Response to reviewer comments

Dear Editor and Reviewer,

We are very grateful for your time and valuable comments, which we found very helpful. We have addressed questions and comments raised by the reviewer in the revised manuscript with tracked changes. Please find our point-by-point response (in blue font) to the comments below. We hope our revisions have properly addressed your concerns.

Thanks again for your time.

Sincerely,
The authors

Reviewer 2

Zhou et al. present a series of machine learning models including VMD-PCA-RF, a combination of Variational Mode Decomposition, Principal Component Analysis, and Random Forest, for correction of errors in WRF-predicted wind speeds. The manuscript presents various machine learning algorithms and uses two sets of experiments with different approaches to arrive at the model with better predictive capabilities. Accurate prediction of wind speed is important for the wind energy market for effective harvesting of wind energy, and this manuscript has potential in improving predictive capabilities for such uses. As a modeling paper it is fit for the scope of GMD, but the manuscript as presented has major shortcomings primarily in its presentation that require major revisions before further considation.

Major comments:

- Many of the figures in the text are unclear both in presentation and in purpose. Generally, the use of figures to illustrate points and their order in the text should be deliberate and help the flow of the reader to understand the text.

For example, figure 1 shows the elevation map of five southern provinces in China where observational data is used. Figure 2 shows the WRF simulation domain which appears to be a direct figure output from the WRF Pre-Processor (WPS). What is the purpose of these figures? It could be merged into one figure where the observation sites and provinces are marked. The purpose of the elevation maps in the analysis only shows up very late in the text in Section 4.2 about the RF feature importance and is not immediately clear to the reader.

Response: Many thanks for your suggestion. Fig. 1 shows the observation data evenly distributed in the five southern provinces, with the purpose of introducing specific locations of the observation data. The purpose of Fig. 2 is to illustrate the scope of WRF nesting regions. We took your advice and have combined the two figure. The combined figure is shown in Fig. 1* below and replaced in the manuscript.

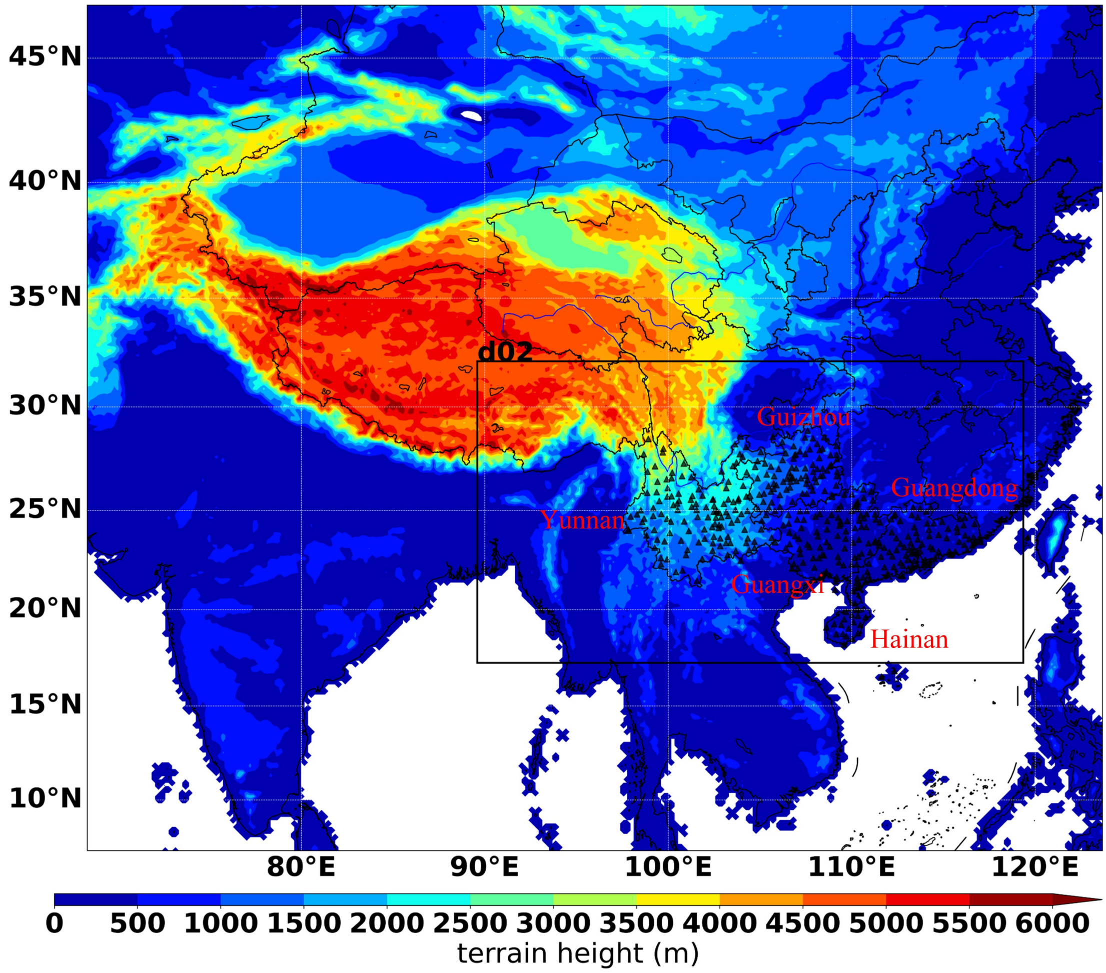

Figure 1*: WRF model simulation area elevation diagram. (d02 represents the nested area of the second layer of the WRF model, and the black triangles represent the meteorological sites).

2. Why was Lechang, Guangdong chosen for Figure 5, and where is this site, was it especially chosen? What is the purpose of the figure to the reader?

Response: Thank you very much for pointing this out. In Fig. 4 and Fig. 5, we randomly selected one (Lechang, Guangdong) of the 410 sites as a case study. Fig. 4 shows the meteorological elements of the station training and the division of the training set and the validation set. Fig. 5 shows the three-dimensional view of 12 wind speed components of the 10-meter forecast wind speed after VMD and PCA processing at the station in experiment 2.

3. In terms of presentation, Figure 3 bottom half is very unclear. The right section of Step 2 is completely unreadable. Step 3 - what do the colored boxes mean? Does their width represent some information? Define the error metrics (FA, ...) before presenting the figure;

Response: Thank you very much for pointing this out. We have changed the information at the bottom of Figure 3 and in step 2. The right half of Step 2 mainly introduces the brief architecture of DBN, MLP, RF, XGBoost and lightGBM models. Each color box represents the training set, the validating set, and the testing set. In this paper, we have introduced the evaluation indicators, such as FA before Fig. 2 below.

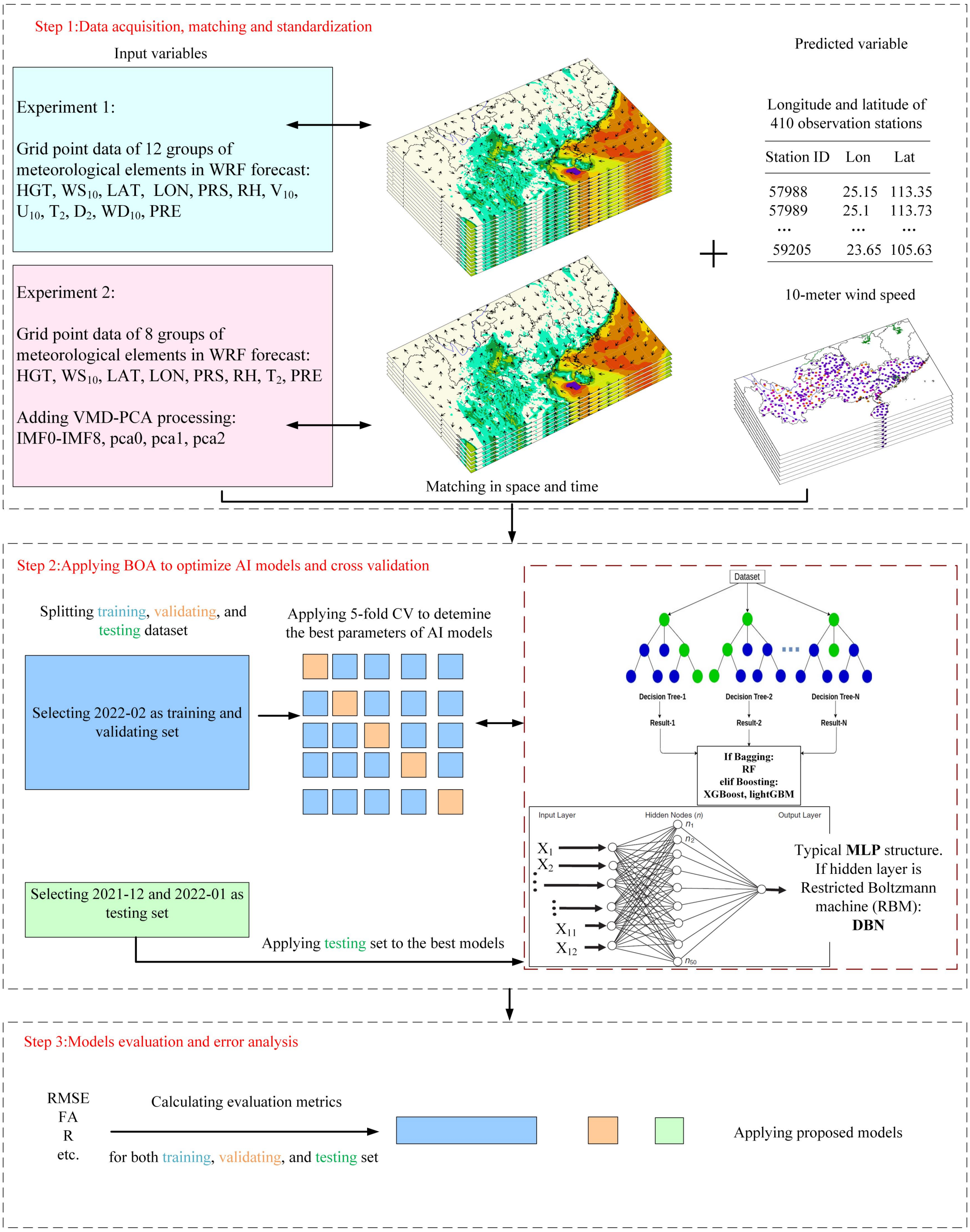

Figure 2: Flowchart of the AI model used to correct WRF-predicted wind speeds in the two main experimental pathways.

4. Figure 4 text is unreadable and the colors do not help discern the lines. Make the lines bolder. The backgrounds could just be white and grey to represent the training+validation & the test sets (label them with a legend).

Response: Many thanks for your suggestion. We have revised it according to your suggestion. The revised figure is shown in Fig. 3 below and in the manuscript.

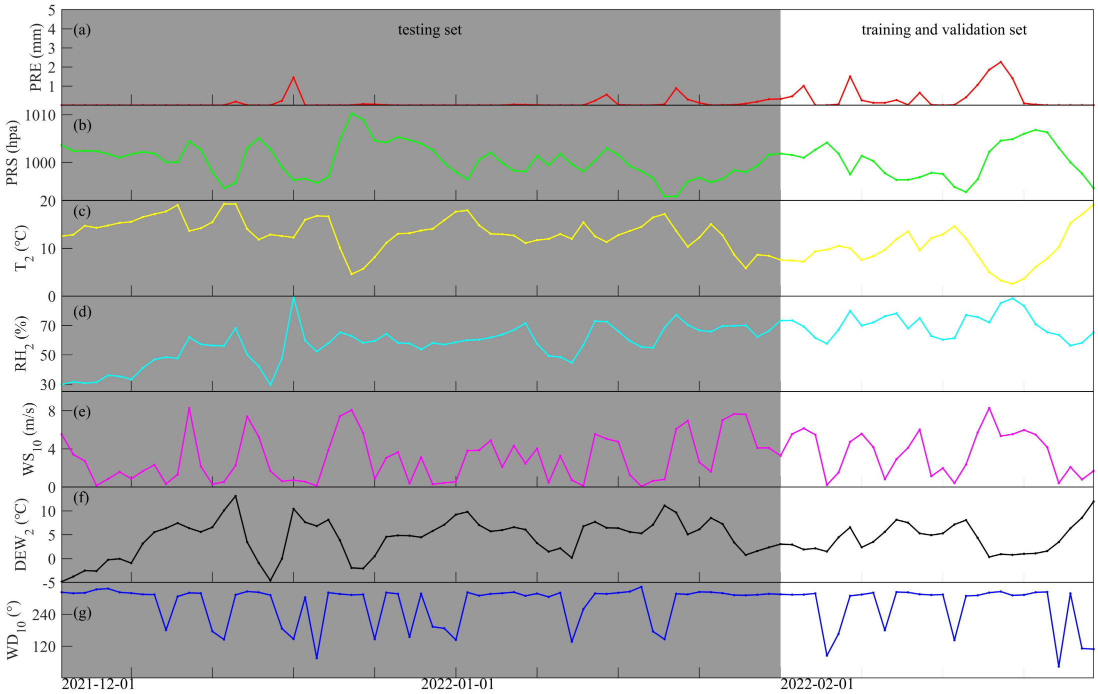

Figure 3: Daily average hourly rainfall (a), surface pressure (b), 2-meter temperature (c), 2-meter relative humidity (d), 10-meter wind speed (e), 2-meter dew point temperature (f), and 10-meter wind direction (g) which are located at Guangdong Lechang Station from December 1, 2021, to February 28, 2022. (February 2022 represents the training and verification sets, and December 2021 to January 2022 represents the testing set).

5. Figure 6 text on the right side is unreadable. Are the specific correlation coefficient text useful to the reader? The colorbar could be sufficient to illustrate the importance. The colorbars of the left and right panels could be the same size. Also, define the feature abbreviations in text as it is impossible to understand the figure and the corresponding feature names in the text if they're not clearly defined. Label the experiments 1 and 2 in Figure 6.

Response: Many thanks for your suggestion. Sure! We have added the explanation of the Pearson correlation coefficient (R) in the paper. We have added the following in the text: "*As illustrated in Fig. 5(a) and Fig. 5(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 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.*"

We have also defined the feature abbreviations in the text. We have added the following in the text: *"In Experiment 1, as shown in Fig. 5(c), 12 sets of data are selected from the WRF forecast field, including altitude (HGT), 10-meter wind speed*

(WS_{10}), latitude (LAT), longitude (LON), surface pressure (PRS), relative humidity (RH), 10-meter meridional wind (V_{10}), 10-meter zonal wind (U_{10}), 2-meter temperature (T_2), 2-meter dew point temperature (D_2), 10-meter wind direction (WD_{10}), and hourly precipitation (PRE).”

We have added the following in the text: “*In this experiment, the wind speed is decomposed into 9 Intrinsic Mode Functions (IMFk, k=0, 1, 2, ..., 8) using VMD. Subsequently, a low-dimensional wind speed vector is extracted from the 9 IMF components via PCA dimensionality reduction (pca0, pca1, pca2), and all data are concatenated to construct the input factors for the model in Experiment 2.*”

We have labeled experiments 1 and 2 in Fig. 5.

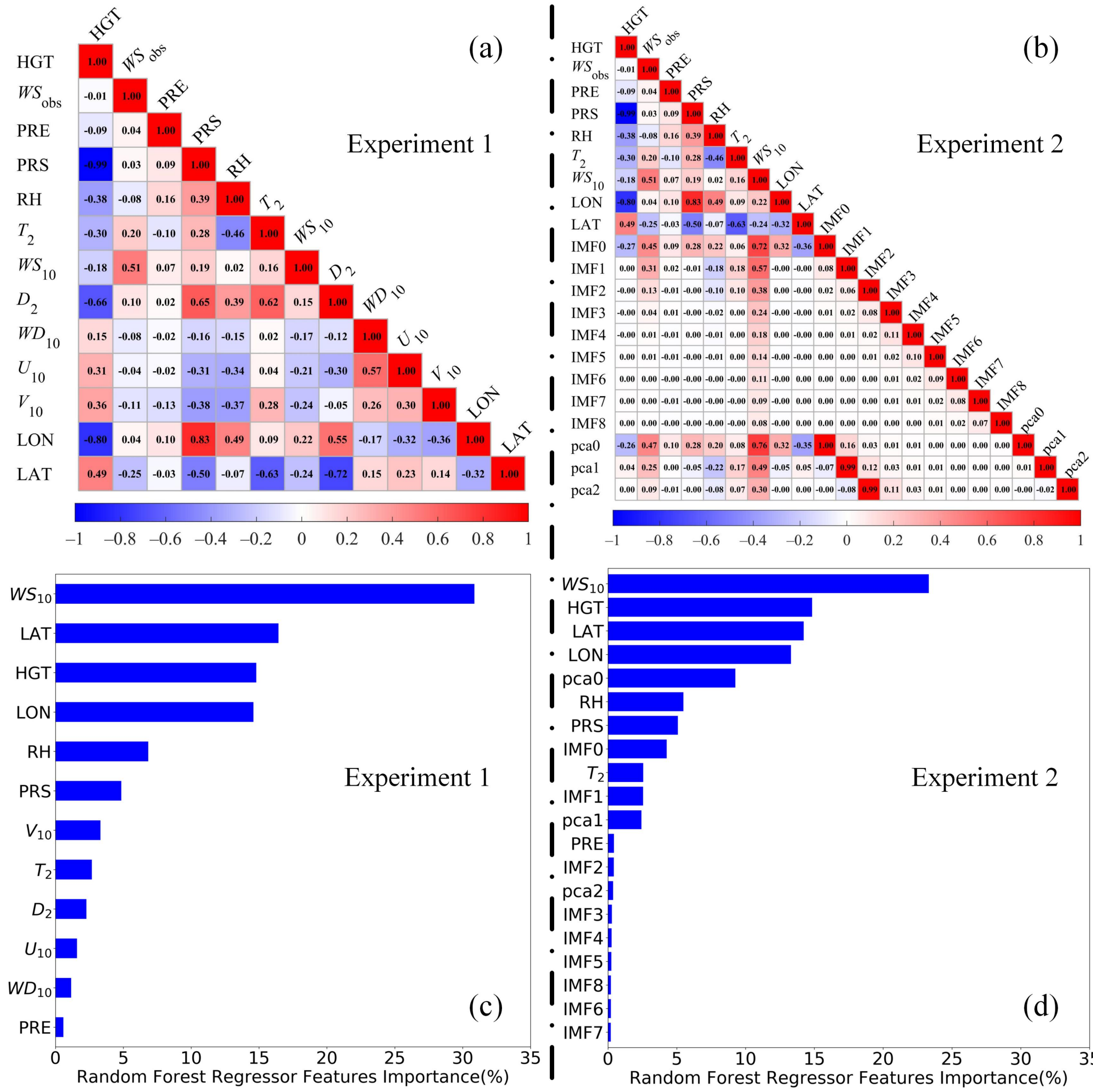

Figure 5: Schematic diagram of correlation and feature importance for two sets of experiments. (a) and (c) represent experiment 1, and (b) and (d) represent experiment 2.

6. Text in Figure 9, 14 is too small.

Response: Thank you very much for pointing this out. We have enlarged the font in Fig. 8 and Fig. 13.

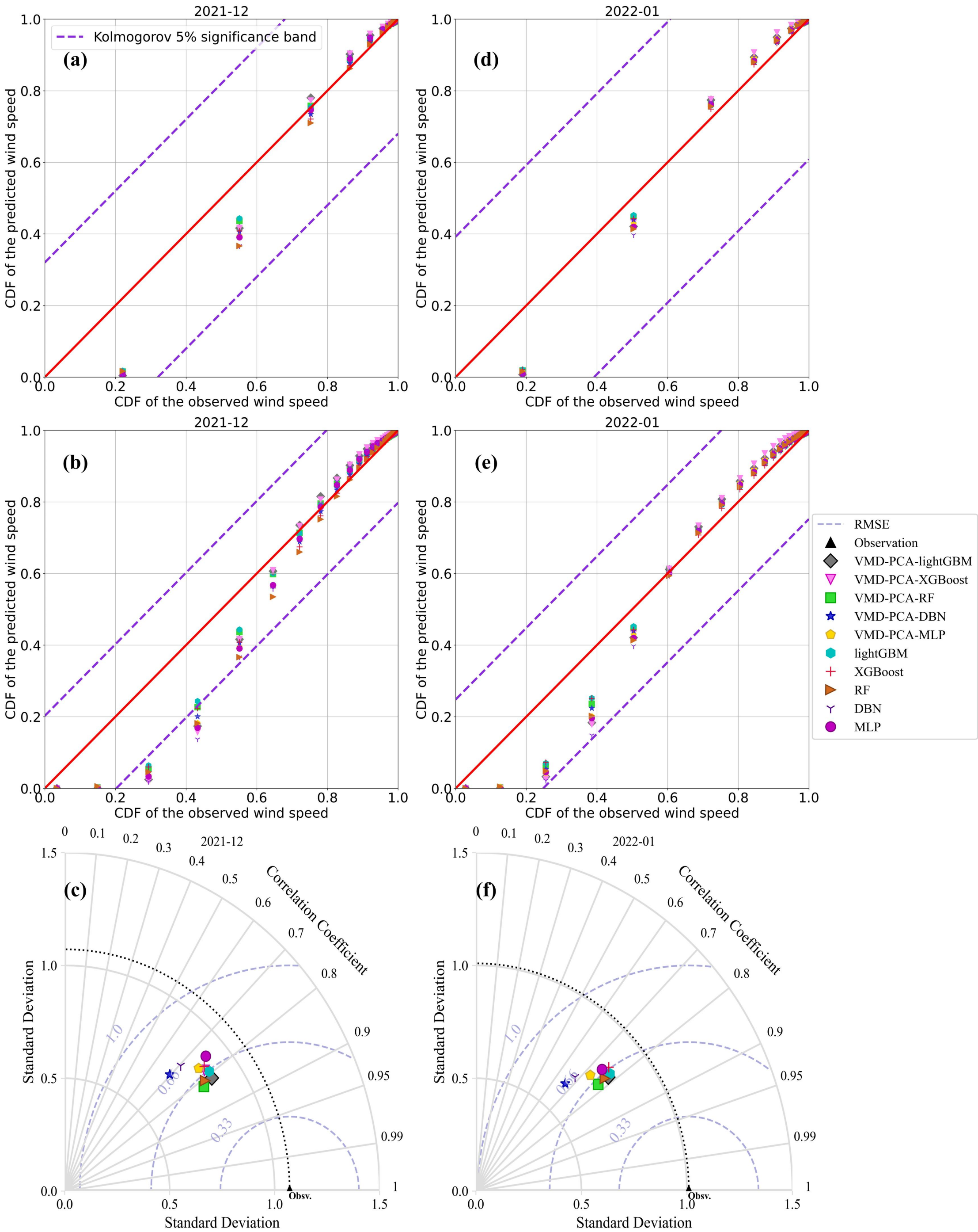

Figure 8: The cumulative distribution probability scatter plots of the actual wind speed and the predicted wind speed of 10 models in wind speed intervals of 0.5 m/s ((a) represents December 2021, (d) represents January 2022) and 0.2 m/s ((b) represents December 2021, (e) represents January 2022) respectively;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

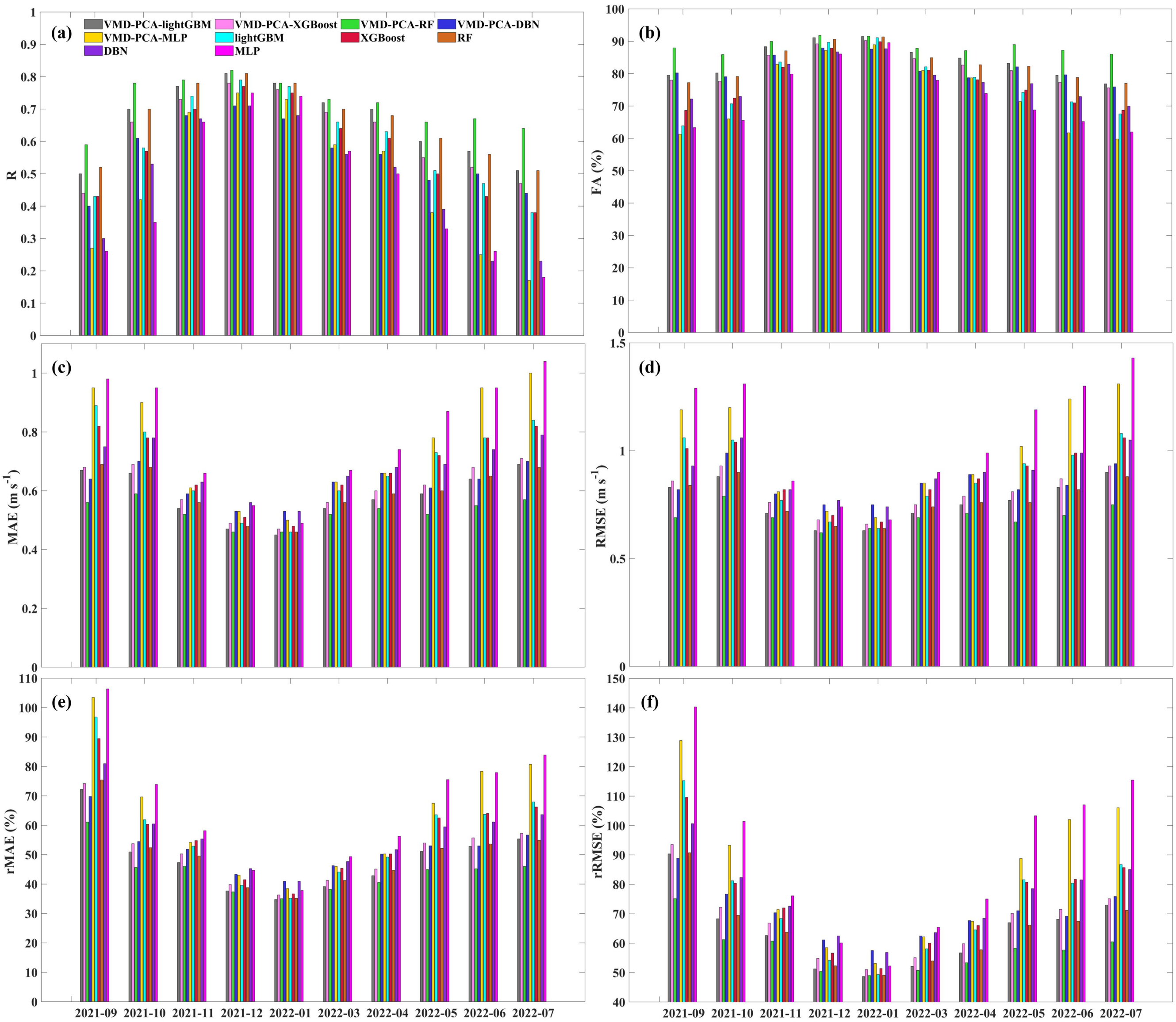

Figure 13: Evaluation histograms of 10-meter wind speed predicted by 10 models and actual wind speed in different months in Experiment 1 and Experiment 2 ((a), (b), (c), (d), (e), and (f) represent R, FA (%), MAE (m/s), RMSE (m/s), rMAE (%), and rRMSE (%) respectively).

7. - As voiced by Reviewer #1, the model was trained mostly based on winter data (DJF). Would the use of data from other seasons help the prediction?

Response: Thank you very much for your question. The purpose of this paper is to compare 5 various machine learning methods, try to introduce additional wind velocity volume, and finally get a hybrid machine learning method with highest robustness and highest wind velocity correction accuracy. Our model was trained in February 2022. the size of our training set mentioned in lines 238-242 is about 2160*410*12. Therefore, even though it only took us a month to train, we actually trained millions of data. It is unclear whether using data from other seasons instead of winter would help with the prediction. But one thing is certain, in general, for machine learning models, the introduction of more training data will improve the prediction effect to a certain extent.

8.The observational dataset presented in Section 2.1 is unclear. Where does this observational dataset come from? Did the authors create this blended data set, and if so what is the source data and the relevant citations?

Response: Thank you very much for pointing this out. The observed data comes from the China Meteorological Administration land data assimilation system (CLDAS-V2.0) real-time product data set (https://data.cma.cn/data/cdcdetail/dataCode/NAFP_CLDAS2.0_RT.html).

After post-processing by the China Meteorological Public Service Center, the data's resolution is reduced to 3km by 3km, and it is interpolated into the meteorological station. The observed data source has been integrated with the observation data of weather stations for consistency.

To clarify this and add more context to the data description, we have added the following in the text: *"The observed data comes from the China Meteorological Administration land data assimilation system (CLDAS-V2.0) real-time product data set (https://data.cma.cn/data/cdcdetail/dataCode/NAFP_CLDAS2.0_RT.html).*

After post-processing by the China Meteorological Public Service Center, the data's resolution is reduced to 3km by 3km, and it is interpolated into the meteorological station. The observed data source has been integrated with the observation data of weather stations for consistency."

8. Specific comments:

- Figure 2 has a contour map but it is not labeled (I assume this is topography), only the unit (m) is specified.

Response: Thank you very much for pointing this out. We have corrected the label of contour map and incorporated Fig. 2 (original) into Fig.1* below (updated).

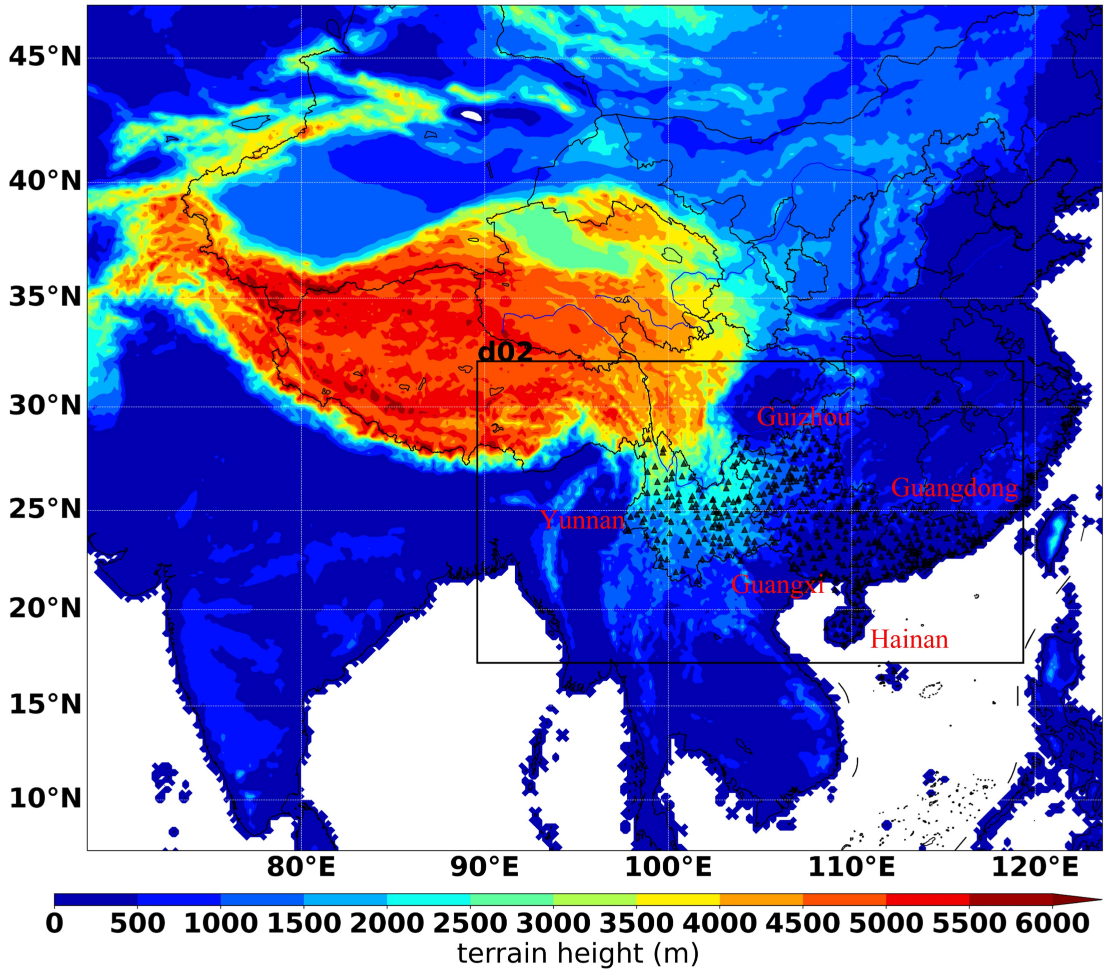

Figure 1*: WRF model simulation area elevation diagram. (d02 represents the nested area of the second layer of the WRF model, and the black triangles represent the meteorological sites).

9.- Line 16: "safe"? Elaborate on the purpose of wind speed prediction for use of wind speed resources.

Response: Thank you very much for pointing this out. In lines 45-48, we summarize the following conclusions based on the literature (Guo et al., 2021; Xiong et al., 2022; Tang et al., 2021): *"Therefore, accurate and stable wind speed prediction (WSP) is very important for the safe and stable operation of the power grid system and improving the utilization rate of wind energy and economic development (Guo et al., 2021; Xiong et al., 2022; Tang et al., 2021)."* Of course, the purpose of accurate prediction of wind speed is also efficient use of wind speed. Therefore, we have updated line 16 to the following text: *"Accurate wind speed prediction is crucial for the safe and efficient utilization of wind resources."*

10.- Line 26: Define "BOA" here.

Response: Thank you very much for pointing this out. "BOA" is defined in line 23 as "Bayesian Optimization Algorithm (BOA)."

11. - Line 26: Why "debug"? Is there a bug in the models? I suggest "analyze".
Response: Thank you very much for pointing this out. We originally used "debug" to mean parameter selection and optimization. There's not a bug in the models. we have corrected line 25-27 to the following text: "*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.*"

12.- Line 33 shows many metrics of the presented model compared to observations. How much better is this against WRF-predicted values before correction?
Response: Thank you very much for your question. We have already expressed the R, FA, and RMSE of WRF-predicted values before correction from September 2021 to June 2022 in FIG. S10 of the supplementary materials and Fig. 7c and Fig. 7e. As seen in the figures above, WRF evaluation indices for 10 months remain relatively poor: correlation coefficient R is below 0.59, accuracy rate FA is below 52%, RMSE is above 1.77m/s. Therefore, The VMD-PCA-RF model proposed can effectively correct the wind speed predicted by WRF and greatly improve the accuracy of wind speed correction.

13. - Line 43-45 talks about the decline of wind markets. Could authors elaborate on the relationship of this to wind speed prediction? It could be more useful for the reader to understand how better wind speed prediction serves the wind energy markets.
Response: Thank you very much for your question. Accurate wind speed prediction is of great significance for the operation and grid connection of wind farms (Huang et al., 2019).
We have added the following in the text: "*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).*"

Huang, Y., Yang, L., Liu, S., and Wang, G.: Multi-Step Wind Speed Forecasting Based On Ensemble Empirical Mode Decomposition, Long Short Term Memory Network and Error Correction Strategy, Energies, 12, 1822, https://doi.org/10.3390/en12101822, 2019.

14.- Line 59: Cite the original WRF whitepapers as well (Skamarock et al.) instead of just the wind speed prediction part.
Response: Thank you very much for pointing this out. we have updated line 59 to the following text: "*… and the Weather Research and Forecasting Model (WRF) (Skamarock et al., 2021) are extensively utilized for wind speed prediction.*"

Skamarock, W. C., Klemp, J. B., Dudhia, J., Gill, D. O., Liu, Z., Berner, J., Wang, W., Powers, J. G., Duda, M. G., Barker, D. M., and Huang, X.-Y.: A Description of the Advanced Research WRF Model Version 4, 2021.

Xu, W., Liu, P., Cheng, L., Zhou, Y., Xia, Q., Gong, Y., and Liu, Y.: Multi-step wind speed prediction by combining a WRF simulation and an error correction strategy, Renewable Energy, 163, 772–782, https://doi.org/10.1016/j.renene.2020.09.032, 2021.

15. - Line 116: Define DBN here.
Response: Thank you. "DBN" was defined in line 22 as “Deep Belief Network (DBN).”

16. - Line 140-141: WRF is not just developed by NCEP. The WRF website states it is a "collaborative partnership of the National Center for Atmospheric Research (NCAR), the National Oceanic and Atmospheric Administration (represented by the National Centers for Environmental Prediction (NCEP) and the Earth System Research Laboratory), the U.S. Air Force, the Naval Research Laboratory, the University of Oklahoma, and the Federal Aviation Administration (FAA)."
Response: Thank you very much for pointing this out. We've corrected line 140-141 to the following text: “*The WRF 4.2 model, developed by the National Center for Environmental Forecasting (NCEP), the National Center for Atmospheric Research (NCAR) and several universities, institutes and business units, ...*”

17. - Line 145-146: WRF can use other input fields other than GFS. I suggest just stating that your run of WRF uses GFS as initial and lateral boundary conditions.
Response: Thank you very much for pointing this out. We have already mentioned in lines 156-157: “*The regular Global Forecast System (GFS) forecast field data serve as the initial field and lateral boundary conditions for the WRF model.*”
Therefore, we have updated line 145-146 to the following text: “*When forecasting meteorological elements, the WRF model normally uses the GFS data developed by NCEP.*”

18. - Overall, section 2.2.1 could be improved to be more relevant and shortened. The background of WRF is well stated in literature and the manuscript should focus on parts relevant to wind speed prediction. "Boilerplate" text about WRF (e.g., L166-167 about "WRFOUT") is not exactly relevant and could be shortened (authors already state previously in text that output frequency is 1-hour to line up with observational data).
Response: Many thanks for your suggestion.
We’ve updated section 2.2.1 to the following text:
“*The WRF 4.2 model, developed by the National Center for Environmental Forecasting (NCEP), the National Center for Atmospheric Research (NCAR) and several universities, institutes and business units, represents a new generation of*

mesoscale numerical models with numerous applications in research forecasting. When forecasting meteorological elements, the WRF model normally uses the GFS data developed by NCEP. Using the WRF model in combination with daily GFS data resolution of 0.25° × 0.25°, the model initiates at 18:00 UTC and generates forecasts every 3 hours for a total duration of 102 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 (Xu et al., 2021).*"

19. - In Section 2.2.4, first summarize the major difference (and purpose) of experiments 1 & 2. It is hard for the reader to see the importance of the two experiments when it is mixed together with the analysis.

Response: Thank you very much for pointing this out. The correlation between the WRF-predicted 10-m wind speed and the observed wind speed is the highest. The purpose of the second experimental path is using VMD-PCA algorithm to dig out the hidden wind speed characteristics of the 10-meter forecast wind speed, reduce the input of other meteorological factors such as WD_{10} and D_2, and further prove that the VMD-PCA algorithm is effective before correcting the WRF-predicted wind speed.

We have updated the first paragraph of section 2.2.4 to the following text:

"*This study used five machine learning algorithms to conduct ten experiments following two main paths. The first path involves increasing the meteorological variables possibly related to wind speed in the forecast field. The correlation between the WRF-predicted 10-m wind speed and the observed wind speed is the highest. The purpose of the second experimental path is using VMD-PCA algorithm to dig out the hidden wind speed characteristics of the 10-meter forecast wind speed, reduce the input of other meteorological factors such as WD_{10} and D_2, and further prove that the VMD-PCA algorithm is effective before correcting the WRF-predicted wind speed. The overarching goal is to achieve accurate correction of the forecast field wind speed. The flowchart of the artificial intelligence models used to correct the WRF predicted wind speed for the two main experimental paths is illustrated in Fig. 2 and comprises the following three steps:*"

20. - Line 234: "Missing and outlier values are removed from the dataset" - isn't this WRF model outputs, why would there be missing values?

Response: Thank you very much for your question. As mentioned in question 8, we cooperate with China Meteorological Public Service Center through the project (the

second batch of service public bidding projects for EHV transmission companies in 2022 (2022-FW-2-ZB)).
The 3km observation data transmitted by China Meteorological Public Service Center was interrupted or incomplete sometimes. Therefore, we need to eliminate the corresponding time point of the observation data when matching the WRF-predicted and observation data.

21.- Section 3.1: Better to describe the RMSE, R, error metric values of different model configurations in a table for clarity. A table only shows in Section 3.3 in the form of Table 3 & 4 and it is unclear of the relationship of these and experiments 1 & 2. The flow could be much improved here.
Response: Many thanks for your suggestion. The analysis in Section 3.1 is mainly carried out from Fig. S1-5 in supplementary materials. The purposes for section 3.1 and section 3.3 are different. Section 3.1 mainly studies the comparison of the training set and validation set of 5 artificial intelligence models in experiment 1 in February 2022 to further determine whether there is overfitting. Section 3.3 mainly analyzes the comparison of various error indicators in the test sets of December 2021 and January 2022 of the two experiments. Of course, for clarity, we have added Table 3* to show the error indicators of the training set and validation set of the 10 AI models in two sets of experiments in February 2022.

Table 3*. Table of evaluation indices of wind speed error trained and verified by 10 models in February 2022

Model	training set			validation set		
	R	RMSE（m/s）	FA	R	RMSE（m/s）	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

21. - A lot of the feature labels could be better explained instead of being just listed in the text (e.g., in conclusion Line 542). What does pca0, IMF0 represent physically?

Response: Thank you very much for pointing this out.

Xu et al., 2021 states: VMD is adopted to obtain unknown but meaningful features hidden in the wind speed series predicted using the WRF model. The set of stationary sub-series contains more valid information than the previous non-stationary wind speed series when they are used as the inputs of the error correction model. PCA is a dimensional-reduction method that recombines the original variables into a new set of several independent variables and comprehensively reflects the information of the original variables.

In this study, the original variables are a set of sub-series of the wind speed that contain valid features and noise. PCA method is adopted to extract the pcax (x=0, 1, 2) and remove the illusive components.

As shown in Fig. 4, IMF0 physically represents the wind speed stationary series with a specific lowest center frequency after the original wind speed series has been processed by VMD.

pca0 physically represents the lowest frequency wind speed series after PCA treatment of all IMFk (k=0, 1, 2, …, 8) sub-series with reduced dimension.

We have added the following in the text: "*As shown in Fig. 5, IMF0 physically represents the wind speed stationary series with a specific lowest center frequency after the original wind speed series has been processed by VMD. pca0 physically represents the lowest frequency wind speed series after PCA treatment of all IMFk (k=0, 1, 2, …, 8) sub-series with reduced dimension.*"

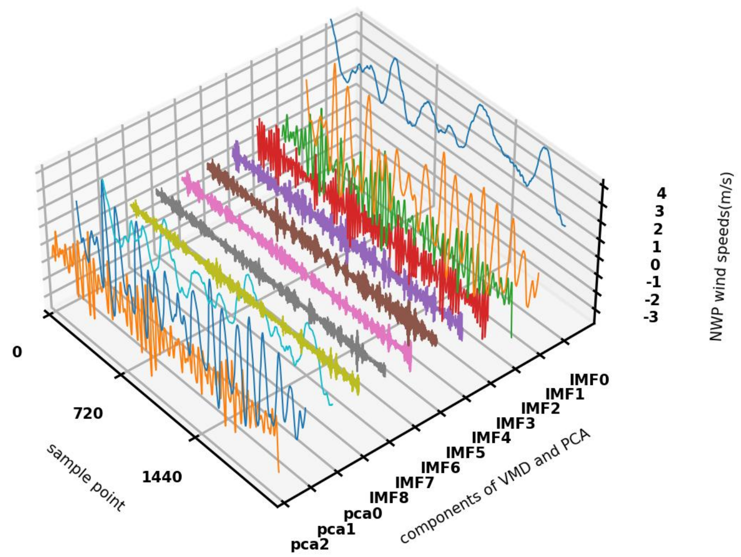

Figure 4: Three-dimensional view of 12 wind speed components after VMD and PCA processing of the 10-meter forecast wind speed at Lechang Station in Guangdong from December 1, 2021, to February 28, 2022.