

Improvement of near-surface wind speed modeling through refined aerodynamic roughness length in high-roughness surface regions: implementation and validation in the Weather Research and Forecasting (WRF) model version 4.0

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Abstract. Aerodynamic roughness length (z_0) is a key parameter determining near-surface wind profiles, significantly influencing wind-related studies and applications. In high-roughness surface areas, surface roughness has been substantially altered by land use changes such as urbanization. However, many numerical models still assign long-standing and fixed z_0 based on traditional land cover types, neither accounting for shifts in land cover nor updating class-specific z_0 , leaving z_0 values in high-roughness surface regions outdated and unreliable. To address this issue, this study proposed a cost-effective method to estimate z_0 values at weather stations by adjusting z_0 values to minimize the wind speed differences between ERA5 reanalysis data and weather station observation data. Using this approach, z_0 values were derived for 1,805 stations in the high-roughness surface areas across China. Based on these estimates, a high-resolution monthly gridded z_0 dataset was then developed for high-roughness surface areas in China using Random Forest Regression algorithm. Simulations with Weather Research and Forecasting (WRF) model show that implementation of the new z_0 dataset significantly improves the accuracy of 10-m wind speed over high-roughness surface areas, reducing mean wind speed errors by 89.9% and 88.9% compared to the default z_0 in WRF and a latest gridded z_0 dataset, respectively. Independent validations of 100-m wind speed against anemometer tower data further confirm the dataset's reliability. Therefore, this approach is valuable for wind-dependent studies and applications, such as urban planning, air quality management, and wind energy utilization, by enabling more accurate simulations of wind speed in high-roughness surface areas.

1 Introduction

With the rapid advancement of urbanization and industrialization, human activities and energy use are increasingly concentrated along the settlement-landscape continuum (Liu et al., 2014), particularly in high-roughness areas such as built-

33 up zones and inhabited vegetated landscapes. High-roughness surface regions not only significantly influence climate change
34 but also are highly sensitive to meteorological and climatic conditions (Kammen and Sunter, 2016). Among various
35 meteorological parameters, wind speed exerts great impacts on both environmental and human systems. One prominent
36 example is that wind speed is a crucial consideration for assessing the atmospheric pollutant dispersion capability (Manju et
37 al., 2002; Han et al., 2017). Specifically, mean flows and atmospheric turbulence are two key factors for pollutant removal
38 (Wong and Liu, 2013; Di Nicola et al., 2022). Also, wind speed regulates pollen dispersion and distribution that are
39 associated with public health (Roy et al., 2023). The utilization of wind energy in high-roughness surface areas also depends
40 on wind speed distribution (Ishugah et al., 2014; Stathopoulos et al., 2018; Tasneem et al., 2020). Proper utilization, through
41 measures such as suburban wind farms or building-integrated turbines, can minimize the need for transmission infrastructure.
42 Beyond energy considerations, wind speed characteristics play a critical role in design and planning of human settlements,
43 influencing both contemporary building practices (Hadavi and Pasdarshahri, 2020) and the preservation of historical-cultural
44 heritage (Li, Y. et al., 2023). Therefore, accurately characterizing wind speed is essential for guiding systematic regulation
45 and promoting sustainable development in high-roughness surface areas.

46 Aerodynamic roughness length (z_0) is a crucial parameter that determines near-surface wind speed profiles (Stull, 1988). As
47 a key input for atmospheric models, z_0 significantly influences wind speed-related applications, however, its representation
48 in existing numerical models often oversimplifies real-world conditions. Specifically, most models, such as the widely used
49 ECMWF Reanalysis v5 (ERA5), determine z_0 with long-standing and fixed values based on traditional land cover types.
50 Such treatment fails to reflect the impact of transitions between surface types and changes in roughness elements within the
51 same type, particularly the complexity of urban structures, thereby posing significant challenges for accurate wind speed
52 simulation and prediction over high-roughness surface areas (Wang et al., 2024). Numerous studies have demonstrated that
53 the changes of z_0 , caused by land use changes, particularly urbanization and industrialization, as well as deforestation and
54 afforestation, significantly impacted wind speed. For instance, the increase in z_0 has explained 70% of the wind speed
55 reduction in Europe (Wever, 2012) and caused a 1.1 m/s decrease in eastern China (Wu et al., 2018). Furthermore, Zhang et
56 al. (2019) identified z_0 changes as a primary driver of long-term wind speed trends in China, Europe, and North America. In
57 line with these findings, Luu et al. (2023) showed that the rise in z_0 , caused by shifts from short vegetation to high
58 vegetation and urbanization, partly contributes to the decline in mean and maximum surface wind speed over Western
59 Europe. A similar mechanism operated in Canada. At Sudbury Airport (Ontario), 10-m wind speeds declined by ~34%
60 during 1975-1995 mainly due to reforestation-induced increases in surface roughness (Tanentzap et al., 2007). These
61 findings highlight the need to refine z_0 in models by incorporating the effects of high-roughness surface areas across urban-
62 town settings and tall-vegetation landscapes. In addition to wind speed, z_0 also plays a significant role in environmental
63 processes. The difference in z_0 between urban and suburban areas is one of drivers causing larger intensity of daytime urban
64 heat islands in humid regions (Zhao et al., 2014; Li et al., 2019). Winckler et al. (2019) showed that roughness changes are a
65 primary control on deforestation's biogeophysical effects, notably surface temperature responses. Therefore, accurate z_0 data

in **high-roughness surface areas** can not only enhance the performance of atmospheric numerical models, but also provide scientific support for formulating sustainable urban environmental management strategies.

The estimation of z_0 in **high-roughness surface areas** traditionally relies on three primary approaches: the micrometeorological method, the morphometric method, and a combination of these two methods. The micrometeorological method, based on the Monin-Obukhov similarity theory (Monin and Obukhov, 1954), typically calculates z_0 using observations from flux or anemometer towers (Grimmond et al., 1998; Liu et al., 2018). Although theoretically robust, this method is limited by high costs of instruments and infrastructure (Grimmond and Oke, 1999), as well as the need for homogeneous surface conditions (Wieringa, 1993; Bottema and Mestayer, 1998). The morphometric method usually formulates mathematical models based on geometric characteristics and distribution density of **high-roughness surface areas** (Raupach, 1992 and 1994; Bottema and Mestayer, 1998; Macdonald et al., 1998; Kanda et al., 2013; Shen et al., 2022; Shen et al., 2024). However, these models often suffer from simplified assumptions and require high-resolution surface feature data, which are costly to acquire (Grimmond and Oke, 1999; Zhang et al., 2017). The combination method, which establishes a relationship between the z_0 ground truth obtained from micrometeorological method and high-resolution surface feature data for regional-scale applications, has shown promise in specific regions, such as Tokyo and Nagoya (Kanda et al., 2013), Beijing (Zhang et al., 2017), and Osaka subregions (Duan and Takemi, 2021). Nevertheless, the limitations of the former two methods hinder its broader applications. Therefore, there is a considerable lack of reliable z_0 data in **high-roughness surface regions**.

To address the aforementioned challenges, this study proposed a low-cost method for estimating z_0 by integrating 10-m wind speed at China Meteorological Administration (CMA) stations with 10-m wind speed and z_0 from ERA5 reanalysis data. This approach takes advantage of the synergy between CMA's high-density station distribution and ERA5 reanalysis' temporal continuity to substantially enhance the sample size of z_0 estimates. Based on these estimates, we have developed a high-resolution monthly z_0 dataset for **high-roughness surface areas** in China using Random Forest Regression (RFR) algorithm. The applicability of the new z_0 dataset have been assessed through its implementation in the Weather Research and Forecasting (WRF) model for wind speed simulation. This study contributes to the advancement of mesoscale wind speed simulation over **high-roughness surface environments**, which can promote wind field-dependent studies, such as urban planning, wind energy utilization, and air quality management.

2 Data and Method

2.1 Data

In this study, we mainly utilized monthly gridded z_0 dataset from ERA5 (Hersbach et al., 2020 and 2023a), referred to as z_{0_ERA5} , along with hourly 10-m wind speed data from both ERA5 (Hersbach et al., 2023b) and surface weather station

96 observations provided by the China Meteorological Administration (CMA) during 2015-2019, to derive z_0 estimates at each
97 CMA station.

98 To extend the site-scale z_0 estimates into a gridded dataset at the regional scale, we applied the RFR algorithm, incorporating
99 six key features: variance of the slope ($\overline{\theta^2}$), terrain standard deviation within 0.01° window (TSD), percent tree cover (PTC),
100 leaf area index (LAI), normalized difference vegetation index ($NDVI$), and urban-rural classification (URC). $\overline{\theta^2}$ was derived
101 as an integral over orographic spectrum, capturing multi-scale orographic complexity with wave length from meter to 10 km
102 (Beljaars et al., 2004). We obtained $\overline{\theta^2}$ from the dataset accompanying the turbulent orographic form drag scheme in WRF
103 (Zhou et al., 2018), which was processed from the global 30" GMTED2010 digital elevation model (Danielson & Gesch,
104 2011). TSD was calculated using elevation data from Shuttle Radar Topography Mission with a spatial resolution of 3
105 arcseconds (Jarvis et al., 2018). The PTC data were obtained from the MOD44B Version 6.1 Vegetation Continuous Fields
106 product (DiMiceli et al., 2022), which provides yearly data at a 250-meter pixel resolution. The monthly 1-km $NDVI$ data
107 were acquired from MOD13A3 product (Didan, 2021). The LAI data with an 8-day temporal interval and 500-meter spatial
108 resolution were sourced from Yuan et al. (2011) and Lin et al. (2023). URC data were extracted from a 1-km global human
109 settlements map, which categorizes the rural-urban continuum into 19 distinct types (Li, X. et al., 2022 and 2023). To
110 generate a monthly z_0 dataset at a spatial resolution of $0.01^\circ \times 0.01^\circ$, all input datasets were linearly interpolated or
111 resampled to the target resolution. LAI data were averaged monthly by assigning each 8-day interval to the closest month.
112 Additionally, to compare with the existed z_0 datasets, a latest z_0 dataset developed by Peng et al. (2022) (denoted as z_{0_peng})
113 was used by integrating it into the WRF model for wind speed simulation. This dataset was generated by applying machine
114 learning techniques to integrate FLUXNET ground-based observations and MODIS remote sensing data. Moreover, 100-m
115 wind speed data from 589 anemometer towers in China were utilized for two critical purposes. First, the comparison between
116 tower observations and ERA5 100-m wind speed data (Hersbach et al., 2023b) was used to validate the feasibility of the
117 assumption in the z_0 estimation method. Second, tower data were used as independent validations to evaluate the impact of
118 refined z_0 on wind speed simulations. These anemometer towers cover varying periods between 2004 and 2022 with a
119 temporal resolution of 10 min.

120 2.2 Method for deriving z_0 at CMA stations

121 First, the theoretical basis for deriving z_0 at CMA stations is presented. In the framework of Monin-Obukhov similarity
122 theory (Monin and Obukhov, 1954), the neutral logarithmic wind profile can be expressed with Equation (1).

$$123 \quad u_z = \frac{u_*}{k} \ln \left(\frac{z - d}{z_0} \right) \quad (1)$$

124 where u_z is the wind speed (m/s) at height z , the measuring height above ground (m); u_* is the friction velocity (m/s); k is
125 the von Karman constant and equals to 0.4, and d is the zero-plane displacement height (m), calculated as $d = 20/3 z_0$ using
126 a widely accepted empirical formula (Watts et al., 2000).

127 Based on Equation (1), the 100-m neutral wind speed for ERA5 and CMA stations can be expressed in Equations (2) and (3),
 128 respectively.

$$129 \quad u_{100_ERA5} = u_{10_ERA5} \frac{\ln\left(\frac{100 - d_{ERA5}}{z_{0_ERA5}}\right)}{\ln\left(\frac{10 - d_{ERA5}}{z_{0_ERA5}}\right)} \quad (2)$$

$$130 \quad u_{100_CMA} = u_{10_CMA} \frac{\ln\left(\frac{100 - d_{CMA}}{z_{0_CMA}}\right)}{\ln\left(\frac{10 - d_{CMA}}{z_{0_CMA}}\right)} \quad (3)$$

131 And then z_0 values at CMA stations can be estimated by the following three steps:

132 First, we assumed: (1) the near-surface wind speed difference between ERA5 and CMA is primarily attributed to z_0 , and the
 133 influence of z_0 diminishes with height. Consequently, the 100-m wind speed from ERA5 reanalysis is considered
 134 comparable to that from observations; (2) the impact of atmospheric stability on wind speed is identical for both ERA5 and
 135 CMA stations, allowing us to neglect stability correction terms under non-neutral conditions when deriving z_0 for each
 136 hourly interval. The validity of these assumptions will be supported by the subsequent validation of wind speed simulations
 137 based on the derived z_0 values (Section 3.3).

138 Second, we calculated the hourly z_{0_CMA} values based on Equations (2) and (3). Given that u_{10_ERA5} , u_{10_CMA} , and z_{0_ERA5}
 139 values are known, an optimal z_{0_CMA} value at each hour was derived through minimizing the difference between u_{100_ERA5}
 140 and u_{100_CMA} calculated using Equations (2) and (3). To align with Assumption (1), we only retained z_{0_CMA} values
 141 corresponding to times when the percentage difference between the calculated u_{100_ERA5} and u_{100_CMA} was less than 10%.

142 Actually, ERA5 provides native 100-m winds, but here we use log-law–reconstructed 100-m winds from u_{10_ERA5} and
 143 z_{0_ERA5} instead. The reason is that the z_{0_CMA} is derived under the assumption that stability-correction term is neglected. This
 144 means that the 100-m wind speeds in Equations (2) and (3) are both calculated without considering stability effects.
 145 However, the native ERA5 100-m wind field inherently embeds model-diagnosed stability influences. Therefore, directly
 146 pairing native ERA5 100-m winds with our CMA log-law construction would amplify the error in the derived $\ln(z_0)$. In
 147 addition, the reconstruction offers two practical advantages. First, it requires fewer variables and a more transparent linkage,
 148 relying only on 10-m wind speeds and z_0 from reanalysis, together with 10-m wind speeds from observations; Second, our
 149 results indicate that the z_0 estimates are not particularly sensitive to the choice of reference height (see Section 4.
 150 Discussion), so there is no need to use native reanalysis winds at heights other than 10 m.

151 Third, these retained z_{0_CMA} values were grouped by months, and the monthly median values were selected as the final
 152 roughness length ($z_{0_optimal}$). To avoid unreasonable estimates, the values of $z_{0_optimal}$ satisfying the condition that the
 153 absolute difference between $\ln(z_{0_optimal})$ and the corresponding $\ln(z_{0_ERA5})$ does not exceed 2 were considered valid.

154 Finally, we obtained monthly z_0 estimates at 1,805 stations out of the 2,162 CMA stations.

155 2.3 Method for estimating gridded z_0 at regional scale

156 Machine learning serves as an effective tool for extending the $z_{0_optimal}$ estimates at CMA stations to the regional scale. In
157 this study, we employed the RFR algorithm (Equation (4)) (Breiman, 2001), a widely used method for similar applications
158 (Duan and Takemi, 2021; Hu et al., 2022; Peng et al., 2022 and 2023). All samples were divided into training and test
159 subsets at a ratio of 8:2 for each bin of $\ln(z_{0_optimal})$, with the bins defined at intervals of 0.2. Sensitivity tests were
160 conducted to determine the optimal number of decision trees in the RFR algorithm (Fig. 3b), resulting in the selection of 300
161 trees. The maximum depth of the trees was set to 18, and the minimum sample split was set to 5. Five-fold cross-validation
162 shows the stable performance (Fig. 3d). Furthermore, the training and test results exhibit minimal sensitivity to the
163 randomization seed used for dataset splitting (Fig. 3a). The resulting gridded aerodynamic roughness length data are referred
164 to as z_{0_RFR} .

$$165 \quad \ln(z_0) = f(\theta^2, TSD, PTC, LAI, NDVI, URC, month) \quad (4)$$

166 2.4 Model configuration

167 To demonstrate the applicability of gridded z_{0_RFR} data, the WRF (Version 4.0) Model (Skamarock et al., 2019) was used in
168 this study to simulate wind speed with z_{0_RFR} . For comparison, two additional simulations were performed: one utilized the
169 WRF model's default roughness length ($z_{0_Default}$) based on land cover types, and the other used z_{0_Peng} .
170 First, we set z_{0_RFR} and z_{0_Peng} in WRF model, respectively. Given that z_{0_RFR} is concentrated in **high-roughness surface**
171 **areas**, the missing values over other regions are filled with $z_{0_Default}$. Notably, the setting of z_{0_Peng} in WRF is different
172 from that of z_{0_RFR} . In the WRF model, z_0 values over bare fraction and vegetated fraction are determined separately.
173 Specifically, in the Noah-MP land surface model, z_0 is set to a constant over bare areas, while it is assigned by a look-up
174 table according to vegetation type over vegetated areas. Peng et al. (2022) only provided the z_0 over vegetation areas, which
175 is the gridded mean effective roughness length including vegetated fraction and bare fraction. Thus, before conducting the
176 simulation of wind speed in the WRF model with the gridded z_{0_Peng} , we adjusted the roughness length over vegetated
177 fraction in each grid from z_{0_Peng} . The specific adjustment of z_{0_Peng} in the WRF model is comprehensively described in the
178 supplementary material Section 1. Apart from the difference in the sources of z_0 , other model configurations for z_{0_RFR} ,
179 $z_{0_Default}$, and z_{0_Peng} are identical. The specific model configurations are as follows.
180 The simulation domains were configured with a “lat-lon” map projection, centered at coordinates 31.5°N, 109.0°E. As
181 illustrated in Fig. 4b, nested domains were employed, with horizontal resolutions of 0.09° for Domain 1 (d01) and 0.03° for
182 Domain 2 (d02). Specifically, d01 consisted of 225 grid points in the west-east direction and 191 in the south-north direction,
183 while d02 consisted of 469 grid points in the west-east direction and 367 in the south-north direction. The vertical level had
184 70 layers and was stretched with $dzstretch_s = 1.1$ and $dzstretch_u = 1.04$. The model top was set to 50 hPa. The
185 simulation periods spanned from March 31st to April 30th in 2019. The integral time interval was set to 30 seconds. The re-

186 initialization simulation was performed. Specifically, each simulation started at 12:00 local time (LT, LT=UTC+8) and ran
 187 for 36 hours until 24:00 LT the next day. The first 12 hours were considered the spin-up time and the remaining hours were
 188 used for analysis. Additionally, the initial and boundary conditions in the simulations were taken from hourly ERA5
 189 reanalysis data, which provide pressure-level variables (geopotential height, air temperature, air humidity, and wind field)
 190 (Hersbach et al., 2023c) and surface variables (surface air temperature, humidity, pressure, 10 m wind field, sea level
 191 pressure, land surface temperature, soil temperature, and soil water content) (Hersbach et al., 2023b).
 192 For physical parameterization schemes, the modified Thompson microphysics scheme (Thompson et al., 2008), Dudhia
 193 scheme for shortwave radiation (Dudhia, 1989), Rapid Radiative Transfer Model (RRTM) scheme for longwave radiation
 194 (Mlawer et al., 1997), Noah-MP land surface model (Niu et al., 2011), Yonsei University scheme for planetary boundary
 195 layer (Hong et al., 2006), and Grell-Freitas for cumulus parameterization (Grell and Freitas, 2013) were adopted. The
 196 cumulus parameterization scheme was exclusively activated in the d02 domain. A turbulent orographic form drag scheme
 197 with description of the dynamic drag caused by sub-grid orography was also applied (Beljaars et al., 2004; Zhou et al., 2018).

198 2.5 Calculation of statistical metrics

199 To evaluate the performance of the simulated wind speed with z_{0_RFR} , $z_{0_Default}$, and z_{0_Peng} , three statistical metrics,
 200 including correlation coefficient (R), mean absolute bias (MAB), and root mean square error ($RMSE$), were used in temporal
 201 and spatial aspects. For the spatial performance assessment, the average 10-m wind speed simulation during April 1st to 30th
 202 in 2019 at each station was used to calculate R , MAB , and $RMSE$ with the CMA observations.
 203 Regarding the temporal evaluation, the *index* (representing R , MAB , and $RMSE$) was calculated as the mean of the
 204 corresponding metric for hourly 10-m wind speed during April 1st to 30th in 2019 across all CMA stations (Equation (5)).

$$205 \quad index = \frac{\sum_{i=1}^M index_i}{M} \quad (5)$$

206 where $index_i$ denotes the respective metric value at the i -th station, and M represents the total number of stations.

207 Additionally, to incorporate the direction of the bias into the wind-speed evaluation, we used the mean bias percentage (MBP)
 208 to quantify the signed bias of ERA5 reanalysis and simulated wind speeds against observations from CMA stations and
 209 anemometer towers (Equation (6)).

$$210 \quad MBP = \frac{\overline{u_{sim}} - \overline{u_{obs}}}{\overline{u_{obs}}} \times 100\% \quad (6)$$

211 where $\overline{u_{sim}}$ represents mean wind speed from ERA5 or model simulations, and $\overline{u_{obs}}$ represents observed mean wind speed
 212 from CMA stations and anemometer towers.

213 To more intuitively compare the performance of wind speed simulations using $z_{0_Default}$, z_{0_Peng} , and z_{0_RFR} , we also
 214 calculated the percentage reduction in wind speed error (PRE) achieved by z_{0_RFR} relative to $z_{0_Default}$ and z_{0_Peng}
 215 (Equation (7)).

$$PRE = \frac{|\bar{u}_{z_{0,*}} - \bar{u}_{observation}| - |\bar{u}_{z_{0_RFR}} - \bar{u}_{observation}|}{|\bar{u}_{z_{0,*}} - \bar{u}_{observation}|} \times 100\% \quad (7)$$

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).

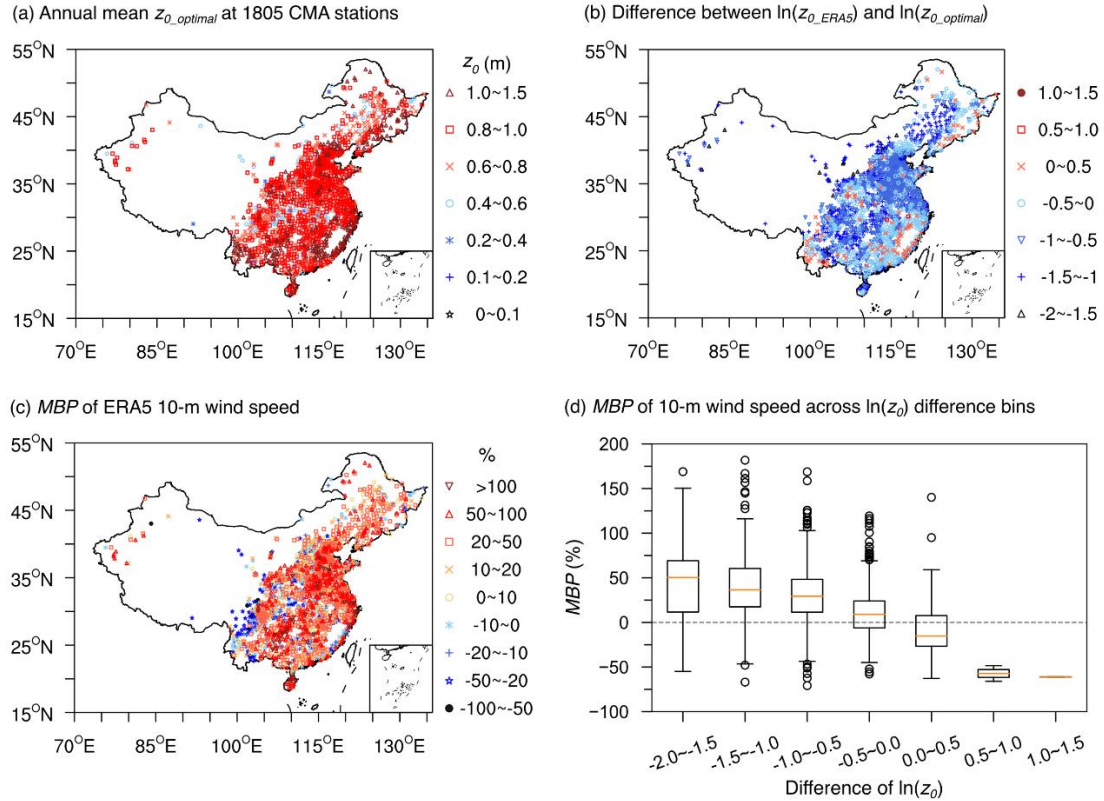
3 Results

3.1 The distribution characteristics of the z_0 estimates at CMA stations

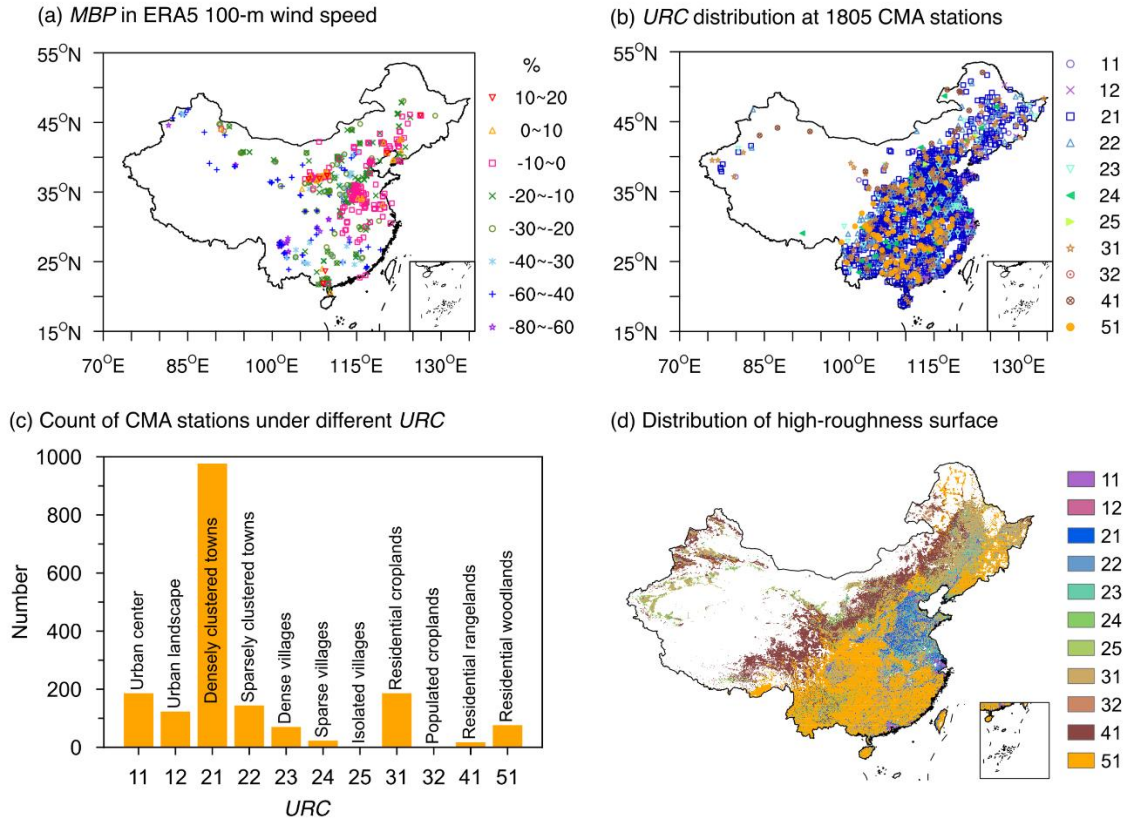
Figure 1a presents the spatial distribution of annual mean $z_{0_optimal}$ values derived from 1,805 CMA stations, representing a subset of all accessible 2,162 stations (Fig. S1a). These 1,805 stations are primarily located in the eastern, southern, and central regions of China, with most stations having z_0 values ranging between 0.6 and 1.5 m. In contrast, the excluded 357 stations are mostly distributed in the western regions of China. 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. To test this, we evaluated the performance of ERA5 100-m wind speed by comparing it with 589 anemometer tower data, since CMA stations only provide 10-m wind speed observations. Overall, ERA5 shows a smaller MBP in the eastern regions compared to the western regions (Fig. 2a). Therefore, the spatial distribution of the 1,805 stations with valid z_0 values is reasonable.

Additionally, as a consistency check, we examined how the difference in $\ln(z_0)$ covaries with the 10-m wind-speed bias between ERA5 reanalysis and station observations. Compared to the annual mean $\ln(z_{0_optimal})$ derived from 1,805 stations, the $\ln(z_{0_ERA5})$ values are systematically lower at most locations, resulting in positive MBP values of 10-m wind speed between ERA5 reanalysis data and station observations (Figs. 1b and 1c). The discrepancies between $\ln(z_{0_ERA5})$ and $\ln(z_{0_optimal})$ are likely due to rapid urbanization around the majority of CMA stations, characterized by extensive construction of buildings, which enhances surface roughness and consequently reduces near-surface wind speeds (Li et al., 2018; Zhang and Wang, 2021). However, the impact of urbanization is likely not considered in the ERA5 reanalysis. Figures 2b and 2c depict the distribution of CMA stations classified by urban-rural categories. All stations are situated in high-roughness surface areas, with the majority located in urban and town regions, highlighting the need to incorporate urbanization effects into wind speed simulations to improve model accuracy. In contrast, at a few locations, where the $\ln(z_{0_ERA5})$ values are higher, the corresponding MBP values of 10-m wind speed are negative (Figs. 1b and 1c). The influence of $\ln(z_0)$ difference on wind speed bias becomes more pronounced as the magnitude of $\ln(z_0)$ deviation increases (Fig. 1d). Because $\ln(z_{0_optimal})$ is defined as a monthly median of hourly $\ln(z_0)$, this cross-time statistic does not trivially inherit the instantaneous relationship implied by Equations (1)-(3). The monotonic, theory-consistent pattern observed in the

245 binned $\ln(z_0)$ difference versus wind-speed MBP therefore serves as a post-aggregation consistency check, rather than as
 246 proof. Accordingly, the robust consistency in the relationship between z_0 and wind speed preliminarily supports that
 247 $z_{0_optimal}$ is reasonable, and suggests that improving z_0 values over high-roughness surface areas in numerical models could
 248 significantly enhance wind speed simulation accuracy. The validity of $z_{0_optimal}$ will be assessed via independent validation
 249 by comparing simulated wind speeds with observations (Section 3.3).



250
 251 **Figure 1.** (a) Spatial distribution of annual mean $z_{0_optimal}$ across 1,805 CMA stations. (b) Difference between annual mean $\ln(z_{0_ERA5})$
 252 and $\ln(z_{0_optimal})$ (i.e., $\ln(z_{0_ERA5})$ minus $\ln(z_{0_optimal})$). (c) MBP of 10-m wind speed between ERA5 and CMA stations. (d) Boxplots
 253 illustrating the statistical distribution of the MBP for 10-m wind speed shown in (c) across different intervals of $\ln(z_0)$ difference shown in
 254 (b).



255

256 **Figure 2.** (a) *MBP* of 100-m wind speed between ERA5 and 589 anemometer towers. (b) Spatial distribution of urban-rural classification
 257 (*URC*) at 1,805 CMA stations. The legend on the right indicates the *URC* codes, with the corresponding *URC* types labeled in panel (c). (c)
 258 Number of CMA stations for each *URC*. The numerical labels on the x-axis represent the *URC* codes, with the specific *URC* types
 259 annotated on the bars. (d) Spatial distribution of **high-roughness surface areas**, which are composed of the 11 types covered by CMA
 260 stations in panel (b).

261 3.2 Development of a gridded z_0 dataset in **high-roughness surface areas** across China

262 To demonstrate the reliability and practicality of the estimated $z_{0_optimal}$, we constructed a gridded z_0 dataset based on these
 263 estimations in order to apply it in numerical simulations. Given that the estimated z_0 values from 1,805 stations are located
 264 within **high-roughness surface areas** consisting of 11 distinct types (Figs. 2b and 2c), this study developed a monthly gridded
 265 z_0 dataset specifically for these **categories** of areas with a spatial resolution of $0.01^\circ \times 0.01^\circ$ using the RFR algorithm,
 266 referred to as z_{0_RFR} . As a representative example, the z_{0_RFR} dataset was generated for the year 2019, and its spatial
 267 coverage is shown in Fig. 2d. Although 2019 was chosen for demonstration, the RFR model itself is year-independent and
 268 can be applied to other years, provided that the required input features are available. Six feature variables closely related to

269 z_0 were used as inputs, encompassing topographic characteristics ($\overline{\theta^2}$ and TSD), vegetation conditions (PTC , LAI , and $NDVI$),
 270 and urban-rural distribution (URC).
 271 Figure 3c shows that the RFR algorithm exhibits satisfactory performance on both training and test subsets. Feature
 272 importance analysis reveals that topographic features and PTC exert the most significant influence on $\ln(z_{0,RFR})$ (Fig. 3e).
 273 z_0 is primarily controlled by the characteristic height of surface roughness elements, particularly their relief. Consequently,
 274 topographic features rank among the most influential factors. For vegetation-related features, PTC not only reflects the
 275 horizontal distribution of vegetation density but also serves as a proxy for the presence of tall roughness elements. By
 276 contrast, LAI mainly represents vegetation density, making it relatively less critical. Although LAI is strongly correlated with
 277 $NDVI$ ($R = 0.72$), its low importance is not driven by this collinearity. The URC ranks only fourth in feature importance.
 278 This ranking should not be interpreted as implying that land use or urbanization is insignificant. Rather, in our framework,
 279 URC is used mainly to delineate the study domain and to ensure that the RFR algorithm is applied only to high-roughness
 280 surface areas. The aerodynamic effects of high-roughness elements, such as tall vegetation, buildings, and other
 281 infrastructure, are already embedded in the wind observations from CMA stations. As a result, the influence of these
 282 roughness elements is directly reflected in the z_0 values themselves, rather than being captured by the URC . Essentially,
 283 URC is not defined in terms of the morphological height and density of roughness elements; instead, it is derived from global
 284 land-cover and population data (Li, X. et al., 2023), and is therefore weakly sensitive to z_0 . For example, in categories of
 285 Urban center and Urban landscape, there remains non-negligible tree cover, mean tree fractions of approximately 10% and
 286 11%, respectively (Fig. S1b). This lowers URC 's ranking in feature-importance analyses. To better capture the influence of
 287 roughness elements, more detailed surface parameters, such as building height and building density, would be helpful. Once
 288 such data are widely accessible, they should be incorporated to further improve the accuracy of z_0 estimates.

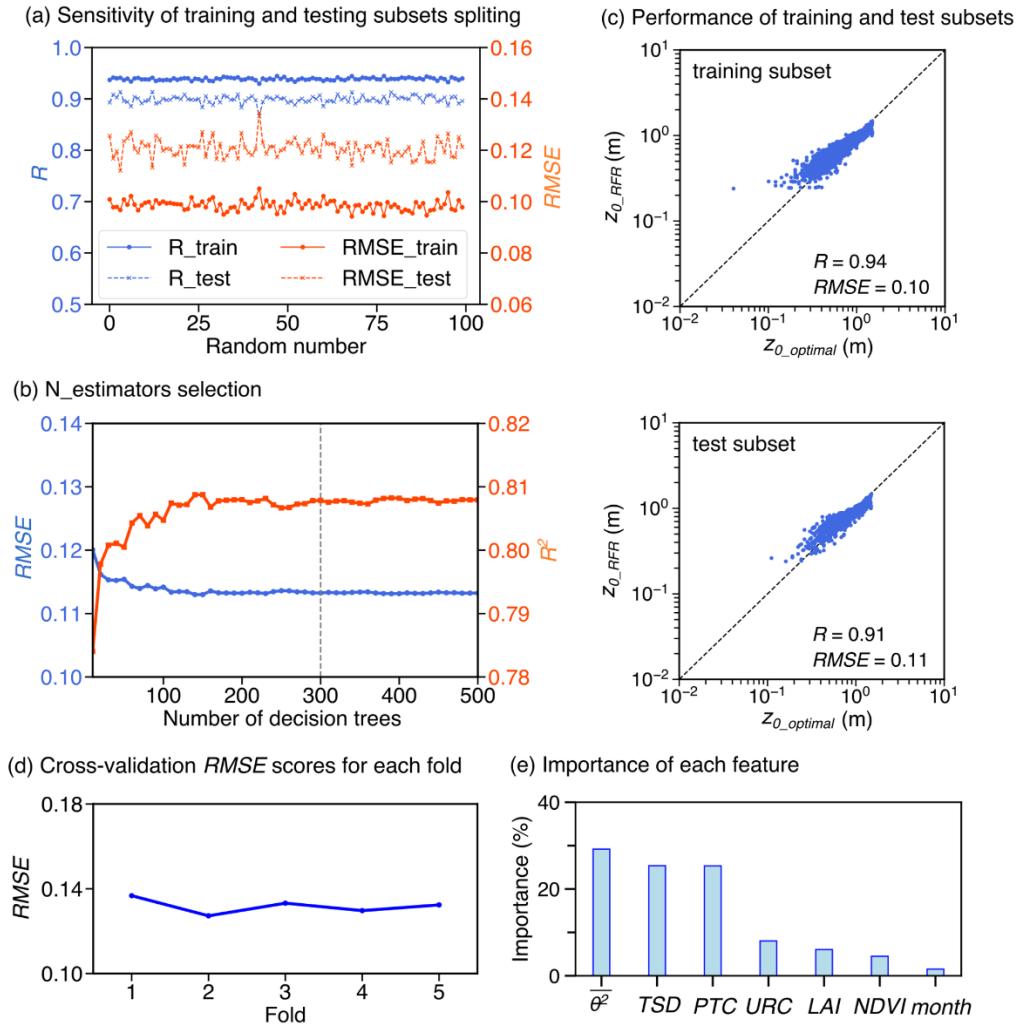
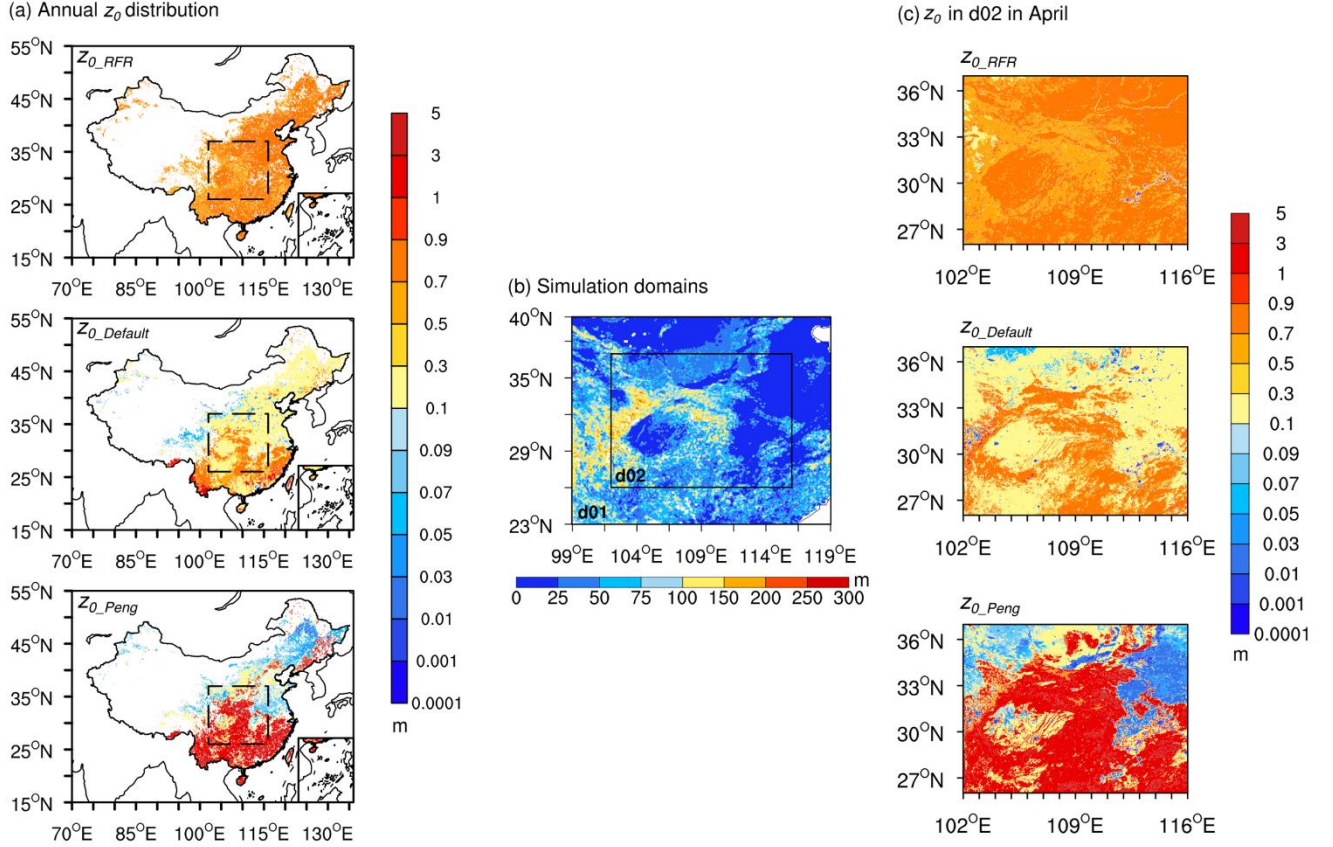


Figure 3. Sensitivity analysis and performance evaluation of the Random Forest Regression (RFR) algorithm. (a) Sensitivity of RFR results to the randomization seed for training and test subsets splitting. R and $RMSE$ represent correlation coefficient and root mean square error, respectively. (b) Determination of the optimal number of decision trees. R^2 represents determination coefficient. (c) Performance of the RFR algorithm on the training and test subsets. The R and $RMSE$ values are displayed. (d) Performance evaluation using five-fold cross-validation. (e) Importance scores of different feature variables.

The spatial distribution of $\ln(z_{0_RFR})$ shows limited monthly variability (Fig. S2). The most pronounced monthly variations occur predominantly in the surrounding areas of the Sichuan Basin, likely due to the prevalence of residential woodlands in these regions that have seasonal variations in vegetation structure and biomass. The annual mean spatial distribution of $\ln(z_{0_RFR})$, with values in high-roughness surface areas generally falling within the range of -1 to 0, exhibits distinct patterns compared to $\ln(z_{0_Default})$ and $\ln(z_{0_Peng})$ (Fig. 4a). In comparison with $\ln(z_{0_Default})$ and $\ln(z_{0_Peng})$, $\ln(z_{0_RFR})$ shows a

301 more homogeneous spatial distribution pattern across China. Specifically, in northern China, $\ln(z_{0_RFR})$ values are
 302 consistently higher than those of both $\ln(z_{0_Default})$ and $\ln(z_{0_Peng})$, with $\ln(z_{0_Default})$ generally higher than $\ln(z_{0_Peng})$.
 303 Conversely, in southern China, $\ln(z_{0_Peng})$ values are significantly higher than both $\ln(z_{0_Default})$ and $\ln(z_{0_RFR})$. However,
 304 in southeastern and southwestern China, $\ln(z_{0_Default})$ values exceed those of $\ln(z_{0_RFR})$, while in the remaining southern
 305 areas, $\ln(z_{0_RFR})$ maintains higher values compared to $\ln(z_{0_Default})$.



306
 307 **Figure 4.** (a) Spatial distributions of annual mean z_{0_RFR} , $z_{0_Default}$, and z_{0_Peng} . The dashed rectangular box indicates the simulation
 308 domain (d02) in panel (b). (b) Nested simulation domains (d01: outer domain; d02: inner domain) with terrain standard deviation within
 309 0.01° window (TSD) represented by color shading. (c) Spatial distributions of z_0 used in simulations over d02 in April.

310 3.3 Application of the produced z_0 datasets in wind speed simulation

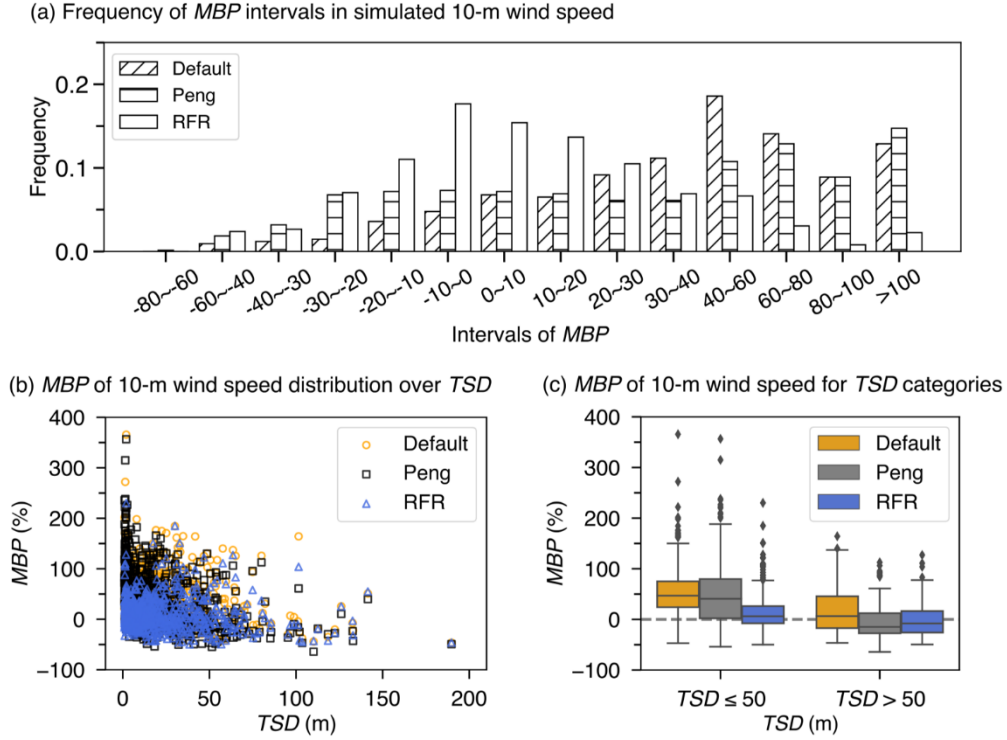
311 To evaluate the performance of z_{0_RFR} , we implemented it in the WRF model for wind speed simulations, as z_0 directly
 312 affects near-surface wind speed. A 3-km simulation for April 2019 was conducted using the WRF model with z_{0_RFR} over
 313 the regions outlined in Fig. 4a, which correspond to the d02 domain in Fig. 4b and represent the primary areas of z_{0_RFR}

314 concentration. April was selected because it is the month with the highest average wind speed in the target domain (Fig. S3),
 315 thus better reflecting the impact of z_0 on wind speed. For comparison, two additional simulations were performed: one
 316 utilizing the WRF model's default roughness length ($z_{0_Default}$) based on land cover types, and the other employing a recent
 317 z_0 dataset (z_{0_Peng}). In the northeastern, northern, and western regions of the d02 domain, both $\ln(z_{0_Default})$ and
 318 $\ln(z_{0_Peng})$ are generally lower than $\ln(z_{0_RFR})$ estimates, with $\ln(z_{0_Peng})$ having even lower values than $\ln(z_{0_Default})$
 319 (Fig. 4c). However, this pattern reverses in the southeastern areas and along the surrounding area of the Sichuan Basin,
 320 where both $\ln(z_{0_Default})$ and $\ln(z_{0_Peng})$ surpass $\ln(z_{0_RFR})$ estimates, and notably, with $\ln(z_{0_Peng})$ having significantly
 321 higher values than $\ln(z_{0_Default})$ in these regions. These discrepancies in z_0 would inevitably directly affect the accuracy of
 322 wind speed simulation. To evaluate the influence, we conducted a comprehensive assessment on both 10-m and 100-m wind
 323 speed simulations, which represent typical heights for meteorological observations and wind energy applications,
 324 respectively.

325 3.3.1 Evaluation of the simulated 10-m wind speed

326 We first compared the simulated 10-m wind speed with observations from 753 CMA stations in study areas (d02 domain),
 327 showing that z_{0_RFR} significantly enhances the accuracy of simulations. The improvement due to z_{0_RFR} is evident in the
 328 smaller *MBP* values of the simulated wind speed (Figs. 5a and S4) and the closer alignment of average wind speed with
 329 observational data (Fig. 6a).
 330 Specifically, the frequency histogram of *MBP* values reveals that the simulation results using z_{0_RFR} mostly fall within an
 331 absolute *MBP* range of less than 30%, with a substantial proportion concentrated below 10%. In contrast, simulations
 332 employing $z_{0_Default}$ display a majority of *MBP* values exceeding 30%, while simulations using z_{0_Peng} are even poorer,
 333 with a larger number of stations falling within higher *MBP* ranges (Fig. 5a). The improvement in 10-m wind speed induced
 334 by z_{0_RFR} is primarily evident in relatively flat regions. As *TSD* increases, the improvement gradually diminishes (Fig. 5b).
 335 z_{0_RFR} outperforms both $z_{0_Default}$ and z_{0_Peng} when *TSD* does not exceed 50 m, while it shows superior performance to
 336 $z_{0_Default}$ and comparable results to z_{0_Peng} when *TSD* is greater than 50 m (Fig. 5c). Spatially, significant improvements are
 337 observed in the relatively flat eastern and northern study areas, whereas limited enhancements are found in regions with
 338 higher *TSD* surrounding the Sichuan Basin (Fig. S4). The limited improvement in relatively complex terrain arises because,
 339 in addition to z_0 , wind speed over these regions is influenced by multi-scale factors, including microscale terrain features
 340 (Ge et al., 2025), turbulent orographic form drags (Beljaars et al., 2004; Jiménez and Dudhia, 2011; Zhou et al., 2018),
 341 surface heating-induced mountain-valley circulations (Kim et al., 2021), mountain waves (Draxl, et al., 2021) and other
 342 processes. Inaccurate parameterizations of these factors in numerical models can all lead to errors in wind speed simulations.
 343 For the mean 10-m wind speed, simulations using z_{0_RFR} (2.17 m/s) show better agreement with the CMA observations (2.08
 344 m/s), whereas simulations with $z_{0_Default}$ and z_{0_Peng} show greater overestimations, producing mean wind speeds of 2.97

345 m/s and 2.89 m/s, respectively (Fig. 6a and Table 1). In other words, z_{0_RFR} decreases mean bias of 10-m wind speed by 89.9%
 346 and 88.9% compared to $z_{0_Default}$ and z_{0_Peng} , respectively. Independent validations across 155 stations (Fig. 6b), from the
 347 test subset in the generation of z_{0_RFR} , further confirm the superiority of z_{0_RFR} (Fig. 6a). In addition, the improvements in
 348 10-m wind speed were observed throughout the entire simulation period (Fig. 6c). Note that our experimental design,
 349 employing a re-initialization strategy, means that 30 independent simulation experiments were conducted in April. Thus,
 350 although the simulations were only conducted for a month, the consistent improvement across all days shows that the
 351 enhancement achieved by z_{0_RFR} is robust. Moreover, the statistical metrics also show that the simulated 10-m wind speed
 352 using z_{0_RFR} outperforms those using $z_{0_Default}$ and z_{0_Peng} in temporal and spatial *MAB* and *RMSE* (Fig. 6d).



353
 354 **Figure 5.** (a) Frequency distribution of *MBP* in simulated 10-m wind speed in April using $z_{0_Default}$, z_{0_Peng} , and z_{0_RFR} against
 355 observations from CMA stations. (b) Distribution of *MBP* in 10-m wind speed as a function of *TSD*. (c) Box plot of *MBP* in 10-m wind
 356 speed across different *TSD* bins.

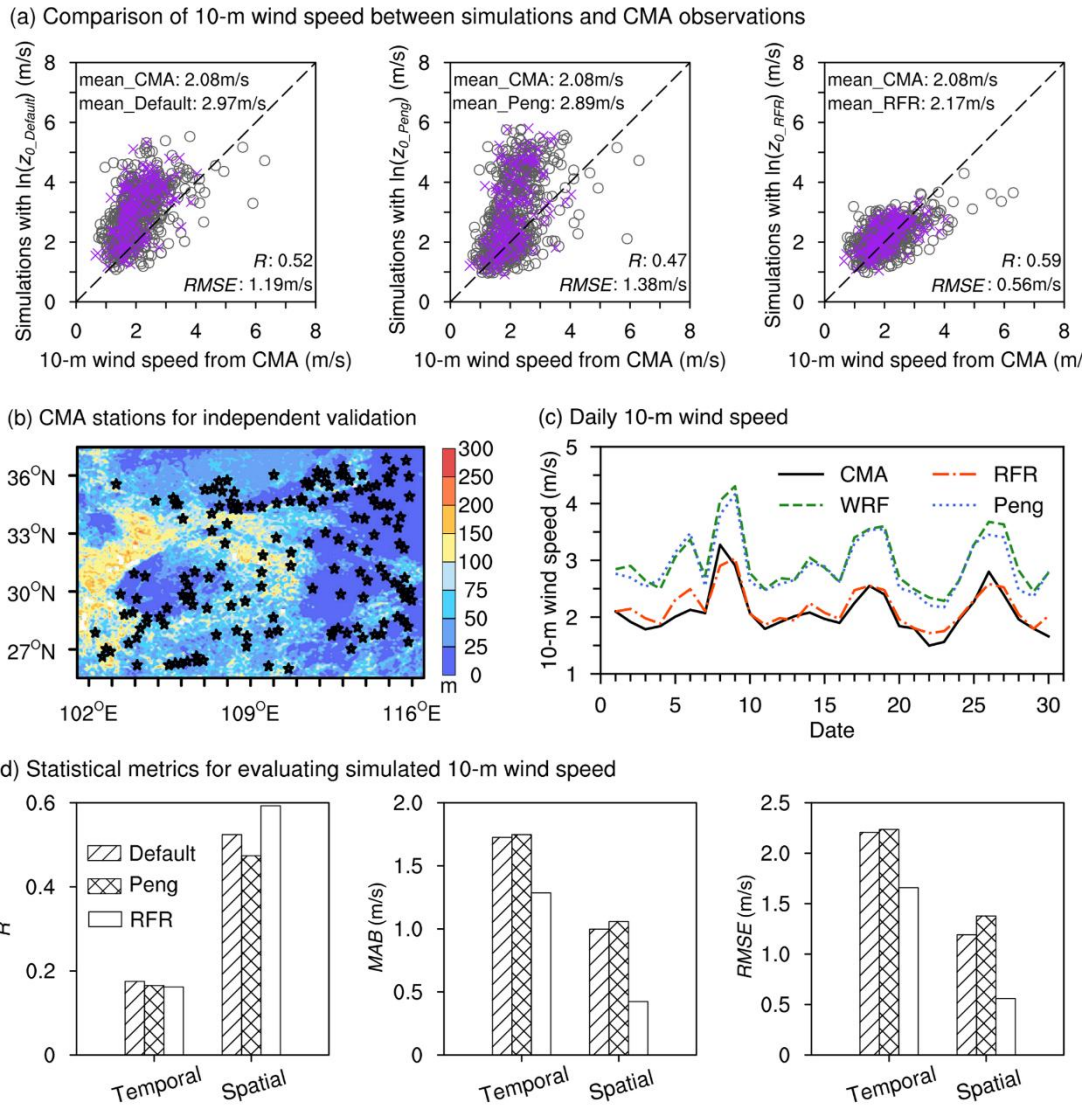


Figure 6. (a) Comparisons of mean 10-m wind speed in April between the simulations using $z_{0_Default}$, z_{0_Peng} , and z_{0_RFR} versus observations from CMA stations. All points (grey circles and purple crosses) represent the 753 CMA stations within the d02 domain available for comparison, while 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, R , and $RMSE$ 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 , MAB , and $RMSE$.

366 **Table 1.** Mean 10-m wind speed at 753 CMA stations and mean 100-m wind speed at 50 anemometer towers from simulations and
 367 observations. Simulations were performed using $z_{0_Default}$, z_{0_Peng} , and z_{0_RFR} . Also shown is the percentage reduction in wind speed
 368 error (*PRE*) achieved by z_{0_RFR} relative to $z_{0_Default}$ and z_{0_Peng} .

	$z_{0_Default}$	z_{0_Peng}	z_{0_RFR}	Observations
Mean 10-m wind speed (m/s)	2.97	2.89	2.17	2.08
<i>PRE</i> in 10-m wind speed (%)	89.9%	88.9%	-	-
Mean 100-m wind speed (m/s)	7.10	7.27	6.38	6.26
<i>PRE</i> in 100-m wind speed (%)	85.7%	88.1%	-	-

369 **3.3.2 Evaluation of the simulated 100-m wind speeds**

370 In addition to 10-m wind speed, the simulated 100-m wind speed was also improved through the use of z_{0_RFR} (Fig. 7a and
 371 Table 1). Compared to observations from 50 anemometer towers (Fig. 7b), with an average 100-m wind speed of 6.26 m/s,
 372 simulations based on $z_{0_Default}$ and z_{0_Peng} overestimate the wind speed, with averages of 7.10 m/s and 7.27 m/s,
 373 respectively. However, the mean 100-m wind speed simulated using z_{0_RFR} is 6.38 m/s, closer to the observations (Table 1).
 374 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} ,
 375 respectively. Consistent with the performance of z_{0_RFR} at 10-m wind speed, the improvement in 100-m wind speed is more
 376 pronounced in relatively flat regions (Fig. 7c). The outliers in Fig. 7a, where wind speed biases remain significant despite
 377 using z_{0_RFR} , are located in areas with higher *TSD*. Furthermore, similar to its performance at 10-m height, z_{0_RFR}
 378 demonstrates superior performance in simulated 100-m wind speed across both temporal and spatial metrics, with the
 379 exception of the temporal correlation coefficient (Fig. 7d). The relatively lower temporal *R* is reasonable, as the
 380 improvement in wind speed induced by z_0 primarily stems from enhancements in the vertical profile.
 381 In summary, the 30 independent simulation cases conducted for April demonstrate that the z_0 values derived from the
 382 combination of CMA observations and ERA5 data are highly reliable. The resulting gridded z_0 dataset significantly reduces
 383 uncertainties in mesoscale near-surface wind speed simulations, particularly over relatively flat **high-roughness surface areas**.
 384 To further validate the robustness of the z_0 estimation method and the resulting dataset, we conducted additional simulations
 385 for October 2019, a month characterized by generally weaker wind conditions (Fig. S3), using the same model configuration
 386 as in April. The results (Figs. S5-S7) also show consistent improvements when using z_{0_RFR} . **Station-wise correlations**
 387 **increase and errors decrease to a similar extent in both months, and the daily time series likewise show closer tracking of**
 388 **peaks and lulls. Taken together, these results further reinforce the reliability and applicability of the proposed z_0 estimation**
 389 **under varying meteorological conditions. They also indicate that although phenology-driven changes in canopy structure and**
 390 **seasonal circulation modulate wind speeds, the performance advantage of the proposed z_0 is not diminished.**

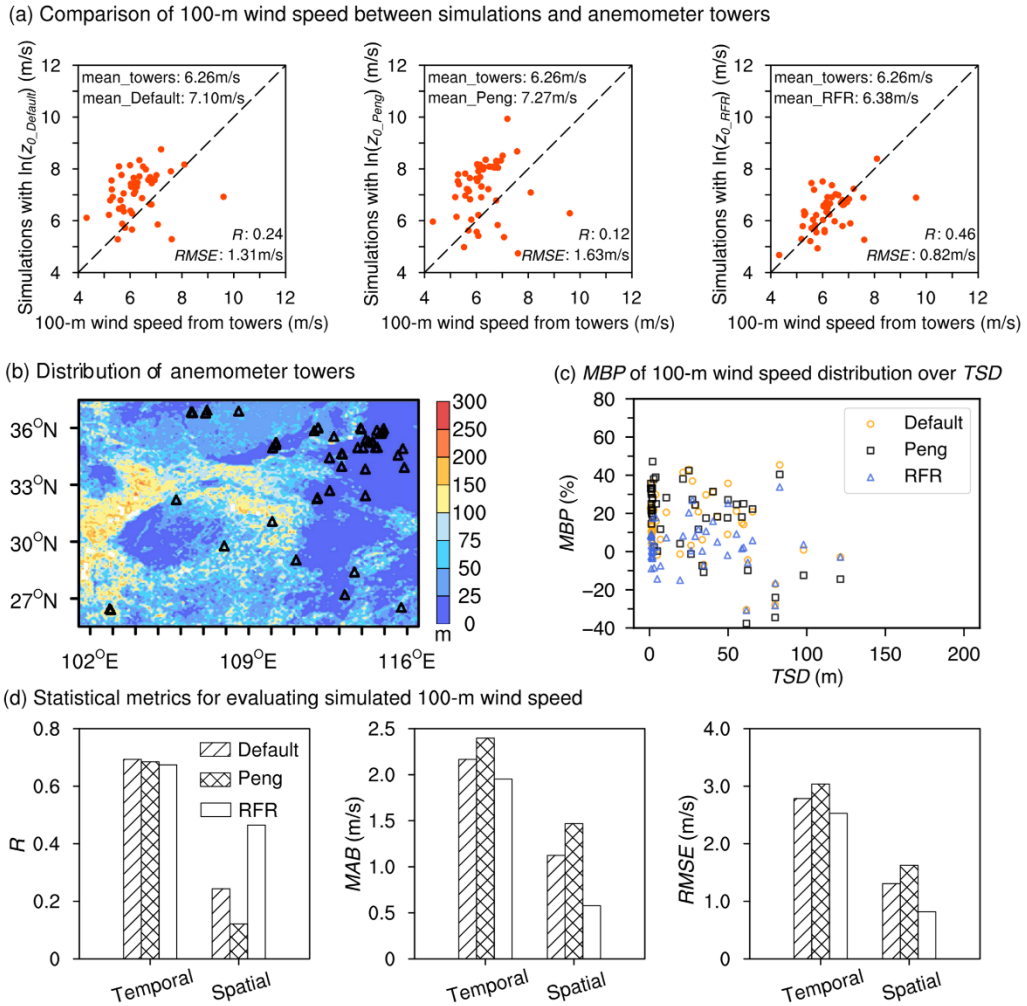


Figure 7. (a) Comparisons of mean 100-m wind speed in April between the simulations using $z_{0_Default}$, z_{0_Peng} , and z_{0_RFR} versus observations from anemometer towers. The corresponding wind speed means, R , and $RMSE$ of all towers are also indicated. (b) The locations of 50 anemometer towers (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 . (d) Statistical metrics comparing simulated and observed 100-m wind speeds, including temporal and spatial R , MAB , and $RMSE$.

4. Discussion

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

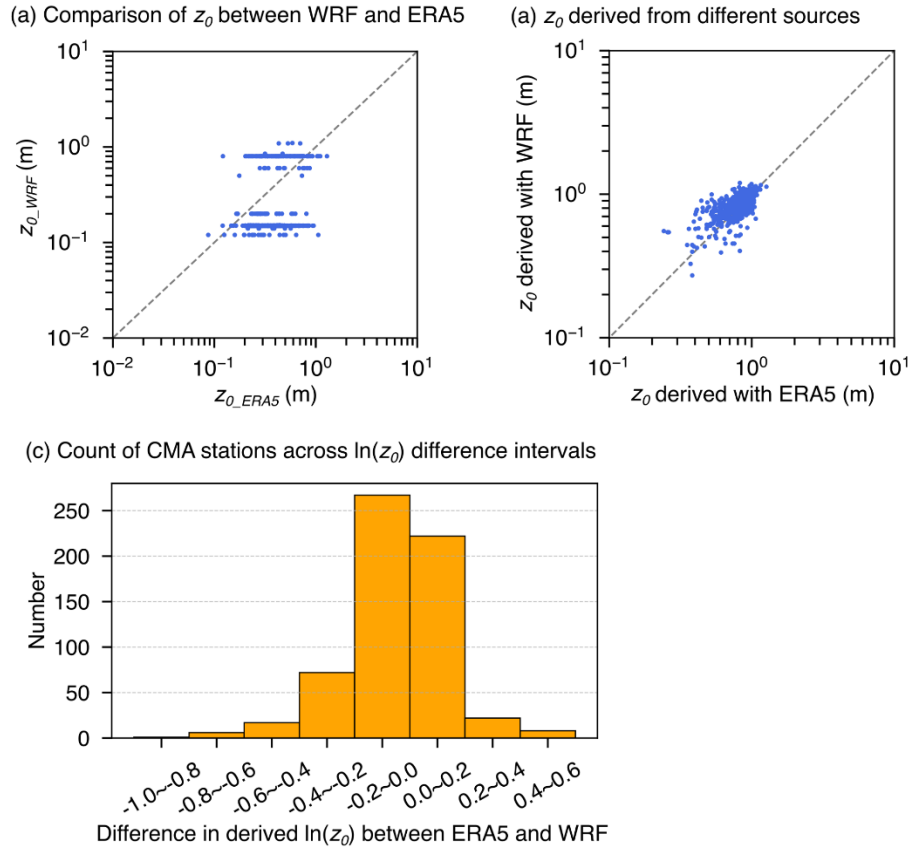
401 methods, our approach can provide z_0 values at large spatial coverage and low cost, and these values lead to clear
 402 improvements in WRF-simulated wind speeds at both 10 m and 100 m above ground level. To assess whether the
 403 performance gain stems from improved z_0 representation rather than from alignment with ERA5 reanalysis data, we carried
 404 out two additional sets of evaluations.

405 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
 406 ($0.03^\circ \times 0.03^\circ$), instead of ERA5. The z_0 values estimated using this alternative dataset were found to be highly similar to
 407 those derived from ERA5 (Fig. 8), indicating that the method is not inherently reliant on ERA5 as a data source. The primary
 408 advantage of using ERA5 lies in its extensive spatiotemporal coverage, which offers greater convenience and consistency
 409 with observational data. Meanwhile, although 10-m and 100-m winds over lands are not assimilated directly in ERA5, its
 410 4D-Var system ingests a wide range of surface and upper-air observations that constrain boundary-layer structure and
 411 indirectly improve near-surface winds; this strengthens the credibility of using ERA5 as the reference field (Hersbach et al.,
 412 2020). However, the methodology itself is general and transferable to other datasets.

413 Moreover, the agreement between ERA5- and WRF-derived z_0 values suggests that the spatial extent represented by the
 414 estimated site-level z_0 values is not determined by the resolution of the reanalysis or simulation dataset used, but rather by
 415 the measurement height of wind observations at the stations. In this study, 10-m wind speeds from CMA stations were used.
 416 As a rule of thumb, the horizontal representativeness of wind measurements is approximately 10-100 times the measurement
 417 height. Therefore, z_0 values estimated from 10-m wind observations are reasonably representative at ~ 100 m-1 km scales,
 418 making the generation of 0.01° gridded z_0 datasets for use in mesoscale simulations both appropriate and justified, with no
 419 evident resolution dependence observed. We compared simulation results at different resolutions. Leveraging the nested
 420 modeling setup used in this study, the d01 domain with a 0.09° resolution was treated as the coarse-resolution simulation,
 421 while d02 at 0.03° served as the fine-resolution simulation. The results show that, even at the coarser resolution, our gridded
 422 z_0 dataset provides a clear advantage and substantially improves near-surface wind speed simulations (Fig. S8 and S9).
 423 However, for simulations at ~ 1 km resolution and finer, such as urban-scale wind modelling, our z_0 dataset cannot fully
 424 capture urban heterogeneity, because it did not incorporate key morphological parameters (e.g., building height and density)
 425 to distinguish between different urban forms. Therefore, an urban canopy model (UCM) would be a more appropriate choice.
 426 UCMs were conceived to operate at ~ 0.5 -1 km grid spacing to bridge mesoscale forecasting ($\sim 10^5$ m) with microscale
 427 transport/dispersion ($\sim 10^0$ m) models (Tewari et al., 2006; Chen et al., 2010), and they have been widely applied and
 428 validated in subsequent urban studies (Lian et al., 2018; Salamanca et al., 2018; Wang et al., 2021). Therefore, our z_0 data
 429 are suitable and effective for mesoscale simulations at kilometer-level resolutions.

430 Second, we further validated the robustness of the refined z_0 dataset (z_{0_RFR}) by conducting additional WRF simulations
 431 driven by the reanalysis from National Centers for Environmental Prediction (NCEP) instead of ERA5. These results (Fig.
 432 S10 and Table S1) still showed significant improvement in wind speed simulation performance when using z_{0_RFR} ,

433 consistent with those driven by ERA5. This cross-reanalysis consistency demonstrates that the benefits are attributable to the
 434 improved surface representation through z_{0_RFR} refinement, not simply tuning to match ERA5-driven wind fields.
 435 Taken together, these findings confirm that the z_0 estimation method proposed in this study is robust, flexible, and not
 436 dependent on alignment with a specific reanalysis dataset. It provides a practical framework for z_0 estimation that can be
 437 widely applied across different reanalysis/simulation datasets and observational data with consistent benefits. However, this
 438 method is limited in regions with sparse or no surface weather stations. Notably, these regions, such as western and northern
 439 China, are rich in wind resources and are key targets for wind energy development. Therefore, producing high-quality
 440 gridded z_0 datasets in these regions warrants further study by exploring alternative data sources, such as anemometer tower
 441 wind profiles, to supplement z_0 truth values (Wang et al., 2024).



442
 443 **Figure 8.** (a) Comparison of z_0 values from default WRF model (z_{0_WRF}) and ERA5 (z_{0_ERA5}). (b) Comparison of z_0 estimates using
 444 different datasets. z_0 derived from WRF represents the estimated values based on WRF simulations (10-m wind speed and default z_0) and
 445 CMA station observations (10-m wind speed) during April 2019, while z_0 derived from ERA5 denotes the estimates obtained in this study
 446 using ERA5 reanalysis data in April. (c) Distribution of station counts across intervals of the difference in derived $\ln(z_0)$ ($\ln(z_0)$ derived
 447 from ERA5 minus $\ln(z_0)$ derived from WRF).

The two assumptions used in the z_0 estimation are also discussed. Although these assumptions cannot be fully verified with the available data, they are pragmatically motivated and indirectly supported by the improved performance of wind-speed simulations using the resulting z_0 estimates. Assumption 1 posits that the near-surface wind-speed discrepancy between ERA5 reanalysis and CMA observations is dominated by z_0 and that the influence of z_0 weakens with height, making ERA5 winds at higher levels within the surface layer comparable to observations. This is partly supported by the spatial pattern of estimated z_0 (denser over eastern China, where 100-m wind-speed biases between ERA5 reanalysis and anemometer tower observations are smaller (Figs. 1c and 2a)) and by a sensitivity test on the reference height (Figs. S11a and S11c). When re-estimating annual-mean z_{0_CMA} at 150 m and 200 m, 88.6% and 87.3% of stations, respectively, show an absolute difference from the 100-m-based estimate below 0.5, indicating broad consistency across heights. A minority of stations exhibit larger deviation, which may be influenced by local terrain complexity (Figs. S11b and S11d). Assumption 2 treats the effects of atmospheric stability on wind speed as effectively similar in ERA5 and at CMA sites, allowing us to omit explicit stability corrections in estimating z_{0_CMA} . This simplification enhances methodological consistency and computational efficiency, and it is indirectly supported by the validation of simulated winds. Moreover, prior work has shown that neutral log-law method can perform comparably to stability-corrected scheme for vertical interpolation in U.S. wind-resource assessments (Duplyakin et al., 2021), suggesting that such an approximate treatment seems feasible and a widely adopted simplification. Overall, although neither assumption can be fully verified with the presently available data, their practical applicability is evidenced by improved WRF wind-speed simulations. Future work, ideally leveraging multi-height wind profile observations and coincident stability metrics could further test these assumptions, yield more precise z_0 estimates.

5. Conclusion

The representation of z_0 in numerical models, typically determined by land cover types, may lead to significant uncertainties in wind speed simulations and predictions. Traditional methods for obtaining z_0 ground truth are mainly constrained by high costs. 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. Based on this approach, we derived z_0 values at 1,805 CMA stations out of a total of 2,162 stations. These stations are located in **high-roughness surface regions**, indicating the estimated z_0 values inherently include the effects of built-up and tall vegetation.

To validate the reliability and practicality of the estimation method, we utilized a Random Forest Regression algorithm, incorporating feature variables closely related to z_0 , to develop a monthly gridded z_0 dataset for **high-roughness surface areas** in China with a spatial resolution of $0.01^\circ \times 0.01^\circ$. The resulting $\ln(z_0)$ values mainly range from -1 to 0. Simulations

with WRF model show that, compared to the default z_0 in WRF and a recent gridded z_0 dataset developed by Peng et al. (2022), the z_0 dataset constructed in this study has significantly improved the accuracy of near-surface wind speed simulations in **high-roughness surface areas**, particularly in relatively flat regions. Evaluations against independent weather station data and anemometer tower data show simulations with the new z_0 dataset mitigates mean bias of 10-m wind speed by 89.9% and 88.9%, and mean bias of 100-m wind speed by 85.7% and 88.1%, respectively, compared to the default z_0 in WRF and the z_0 dataset from Peng et al. (2022).

In summary, this study developed a simple yet effective approach for correcting model z_0 , addressing the limitations of relying on empirical values assigned based on land cover types. The method shows particular effectiveness in z_0 correction for **high-roughness surface areas** and offers valuable support for wind field-dependent studies and applications.

Code and data availability.

- Code required to conduct the analyses herein is available at <https://doi.org/10.5281/zenodo.15108200> (Wang, 2025).

The datasets used in this study fall into two categories based on their accessibility:

1. Publicly Available Datasets (accessible via DOI/URL).

- The hourly wind speed data at 10 m and 100 m heights are obtained from the ERA5 reanalysis dataset (Hersbach et al., 2020), accessible at <https://doi.org/10.24381/cds.adbb2d47> (Hersbach et al., 2023b).
- For the gridded datasets of z_0 used in this study, z_{0_ERA5} (Hersbach et al., 2020) is available at <https://doi.org/10.24381/cds.fl7050d7> (Hersbach et al., 2023a), while z_{0_Peng} (Peng et al., 2022) can be acquired by contacting the corresponding authors.
- The initial and boundary conditions for the simulations are from the ERA5 dataset (Hersbach et al., 2020), which can be downloaded from <https://doi.org/10.24381/cds.adbb2d47> (Hersbach et al., 2023b) and <https://doi.org/10.24381/cds.bd0915c6> (Hersbach et al., 2023c).
- The digital elevation data, with a spatial resolution of 3 arc-seconds, are sourced from the Shuttle Radar Topography Mission (SRTM) and can be downloaded from <https://csidotinfo.wordpress.com/data/srtm-90m-digital-elevation-database-v4-1/> (Jarvis et al., 2008).
- The urban-rural classification data (Li, X. et al., 2023) are available at <https://doi.org/10.6084/m9.figshare.21716357.v6> (Li et al., 2022).
- The variance of the slope ($\overline{\theta^2}$) data can be obtained by contacting Zhou et al. (2018).
- The Leaf Area Index (LAI) data (Lin et al., 2023; Yuan et al., 2011) are accessible at <http://globalchange.bnu.edu.cn/research/laiv061> (Beijing Normal University Global Change Data Archive, 2022).
- The percent tree cover data (DiMiceli et al., 2022) can be obtained from <https://doi.org/10.5067/MODIS/MOD44B.061> and [https://search.earthdata.nasa.gov/search/granules?p=C2565805839-LPCLOUD&pg\[0\]\[v\]=f&pg\[0\]\[gsk\]=-start_date&q=MOD44B&tl=1733462795.688!3!!&lat=-0.140625](https://search.earthdata.nasa.gov/search/granules?p=C2565805839-LPCLOUD&pg[0][v]=f&pg[0][gsk]=-start_date&q=MOD44B&tl=1733462795.688!3!!&lat=-0.140625) (NASA EOSDIS, 2024a).
- The NDVI data (Didan, 2021) are available from <https://doi.org/10.5067/MODIS/MOD13A3.061> and [https://search.earthdata.nasa.gov/search/granules?p=C2327962326-LPCLOUD&pg\[0\]\[v\]=f&pg\[0\]\[gsk\]=-start_date&q=MOD13A3&tl=1732851935.718!3!!&lat=-0.140625](https://search.earthdata.nasa.gov/search/granules?p=C2327962326-LPCLOUD&pg[0][v]=f&pg[0][gsk]=-start_date&q=MOD13A3&tl=1732851935.718!3!!&lat=-0.140625) (NASA EOSDIS, 2024b).
- The NCEP forcing data (National Centers for Environmental Prediction/National Weather Service/NOAA/U.S. Department of Commerce, 2025) are available from <https://rda.ucar.edu/datasets/d083002/dataaccess/>.

2. Restricted Datasets. We would like to clarify that the meteorological station data from the China Meteorological Administration (CMA) and the anemometer tower data used in this study are not publicly accessible but can be accessed through the following way. Specifically:

- The data from anemometer towers are provided by China State Shipbuilding Corporation Haizhuang Windpower Co., Ltd., however, they are not accessible publicly because of their commercial interests. These data can be obtained by

cooperation with the company.

- The hourly 10-m wind speed data at meteorological stations are from the China Meteorological Administration (CMA). In accordance with the data policy of China, these data record are not directly accessible for public download via a website. Nevertheless, individuals interested in obtaining detailed information about data acquisition can reach out to the China Meteorological Data Service Center at their official website (<http://data.cma.cn/en/?r=data/detail&dataCode=A.0012.0001>, China meteorological data service centre, 2023).

Author contributions. All authors contributed to the study. JW and KY conceived the study and conducted the design; JW, KY, and JL carried out data analyses; JW, XZ and XM performed the configuration of WRF model; WT processed data from CMA stations; LY provided the data from anemometer towers; ZR conducted data collection and cleaning of anemometer towers; JW and KY wrote the manuscript; all authors discussed, reviewed and edited the manuscript.

Competing interests. The contact author has declared that none of the authors has any competing interests.

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Financial support. This work was supported by the National Natural Science Foundation of China (Grant Nos. 42475138 and 42361144875).

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