Responses to the Reviewers

We would like to express our profound gratitude to the reviewers for their insightful comments and suggestions. Their expertise has significantly contributed to the enhancement of our study. In response to their valuable feedback, we have made corresponding revisions and additions to the manuscript. The detailed responses to each point raised by the reviewers are presented in the following sections. The responses are highlighted in blue, and the changes made in the manuscript are marked in red. We sincerely hope that these revisions adequately address the reviewers' concerns.

Reviewer #1:

General Comments:

This study estimated the aerodynamic roughness length (z_0) values using ERA5 analyses and weather station observations to improve the near-surface wind speed modeling. Technically, the Random Forest Regression algorithm is suitable for the estimation of z_0, and the results are encouraging, significantly improving the wind speed simulation in the WRF model. However, the evaluation of the improved z_0 on the WRF near-surface wind simulation was only for one month, and a longer time evaluation is needed. Therefore, I recommend Major Revision in this round.

Response: We are sincerely grateful for your positive feedback and constructive comments. Your comments have been thoroughly considered and have greatly contributed to the improvement of our manuscript. Our point-by-point responses are detailed below.

Specific comments:

Major comments:

1. The new estimated z_0 values were only evaluated for 1 month. A longer time evaluation should be conducted for a thorough evaluation.

Response: Thank you for your insightful comment. In our study, we initially evaluated the performance of the newly estimated aerodynamic roughness length (z_0) using wind simulations for the month of April in 2019. April was deliberately chosen as the primary evaluation period because it exhibits the highest mean wind speeds across our study domain (Fig. R1), making the simulated wind fields particularly sensitive to z_0 effects. This characteristic provides an ideal scenario for testing the impact and effectiveness of our proposed estimation method. To balance computational cost with scientific rigor, we implemented a re-initialization strategy whereby each 36-hour simulation was initialized daily at 12:00 LT (LT = UTC+8). Each simulation included a 12-hour spin-up period followed by 24 hours of analysis, yielding 30 independent realizations. This approach ensured the capture of a wide range of meteorological conditions while maintaining statistical independence among daily cases. As presented in Section 3.3, the consistent improvement in simulated wind speeds across all April cases demonstrates the robustness of the newly estimated z_0.

To address the concern regarding longer-term evaluation, we additionally conducted WRF simulations for October 2019, a month characterized by generally weaker wind conditions (Fig. R1), using the same model configuration and evaluation framework as applied for April. The results from these additional simulations (Figs. R2-R4) further confirm the robustness of our method, as the use of the newly estimated z_0 values consistently improves the accuracy of simulated wind speeds.

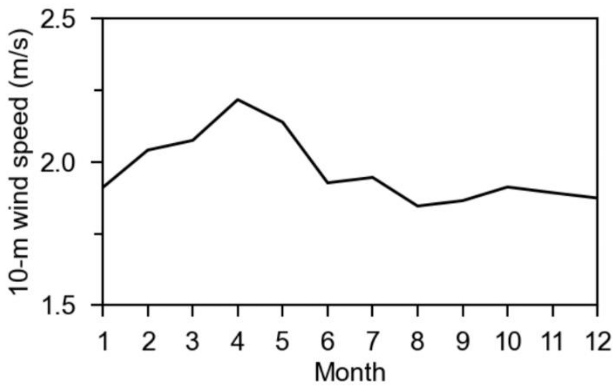

Figure R1 (**Figure S3 in the Supplement**). Monthly variations of the 10-m wind speed averaged over the d02 domain during 2015-2019 from ERA5.

The results of these additional simulations have been included in the Supplement (Figs. S5-S7), and a corresponding explanation has been incorporated into the revised manuscript in lines 332-338, replacing the original sentence: "In summary, the z_0 derived from the combination of CMA and ERA5 data shows high reliability, and the resulting gridded z_0 dataset in built-up areas can effectively reduce uncertainties in mesoscale near-surface wind speed simulations, especially over relatively flat built-up regions." with the following revised version: "In summary, the 30 independent simulation cases conducted for April demonstrate that the z_0 values derived from the combination of CMA observations and ERA5 data are highly reliable. The resulting gridded z_0 dataset significantly reduces uncertainties in mesoscale near-surface wind speed simulations, particularly over relatively flat built-up areas. To further validate the robustness of the z_0 estimation method and the resulting dataset, we conducted additional simulations for October 2019, a month characterized by generally weaker wind conditions (Fig. S3), using the same model configuration as in April. The results (Figs. S5-S7) also show consistent improvements when using z_{0_RFR}, further reinforcing the reliability and applicability of the proposed z_0 estimation approach under varying meteorological conditions."

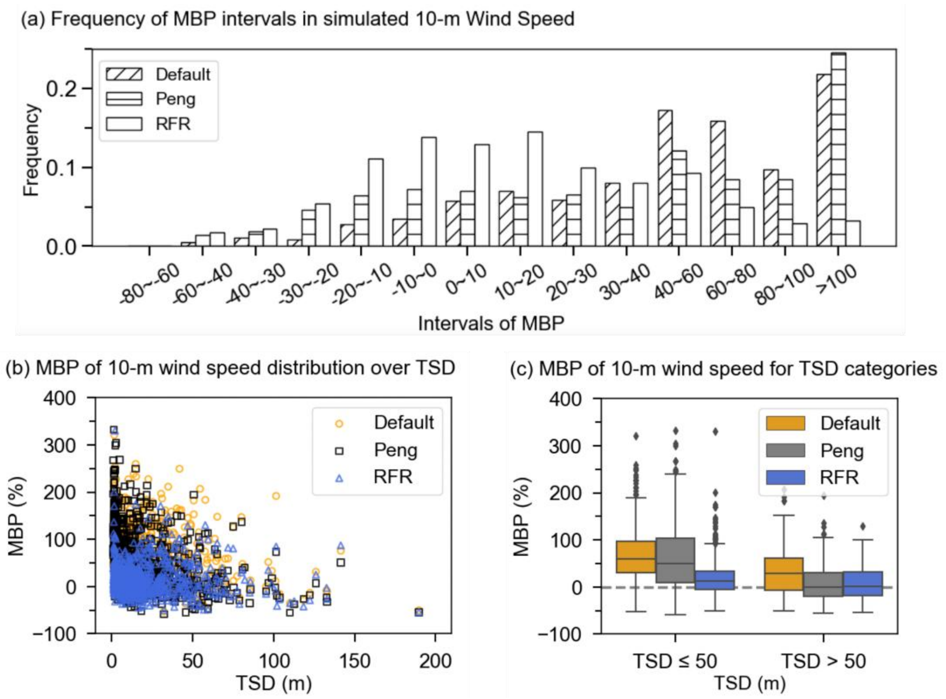

Figure R2 (**Figure S5 in the Supplement**). (a) Frequency distribution of *MBP* in simulated 10-m wind speed in October using $z_{0\_Default}$, z_{0_Peng}, and z_{0_RFR} against observations from CMA stations. *MBP* was calculated as $[u_{simulations} - u_{CMA}]/u_{CMA} \times 100\%$. (b) Distribution of *MBP* in 10-m wind speed as a function of *TSD*. (c) Box plot of *MBP* in 10-m wind speed across different *TSD* bins.

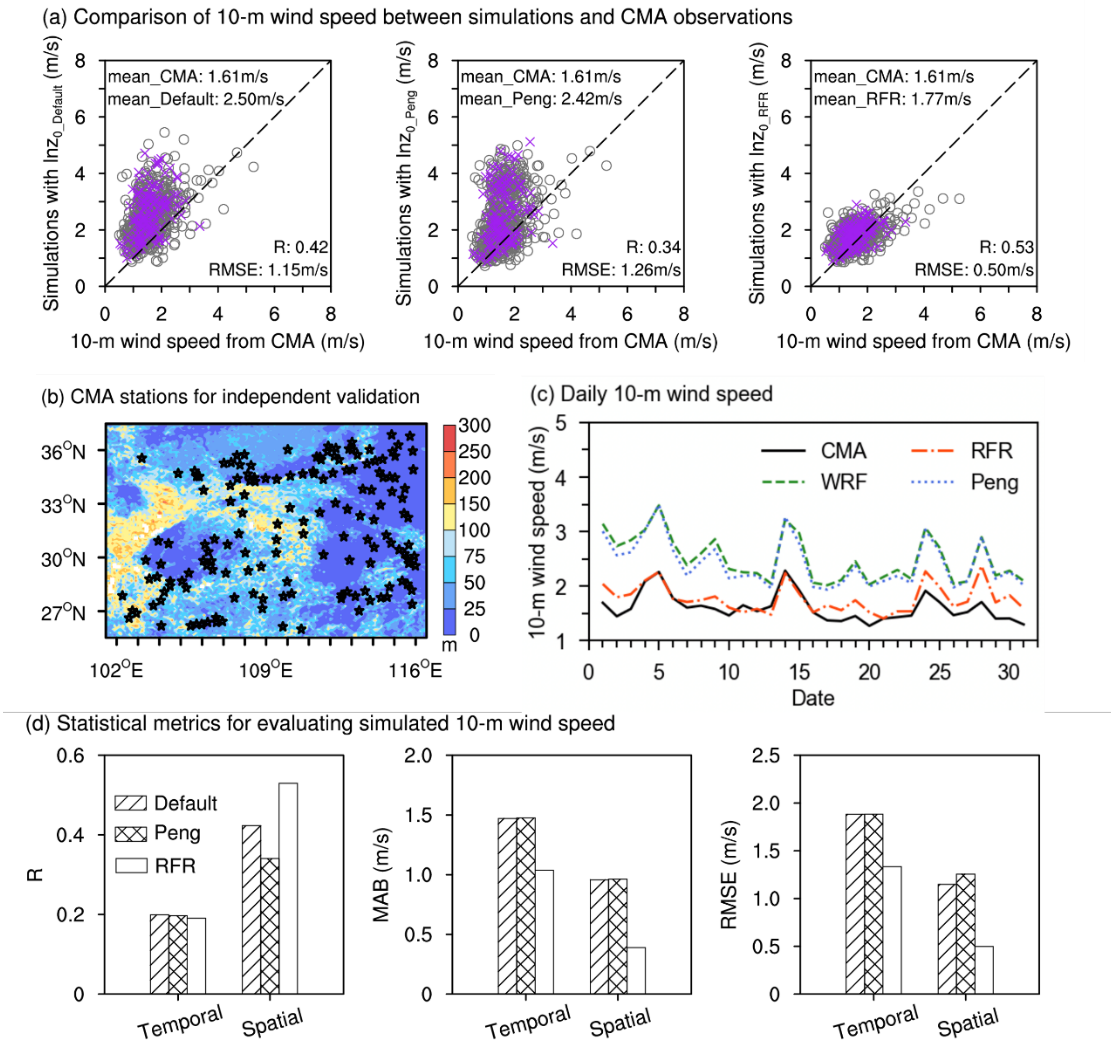

Figure R3 (**Figure S6 in the Supplement**). (a) Comparisons of mean 10-m wind speed in October between the simulations using $z_{0\_Default}$, z_{0_Peng}, and z_{0_RFR} versus observations from CMA stations. All points (grey circles and purple crosses) represent the 753 CMA stations within the d02 domain available for comparison, while the purple crosses represent the 155 stations utilized for independent validation, which were not used in training the z_{0_RFR} model. The corresponding wind speed means, correlation coefficients (*R*), and root mean square errors (*RMSE*) of all stations are also indicated. (b) Distribution of the 155 independent CMA stations (black stars). Colored shaded areas represent *TSD*. (c) Comparison of daily mean 10-m wind speed between simulations and observations from 753 CMA stations. (d) Statistical metrics comparing simulated and observed 10-m wind speeds, including temporal and spatial *R*, mean absolute bias (*MAB*, $\frac{1}{N}\sum_{i=1}^{N}\left|u_i^{simulation} - u_i^{observation}\right|$, where N represents the number of hours for temporal *MAB*, and the number of stations for spatial *MAB*) and *RMSE*.

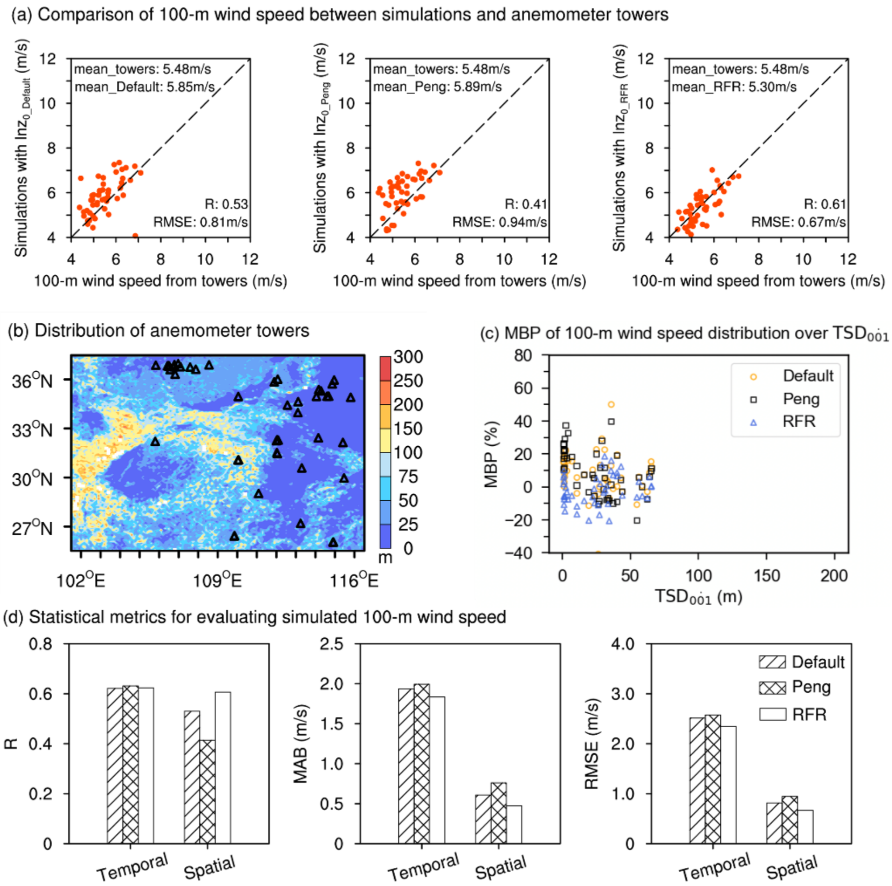

Figure R4 (Figure S7 in the Supplement). (a) Comparisons of mean 100-m wind speed in October between the simulations using $z_{0\_Default}$, z_{0_Peng}, and z_{0_RFR} versus observations from anemometer towers. The corresponding wind speed means, *R*, and *RMSE* of all towers are also indicated. (b) The locations of 48 anemometer towers (black triangles) utilized for 100-m wind speed evaluation. Colored shaded areas represent *TSD*. (c) Distribution of *MBP* in 100-m wind speed as a function of *TSD*. *MBP* was calculated as $[u_{simulations} - u_{towers}]/u_{towers} \times 100\%$. (d) Statistical metrics comparing simulated and observed 100-m wind speeds, including temporal and spatial *R*, *MAB*, and *RMSE*.

2. The grid-based z_0 statistics are only available in the inner domain. This indicates that the z_0 could only be improved where there are surface weather station observations. How to improve the z_0 destination in areas where there is no good coverage of surface weather station observations? More discussions should be included.

Response: We greatly appreciate your valuable question. We agree that the current implementation of our method is limited by the availability of surface weather station observations, which poses a challenge for estimating z_0 in areas with sparse or no such coverage. Nevertheless, these under-observed regions, such as northern and northwestern China, are key zones for wind energy development. Thus, producing high-quality gridded z_0 datasets in these areas is not only of scientific interest but also crucial for enhancing the accuracy of wind speed simulations in practical applications.

A sufficient number of z_0 truth values is essential for generating such gridded datasets. The lack of z_0 truth values in station-sparse regions remains a major barrier. With the rapid growth of the wind energy industry, tens of thousands of such towers have been deployed for wind resource assessments. This development may offer a valuable opportunity to expand z_0 truth values and to construct a gridded z_0 dataset once these tower data are accessible.

We have included a discussion on this point in Section "4 Discussion" of the revised manuscript (Lines 371-375), where we state: "However, this method is limited in regions with sparse or no surface weather stations. Notably, these regions, such as western and northern China, are rich in wind resources and are key targets for wind energy development. Therefore, producing high-quality gridded z_0 datasets in these regions warrants further study by exploring alternative data sources, such as anemometer tower wind profiles, to supplement z_0 truth values (Wang et al., 2024)."

Minor comments:

1. Line 39-41: It is a little bit causing here. Please revise it to be more clear.

Response: Thank you for your constructive reminder. We have revised "The utilization of wind energy in built-up areas also depends on wind speed distribution (Ishugah et al., 2014; Stathopoulos et al., 2018; Tasneem et al., 2020). Whether establishing wind farms in urban suburbs or integrating wind turbines into building designs, both can help to reduce generation load and the need for transmission infrastructure. Additionally, wind speed profoundly affects building design and urban planning (Hadavi and Pasdarshahri, 2020) and even the preservation of historical-cultural heritage (Li, Y. et al., 2023)." into "The utilization of wind energy in built-up areas also depends on wind speed distribution (Ishugah et al., 2014; Stathopoulos et al., 2018; Tasneem et al., 2020).

Proper utilization, through measures such as suburban wind farms or building-integrated turbines, can minimize the need for transmission infrastructure. Beyond energy considerations, wind speed characteristics play a critical role in urban design and planning, influencing both contemporary building practices (Hadavi and Pasdarshahri, 2020) and the preservation of historical-cultural heritage (Li, Y. et al., 2023)." in lines 37-42 of the revised manuscript.

2. Line 47: ERA5 is the analysis from a DA system. In my opinion, it is the blend of observations and model forecasts. Therefore, it is not proper to use it as an example.

Response: Thank you for your comment. We fully acknowledge that ERA5 is a reanalysis dataset generated through a data assimilation (DA) system, produced using 4D-Var DA and model forecasts in CY41R2 of the ECMWF Integrated Forecast System (IFS). However, it is important to note that the assimilated observations, especially over regions such as China, are relatively limited in spatial coverage. This partly explains the poor performance of ERA5 in representing wind speeds near the surface. Wang et al. (2024) evaluated the performance of ERA5 10-m wind speeds in China using data from both surface weather stations and anemometer towers, and found significant biases (Fig. R5). These biases indicate that the representation of near-surface wind conditions in ERA5 still heavily relies on the underlying model parameterizations, including the use of fixed z_0 based on land cover types. Therefore, we believe that using ERA5 as an example remains appropriate in the context of illustrating the limitations of z_0 treatment in current model frameworks.

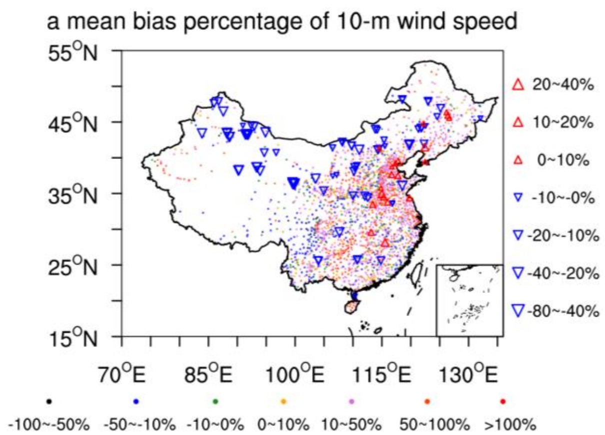

Figure R5 (**Figure 4a from Wang et al. (2024)**). The distribution of *MBP* of 10-m wind speed between ERA5 and measurements ($(ERA5 - measurements)/measurements \times 100\%$). The dots and triangles represent the measurements from CMA stations and anemometer towers.

3. Line 54: What does it mean here "low-type" and "high-type"?

Response: Thank you for your insightful question. In this context, "low-type" and "high-type" vegetation refer to categories based on vegetation height. Specifically, "low-type" vegetation typically includes shorter land cover types such as grasslands and croplands, while "high-type" vegetation refers to taller vegetation such as forests. To enhance clarity, we have revised the sentence as follows: "In line with these findings, Luu et al. (2023) showed that the rise in z_0, caused by shifts from short vegetation to high vegetation and urbanization, partly contributes to the decline in mean and maximum surface wind speed over Western Europe." in lines 53-55 of the revised manuscript.

4. Line 87: Better to add surface weather station observations before CMA.

Response: Thank you for your useful suggestion. We have added "surface weather station observations" before "CMA" in lines 87-88 of the revised manuscript.

5. Line 192: This could be because of the altitude differences between observation sites and the model terrain.

Response: Thank you for your insightful comment. The altitude differences between observation sites and the model terrain could indeed contribute to the poor performance of ERA5 100-m wind speed data in these areas. To reflect this, we have revised the sentence as follows: "The exclusions of these stations can be attributed to the poor performance of ERA5 100-m wind speed data, which may result from altitude differences between the observation sites and the model terrain, thereby rendering our initial assumption, i.e. ERA5 100-m wind speed data are reliable for z_0 estimation, invalid in these areas." in lines 192-195 of the revised manuscript.

6. Line 227: What is the temporal coverage of this monthly z_0 dataset?

Response: Thank you for your insightful question. In this study, our primary objective was to propose a cost-effective method for estimating z_0 using weather station observations and reanalysis data. Accordingly, the monthly gridded z_0 dataset we produced, referred to as z_{0_RFR}, was mainly intended to demonstrate the feasibility and effectiveness of the z_0 estimation approach through wind speed simulations. For this purpose, the z_{0_RFR} dataset was generated for the year 2019 as a representative example. It is important to note, however, that the Random Forest Regression (RFR) model developed for generating the gridded z_{0_RFR} dataset is not limited to a specific year. It can readily be applied to other years, provided that the corresponding input features are available.

To clarify this point, we have revised the manuscript and added the following statements: "As a representative example, the z_{0_RFR} dataset was generated for the year 2019, and its spatial coverage is shown in Fig. 2d." (lines 231-232) and "Although 2019 was chosen for demonstration, the RFR model itself is year-independent and can be applied to other years, provided that the required input features are available." (lines 235–237).

7. Figure 5: better to a reference line of y = 0 in panel (c) for reference, indicating which has a smaller bias.

Response: Thank you for your constructive suggestion. We have added a reference line at $y = 0$ in Fig. 5c to indicate the direction and magnitude of the bias more clearly.

8. Line 317: The values are significantly large when verified against the Mean values. However, if you take a deep look at Fig. 7d, the improvements are not that large from the perspective of MAB and RMSE.

Response: Thank you for your insightful comment. In line 317 of the original manuscript, we stated: "This improvement using z_{0_RFR} reduces wind speed mean bias by 85.7% and 88.1% compared to $z_{0\_Default}$ and z_{0_Peng}, respectively.", which indeed shows a substantial improvement. While this appears to contrast with the results presented in Fig. 7d, where the reductions in *MAB* and *RMSE* seem less pronounced, this discrepancy arises from the use of different evaluation metrics. Specifically, the percentage reduction of wind speed mean bias refers to the relative decrease in mean error. For example, in the simulation based on $z_{0\_Default}$ the average 100-m wind speed is 7.10 m/s; while using z_{0_RFR}, it is 6.38 m/s. The corresponding observed value from the anemometer towers is 6.26 m/s. Thus, the mean bias is reduced from 0.84 m/s $(7.10 - 6.26)$ to 0.12 m/s $(6.38 - 6.26)$, leading to a bias reduction of $(0.84 - 0.12) \div 0.84 \times 100\% = 85.7\%$.

In addition, even when evaluated using the *MAB* and *RMSE* metrics shown in Fig. 7d, the improvements brought by z_{0_RFR} are still considerable. Specifically, in the spatial dimension, the 100-m wind speed simulations based on $z_{0\_Default}$ and z_{0_Peng} show *MAB* values of 1.12 m/s and 1.47 m/s, respectively, while the simulation using z_{0_RFR} yields a significantly lower *MAB* of 0.58 m/s. Similarly, the corresponding *RMSE* values are 1.31 m/s for $z_{0\_Default}$, 1.63 m/s for z_{0_Peng}, and 0.82 m/s for z_{0_RFR}. Although the improvements in the temporal dimension are not as pronounced as those in the spatial dimension, they are still evident. These results further confirm the overall improvement achieved by incorporating the z_{0_RFR}.

To enhance clarity, we have added the formula used to calculate the percentage reduction in wind speed mean bias to the revised manuscript, as shown in the caption of Table 1: "The percentage reduction in wind speed error is caused by z_{0_RFR}, compared to $z_{0\_Default}$ and z_{0_Peng}, which is calculated as $\left[\left|\bar{u}_{z_{0\_*}} - \bar{u}_{observation}\right| - \left|\bar{u}_{z_{0\_RFR}} - \bar{u}_{observation}\right|\right] / \left|\bar{u}_{z_{0\_*}} - \bar{u}_{observation}\right| \times 100\%$, where $\bar{u}_{z_{0\_*}}$ represents $\bar{u}_{z_{0\_Default}}$ or $\bar{u}_{z_{0\_Peng}}$, and $\bar{u}$ denotes the mean 10-m or 100-m wind speed from simulations based on $z_{0\_Default}$, z_{0_Peng}, and z_{0_RFR}, as well as from observations (CMA stations or anemometer towers)."

9. Figure 7: Better to add statists of mean/rms/r in the panels of (a). For (d), the units of MAB is not m/s, likely %.

Response: Thank you for your suggestion. We have added the statistics of mean, *RMSE*, and correlation coefficient (R) to both Fig. 6a and Fig. 7a in the revised manuscript.

MAB refers to mean absolute bias, which is calculated as $\frac{1}{N}\sum_{i=1}^{N}\left|u_i^{simulation} - u_i^{observation}\right|$, where N represents the number of stations for spatial *MAB*, and the number of hours for temporal *MAB*. Therefore, the unit of *MAB* is m/s.

To enhance clarity, we have included the formula for *MAB* at its first occurrence, in the caption of Fig. 6 in the revised manuscript, as follows: "Figure 6. (a) Comparisons of mean 10-m wind speed in April between the simulations using $z_{0\_Default}$, z_{0_Peng}, and z_{0_RFR} versus observations from CMA stations. All points (grey circles and purple crosses) represent the 753 CMA stations within the d02 domain available for comparison, while the purple crosses represent the 155 stations utilized for independent validation, which were not used in training the z_{0_RFR} model. The corresponding wind speed means, correlation coefficients (*R*), and root mean square errors (*RMSE*) of all stations are also indicated. (b) Distribution of the 155 independent CMA stations (black stars). Colored shaded areas represent *TSD*. (c) Comparison of daily mean 10-m wind speed between simulations and observations from 753 CMA stations. (d) Statistical metrics comparing simulated and observed 10-m wind speeds, including temporal and spatial *R*, mean absolute bias (*MAB*, $\frac{1}{N}\sum_{i=1}^{N}\left|u_i^{simulation} - u_i^{observation}\right|$, where N represents the number of hours for temporal *MAB*, and the number of stations for spatial *MAB*) and *RMSE*."

Reference

Wang, J., Yang, K., Yuan, L., Liu, J., Peng, Z., Ren, Z. and Zhou, X.: Deducing aerodynamic roughness length from abundant anemometer tower data to inform wind resource modeling, Geophys. Res. Lett., 51, e2024GL111056, doi:10.1029/2024GL111056, 2024.

Reviewer #2:

General Comment:

This manuscript presents a novel and practical approach to improving the simulation of near-surface wind speed over built-up areas by refining the aerodynamic roughness length (z_0) using a combination of ERA5 reanalysis and ground-based observations from the China Meteorological Administration (CMA). The authors developed a high-resolution monthly gridded z_0 dataset by applying a Random Forest Regression algorithm, and demonstrated its effectiveness through WRF simulations. The study is timely and potentially impactful for urban climate modeling and wind-related applications.

While the manuscript introduces a potentially useful methodology, the current version does not provide sufficient critical evaluation or methodological transparency. To be suitable for publication, the manuscript requires revision, including clarification of the observational setup, deeper theoretical consideration of the methodology's assumptions, and further analyses related to model resolution and z_0 scale dependency.

Response: We would like to express our sincere gratitude for your positive feedback and insightful comments and suggestions. These have significantly enhanced the quality of our manuscript. We have carefully considered all your points. In the following sections, we provide a detailed response to each of your comments.

Major comments:

1. Uncertainty about CMA Wind Observation Heights: The manuscript assumes that CMA stations provide 10-m wind speed observations. However, there is no clear documentation or justification of this assumption in the text. Are all CMA anemometers calibrated and installed precisely at 10 m above ground level? Given that the accuracy of z_0 estimation strongly depends on the reference height of the wind speed, this should be clarified and supported by official metadata or references. Otherwise, the credibility of the derived z_0 values may be significantly undermined.

Response: Thank you for your question. All CMA wind speed observations used in this study were indeed measured at the standard height of 10 meters above ground level, as officially specified in the "China Surface Climate Data Hourly Value Dataset" provided by the China Meteorological Administration (Table R1). In addition, the z_0 estimated from these stations have been independently validated using wind speed simulations against both other CMA stations and anemometer tower observations. The validation results demonstrate that the derived z_0 values lead to significant improvements in simulated wind speeds, thereby supporting the overall reliability of our z_0 estimates.

Table R1. Selected fields from the China Surface Climate Data Hourly Value Dataset provided by the China Meteorological Administration (CMA).

No.	Name	Data Type	Field Name	Unit
1	Station ID	Number(5)	V01000	—
5	Year	Number(4)	V04001	—
6	Month	Number(2)	V04002	—
7	Day	Number(2)	V04003	—
8	Hour	Number(2)	V04004	—
9	Station Pressure	Number(6)	V10004	0.1 hPa
11	Air Temperature	Number(6)	V12001	0.1 °C
19	Precipitation	Number(6)	V13011	0.1 mm
21	Wind Direction (at 10 m above ground)	Number(6)	V11011	16 directions
22	Wind Speed (at 10 m above ground)	Number(6)	V11012	0.1 m/s

2. Circular Logic in Using ERA5 to Derive z_0 and Then Evaluating WRF Performance: The method uses ERA5 as the basis to derive optimal z_0 values, and then uses these z_0 values in WRF to simulate wind fields, which are subsequently compared to CMA observations. However, since the z_0 is essentially tuned to ERA5 wind characteristics, and WRF is driven by ERA5 data, it is not surprising that the WRF simulations become closer to observations. This circular logic reduces the strength of the validation. A deeper discussion is needed in the Discussion section to acknowledge this

methodological dependency and to better clarify to what extent the improvements stem from z_0 refinement as opposed to alignment with the reanalysis base.

Response: Thank you for raising this important point. We address the concern about potential circular logic from three perspectives, to demonstrate that the improvement on wind speed primarily stems from the refinement of z_0, rather than simply from alignment with the reanalysis dataset.

First, the z_0 values were estimated at 1,805 CMA station locations using CMA-observed 10-m wind speeds, ERA5 10-m wind speeds, and ERA5 z_0. Based on these z_0 estimates, we used 80% of the data to train a machine learning model and construct a gridded z_0 dataset, while the remaining 20% were reserved for independent validation. This gridded dataset (denoted as z_{0_RFR}) was then used in WRF simulations. In evaluating the WRF results, we considered wind speeds at both 10 m and 100 m, which are representative of meteorological observations and wind energy applications, respectively. At 10 m, simulation performance was assessed at all 753 CMA stations in the domain, including both the 598 training stations and the 155 independent validation stations. The results show that WRF simulations using z_{0_RFR} outperform those using the default WRF dataset ($z_{0\_Default}$) and a latest dataset (z_{0_Peng}), as demonstrated in Fig. 6 of the manuscript. At 100 m, further validation was performed using wind measurements from anemometer towers, which were completely independent from both the CMA stations used in training the z_0 model and the z_0 estimation process. These results (Fig. 7 of the manuscript) also confirm the superiority of z_{0_RFR}, strengthening the claim that the improvements stem from the enhanced representation of z_0 rather than any alignment with ERA5 data.

Second, according to your suggestion, we conducted an additional WRF simulation using NCEP reanalysis data instead of ERA5 as the driving input, while keeping all other model settings identical. The results (Figure R1 and Table R2) are consistent with those obtained using ERA5 forcing data (Figure 6a and 7a, and Table 1 in the manuscript), indicating that z_{0_RFR} improves wind speed simulations. This strongly suggests that the improvements are not a result of alignment between the tuned z_0

values and the ERA5 data, but rather due to the intrinsic quality of the refined z_0 dataset itself.

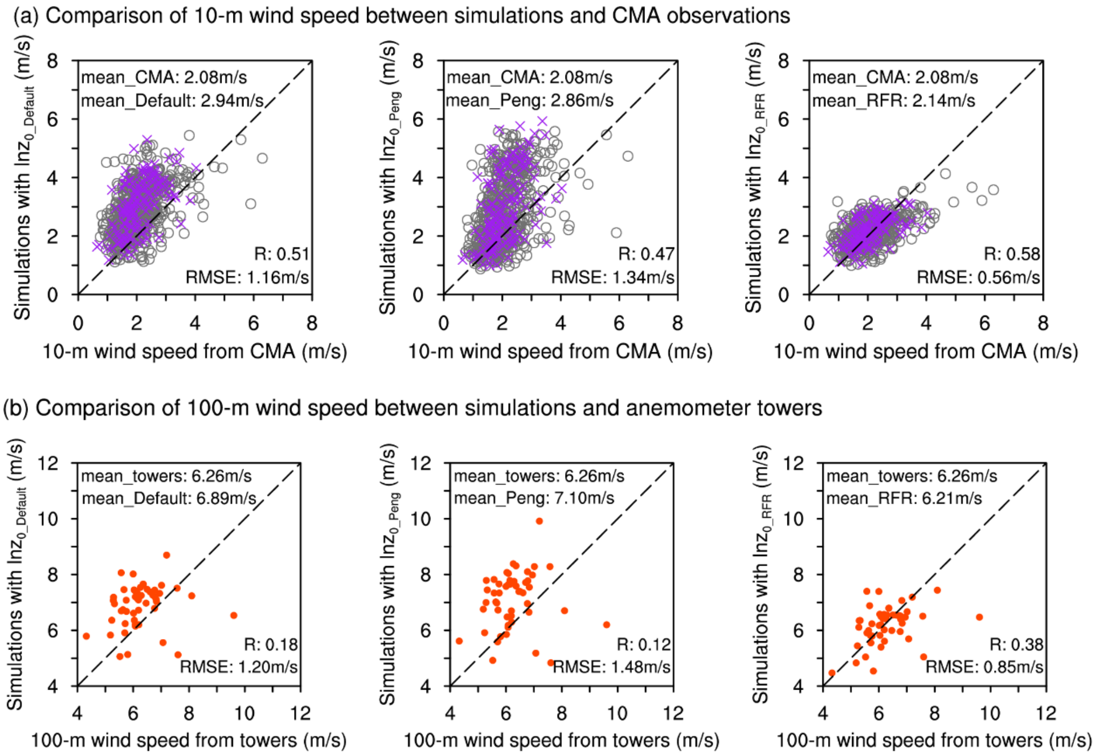

Figure R1 (**Figure S8 in the Supplement**). Comparison between simulated wind speeds and observations, with WRF driven by NCEP reanalysis data. (a) Comparisons of mean 10-m wind speed in April between the simulations using $z_{0\_Default}$, z_{0_Peng}, and z_{0_RFR} versus observations from CMA stations. All points (grey circles and purple crosses) represent the 753 CMA stations within the d02 domain available for comparison, while the purple crosses represent the 155 stations utilized for independent validation, which were not used in training the z_{0_RFR} model. The corresponding wind speed means, correlation coefficients (*R*), and root mean square errors (*RMSE*) of all stations are indicated. (b) Comparisons of mean 100-m wind speed in April between the simulations using $z_{0\_Default}$, z_{0_Peng}, and z_{0_RFR} versus observations from anemometer towers. The corresponding wind speed means, *R*, and *RMSE* of all towers are also indicated.

Table R2 (**Table S1 in the Supplement**). The mean 10-m wind speed from simulations and observations at 753 CMA stations, and the mean 100-m wind speed from simulations and observations at 50 anemometer towers. The simulations were conducted using $z_{0\_Default}$, z_{0_Peng}, and z_{0_RFR}, respectively, with NCEP reanalysis data used as the driving input for the WRF model. The percentage reduction in wind speed error is caused by z_{0_RFR}, compared to $z_{0\_Default}$ and z_{0_Peng}, which is calculated as

$[|\bar{u}_{z_{0\_*}} - \bar{u}_{observation}| - |\bar{u}_{z_{0\_RFR}} - \bar{u}_{observation}|]/|\bar{u}_{z_{0\_*}} - \bar{u}_{observation}| \times 100\%$, where $\bar{u}_{z_{0\_*}}$ represents $\bar{u}_{z_{0\_Default}}$ or $\bar{u}_{z_{0\_Peng}}$, and $\bar{u}$ denotes the mean 10-m or 100-m wind speed from simulations based on $z_{0\_Default}$, z_{0_Peng}, and z_{0_RFR}, as well as from observations (CMA stations or anemometer towers).

	$z_{0\_Default}$	z_{0_Peng}	z_{0_RFR}	Observations
Mean 10-m wind speed (m/s)	2.94	2.86	2.14	2.08
Percentage reduction in 10-m wind speed error caused by z_{0_RFR} (%)	93.0%	92.3%	-	-
Mean 100-m wind speed (m/s)	6.89	7.10	6.21	6.26
Percentage reduction in 100-m wind speed error caused by z_{0_RFR} (%)	92.1%	94.0%	-	-

Third, we have examined whether the effectiveness of the proposed z_0 estimation method is inherently dependent on the use of ERA5 data in Section “4 Discussion” of the manuscript. We applied the same approach to estimate z_0 with 10-m wind speed and default z_0 values from the WRF model itself, instead of ERA5. The estimated z_0 values based on this alternative dataset are similar to those derived from ERA5 (Figure 8b in the manuscript). This demonstrates that the validity of our z_0 estimation method does not rely on alignment with any specific reanalysis dataset, but rather reflects the robustness and general applicability of the method itself.

In summary, through independent validation at both 10 m and 100 m heights, additional experiments using alternative reanalysis inputs (NCEP instead of ERA5), and further tests employing non-ERA5-based inputs for z_0 estimation, we consistently demonstrate that the improved WRF performance arises from the refined characterization of z_0 itself. These results collectively confirm that the effectiveness of our method is not due to any circular logic or alignment with a specific reanalysis dataset, but rather reflects the intrinsic value and robustness of the proposed z_0 refinement approach. Accordingly, we have reorganized Section “4 Discussion” in the revised manuscript.

It was originally: “Here we discuss the sensitivity of the site z_0 estimates to the used simulation/reanalysis data. Our study utilized ERA5 reanalysis and CMA observations for z_0 estimation. Compared to traditional meteorological and morphological methods, the approach can obtain z_0 values at most locations at a low cost, and these values demonstrate satisfactory performance in wind speed simulation. Here we show that the method is not restricted to using ERA5 reanalysis data. When it is applied to 10-m wind speed and default z_0 from WRF model, we can estimate z_0 similarly. The resulting z_0 estimates are comparable to those based on ERA5 (Fig. 8). The primary advantage of ERA5 is its extensive spatiotemporal coverage, which facilitates better alignment with observational data. In contrast, obtaining WRF simulation data with the same spatiotemporal coverage would require considerable computational resources. Therefore, the proposed method in this paper is a robust z_0 estimation approach that can be widely applied to different reanalysis datasets and observational data, offering high flexibility and practicality for aerodynamic roughness length estimation."

It is now revised to: "Here we discuss the sensitivity and generality of the site z_0 estimation approach with respect to the input simulation or reanalysis data, addressing concerns about potential methodological dependence on ERA5. Our study utilized ERA5 reanalysis data and CMA observations for initial z_0 estimation. Compared to traditional meteorological or morphological methods, our approach can provide z_0 values at large spatial coverage and low cost, and these values lead to clear improvements in WRF-simulated wind speeds at both 10 m and 100 m above ground level. To assess whether the performance gain stems from improved z_0 representation rather than from alignment with ERA5 reanalysis data, we carried out two additional sets of evaluations.

First, we applied the same approach to estimate z_0 from WRF-simulated 10-m wind speed and the model's default z_0 values (0.03° × 0.03°), instead of ERA5. The z_0 values estimated using this alternative dataset were found to be highly similar to those derived from ERA5 (Fig. 8), indicating that the method is not inherently reliant on ERA5 as a data source. The primary advantage of using ERA5 lies in its extensive spatiotemporal coverage, which offers greater convenience and consistency with observational data; however, the methodology itself is general and transferable to other datasets. Moreover, the agreement between ERA5- and WRF-derived z_0 values suggests that the spatial representativeness of the estimated site-level z_0 values is not determined by the resolution of the reanalysis or simulation dataset used, but rather by the measurement height of wind observations at the stations. In this study, 10-m wind speeds from CMA stations were used. As a rule of thumb, the horizontal representativeness of wind measurements is approximately 100 times the measurement height. Therefore, z_0 values estimated from 10-m wind observations are reasonably representative at ~1 km scales, making the generation of 0.01° gridded z_0 datasets for use in mesoscale simulations both appropriate and justified.

Second, we further validated the robustness of the refined z_0 dataset (z_{0_RFR}) by conducting additional WRF simulations driven by the reanalysis from National Centers for Environmental Prediction (NCEP) instead of ERA5. These results (Fig. S8 and Table S1) still showed significant improvement in wind speed simulation performance when using z_{0_RFR}, consistent with those driven by ERA5. This cross-reanalysis consistency demonstrates that the benefits are attributable to the improved surface representation through z_{0_RFR} refinement, not simply tuning to match ERA5-driven wind fields.

Taken together, these findings confirm that the z_0 estimation method proposed in this study is robust, flexible, and not dependent on alignment with a specific reanalysis dataset. It provides a practical framework for z_0 estimation that can be widely applied across different reanalysis/simulation datasets and observational data with consistent benefits. However, this method is limited in regions with sparse or no surface weather stations. Notably, these regions, such as western and northern China, are rich in wind resources and are key targets for wind energy development. Therefore, producing high-quality gridded z_0 datasets in these regions warrants further study by exploring alternative data sources, such as anemometer tower wind profiles, to supplement z_0 truth values (Wang et al., 2024)."

3. Lack of Resolution-Dependent z_0 Consideration: The aerodynamic roughness length is known to be resolution-dependent due to varying representations of land cover and orography. However, the manuscript does not address why a single z_0 value (derived from coarser ERA5 resolution) is applied across finer-resolution WRF simulations. A justification is needed as to why scale-dependent roughness parameters

were not considered, especially when moving from ERA5 (~30 km) to WRF (3 km). Moreover, higher-resolution simulations are expected to better resolve local features influencing z_0. Has the relationship between horizontal resolution and z_0 been explored in this study? Such an analysis would greatly strengthen the work, and I recommend adding or expanding this aspect if possible.

Response: Thank you for your valuable question. In this study, we proposed a low-cost z_0 estimation method, allowing the acquisition of z_0 values at routine weather stations. Specifically, this approach leverages 10-m wind speed and z_0 values from ERA5 reanalysis data, along with observed 10-m wind speeds at CMA stations, to derive optimal z_0 at stations by minimizing the difference in 100-m wind speeds between reanalysis and observations. Here, the 100-m wind speed is expressed with 10-m wind speed and z_0 using similarity theory.

Regarding the use of ERA5 data in the estimation, we would like to clarify that although we introduced the assumption that the 100-m wind speed from ERA5 is comparable to that from observations, 100-m wind speed was not directly used in the actual estimation process of z_0. Rather, this assumption served to conceptually support the feasibility of using ERA5 10-m wind speed and z_0 information to estimate z_0 values at observational sites. This assumption implies that the influence of z_0 on wind speed at 100 m is relatively small. While similar assumptions could be made using reanalysis datasets providing wind speeds at even higher levels (e.g., 200 m), we chose to use the 100-m level because ERA5 provides wind speed at this height and there are anemometer tower data at 100 m available for preliminary validation of this assumption. Therefore, this assumption is not constrained by the spatial resolution of the dataset used. In practice, our method estimates z_0 using $0.25° \times 0.25°$ gridded 10-m wind speed and z_0 data from ERA5. Essentially, what we utilize is the relationship between the wind profile and z_0 as represented in ERA5 through similarity theory. The horizontal resolution of ERA5 does not affect the estimated z_0 values at individual stations. To demonstrate this, we substituted ERA5 with higher-resolution WRF outputs ($0.03° \times 0.03°$) to re-estimate z_0, and the results remained consistent, as discussed in Section "4 Discussion" of the manuscript.

More importantly, the spatial representativeness of the derived z_0 values is determined primarily by the measurement height of wind observations, rather than the resolution of the background dataset. As a rule of thumb, the effective fetch area influencing a wind measurement is approximately 100 times the measurement height. Since we used 10-m wind speed data from CMA stations, the estimated z_0 values are representative of a footprint of ~1 km. Therefore, applying these z_0 values to kilometer-scale simulations is scale-consistent and appropriate. In addition, we have previously emphasized in the manuscript that the z_0 values derived in this study are intended for use in mesoscale simulations (see lines 81-83 ("This study contributes to the advancement of mesoscale wind speed simulation over built-up environments, which can promote wind field-dependent studies, such as urban planning, wind energy utilization, and air quality management.") and 333-334 ("The resulting gridded z_0 dataset significantly reduces uncertainties in mesoscale near-surface wind speed simulations, particularly over relatively flat built-up areas.).

Based on the above, the updated Discussion section (lines 357-363) now further elaborates on this point: "Moreover, the agreement between ERA5- and WRF-derived z_0 values suggests that the spatial representativeness of the estimated site-level z_0 values is not determined by the resolution of the reanalysis or simulation dataset used, but rather by the measurement height of wind observations at the stations. In this study, 10-m wind speeds from CMA stations were used. As a rule of thumb, the horizontal representativeness of wind measurements is approximately 100 times the measurement height. Therefore, z_0 values estimated from 10-m wind observations are reasonably representative at ~1 km scales, making the generation of 0.01° gridded z_0 datasets for use in mesoscale simulations both appropriate and justified."