Response to Reviewer #2's Comments

We thank the anonymous reviewer for his/her comprehensive evaluation and thoughtful comments, which greatly improve the quality of our manuscript. We have made efforts to adequately address the reviewers' concern one by one. For clarity purpose, here we have listed the reviewer' comments in plain font, followed by our response in bold italics.

1. First concern relates with the argument of this work, which to me does not seem well related with this journal. As from the journal's homepage, "Atmospheric Chemistry and Physics (ACP) is a not-for-profit international scientific journal dedicated to the publication and public discussion of high-quality studies investigating the Earth's atmosphere and the underlying chemical and physical processes. It covers the altitude range from the land and ocean surface up to the turbopause, including the troposphere, stratosphere, and mesosphere. The main subject areas comprise atmospheric modelling, field measurements, remote sensing, and laboratory studies of gases, aerosols, clouds and precipitation, isotopes, radiation, dynamics, biosphere interactions, and hydrosphere interactions (for details see journal subject areas). The journal scope is focused on studies with important implications for our understanding of the state and behaviour of the atmosphere." Here, the authors have used different machine learning algorithms to investigate the wind energy resource in China, so the connection with the above is not totally convincing. Also because the authors never try to connect or motivate their findings, for instance the construction of the algorithms, with some known physical process and the discussion mostly is narrowed on statistical parameters to compare the results obtained by the algorithms.

Response: Good point! This concern mainly is caused by our inappropriate description on the grand challenge for the current instruments used to provide wind measurements at turbine height for wind energy industry. To this end, we attempt to obtain accurate wind speed at turbine height based on machine learning algorithms. At present, the wind mast or tower can provide wind speed below 100 m AGL (Durisic et al. 2012; Liu et al., 2018). By comparison, the radar wind profiler (RWP) can measure the wind profiles from the ground surface to a height of 5-8 km AGL (Liu et al., 2019). But there is a large uncertainty in the wind profile observations near the ground surface (below 300 m) provided by the RWP, due to the influence of ground and intermittent clutter (May and Strauch 1998; Allabakash et al., 2019). It leads to a gap (100 to 300 m) in the observation of surface layer wind profile. This height (100~300 m) is also the installation height of the wind turbine. The PLM method is most often applied to extrapolate the surface wind speed to the wind turbine hub height. Previously, a semi-empirical relationship, termed "log wind profile", is commonly used to describe the vertical pattern of horizontal wind speeds within the surface layer. However, a recent study (i.e., Jung et al., 2021) suggested that the error in the wind power density estimation over China can reach to 30 % by taking the

above-mentioned relationship. This is largely due to the inconsideration of turbulence nature in the boundary layer, and to the ignorance of the impact induced by multi-scale circulation. To better fit the scope of ACP, we have made substantial changes to the original manuscript.

First of all, the title is modified to "Estimating hub height wind speed based on machine learning algorithm: Implications for the wind energy assessment".

Secondly, the motivation of this manuscript has been rewritten in Introduction part by highlighting the challenges we are facing in estimating the wind speed at turbine hub height. In this context, machine learning algorithms have been reviewed as well. The updated introduction part goes as follows:

"Characterizing the wind speed at wind turbine hub height is key for wind energy assessment (Yu et al., 2022). The wind turbine is usually installed at the top of wind mast with a height of 100-120 m above ground level (AGL), which roughly corresponds to the surface layer (Veers et al., 2019). The wind speed data that have been widely used for wind energy assessment are mainly obtained from wind mast, Doppler lidar or reanalysis data (Debnath et al., 2021). The 10 m wind data measured by the ground meteorological station can be used for wind energy assessment (Oh et al. 2012; Liu et al., 2019). The wind tower or mast can also provide wind speed observation data below 100 m AGL (Durisic et al. 2012; Liu et al., 2018). Moreover, the reanalysis data, such as the fifth generation European Centre for Medium-Range Weather Forecasts atmospheric reanalysis system (ERA5), can provide the hourly wind speed at a height of 10 or 100 m AGL for wind energy assessment (Laurila et al., 2021; Gualtieri, 2021). However, the wind turbines are increasing in height and rotor diameter with the development of technology, which go beyond the surface layer and enter the Ekman layer. Such as some offshore wind power plants, the blade tips of the largest wind turbine can reach heights of 250 m AGL (Gaertner et al. 2020). In addition, increasing wind turbine hub height reduces the impact of surface friction, enabling wind turbines to operate in high-quality wind resource environments (Veers et al., 2019). Therefore, the wind profile is important for the selection of wind turbine hub height and the assessment of wind energy.

It is widely recognized that the wind profile is mainly obtained by empirical formulae (Li et al., 2018), such as the power law method (PLM) . The PLM method generally assumes that the wind speed below 150 m in the planetary boundary layer (PBL) varies exponentially with height (Hellman et al. 1914). This means that the wind speed at the wind turbine hub height can be calculated from the surface wind speed based on a constant power law exponent (α). But the surface layer wind profile is mainly controlled by the surface roughness, friction velocity and the atmospheric stability (Gryning et al., 2007). The surface layer is where obstructions such as trees, buildings, hills, and valleys cause turbulence and reduce the wind speed (Coleman et al., 2021; Solanki et al., 2022). Due to the influence of inhomogeneous underlying surface and ubiquitous atmospheric turbulence, wind speed varies constantly and greatly in the vertical (Tieleman 1992). Especially above surface layer, the factors, such as the Coriolis force, baroclinity and wind shear, increase the complexity of the wind profile (Brümmer 1991). As a result, the α has spatiotemporal variability and depends on a variety of factors, such as terrain, time and height (Li et al., 2018). Therefore, the assumption of a constant α poses great challenges and uncertainties to wind energy assessment. Some studies use more complex models to improve the PLM, such as the perturbation theory (Sen et al., 2012) and the bivariate wind speed-

wind shear model (Jung et al., 2017). These studies confirm that there is a complex nonlinear relationship between surface observations and wind speed at the wind turbine hub height. Therefore, one of the greatest challenges is to develop an accurate method to describe the nonlinear transfer from surface observations to wind speed at wind turbine hub height.

With the development of machine learning (ML) technology, the ML algorithms have been widely used in the field of wind speed and wind power prediction (Magazzino et al., 2021). Chi et al. (2015) compared two wind speed-forecasting mechanisms in China based on linear regression and support vector machine algorithm. They find that the ML algorithms have better accuracy in solving the nonlinear problem. Lahouar and Slama et al. (2017) use several meteorological factors to forecast wind power based on a random forest (RF) model. The results indicate that compared with physical and statistical approaches, the ML model can achieve better accuracy when coping with problems that cannot be analytically defined. Therefore, it is worth trying to use ML algorithms to retrieve the wind speed at wind turbine hub height from available observations."

Thirdly, in the methods section, we focused on the inversion of surface layer wind profile based on the RF model. We try to clarify the scientific significance and connect the construction of the models with the known physical process:

"The schematic diagram of surface layer wind profile observations is shown in Fig. 2. The wind mast or tower can provide wind speed data below 100 m AGL (Durisic et al. 2012; Liu et al., 2018). The RWP can measure the wind profiles from the 300 m to a height of 5-8 km AGL (Liu et al., 2019). It leads to a gap (100 to 300 m) in the observation of wind profile. At present, the PLM method is most often applied to extrapolate the surface wind speed to the wind turbine hub height, such as wind speed at 120 m (WS_{120}), 160 m (WS_{160}) and 200 m (WS_{200}) AGL."

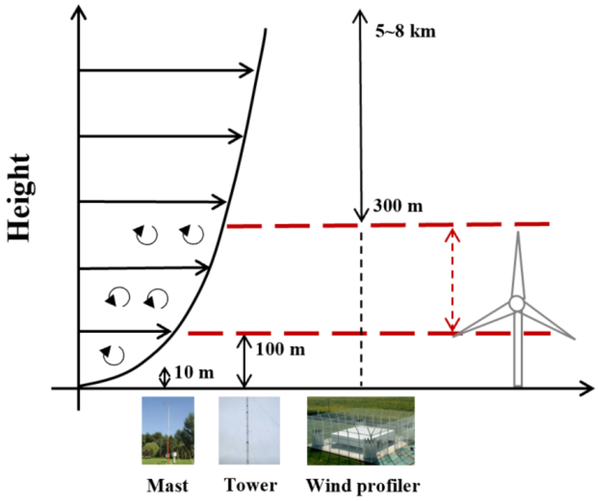

Figure. 2 The schematic diagram of surface layer wind profile observation.

"In the construction of the RF model, it is necessary to obtain the relevant variables that may affect the surface wind profile according to the physical mechanism and previous research. At present, the PLM is often used to calculate the wind speed at hub height. It confirms that the wind speed at hub height is related to the wind speed at other heights (Durisic et al., 2012; Li et al., 2018). Therefore, the WS_{10}, WD_{10}, WS_{300} and WD_{300} are selected as inputs. The surface wind profile also

depends on the surface roughness, friction velocity and the atmospheric stability (Smith, 1988; Gryning et al., 2007), so that FSR, FV and Char are also regarded as inputs. The higher FSR causes a slower wind speed in the surface layer. The FV is a theoretical wind speed at the Earth's surface, which is used to calculate the way wind changes with height in near surface (Stull, 1988). Moreover, considering that the generation of wind is closely associated with uneven heating of the Earth's surface by solar radiation (Solanki et al., 2022), the Rn, LHF and SHF are also selected as input variables. Additionally, some studies use atmospheric temperature and pressure as input to improve the accuracy of wind speed prediction (Chi et al., 2015). Here, we also regard DP, Temp and Press as the input variables. The reference value, also included as input in the RF model, is the WS_{120}, WS_{160} and WS_{200} measured from RS."

"To estimate the WS_{120}, WS_{160} and WS_{200}, we need to build RF model on 120 m (RF_{120}), 160 m (RF_{160}) and 200 m (RF_{200}), respectively. For each model, it is necessary to select the main features from the inputs to avoid data redundancy and reduce the complexity of the model (Ma et al., 2021). Following the research of Gregori et al. (2022), the inputs which cannot cause a 2% reduction in correlation coefficient are regarded as irrelevant feature and removed. Figure 3 shows the importance analysis of inputs for three RF models. The relevant features are marked by red bars. The irrelevant features are marked by blue bars, which are not regarded as final inputs in three RF models. For three RF models, the relevant features are both WS_{10}, FV, Char, SHF and WS_{300}. It indicates that the factors such as surface friction, heat transfer and high-altitude wind speed constraints are considered in the construction of RF models. In addition, it is surprising that FSR has such low importance in three RF models construction. FSR is a measure of surface resistance, which directly affects the near-surface wind speed (Smith, 1988). At a land station, the FSR is derived from the vegetation type (Li et al., 2021). The surface type of Qingdao station is cropland. Li et al. (2021) confirms that the FSR at cropland is most likely to 0.3 m. In training data, the FSR from ERA5 also approximates a constant value (0.3 m). Since the constant variable has no meaning for RF model construction, the RF model divides FSR into irrelevant variable. Therefore, the final inputs for three RF models are WS_{10}, FV, Char, SHF and WS_{300}."

Finally, we add more physical process discussions in the discussion section. We try to explain the performance difference of the method from the perspective of physical mechanism.

"Figure 4 shows the wind profile from different methods under different time. The red, black and blue lines represent the mean wind speed from RS, PLM and RF, respectively. For the PLM, the retrieved results below 80 m AGL are consistent with the RS observations. Gryning et al. (2007) also pointed out that the wind profile based on surface-layer theory is valid up to a height of 50–80 m. Above 80 m AGL, the wind speeds retrieved by PLM deviate from the RS observations. This deviation is increasing with the height. The comparison results between PLM and RS at 120 m, 160 m and 200 m AGL (Fig. 5) are also confirmed it. This is due to that above surface layer, the Coriolis force, baroclinity and wind shear increase the complexity of the wind profile (Brümmer 1991). Moreover, most of estimated results from PLM are underestimated when the observed wind speed is high, especially at 200 m AGL. This is due to the surface wind profile is affected by turbulence, surface friction and other factors (Tieleman 1992; Solanki et al., 2022). The turbulence caused by

inhomogeneous underlying surface can change the wind direction and reduce the horizontal wind speed (Coleman et al., 2021). Especially in coastal areas, the sea land interaction and complex surface types make the variations of near surface wind profiles more complex. The simple exponential relationship is unable to obtain the surface wind profile with high accuracy, especially at high wind speed condition. By comparison, the WS_{120}, WS_{160} and WS_{200} retrieved from RF are closer to RS observations. Compared with PLM, the R and RMSE between the observed wind speed and the estimated wind speed from RF at three heights are significantly improved (Fig. 5). This is due to the fact that the surface friction (FV), heat transfer (SHF) and high-altitude wind speed constraints (WS_{300}) are considered in construction of RF, which can improve the accuracy of the model. Moreover, it notes that three RF models tend to slightly overestimate small values and underestimate high values. This may be due to the small number of training samples at high and low values, resulting in the reduction of RF model generalization. Overall, it can be seen from the metrics of R and RMSE that the wind speed from RF model is better than that from PLM.

In addition, for both PLM and RF, the retrieved wind profile at 2000 LST is closer to the RS observations. The comparisons between the observed wind speed and the estimated wind speed for PLM and RS under different time is shown in Fig. S7. The fitting results of PLM and RF at 2000 LST are slightly higher than that at 0800 LST. It indicates that the performance of PLM and RF vary with hour of the day. This is due to the wind profile depends not only on the surface friction but also on the atmospheric stratification (Gryning et al., 2007). The surface layer is in an unstable stratification due to heat transfer caused by solar radiation during daytime, while the surface layer tends to stable stratification due to surface radiation cools during nighttime (Yu et al., 2022; Solanki et al., 2022). The WS_{120}, WS_{160} and WS_{200} are more vulnerable to the surface turbulence due to the unstable stratification during daytime. Therefore, the performance of PLM and RF at nighttime is better than that at daytime.

Figure 6 shows the comparisons between the observed results and the estimated results for PLM and RF under different season. The red, green, blue and black represent the spring, summer, autumn and winter, respectively. At three heights, the performance of PLM is the best in winter and the worst in summer. It shows that the performance of PLM is affected by seasonal factors, which is likely due to the wind shear varying dramatically with season (Banuelos-Ruedas et al., 2010). Pérez et al. (2005) indicates that the surface layer wind speed profile is mainly affected by the convection produced by surface heating in summer. The WS_{120}, WS_{160} and WS_{200} affect by the surface due to the unstable stratification, which leads that the PLM performs worst in summer. In contrast, during winter, the surface temperature is generally lower than the air temperature aloft creating a stable inversion (Yu et al., 2022; Liu et al., 2022). The WS_{120}, WS_{160} and WS_{200} are disconnected from the surface due to stable stratification. It leads that the PLM performs best in winter. As for RF, although the performance in spring is slightly lower than that in other seasons, the fitting results at four seasons are significantly improved compared with the PLM. This indicates that RF is least affected by seasons. The reason is that the RF model is less subjective than PLM because they are data driven. Overall, in terms of stability and accuracy, the RF is more suitable for estimating wind speed at hub height."

All these revisions had been incorporated in this revised manuscript.

2. Second point is that although they present limitations coming from the use of ERA5 reanalysis due to its coarse resolution, they have used this dataset for information on local parameters, such as surface roughness, friction, besides wind speed so I do not understand how they can overcome those limitations with their method. In my opinion, at least some of these parameters would need much fine resolution to be representative of the site.

Response: Good question! As your said, some parameters, such as surface roughness (FSR), friction velocity (FV), temperature (Temp) and pressure (Pres), need much fine resolution to be representative of the site. In the surface layer, the FSR, FV and the atmospheric stability are the main factors controlling the wind profile (Gryning et al., 2007). Unfortunately, there is no field observation data of FV and FSR at Qingdao station. Therefore, we can only obtain the corresponding parameters from the reanalysis data (ERA5). However, it should be noted that for some parameters, such as FSR, Temp and Press, we have used the fine resolution or site observation data to investigate their impact on model accuracy. At land stie, FSR is a measure of surface resistance, which is derived from the vegetation type and snow cover (Smith, 1988). Li et al. (2021) retrieved the FSR in Chinese mainland based on MODIS 0.05 * 0.05-degree surface type data. They confirm that the FSR at cropland is most likely to 0.3 m. The surface type of Qingdao station is cropland. Therefore, we set the FSR to 0.3 to compare with the FSR from ERA5. In fact, the FSR from ERA5 also approximates a constant value (0.3 m). In addition, the Temp and Press obtained from field observation are also compared with that from ERA5. Fig. S1 shows the influence of different sources of parameters on RF model accuracy. It can find that for these three parameters, the use of field observation or ERA5 data has little impact on the accuracy of the RF model. Therefore, we finally decided to use ERA5 data as input.

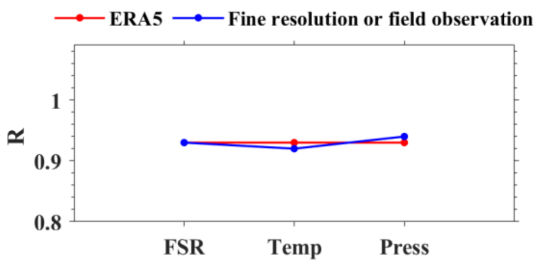

Figure S1. Comparison of the RF model accuracy under different input. Red and blue points represent the results from ERA5 data and field observation (or fine resolution), respectively.

In the revised manuscript, we added a section about the feature selection of RF model. Following the research of Gregori et al. (2022), the inputs, which cannot cause a 2% reduction in correlation coefficient, are regarded as irrelevant feature and removed. The final input variables of RF are WS_{10}, FV, Char, SHF and WS_{300}. The specific modifications are as follows:

"To estimate the WS_{120}, WS_{160} and WS_{200}, we need to build RF model on 120 m (RF_{120}), 160 m (RF_{160}) and 200 m (RF_{200}), respectively. For each model, it is necessary to select

the main features from the inputs to avoid data redundancy and reduce the complexity of the model (Ma et al., 2021). Following the research of Gregori et al. (2022), the inputs, which cannot cause a 2% reduction in correlation coefficient, are regarded as irrelevant feature and removed. Figure 3 shows the importance analysis of inputs for three RF models. The relevant features are marked by red bars. The irrelevant features are marked by blue bars, which are not regarded as final inputs in three RF models. For three RF models, the relevant features are both WS_{10}, FV, Char, SHF and WS_{300}. It indicates that the factors such as surface friction, heat transfer and high-altitude wind speed constraints are considered in the construction of RF models. In addition, it is surprising that FSR has such low importance in three RF models construction. FSR is a measure of surface resistance, which directly affects the near-surface wind speed (Smith, 1988). At a land station, the FSR is derived from the vegetation type (Li et al., 2021). The surface type of Qingdao station is cropland. Li et al. (2021) confirms that the FSR at cropland is most likely to 0.3 m. In training data, the FSR from ERA5 also approximates a constant value (0.3 m). Since the constant variable has no meaning for RF model construction, the RF model divides FSR into irrelevant variable. Therefore, the final inputs for three RF models are WS_{10}, FV, Char, SHF and WS_{300}."

All the above response and revisions had been incorporated into section 3.2 of this revised manuscript.

3. In any case, as regards the revision, the authors have tried to address all the comments from the two reviewers. Grammatical and spelling mistakes are still there, both in the original and in the newly added or modified parts.

Response: Thanks for pointing these issues out. We tried our best to correct spelling and grammatical errors in the revised manuscript.

4. In reference to my previous question 4 (A strong limitation of the work is that the comparison of observations with model estimations is carried out at a single location, whereas the retrievals are then used at eight different stations. It is not clear if the results obtained at the single station, from which a single ML algorithm was selected, also apply to the other stations, and why.), I am not satisfied with the answer as it refers to a general statement on the method not specific to this work.

Response: In the revised manuscript, we focused on the inversion of near-surface wind profile based on the data of Qingdao station. Therefore, this section is changed to analyze the generalization and applicability of RF in Qingdao Station. The specific modifications are as follows:

"The accuracy and generalization of the RF model depend on training and testing samples (Ma et al., 2021). However, the training and testing samples are obtained at 0800 and 2000 LST. It needs to discuss whether the RF model also applies to other times. This depends on whether the RF model has enough generalization for the training samples, and whether the inputs at other times have appeared in the training samples. Fig. S3-S5 shows the difference between estimated wind speed and observed wind speed of three RF models, which as a function of the inputs. For three

RF models, the deviations are relatively stable and not change with the increase of inputs. It indicates that three RF models have good generalization for the training and testing samples. This is due to the fact that RF tends to increase random disturbance in the sample space, parameter space and model space, thereby reducing the impact of "cases" and improving the generalization ability (Breiman, 2001). Moreover, Fig. S6 shows the distribution of inputs at different time. The red dashed lines represent the maximum and minimum values of each variable at training samples. In the range of the red line, three RF models can provide stable output due to its good generalization ability. It can be found that almost all the inputs have appeared in training samples. Therefore, three RF models have sufficient generalization and can be used at other times."

5. Also the response to question 5 (What do you mean by "goal of carbon emission peak"? Revise) is not satisfying since it refers to a policy perhaps well known for Chinese but not to the general reader.

Response: Yes, it refers to a policy in China. The Chinese government proposes to peak its carbon dioxide emissions before 2030 and achieve carbon neutrality before 2060. To facilitate understanding, we deleted this sentence.

6. Finally, response to question 45 (Lines 248-257: The explanation is not clear: revise. Also, I don't understand the need to discuss the difference (a sort of mean bias) when you were discussing the RMSE and R values. Also, it would be needed to understand if the fitting and comparison of model estimations with observations vary with hour of the day, season, or other factors. Also, the discussion could be improved because for instance from Figure 5 I can observe that: RF model is the best but tends to overestimate small values and underestimate high values; similar discussions also for the other models.) is not convincing enough because it does not explain why there are different effects of the seasonal variability on the various models (some are not affected). Also, it does not focus on the subdiurnal variability.

Response: According to your suggestion, we have added many discussions and explanations in this section. The specific modifications are as follows:

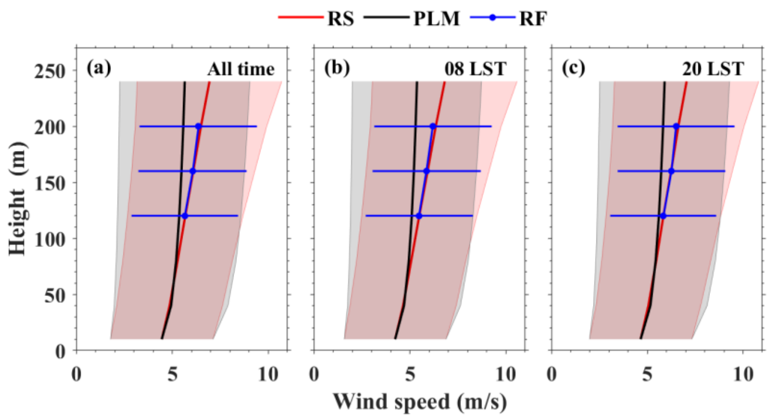

Figure 4. Vertical profiles of the mean wind speed from different methods at (a) all time, (b) 0800 and (c) 2000 LST. Red, black and blue lines represent mean wind

profile from RS, PLM and RF, respectively. Corresponding color shading areas represent one standard deviation.

"In addition, for both PLM and RF, the retrieved wind profile at 2000 LST is closer to the RS observations. The comparisons between the observed wind speed and the estimated wind speed for PLM and RS under different time is shown in Fig. S7. The fitting results of PLM and RF at 2000 LST are slightly higher than that at 0800 LST. It indicates that the performance of PLM and RF vary with hour of the day. This is due to the wind profile depends not only on the surface friction but also on the atmospheric stratification (Gryning et al., 2007). The surface layer is in an unstable stratification due to heat transfer caused by solar radiation during daytime, while the surface layer tends to stable stratification due to surface radiation cools during nighttime (Yu et al., 2022; Solanki et al., 2022). The WS_{120}, WS_{160} and WS_{200} are more vulnerable to the surface turbulence due to the unstable stratification during daytime. Therefore, the performance of PLM and RF at nighttime is better than that at daytime.

Figure 6 shows the comparisons between the observed results and the estimated results for PLM and RF under different season. The red, green, blue and black represent the spring, summer, autumn and winter, respectively. At three heights, the performance of PLM is the best in winter and the worst in summer. It shows that the performance of PLM is affected by seasonal factors, which is likely due to the wind shear varying dramatically with season (Banuelos-Ruedas et al., 2010). Pérez et al. (2005) indicates that the surface layer wind speed profile is mainly affected by the convection produced by surface heating in summer. The WS_{120}, WS_{160} and WS_{200} affect by the surface due to the unstable stratification, which leads that the PLM performs worst in summer. In contrast, during winter, the surface temperature is generally lower than the air temperature aloft creating a stable inversion (Yu et al., 2022; Liu et al., 2022). The WS_{120}, WS_{160} and WS_{200} are disconnected from the surface due to stable stratification. It leads that the PLM performs best in winter. As for RF, although the performance in spring is slightly lower than that in other seasons, the fitting results at four seasons are significantly improved compared with the PLM. This indicates that RF is least affected by seasons. The reason is that the RF model is less subjective than PLM because they are data driven. Overall, in terms of stability and accuracy, the RF is more suitable for estimating wind speed at hub height."

7. Line 9: Perhaps you mean "goal of reducing carbon dioxide emissions"?

Response: Yes, amended as suggested.

8. Line 11: change "the" with "a"

Response: Amended as suggested.

9. Lines 40-43: Quite simplicist explanation.

Response: We have revised the introduction. This sentence has been deleted.

10. Line 64: What is the "peak carbon dioxide emissions"? It is not clear to the non-Chinese reader.

Response: Amended as "The Chinese government proposes to peak its carbon dioxide emissions before 2030 and achieve carbon neutrality before 2060 (Pei et al., 2022)".

11. Lines 82-85: Revise this sentence, there is no principal sentence.

Response: Amended as "Due to the influence of inhomogeneous underlying surface, land sea difference and ubiquitous atmospheric turbulence, wind varies constantly and greatly in the vertical (Tieleman 1992; Coleman et al., 2021)."

12. Lines 92-93: WRF is just one of the regional/mesoscale models available. Need to clarify better this aspect and the comparison with ERA5 (based on reanalysis and not on a simulation)

Response: We have revised the introduction. This sentence has been deleted.

13. Line 94: Not relevant if you do not specify which are those limitations.

Response: We deleted it.

14. Lines 127-134: Geographic information and background are not enough for a non-chinese reader.

Response: In the revised manuscript, we focused on the inversion of near-surface wind profile based on the data of Qingdao station. Therefore, this section is modified as follows:

"The spatial distribution and surface type of this station are shown in Fig. 1. Geographically, Qingdao station is located on the south of Shandong Peninsula and lies to the west of the Yellow Sea. To be more specific, this station is set up in the suburb, surrounded by cropland. The altitude of this station is 12 m above mean sea level."

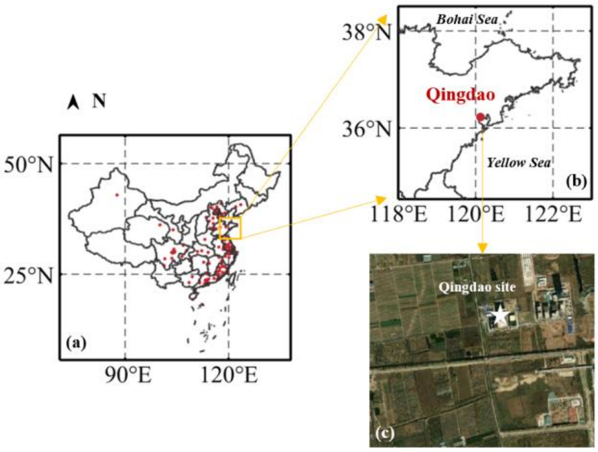

Figure 1. Geographical distribution and surface type of the radar wind profiler observational station at Qingdao.

15. Line 218: change “need” to “needs.”

Response: Amended as suggested.

16. Lines 589-595: What about the output data and the codes used in this work?

Response: Amended as “The output data and codes used in this paper can be provided for non-commercial research purposes upon motivated request (Jianping Guo, Email: jpguocams@gmail.com)”.