Responses to the Reviewer

We would like to express our profound gratitude to you for your insightful comments and suggestions. Your expertise has significantly contributed to the enhancement of our study. In response to your valuable feedback, we have made corresponding revisions and additions to the manuscript. The detailed responses to each point raised 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 your concerns.

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.

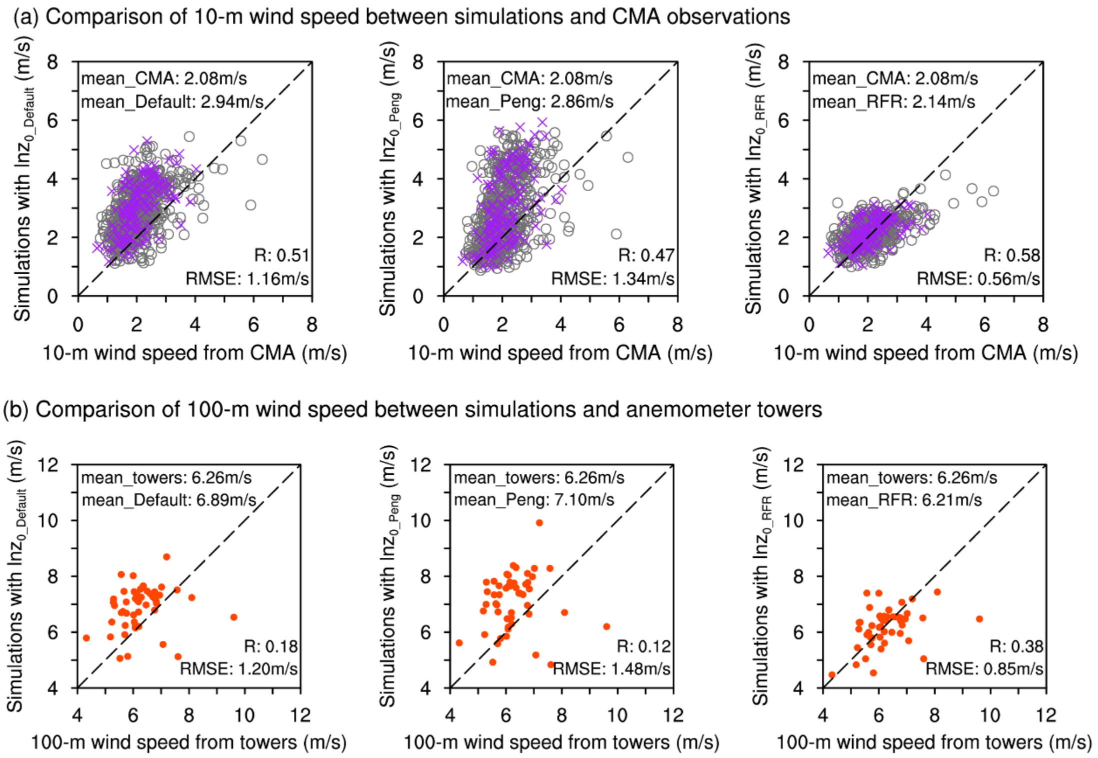

Figure R1 (**Figure S8 in the Supplement**). Comparison between simulated wind speeds and observations, with WRF driven by NCEP reanalysis data. (a) Comparisons of mean 10-m wind speed in April between the simulations using $z_{0\_Default}$, z_{0_Peng}, and z_{0_RFR} versus observations from CMA stations. 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 $\left[\left|\bar{u}_{z_{0\_*}} - \bar{u}_{observation}\right| - \left|\bar{u}_{z_{0\_RFR}} - \bar{u}_{observation}\right|\right] / \left|\bar{u}_{z_{0\_*}} - \bar{u}_{observation}\right| \times 100\%$, 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).

	$z_{0\_Default}$	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 ($0.03° \times 0.03°$), 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."