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Impact of near-surface turbulence on PM$_{2.5}$ concentration in Chengdu during the COVID-19 pandemic

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**HIGHLIGHTS**

- Lockdown measures during COVID-19 helps improve the air quality in Chengdu.
- TKE positively correlated with PBL height and had a negative correlation with PM$_{2.5}$
- Near-surface turbulence has significant impact on the variation of aerosol concentration.

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**ABSTRACT**

The role of meteorological conditions has long been recognized in modulating regional air quality. The impact of near-surface turbulence, nevertheless, remains poorly understood. To curb the spread of COVID-19, a variety of lockdown measures were implemented, providing us an unprecedented opportunity to examine the joint impact of emission control and meteorology on regional air quality. Here we examined the variations of planetary boundary layer (PBL) height, PM$_{2.5}$ concentrations, turbulence kinetic energy (TKE), vertical wind shear, and their associations in Chengdu, Sichuan province in Southwest China between January 13 and February 24, 2020, by synergistically using micro pulse lidar, ground-level meteorological and PM$_{2.5}$ measurements, as well as ultrasonic anemometer observations. During the study period, Sichuan basin was primarily regulated by the straight west wind, with an averaged wind speed of 2–3 m/s at 850 hPa, indicative of a relatively stable atmospheric dispersion condition. TKE was positively correlated with PBL height but negatively correlated with PM$_{2.5}$. The PM$_{2.5}$ concentration varied dramatically during pre- and post-lockdown periods but remained near constant at a relatively low level during the lockdown period. Meanwhile, the negative correlation between TKE and PM$_{2.5}$ was much stronger during the lockdown and post-lockdown periods, when aerosol emissions were significantly reduced. Moreover, the correlation between TKE and PM$_{2.5}$ exhibited large diurnal variability, with the strongest correlation observed during the daytime when solar radiation and turbulent mixing generally reached their peaks. Overall, the observational results in Chengdu underscore the non-negligible impact of turbulence on regional PM$_{2.5}$ concentrations, which could help better understand the variation of regional air pollution events.

1. Introduction

Air pollution has raised great public concern worldwide due to its adverse impacts on human health (Cohen et al., 2017; Yin et al., 2020) and its disputed role in affecting Earth’s weather and climate system (Koren et al., 2012; Guo et al., 2019; Li et al., 2020). It has been long recognized that aerosol particles, especially the fine mode particle like PM$_{2.5}$ (aerosol particles with aerodynamics diameters no more than 2.5 μm), can significantly alter the planetary boundary layer (PBL) structure due to the radiative effects (Wang et al., 2013). The temporally varying
nature of PBL structure governs the dilution and diffusion of atmospheric pollutants, especially during severe haze episodes (Chow et al., 1994; Querol et al., 2001; He et al., 2002; Chaloulakou et al., 2003; Ding et al., 2005). Owing to the complex aerosol-PBL interaction, it is challenging to quantify the aerosol effect on the evolution of PBL (Li et al., 2017; Lou et al., 2019), especially in mainland China, where PM$_{2.5}$ loading has been significantly reduced due to the substantial emission reduction attributed to the implementation of clean air actions (Bai et al., 2019).

Severe haze pollution events tend to frequently occur under unfavorable meteorological conditions (Xu et al., 2004; Yang et al., 2005; Wang et al., 2015; Reid et al., 2016; Lolli, 2021), such as abnormally low PBL (Su et al., 2020), weak wind shear (Zhang et al., 2020), high humidity, frequent temperature inversion and small turbulent kinetic energy (TKE). Numerical simulations have been extensively conducted to examine the response of regional air quality on emission control and meteorological conditions. For instance, the pollution control measures during the 2008 Beijing Olympic Games had significantly reduced particle matter loadings, especially coarse particles. Few emissions from local sources and weak transboundary transport were two major causes for the significant decrease in particles concentrations. Similar effect was also revealed during the APEC China held in 2014, and the local emission reduction in Beijing was found to play more important roles than that in the surrounding regions in improving Beijing’s air quality (Guo et al., 2016; Liu et al., 2017). Recently, many scholars have examined the impact of COVID-19 pandemic on regional air pollution events (Chen et al., 2020; Lolli et al., 2020; Wang et al., 2020). During the stringent COVID-19 lockdowns, the Ozone Monitoring Instrument observed a 48% decrease in tropospheric NO$_2$ column densities over eastern China, and a recent study by Yue et al. (2020) pointed out that the national carbon emissions decreased by 9.8% in 2020, with the maximum reduction by 43.4% in transportation sector, compared to the first quarter of 2019. Surface PM$_{2.5}$ concentrations decreased by 12.6 μg m$^{-3}$ (24.9%), with the maximum reduction observed in the Yangtze River Delta.

Given its unique terrain and topography, Sichuan Basin located in the southwest of China suffers from air pollution events for years. Yet previous studies mainly focused on analyzing spatial and temporal variation patterns of air pollutants concentrations, few examined the impacts of meteorological conditions and emission sources (Wang et al., 2004; Li et al., 2007). Deng et al. (2012) analyzed the associations between PM$_{2.5}$ and PM$_{10}$ in Chengdu and meteorological conditions, indicative of significant impacts of air temperature, precipitation, wind speed, and high humidity on PM loadings. Besides, the synoptic-scale weather patterns and topography were also found to play important roles (Ning et al., 2019), mainly because they tend to induce changes in multi-scale circulation (Miao et al., 2017) and the subsequent evolution of PBL (Li et al., 2017; Cao et al., 2020). Bai et al. (2021) found that PM$_{1}$ pollution levels in Chengdu were mainly regulated by secondary aerosol formation and wind speed. Although many previous studies examined the impact of COVID-19 on regional air quality, few examined the interactions between PM$_{2.5}$ and TKE in China, particularly over the Sichuan Basin. To gain better understanding of the impact of boundary layer meteorological condition on regional air pollution over Sichuan basin, here we examined the possible associations between TKE and PM$_{2.5}$ concentration in Chengdu, by comparing their variations during different periods of the COVID-19 pandemic. The findings in this study would help better understand the critical role of meteorological conditions in favoring the formation of haze pollution.

2. Data and methods

2.1 Near-surface turbulence measurements

In this study, turbulence kinetic energy (TKE), a measure of near-surface turbulence, was calculated from the eddy covariance fluxes sampled at the Pengzhou meteorology tower (103.92°E, 30.03°N) in Chengdu. Fig. 1 shows the location of the monitoring tower. Specifically, wind speed, air temperature, relative humidity and atmospheric pressure were measured at nine specific layers from 10 m above ground level (AGL) up to 100 m at a 10-m interval, while the eddy covariance fluxes were collected at 60 m AGL, reporting TKE with a sampling frequency of 10 Hz. In order to ensure the validity and reliability of near-surface turbulence data, EasyFlux™-DL software (https://www.campbellsci.com/easyflux-dl) was used to perform corrections, including outliers removal and coordinate rotation. The TKE was calculated based on the following equation:

$$\text{TKE} = \frac{1}{2}(u'^2 + v'^2 + w'^2)$$

where $u$, $v$ and $w$ represent wind speeds along x, y, and z direction, respectively. Note that $u$, $v$ and $w$ are not just the wind speed along the 3 directions, but the sum of variances of velocity components. Although TKE measurements were estimated on a 30-min basis, the hourly averaged TKE data were applied in the following analysis.

2.2 PM$_{2.5}$ data

The hourly PM$_{2.5}$ concentrations measured at three stations deployed in Pengzhou, Pidu and Dujiangyan were averaged to indicate regional mean PM$_{2.5}$ loading. These three stations were all operated by the Chengdu Ecological and Environment Bureau, and their spatial distribution was shown in Fig. 1. To guarantee data quality, abnormal samplings in raw PM$_{2.5}$ observations were firstly removed before averaging by following the same criteria used in Bai et al. (2020). Specifically, PM$_{2.5}$ measurements out of the range between 1 and 1000 μg m$^{-3}$ and more than three standard deviations from the median of observations within a 24-h time window were all excluded.

2.3 PBL height

The profiles of aerosol backscattering coefficient acquired from the micro-pulse Mie scattering polarized laser LiDAR (EV-LIDAR, Beijing Yifu Herong Technology Co., Ltd.) were applied to obtain a continuous observation of PBL characteristics in Chengdu. The laser wavelength is 532 nm with a minimum vertical resolution of 15 m. Noteworthy is that only daytime measurements between 0800 and 1800 Beijing time (BJT=UTC+8 h) from non-rainy periods were utilized here until noted otherwise, given the dominance of buoyantly driven turbulence during daytime (Petaja et al., 2016; Lou et al., 2019).

Although there exists a variety of algorithms that can be applied to estimate PBL height from LiDAR measurements (Wang et al., 2012), such as gradient method (Wang et al., 2008), curve fitting (Steyn et al., 1999), wavelet covariance transformation (Brooks et al., 2003), standard deviation method (Hooper et al., 1986), and morphological filters (Vivone et al., 2021), here we used the covariance wavelet transform (CWT) method (Mei et al., 2019). A comparison analysis concerning the limitations and capabilities of several retrieval algorithms can be found in Haefelin et al. (2012). In this study, 27% of samples were filtered out after essential quality control. To evaluate the robustness of PBL height determined by micro-pulse lidar, radiosonde observations were also applied to retrieve PBL height based on the well-established potential temperature profile method (Bhurulkar, 1976). As shown in Fig. 2, both retrievals agreed well with each other, with a correlation coefficient (R) of 0.77 at 2000 BJT.

2.4 Auxiliary data

Meteorological factors such as pressure, wind, rainfall, and air temperature collected from the national meteorological observation station
in Pengzhou were used as well. In addition, motor vehicle flow data were acquired from the Chengdu Traffic Management Bureau. To characterize the large-scale circulation pattern, the ERA5 atmospheric reanalysis data were also used, which was provided at a grid resolution of $0.25^\circ \times 0.25^\circ$ at 1-h interval (Hersbach et al., 2020).

3. Results and discussion

3.1. PM$_{2.5}$ variations in Chengdu during the COVID-19 pandemic

On the afternoon of January 24, 2020, Sichuan province initiated the lockdown as the first-level public health emergency response to curb the spread of COVID virus. The resumption date (back-to-work) was set on February 4 by the local government. On the first day of the resumption, the total passenger volume of Chengdu Metro was only 431,100, whereas it was 3.19 million during the same period in 2019. To better examine the changes of air quality at different stages of COVID-19, we hereby postponed the date of resumption by 1 week later to February 9. Therefore, we defined the period of January 13 to 23 (11 days) as the pre-lockdown period, and January 24 to February 9 (17 days) as the lockdown period, while February 10 to 24 (15 days) as the post-lockdown period.

As shown in Fig. 3, prior to the outbreak of COVID-19 pandemic, motor vehicle flow in Chengdu was about 1 million per day, at which air quality was largely moderate to slightly polluted. In contrast, the daily flow of motor vehicles was significantly reduced to below 500,000 during the lockdown period. Noteworthy is that AQI decreased simultaneously with the air quality maintained a good level during most days. After the resumption, the flow of motor vehicles remained at a low level comparable to that during the lockdown period. However, AQI was found to increase apparently, with the air quality dominated by moderate to slightly polluted like those during the pre-lockdown period. To examine whether the observed air quality improvement could be attributable to the lockdown induced emission reduction or changes in meteorological conditions (Chang et al., 2020), we did a further comparison analysis of PM$_{2.5}$ concentrations between the same period of 2019 and 2020. Fig. 4 shows that the PM$_{2.5}$ concentrations during the same period of 2020 were significantly lower than in the same period of 2019.
2019, irrespective of sub-time period. Intriguingly, the reduction of PM$_{2.5}$ concentration during the lockdown period of 2020 reaches 47.5 μg m$^{-3}$, as compared with 2019, which is much larger than that other subperiods. This substantial decrease in mean PM$_{2.5}$ concentration could be due largely to emission reduction rather than meteorological conditions given its large magnitude.

Additionally, we compared the diurnal variability of PM$_{2.5}$ during these three subperiods. As can be seen from Fig. 5 a, the diurnal cycle of PM$_{2.5}$ was consistent with each other but with different magnitudes. Specifically, PM$_{2.5}$ concentration during the lockdown period was found the smallest among these three periods, followed by the post-lockdown and pre-lockdown periods. A shift in baseline PM$_{2.5}$ loading, while similar diurnal cycles likely suggest that local effects did not change much. Simultaneously, the diurnal cycle was not pronounced, which suggests that local effect was smaller compared to regional impact.

3.2. Impacts of synoptic circulation patterns

Fig. 7 compares the circulation patterns surrounding the study area during three subperiods of lockdown period caused by COVID-19 epidemics. The circulation in middle and high latitudes remained near constant during the whole study period, which was characterized by two low-pressure trough and one high-pressure ridge (Lake Baikal). In terms of the mean geopotential height at 500 hPa, Sichuan basin was primarily regulated by the straight west wind during pre- and post-lockdown periods. Meanwhile, the synoptic weather was dominated by cloudy to...
overcast weather with poor vertical dispersion conditions. Such a regime is favorable to the accumulation of atmospheric pollutants in a basin terrain. In contrast, during the post-lockdown period, the northwest flow from the plateau to Sichuan basin was mainly located in front of the ridge, while it was largely sunny and cloudy and the vertical turbulent mixing conditions were generally good. At the meantime, the low trough of India-Myanmar was relatively weak, thereby suppressing the long-range transport of water vapor. With respect to the average wind field at 850 hPa, the study area was calm with an average wind speed of 2–3 m/s. The results clearly indicated that the synoptic pattern during the post-lockdown period was favorable to the dispersion of atmospheric particles, differing largely from the worst synoptic circulation pattern observed during the pre-lockdown period.

It is well recognized there exists close connection between cold air and dispersion of atmospheric pollutant, and the changes of sea level pressure changes is generally thought as proxy for cold air outbreak. In terms of sea level pressure sampled at ground weather stations (Fig. 8a), no significant variations were observed during the pre-lockdown period. In contrast, there were apparent variations in sea level pressure after the lockdown, with a persistent pressure increase after February 7, which suggests the occurrence of cold air mass intrusion. Conversely, sea level pressure was observed to decrease after the lockdown till February 13,

Fig. 7. Spatial distribution of wind field at 850 hPa (black arrows) and geopotential height at 500 hPa (blue lines) during three different periods: (a) pre-lockdown, (b) lockdown, and (c) post-lockdown. Note that the region outlined by the red rectangle refers to the location of Chengdu. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Fig. 8. (a) Temporal variation of daily averaged sea level pressure at 1400 BJT, and (b) their corresponding anomalies of day-by-day variation of sea level pressure at 1400 BJT during three subperiods in 2019 (in blue) and 2020 (in red). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)
and negative anomalies in Fig. 8b imply a low-pressure control and temperature increase in turn. During the period of February 14 to 17, sea level pressure was on an increasing path with values even greater than 1035 hPa on February 15. An abrupt increase of 20 hPa in pressure implies that Chengdu was largely controlled by strong cold air till February 17.

Furthermore, we analyzed the temporal variation of averaged sea level pressure during the same period in 2019. Coincidently, there were four periods that experienced apparent increase of sea level pressure for the lockdown period for 2019 and 2020 (Fig. 8a), which indicates that cold air mass intrusion occurred. Also, the variation range of sea level pressure in 2019 is significantly higher than that in 2020 (Fig. 8b), indicating the cold air activity was much stronger in 2019. Therefore, the meteorological conditions during lockdown period in 2019 are much favorable for aerosol dispersion than those in 2020, but the PM$_{2.5}$ concentration in 2019 is higher than that in 2020. Therefore, it can be inferred that the lockdown measures play important roles in the reduction of PM$_{2.5}$ concentration.

Except for dispersion effect, the transboundary transport should be considered. Therefore, here we also compared the backward trajectory of air mass during this period simulated using the HYSPLIT model (Stein et al., 2015). As shown in Fig. 9, northeast winds dominated the air flow during our study period (8 out of 13 days during the pre-lockdown period and 12 out of 17 days during the lockdown period). In terms of the backward trajectory ending at 100 m AGL (right panel of Fig. 9), it is found that the aerosol particles mainly transported at a height below 300 m, except for 2 days at which the height was found to be even greater than 1000 m. The similar air mass trajectories during pre-lockdown and lockdown periods imply little changes in wind fields. Meanwhile, 24% of the air mass during the lockdown period was found coming from the southeast, where high pollutant concentrations were mainly observed (Fig. 10). Nonetheless, PM$_{2.5}$ concentration during this period was much lower than those during the pre-lockdown period. Therefore, we may conclude that the decrease in PM$_{2.5}$ concentration should be largely attributable to the lockdown rather than solely meteorological factors.

3.3. Correlation between TKE and PM$_{2.5}$

To gain insights into how the near-surface turbulence affects PM$_{2.5}$, PM$_{2.5}$ concentrations were grouped into five categories according to the distribution of data. Temporally, data samples were grouped into three clusters in reference to the diurnal cycle, including all-day (0000–2400 BJT), daytime (0800–2000 BJT), and night (2000–0800 BJT). Table 1 summarizes the correlation coefficients between TKE and PM$_{2.5}$ concentrations at different time periods. Overall, the PM$_{2.5}$ concentrations were negatively associated with TKE, which varied significantly throughout the day. Strong correlations were more likely to be observed during the daytime than at night. In other words, PM$_{2.5}$ concentration and TKE are increasingly correlated when the turbulence increases, indicative of the important role of TKE in determining diurnal variability of PM$_{2.5}$ concentrations.

As shown in Fig. 11, TKE gradually decreased with the increase of PM$_{2.5}$ concentration throughout the day, implying a negative correlation between them. The largest correlation coefficient (R of $-0.82$) was observed during 1000–1800 BJT and the effect of TKE on PM$_{2.5}$ concentration enhanced significantly. During the nighttime (2000–0800 BJT), correlation coefficient was the smallest (R of $-0.46$). Meanwhile, the standard deviation was the largest during the daytime whereas the
smallest at the night, indicative of more significant PM$_{2.5}$ variations in daytime than at the night.

Figs. 12–14 further compare the correlation between TKE and PM$_{2.5}$ at each individual period. Prior to the lockdown, the largest negative correlation ($R$ of $-0.83$) was observed mainly between daily averaged TKE and PM$_{2.5}$ (Fig. 12a), followed by the daytime (Fig. 12b and d). In contrast, the smallest correlation coefficient ($R$ of $-0.24$) was observed at night (Fig. 12c). In terms of the standard deviation, the maximum was found in the daytime at 1300–1500 BJT, and the minimum was observed during the nighttime. Distinct patterns were revealed during the lockdown period, at which the correlation differed small between day and night times (Fig. 13). The most significant negative correlation between PM$_{2.5}$ and TKE was found during the daytime at 1000–1800 BJT, followed by the night time (2000–0800 BJT), daytime at 0800–2000 BJT,

Table 1

| Period for $R_{\text{max}}$ (BJT) | All time | P-value | pre-lockdown | P-value | lockdown | P-value | post-lockdown | P-value |
|----------------------------------|----------|---------|--------------|---------|----------|---------|--------------|---------|
| 00–24 (BJT)                      | -0.74    | 0.16    | -0.75        | 0.08    | -0.61    | 0.43    | -0.75        | 0.17    |
| 08–20 (BJT)                      | -0.76    | 0.13    | -0.69        | 0.3     | -0.63    | 0.4     | -0.85        | 0.09    |
| 20–08 (BJT)                      | -0.49    | 0.44    | -0.24        | 0.7     | -0.5     | 0.37    | -0.53        | 0.35    |
| $R_{\text{max}}$                 | -0.96    | 0.01    | -0.93        | 0.02    | -0.89    | 0.04    | -0.95        | 0.01    |

$^a$ $R_{\text{max}}$ denotes maximum correlation coefficient and BJT denotes Beijing time (UTC+8).

Fig. 11. TKE shown as a function of ground-based PM$_{2.5}$ concentration for (a) the whole day (0000–2400 BJT), (b) daytime (0800–2000 BJT), (c) nighttime (2000–0800 BJT), and (d) daytime (1000–1800 BJT) during January 13 to February 24, 2020. Note that the correlation coefficients are calculated based on five bins of samples, each of which has an equal number of matchup samples.

Fig. 12. Same as Fig. 11, but for the period of pre-lockdown (January 13 to January 23, 2020).
and all-day. After the lockdown (Fig. 14), the most significant negative correlation was observed during the daytime at 0800–2000 BJT, whereas the weakest correlation was observed at night (R of −0.54). The varied correlation coefficients indicate that the correlation between TKE and PM$_{2.5}$ is elusive, which could be easily influenced by other factors.

3.4. Impact of wind field on the correlation between TKE and PM$_{2.5}$

Vertical wind shear (VWS) significantly influences TKE, thereby could change the correlation between TKE and PM$_{2.5}$. As shown in Fig. 15a, VWS varied significantly, ranging 0–8 m/s with the most majority below 4 m/s. Generally, the VWS in Chengdu was relatively small. Temporally, the VWS gradually increased along with TKE. Nevertheless, this positive response was reversed (i.e., VWS decreased with the increase in TKE) when TKE was greater than 1 m$^2$/s$^2$. Generally, VWS concentrated within 4 m/s, ranging 2–4 m/s when pollution events occurred (Fig. 15b). When TKE was greater than 0.7 m$^2$/s$^2$, the VWS decreased significantly as the turbulent diffusion rate increased. Besides, the distribution of TKE and VWS during the lockdown period (Fig. 15c) was similar to that of the post-lockdown period (Fig. 15d) as VWS increased along with the increase in TKE. Overall, the VWS in Chengdu was relatively small with most ranging below 4 m/s, and air pollution events were more likely to occur when VWS varied between 2 and 4 m/s. Fig. 16 presents the possible impacts of horizontal wind speed (WS$_{10}$, the horizontal wind at 10 m) on the correlation between TKE and PM$_{2.5}$. Shown is that WS$_{10}$ varied largely between 0 and 4 m/s with mostly below 2 m/s. The wind speed increased gradually with the increase in TKE. However, similar to VWS, the wind speed decreased slightly with the increase in TKE when it exceeded 1.05 m$^2$/s$^2$. Prior to the lockdown, the wind speed increased first and then decreased as TKE increased. Meanwhile, air pollution events occurred with the largest frequency when wind speed was less than 2 m/s and TKE was below 0.2 m$^2$/s$^2$. During the lockdown (Fig. 16c) and post-lockdown periods (Fig. 16d), WS$_{10}$ changed very little and remained less than 2 m/s. In summary, as TKE increased, the wind speed increased as well, but when TKE was greater than 1.2, the wind speed remained stable or decreased slightly as TKE increased. Similarly, Fig. 17 examined the possible dependence of correlation on horizontal wind speed at 60 m (WS$_{60}$). WS$_{60}$ generally varied between 0 and 6 m/s with most cases lower than 4 m/s. Prior to the lockdown, WS$_{60}$ was mainly between 0 and 3 m/s and the frequency of air pollution was the largest. Likewise, WS$_{60}$ gradually increased with the increase in TKE, and this trend reversed when TKE was greater than 1.0 m$^2$/s$^2$. Evident increases (>4 m/s) in WS$_{60}$ were observed during the lockdown (Fig. 17c) and the post-lockdown period (Fig. 17d).
4. Conclusions and summary

In this study, the impacts of TKE on PM$_{2.5}$ pollution during three subperiods of lockdown caused by the COVID-19 pandemic in Chengdu were investigated, with possible influential factors examined as well. The results indicate that the air quality in Chengdu was significantly improved due to the reduced human activity because of the lockdown measures. Generally, PM$_{2.5}$ concentrations in Chengdu fluctuated significantly with evident diurnal variability before and after the lockdown. Conversely, small PM$_{2.5}$ concentration variations were observed during the lockdown period. Overall, there was a positive correlation between TKE and PBL height, both of which were negatively correlated with PM$_{2.5}$ concentrations. When PM$_{2.5}$ concentration continued to increase or decrease significantly, there were persistent decrease or
increase in TKE. The correlation between PM$_{2.5}$ concentration and TKE was generally high during the daytime and decreased dramatically at night, with the largest correlation mainly observed during 1000–1800 BJT.

The VWS in Chengdu was relatively small and mainly varied below 4 m/s. When VWS ranged 2–4 m/s, the probability of the occurrence of pollution events was the largest. VWS and TKE were overall positively correlated. Also, the wind speed before the COVID-19 pandemic was less than that during the latter two stages. WS$_{10}$ was mainly below 2 m/s while 4 m/s for WS$_{50}$. Prior to the epidemic, the wind speed first increased and then decreased with the increase in TKE. However, during the rest two phases, the wind speed increased with the elevation in TKE. Overall, the findings revealed in this study would help inform us of the potential influences of near-surface turbulence on the variability of PM$_{2.5}$ concentration in Southwest China.

CRediT authorship contribution statement

**Xin Xia:** Conceptualization, Methodology, Writing – original draft. **Kui Zhang:** Conceptualization, Methodology, Writing – original draft. **Rong Yang:** Data curation, Software. **Yiwen Zhang:** Visualization, Investigation. **Dongfu Xu:** Validation, Writing – review & editing. **Jianping Guo:** Conceptualization, Methodology, Writing – original draft, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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