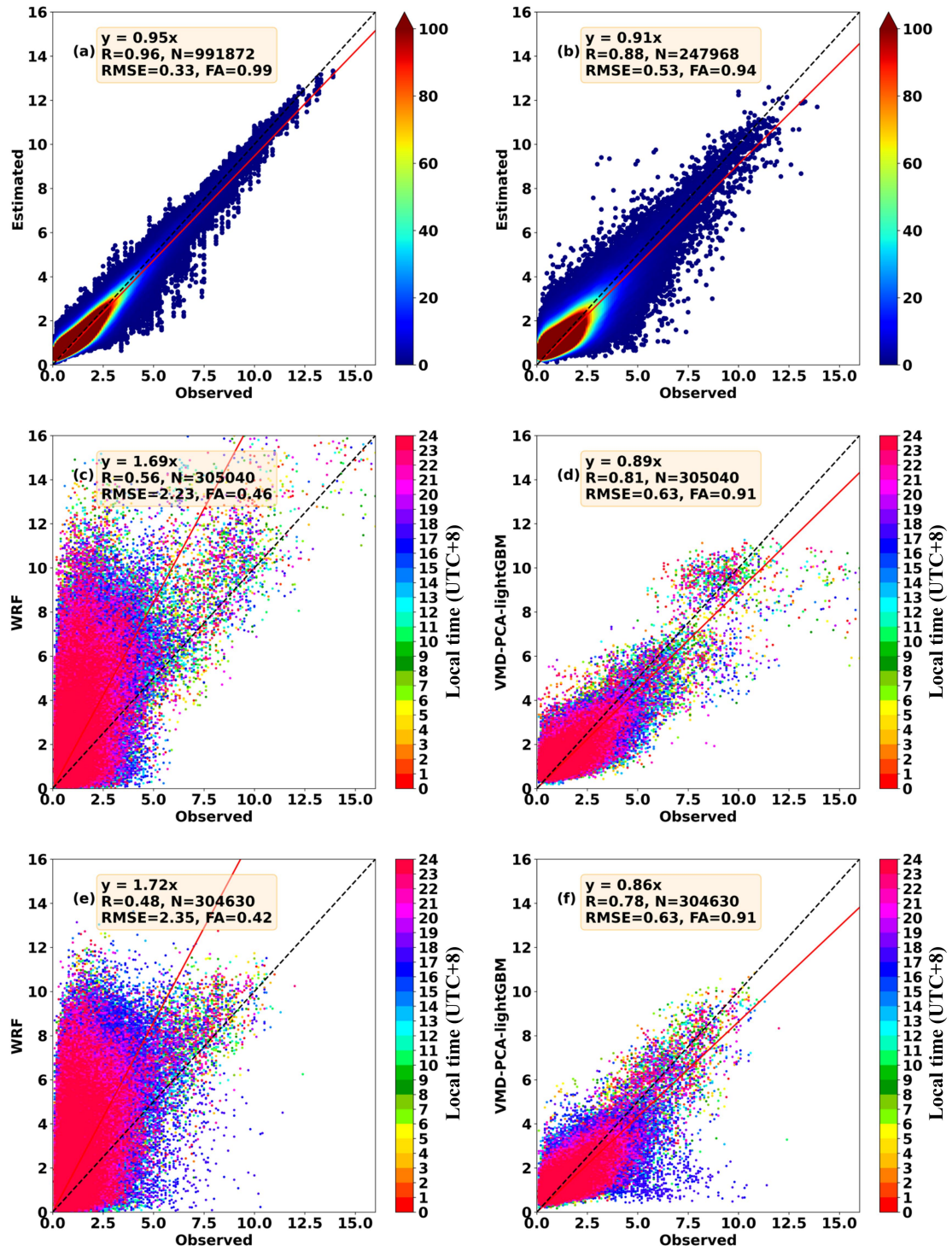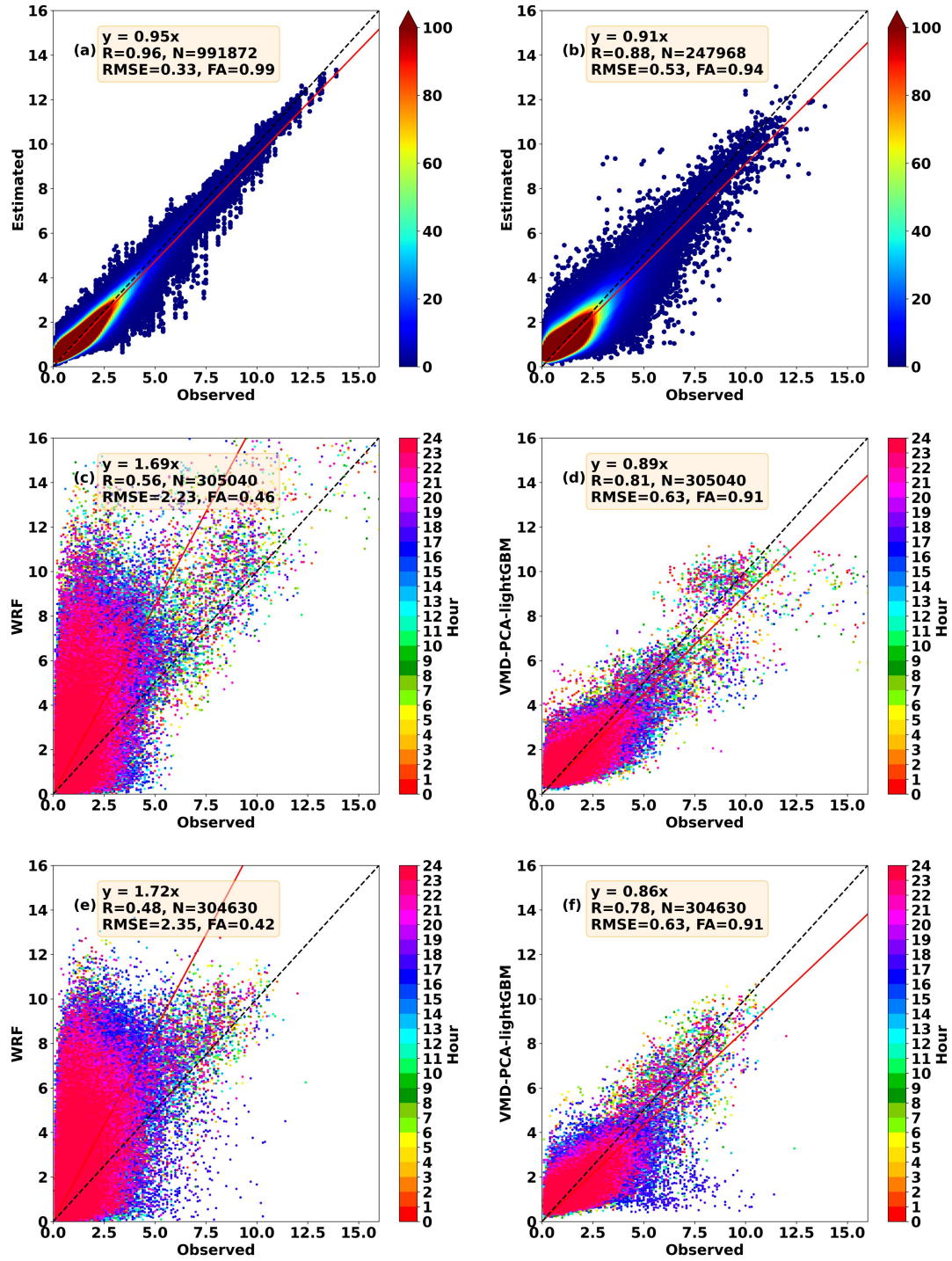
Figure 7. The scatter density map compared with the actual 10-meter wind speed: (a) 10-fold cross-validation training set of VMD-PCA-lightGBM model in February 2022, (b) 10-fold cross-validation validation set of VMD-PCA-lightGBM model in February 2022. The 24-hour scatter map compared with the actual 10-meter wind speed: (c) WRF forecasts in December 2021, (d) VMD-PCA-lightGBM model forecasts in December 2021, (e) WRF forecasts in January 2022, and (f) VMD-PCA-lightGBM model forecasts in January 2022. (The time is UTC + 08:00.)

382   **3.3 Comparison of the two experiments**

383   Firstly, all 10 models effectively corrected the 10-meter wind speed forecasted by WRF. Table S2

384   and Table S3 represent the evaluation indices of wind speed errors predicted by 10 models in

385   December 2021 and January 2022. From the two tables, it is evident that the VMD-PCA-RF and

386   VMD-PCA-lightGBM models have the best performance in December 2021 and January 2022,

387   respectively, with the most comprehensive performance of the forecast indicators. The MAE, RMSE,

388   rMAE, rMAE, and FA for the two models VMD-PCA-RF (VMD-PCA-lightGBM) were 0.46 m s^{-1}

389   (0.45 m s^{-1}), 0.62 m s^{-1} (0.63 m s^{-1}), 37.36 % (34.75 %), 50.39 % (48.65 %), and 91.79 % (91.49 %) in

390   December 2021 (January 2022). Additionally, based on the analysis of the Taylor chart (Fig. 8e, f) of

391   10 models in Fig. 8, it can also be seen that the scatter distance of VMD-PCA-RF and

392   VMD-PCA-lightGBM models is closest to the observed black dotted line and the black triangle

393   position. The two models show that the standard deviation is close to the observed wind speed, with the

394   lowest RMSE and the highest R. Secondly, in the comparison of cumulative probability distributions,

395   all models passed Kolmogorov's 5 % confidence interval test when the interval of wind speed is 0.5 m

396   s^{-1} (Fig. 8a, d). However, when the interval of wind speed is 0.2 m s^{-1} (Fig. 8b, e), the

397   VMD-PCA-lightGBM model deviated from Kolmogorov's 5 % confidence interval detection in

398   December 2021. This indicates that the VMD-PCA-RF model has a better predictive effect than the

399   VMD-PCA-lightGBM model in December 2021 when the actual wind speed is within the range of 0.4

400   m s^{-1}-0.8 m s^{-1}.

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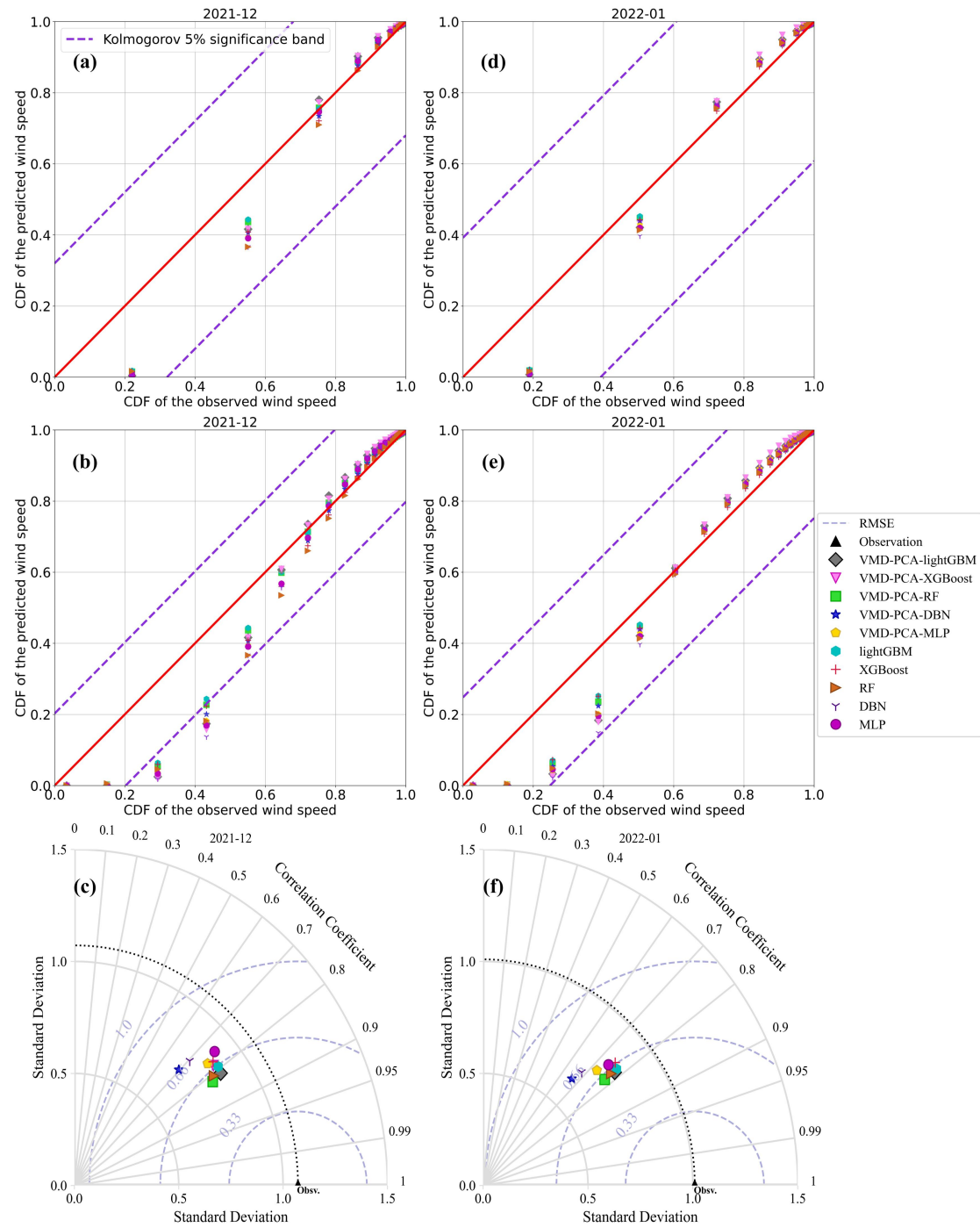
Figure 8. The cumulative distribution probability scatter plots of the actual wind speed and the predicted wind speed of 10 models in wind speed intervals of 0.5 m s⁻¹ ((a) represents December 2021, (d) represents January 2022) and 0.2 m s⁻¹ ((b) represents December 2021, (e) represents January 2022) respectively; Taylor distribution map ((c) represents December 2021, (f) represents January 2022).

3.4 Spatial-temporal variations in the best models

Based on our comparative analysis results, we conclude that the best performing combination models in December 2021 and January 2022 are VMD-PCA-RF and VMD-PCA-lightGBM respectively. Fig. 9 and Fig. S9 shows the diurnal variation corrections of the two best models for a given month, as well as the diurnal variation of wind speed in the original WRF forecast. The wind speed of the original WRF numerical weather forecast shows a noticeable overestimation, which is confirmed in Fig. 7c and 7e. The scatters of WRF forecast predominantly deviate towards the upper left corner, with relatively low correlation coefficients, 0.56 and 0.23, respectively. Furthermore, the wind speed forecast by WRF displays obvious diurnal variation traits, characterized by large errors between afternoon and evening, specifically between 11:00 and 20:00 (Fig. 9a, Fig. S9a). Moreover, the actual average wind speed in January 2022 deviates from the range of one standard deviation of the WRF forecast wind speed at 17:00 and 18:00 (Fig. S9a). This demonstrates that the wind speed forecast by WRF is inaccurate and exhibits substantial diurnal variation errors.

After the best model was corrected, the error of diurnal variation was significantly reduced (Fig. 9b, Fig. S9b). First, the average wind speed corrected by the best model is essentially consistent with the actual average wind speed curve, with minimal error and no diurnal variation. Second, the one standard deviation range of the corrected and actual wind speeds is also well-matched, indicating that the corrected and actual wind speed distributions are consistent. The correction effect at 16:00 and 17:00 on January 2022 is suboptimal, which may be due to the insufficient generalization of the training model and the excessive fluctuation of the actual wind speed at these two-time points.

The FA (Fig. 10a, Fig. S10a) and RMSE (Fig. 10b, Fig. S10b) distribution of WRF forecast 10-meter wind speed at 410 stations in the five southern provinces shows that the 10-meter wind speed prediction effect of the WRF model in Yunnan is superior to that in the other four provinces. In the regions of Hainan, Guangxi, and Guangdong, the number of sites with a RMSE for 10-meter wind speed forecast in December 2021 ranging from 5.6 to 6.0 m s^{-1} was significantly higher than in January 2022, especially in coastal areas (Fig. 10b, Fig. S10b). In the Yunnan area, the FA of most WRF forecast station 10-meter wind speeds exceeds 40 %, and the RMSE value is mostly below 2.4 m s^{-1}. Conversely, in other regions, such as Guangxi, Guangdong, and Hainan, the terrain is relatively flat. The FA of the 10-meter wind speed forecast by WRF is as low as 30 % at some stations, and the

438   RMSE reaches up to 5.4 m s^{-1}. However, after the VMD-PCA-RF and VMD-PCA-lightGBM models

439   are corrected, the FA of most stations in the five southern provinces is as high as 90 %, and the RMSE

440   is as low as 0.6 m s^{-1}. Moreover, in Guangxi, Guangdong, and Hainan, where the WRF forecast effect

441   is subpar, the accuracy of the corrected 10-meter wind speed by VMD-PCA-RF

442   (VMD-PCA-lightGBM) is significantly improved.

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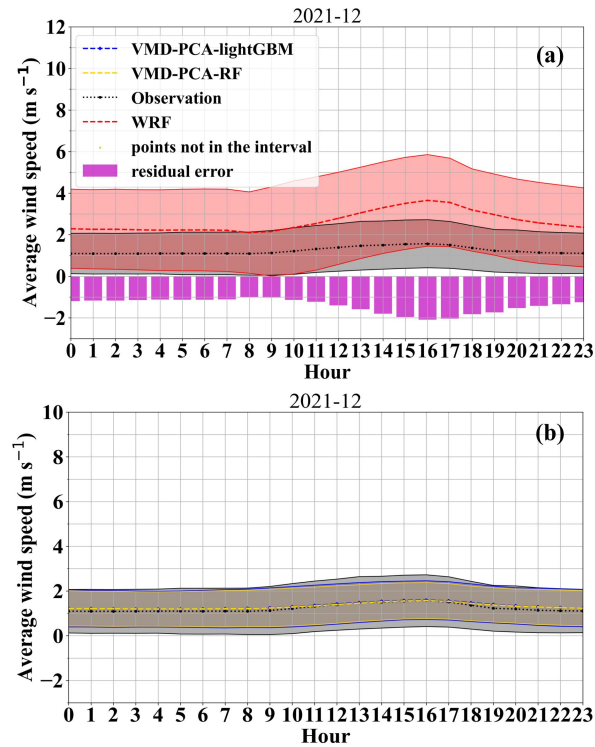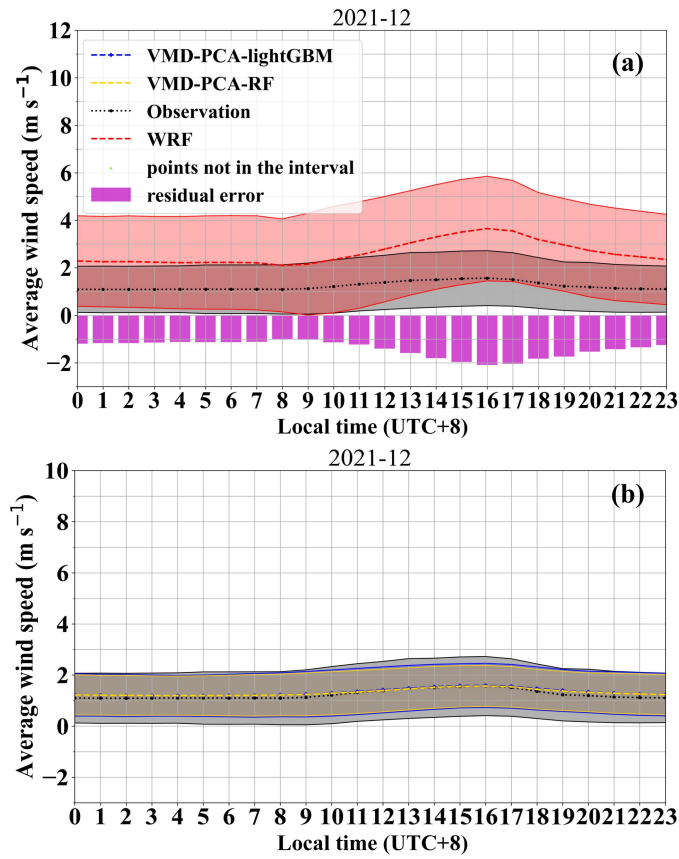
Figure 9. VMD-PCA-lightGBM, VMD-PCA-RF, and WRF daily variation of predicted and actual wind speeds in December 2021. (The shading areas represent an interval of 1 standard deviation, which is a 68% confidence interval. ~~The time is UTC + 08:00.~~**)**

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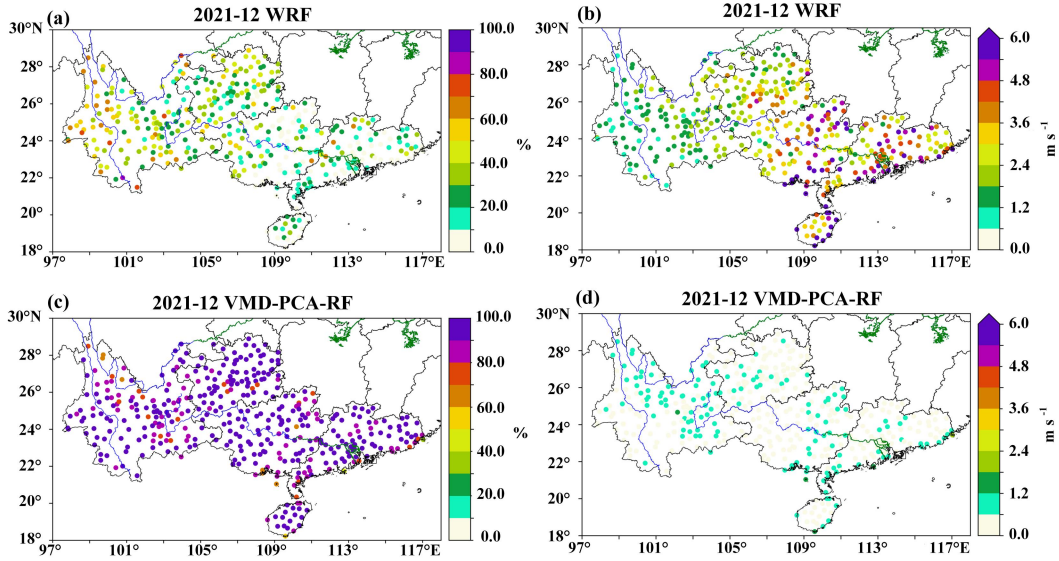
Figure 10. FA ((a), (c)) and RMSE ((b), (d)) distribution maps of VMD-PCA-RF and WRF models on 410 sites in five southern provinces in December 2021.

4. Discussion

4.1 The effects of BOA-VMD-PCA

It is shown in Table S1 that the hyper-parameters of the 10 models in the two experiments are different. Since the DBN model is not added to the scikit-learn Python learning package, it is challenging to call the BOA algorithm for tuning parameters. Apart from the DBN model, all the other models are optimized using the BOA algorithm. From the various evaluation indicators in Table S2 and Table S3, the DBN model, which does not use the BOA algorithm to adjust the model parameters to obtain an optimal parameter configuration, yields the worst prediction results in December 2021 and January 2022. Moreover, studies (Xiong et al., 2022) also have shown that BOA can further improve the model's prediction accuracy by configuring optimal hyper-parameters. The hyper-parameters such as the number of neurons and learning rate in the hidden layer, significantly impact the model's performance. When the same model is applied to different data sets of two experiments, the BOA adaptively obtains the optimal combination of hyper-parameters, overcoming the limitations of manual parameter adjustment (Guo et al., 2021). This suggests that the selection of model hyper-parameters introduces considerable uncertainty in our prediction results. Therefore, the choice of optimization model parameters represents one source of uncertainty in the correction results, which entails the

468 complexity of parameter selection. However, a more advanced parameter tuning method, such as the

469 BOA tuning algorithm, is essential.

470 The VMD is used to obtain unknown but meaningful features hidden in the 10-meter wind speed

471 sequences predicted using WRF models (Li et al., 2022). In addition, the PCA can extract important

472 components of anemometer subsequences. When the stationary subsequence serves as an input to the

473 error correction model, it contains more valuable information than the previous non-stationary wind

474 speed sequences (Xu et al., 2021).

475 The complexity of the input factors in this study is one of the sources of uncertainty in the process

476 of correcting WRF prediction results. The input factors of the two experiments are not identical. In the

477 second set of experiments, the input of meteorological factors is reduced based on the first set of

478 experiments, while component information of the 10-meter wind speed predicted by WRF is increased.

479 Multiple wind speed components processed by VMD-PCA and noise reduction are introduced. Among

480 them, the importance of pca0 and IMF0 introduced is approximately 5 %. In the 13-month test sets, the

481 correction accuracy of experiment 2 is no less than the results of experiment 1 (Figs. S11, 12),

482 indicating that the 10-meter wind speed components introduced by the VMD-PCA contribute

483 positively to the correction results.

484

4.2 RF feature importance

486 To further understand the feature importance ranking of the RF models, we divided the model

487 prediction results and actual wind speeds of the 410 stations into 20 equal parts according to terrain

488 height above sea level (Fig. 11). First of all, the actual wind speed in December 2021 and January 2022

489 varies with the height of the station, showing that the lower the height of the station, the more

490 significant the change of wind speed. This relationship is associated with the wind speed profile of the

491 atmosphere, where wind speed increases as height decreases. Secondly, the wind speed during the day

492 is generally greater than the wind speed at night, which is related to the turbulent motion of the

493 atmosphere during the day. Solar radiation causes the atmosphere to mix, resulting in convective

494 movement. The 10-meter wind speed at night is affected by the cooling radiation of the surface, and the

495 atmosphere is relatively stable.

496   The 10-meter wind speed predicted by WRF has the highest feature importance in the correction

497   process of the RF models. Input factors with distinct geographic information, such as latitude,

498   longitude, and height, rank highly in feature importance. Similarly, when Sun et al. 2019 used machine

499   learning to correct the 10-meter wind speed predicted by the numerical weather prediction model

500   ECMWF, the characteristic weight of the 10-meter wind speed predicted by the model was the highest,

501   followed by the sea-land factor. Also, as the 10-meter wind speed forecast by WRF increases, the

502   instability of the 10-meter wind speed corrected by the 10 machine learning models gradually increased,

503   and the correction accuracy gradually decreased (Fig. 12). This partly explains the higher importance

504   of the 10-meter wind speed forecast by WRF.

505   With 1 km as the center, the measured 10-meter wind speed is more variable in areas where the

506   station terrain height increases or decreases. However, the pink box of the 10-meter wind speed

507   predicted by WRF becomes wider as the station terrain height decreases (Fig. 11). The distance

508   between the gray box and the pink box is greater as the station terrain height decreases. It shows that

509   the 10-meter wind speed predicted by WRF has less accuracy with the station terrain height decreases.

510   The VMD-PCA-RF and VMD-PCA-lightGBM models significantly reduce the variability of the

511   10-meter wind speed predicted by WRF. When the height of the station increases or decreases at 1 km,

512   the correction intensity tends to increase gradually. This further explains the higher importance of the

513   height factor in the RF model training.

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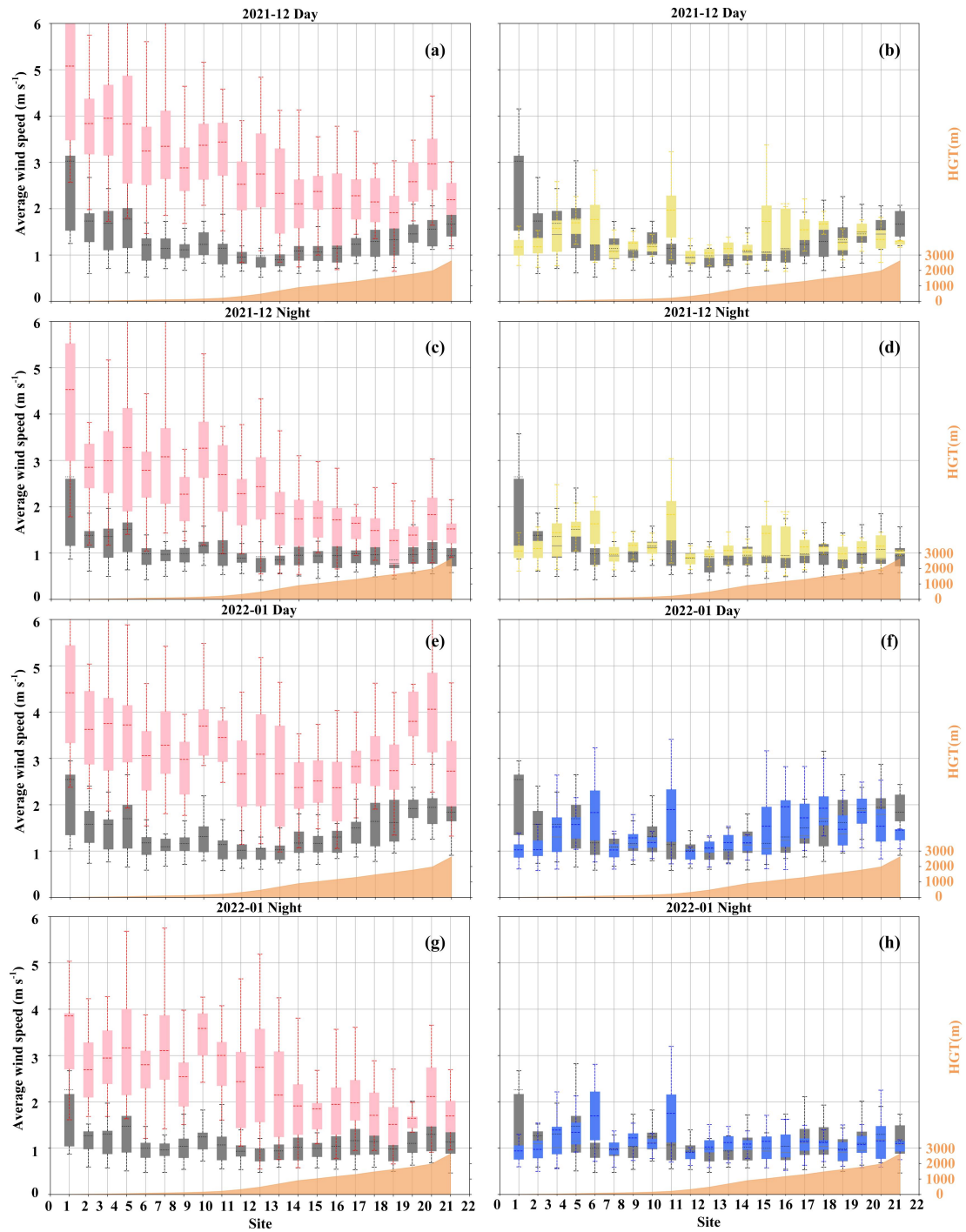
515 **Figure 11. The boxplots of the predicted wind speeds of the VMD-PCA-RF (yellow), VMD-PCA-lightGBM**

516 **(blue), and WRF (pink) models at 20 stations at different height intervals, and the boxplots of the actual**

517 **wind speeds (gray).**

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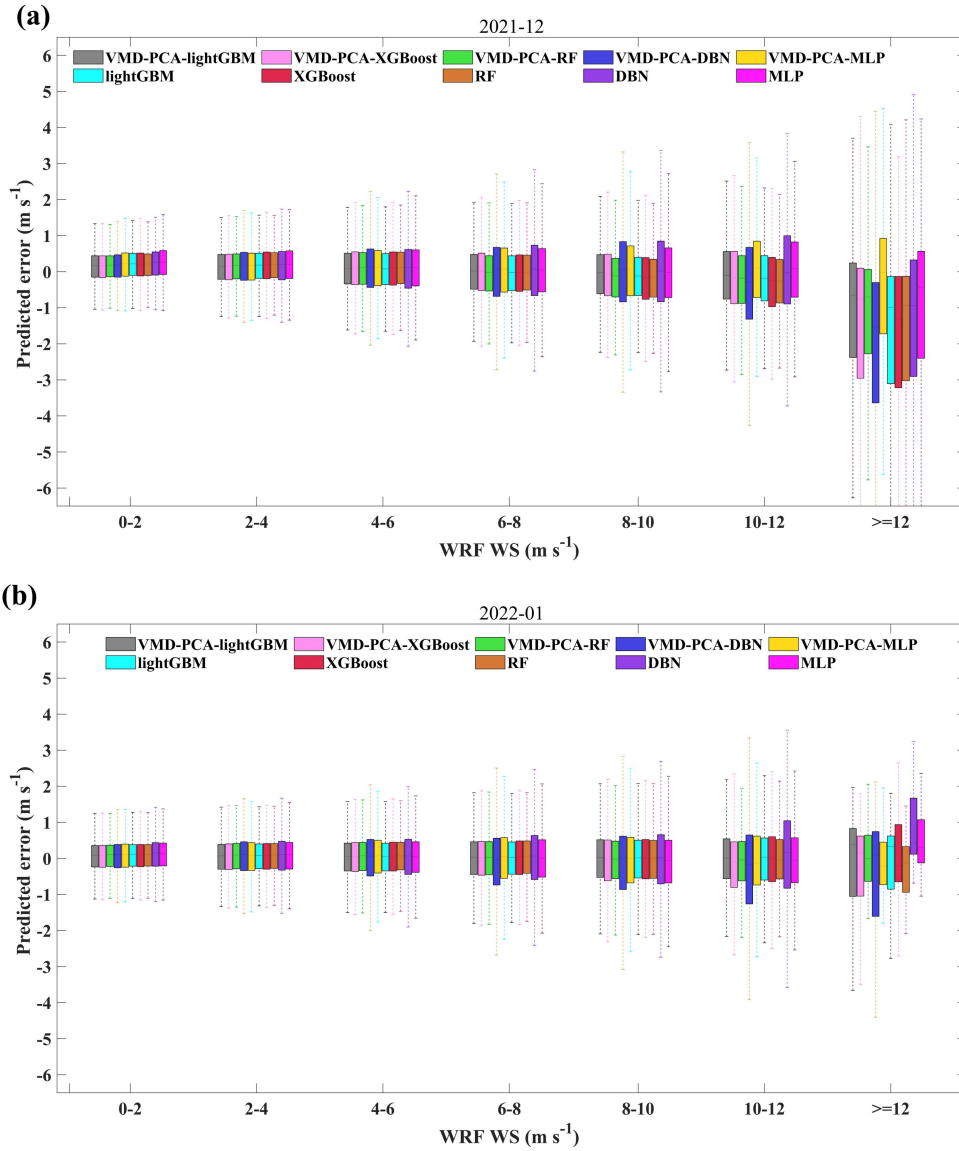
Figure 12. The prediction error boxplots of 10 models in different WRF prediction intervals.

4.3 Stability analysis of the proposed models

In order to identify the best model of the five southern provinces and assess the model's stability, we evaluated all 10 models over 13 different months. Fig. 13 shows the evaluation histogram of the 10-meter wind speed predicted by the 10 models in Experiment 1 and Experiment 2, as well as the actual wind speed in various months. Meanwhile, Fig. S11 and Fig. S12 can more effectively illustrate the daily changes of the revised results of 10 models in 13 different months. As shown in Fig. 13, the evaluation indices of the model trained in Experiment 2, after VMD-PCA processing, outperform those of the model trained in Experiment 1. The RF model demonstrates exceptional robustness, while the

530   MLP model exhibits the poorest performance. VMD-PCA-RF evaluation indices are relatively stable

531   across the 13 months, with a correlation coefficient R above 0.6, FA above 85 %, MAE below 0.6 m s^{-1},

532   RMSE below 0.8 m s^{-1}, rMAE below 60 %, and rRMSE below 75 %. However, the robustness of the

533   VMD-PCA-lightGBM and VMD-PCA-XGBoost models is inferior to that of the VMD-PCA-RF, with

534   all six evaluation indices performing worse than the VMD-PCA-RF as the seasons and months change.

535   In general, VMD-PCA-lightGBM is the superior wind speed correction model for the winter, and

536   VMD-PCA-RF performs the best throughout the entire year in the five southern provinces. In cases

537   where ample machine CPU and other hardware resources, as well as training time, are available, we

538   recommend using VMD-PCA-lightGBM for modeling each season. However, when dealing with

539   limited resources such as a laptop and constrained training time, we recommend using VMD-PCA-RF

540   to train data for a single month, as this yields the most robust correction results.

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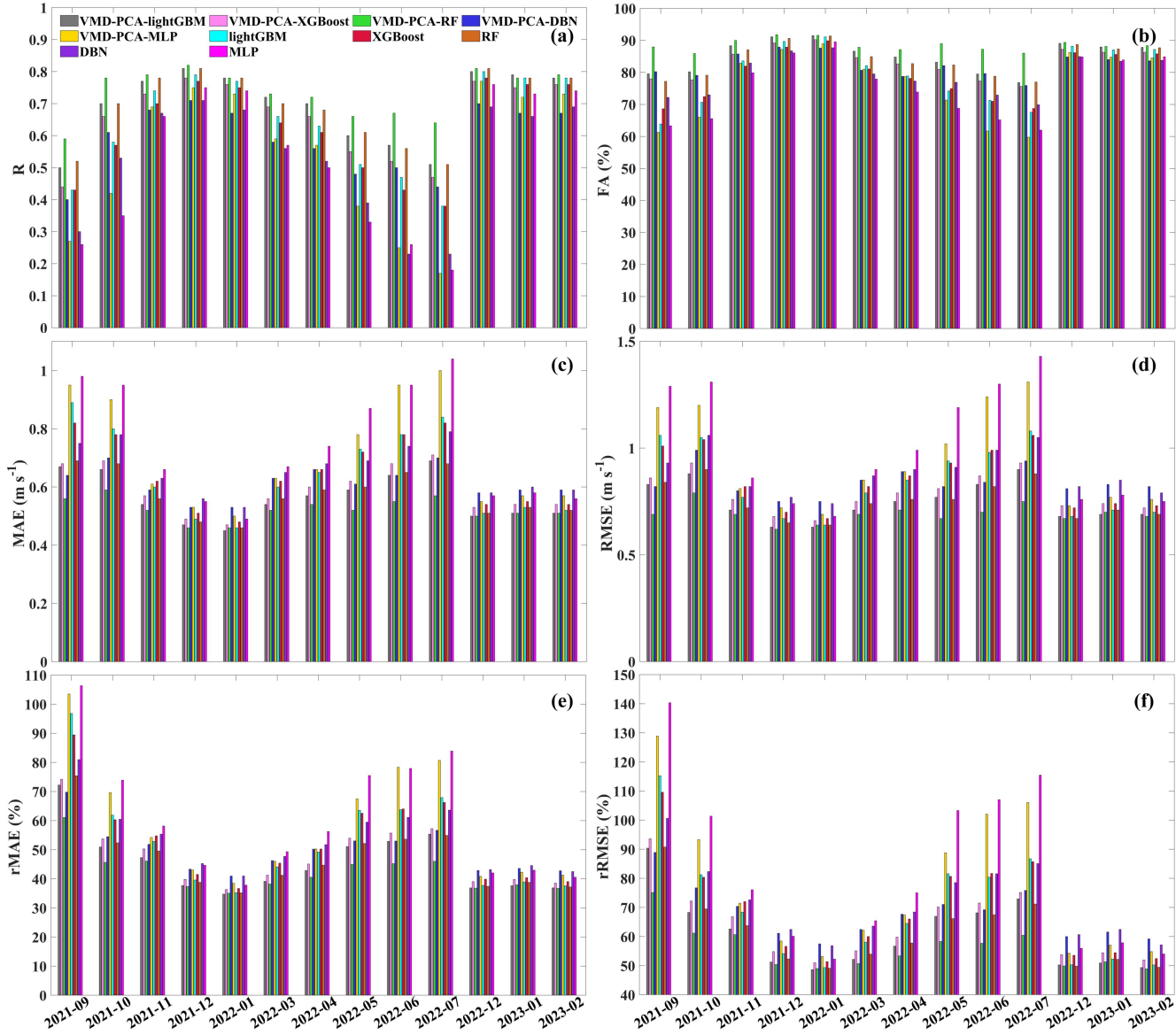
Figure 13. Evaluation histograms of 10-meter wind speed predicted by 10 models in different months in Experiment 1 and Experiment 2 ((a), (b), (c), (d), (e), and (f) represent R, FA (%), MAE (m s⁻¹), RMSE (m s⁻¹), rMAE (%), and rRMSE (%) respectively).

5. Conclusions

In an effort to enhance the wind speed prediction performance for wind farms, this study developed a WRF-based multi-step wind speed prediction model. A hybrid error correction strategy combining BOA, VMD, PCA, and RF (LightGBM) is proposed to increase the accuracy of WRF simulations. The first group of experiments used various meteorological elements as input factors in a control experiment. In the second group of experiments, the wind speed sequence predicted by the

552 WRF model was decomposed into multiple IMFs using the VMD algorithm for feature extraction. A

553 principal component analysis method is used to extract meaningful principal components from these

554 subsequence IMFs to improve computational efficiency. In the error correction model, RF (lightGBM)

555 and other algorithms are used to train the relationship between different input factors and the actual

556 wind speed error, respectively.

557   Through a case analysis of 410 stations in five southern provinces in China, the following

558 conclusions can be drawn: (1) The machine learning models tuned by the BOA-VMD-PCA algorithm

559 exhibit a positive impact on wind speed error correction; (2) Feature importance analysis revealed that

560 the top eight contributing factors for correcting WRF forecasted wind speed include WRF forecast

561 10-meter wind speed (WS_{10}), latitude, longitude, altitude, pca0 (pca0 physically represents the lowest

562 frequency wind speed series after PCA treatment of all IMF_k (k=0, 1, 2, …, 8) sub-series with reduced

563 dimension), humidity, pressure, IMF0 (IMF0 physically represents the wind speed stationary series

564 with a specific lowest center frequency after the original wind speed series has been processed by

565 VMD); (3) VMD-PCA-RF and VMD-PCA-lightGBM are the most suitable wind speed correction

566 algorithms for December 2021 and January 2022, respectively. The MAE, RMSE, FA, rMAE, rRMSE,

567 and R of the corrected wind speed and the actual wind speed are 0.46 (0.45), 0.62 m s^{-1} (0.63 m s^{-1}),

568 37.36 % (34.75 %), 50.39 % (48.65 %), 91.79 % (91.49 %), and 0.82 (0.78); and (4) The proposed

569 wind speed correction model (VMD-PCA-RF) demonstrates the highest prediction accuracy and

570 stability in the five southern provinces in nearly a year and at different heights. VMD-PCA-RF

571 evaluation indices for 13 months remain relatively stable: R is above 0.6, FA is above 85 %, MAE is

572 below 0.6 m s^{-1}, RMSE is below 0.8 m s^{-1}, rMAE is below 60 %, and rRMSE is below 75 %. In future

573 research, the proposed VMD-PCA-RF algorithm can be extrapolated to the 3 km grid points of the five

574 southern provinces to generate a 3km grid-corrected wind speed product.

575

576

Code availability

The code and model are available as a free-access repository on Zenodo at https://doi.org/10.5281/zenodo.8108889 (Zhou, 2023).

Data Availability

The data is available as a free-access repository on Zenodo at https://doi.org/10.5281/zenodo.8108889 (Zhou, 2023).

Author contributions

SZ developed the software, visualized the data, and prepared the original draft. SZ and YG developed the methodology and carried out the formal analysis. XX and SZ validated data. SZ, YG, XX, ZD, and YL reviewed and edited the text. All authors have read and agreed to the published version of the paper.

Competing interests

The authors declare that they have no conflict of interest.

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