Responses to Reviewer Comments

Dear Editor and Reviewers,

We thank you very much for the valuable suggestions and comments, which are very helpful for improving the quality of our manuscript. All the comments raised by the reviewers have been addressed carefully and we prepared a list of point-by-point responses as below, and you can find our revisions in the change-tracked manuscript. Please note that reviewers' comments are in **black**, and our responses are in **blue**.

Sincerely yours,
Guicai Ning, representing all co-authors

Reviewer #1:

The manuscript by Debing Kong et al. provides the first attempt to examine the diurnal cycles of day-to-day temperature change and then investigates their possible impacts on winter air quality forecasting over the Sichuan Basin in China. A classification of meteorological situations is used to sort the main diurnal cycles of day-to-day temperature change occurring over this region. Three different diurnal cycles of the preceding day-to-day temperature change are identified. More interestingly, these identified diurnal cycles exhibit notably distinct effects on the evolutions of atmospheric dispersion conditions and air quality on the following day. These findings exhibit promising potential for air quality forecasting and are also critical to improve our understanding of air pollution in mountain-basin areas. The paper is well presented and logically organized. The proposed study is clear and methodologically robust. I recommend this paper to be published after these comments as follows are addressed.

Response: We thank you very much for your helpful comments. We have revised our manuscript carefully and prepared a list of point-by-point responses as below.

Comments

(1) The K-means clustering method used for classifying the diurnal cycles of day-to-day temperature change is one of the most important points in this paper. However, the methods discussion of the diurnal cycles' classification method used is too brief. For instance, the variable used in the K-means clustering is not made clear. This section needs to be much more comprehensive.

Response: Thanks very much for your valuable comment. According to your suggestion, the method discussion of K-means clustering has been rewritten to make this section much more comprehensive. The detailed revisions are shown as following:

Clustering methods divide the objects into specific groups, with the goal that all data objects assigned to the same cluster have common characteristics while different clusters have distinct characteristics (Darby, 2005). The clustering methods have been widely used in climate and environmental researches (Bardossy et al., 1995; Cavazos, 2000; Luo and Lau, 2017; Bernier et al., 2019). In this study, the regional average values of day-to-day temperature change in SCB and the K-means clustering method (MacQueen, 1967) are selected to classify the diurnal cycles of day-to-day temperature change, because of the simplicity and convergence characteristics of K-means clustering method. The details of K-means clustering method can refer to MacQueen (1967) and (Mokdad and Haddad, 2017) and is also provided in the **supplementary document**.

K-means is one of the most commonly used unsupervised learning algorithms that treat the renowned clustering problem (MacQueen, 1967; Hartigan and Wong, 1979; Mokdad and Haddad, 2017). This is, by automatically partitioning the given data set into a certain number of groups selected a priori (assume k clusters). The aim of the K-means algorithm is to divide M points in N dimensions into K clusters so that the within-cluster sum of squares is minimized. Then, the initial cluster centers are iteratively refined as follows.

Each data point is assigned to its neighboring cluster centroid based on the Euclidean distance metric.

Each cluster centroid is then re-calculated to be the mean of its constituent data points. This can be achieved by minimizing an objective function known as a squared error function. It is defined as:

$$J(v) = \sum_{i=1}^{k}\sum_{j=1}^{c_i}(||x_i - v_j||)^2$$

where

k: is the number of cluster centers;

c_i: is the number of data points in the i^{th} cluster;

$||x_i - v_j||$: is the Euclidean distance between x_i and v_j;

v_j: is the data points in the i^{th} cluster;

x_i: is the centroid vector of the i^{th} cluster.

When there is no further change in assignment of data point to clusters, the K-means algorithm converges to the optimal solution.

(2) In this paper, the authors found that the three different diurnal cycles of the preceding day-to-day temperature change exhibit notably distinct effects on the evolutions of air pollutants' concentrations on the following day. However, Figure 4&5 only depict the spatial distributions of the following day-to-day changes in absolute concentrations of particulate pollutants and gaseous pollutants. To exhibit the change range of air pollutants' concentrations on the following day more intuitively, I suggest the authors to add some investigations about the percentage values of the changes in air pollutants' concentrations.

Response: Thanks very much for your valuable comment. According to your comment, the percentage values of the air quality changes are also investigated and are shown as the follow figure. Moreover, the descriptions of the percentage values are also added in the revised manuscript.

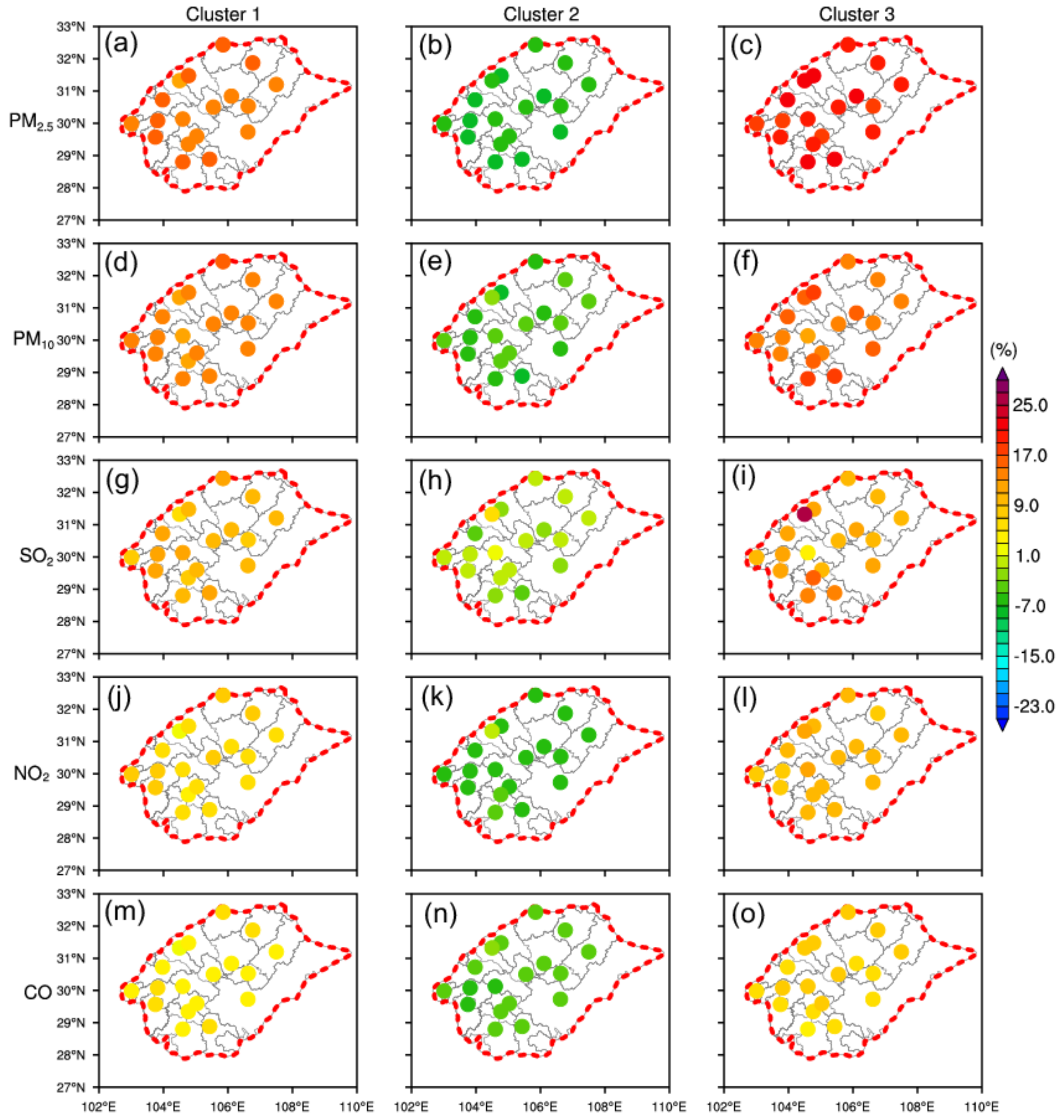

Figure S1 Spatial distribution of percentage values of the day-to-day changes in surface $PM_{2.5}$ (**a–c**), PM_{10} (**d–f**), SO_2 (**g–i**), NO_2 (**j–l**), and CO (**m–o**) concentrations following the three identified diurnal cycles within one day.

(3) By using K-means clustering method, three dominant diurnal cycles of day-to-day temperature change are identified in Sichuan Basin. The basic features of the three diurnal cycles are shown in Figure 3, Cluster 1 exhibits diurnal cycle with increasing temperature throughout all day, Cluster 2 shows diurnal cycle with decreasing temperature in the afternoon, and Cluster 3 exhibits diurnal cycle with decreasing temperature in the morning. As shown in Figure 3, the diurnal distributions of temperature changes corresponding to different clusters are very different, which also pose notably effects on the atmospheric

dispersion conditions and air quality. In general, atmospheric radiation and temperature advection are the important factors leading to changes in air temperature. In particular, atmospheric radiation could play a key role in resulting the different features in temperature changes between daytime and nighttime. Thus, the authors should investigate the behaviors of cloud cover (including low cloud cover and total cloud cover) to reveal the possible causes inducing the above three dominant diurnal cycles of day-to-day temperature change.

Response: Thanks very much for your valuable comment. In the revision, to reveal the underlying mechanism of the formation of the above three diurnal cycles of day-to-day temperature change, we also investigate the nighttime and daytime day-to-day changes in total cloud cover that could play a key role in temperature changes by modulating atmospheric radiations. **Figure 4** shows the nighttime and daytime day-to-day changes in total cloud cover associated with the three diurnal cycles. Corresponding to the diurnal cycle with increasing temperature (*Cluster* 1), the total cloud exhibits slightly increase in the eastern of SCB, while decrease in the western of SCB (**Figure 4a**). The dipole spatial distribution could result in a weak changes in the regional average temperature across SCB during nighttime (**Figure 3**). During daytime, negative changes in total cloud cover are observed in the entire basin (**Figure 4d**) that are beneficial to the obviously increasing in temperature in the afternoon (**Figure 3**). On the contrary, both the nighttime and daytime changes in total cloud cover are positive in the entire basin for *Cluster* 2 (**Figure 4b and e**), which could induce the increasing temperature during nighttime and decreasing temperature during afternoon (**Figure 3**). Corresponding to the diurnal cycle with decreasing temperature in the morning (*Cluster* 3), obviously decreasing in the total cloud cover are observed in the entire basin during nighttime (**Figure 4c**) that are beneficial to the temperature decreasing.

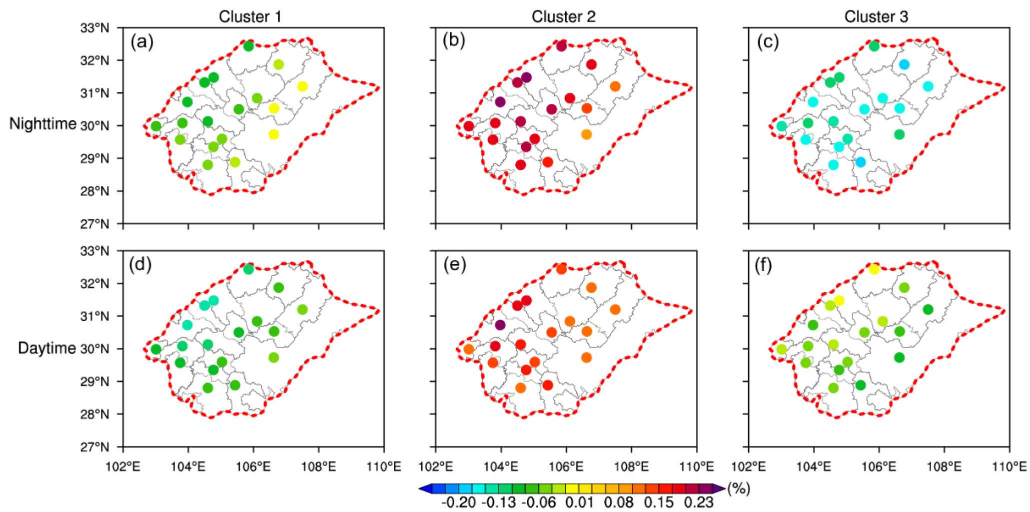

Figure 4 The nighttime (**a-c**) and daytime (**d-f**) day-to-day changes in total cloud cover associated with the three diurnal cycles.

(4) The blank space on the right side of Figure 1a is too large. I suggest the authors to adjust the X coordinate axis of Figure 1a to 70 °E~140 °E.

Response: The updated figure is shown as below.

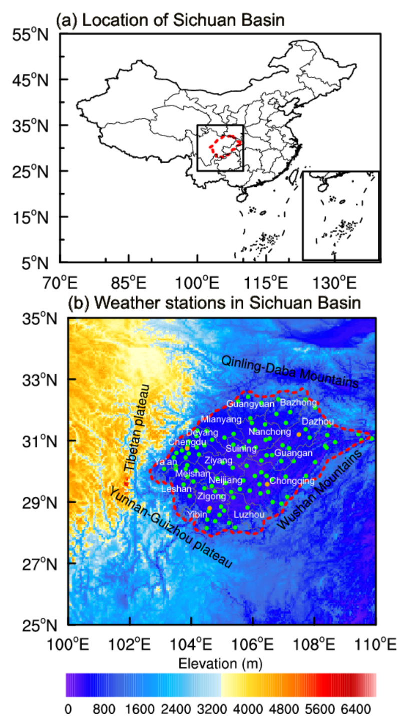

Figure 1 Map of Sichuan Basin (SCB) in Southwest China. (a) Location of SCB; (b) Topography of SCB (shading) and the spatial distribution of 105 meteorological stations (dots) in SCB. The dashed red line indicates the border of SCB. The orange dots indicate the meteorological stations with radiosonde measurements. The white text indicate the name of the major cities in SCB.

(5) Line 211 show higher temperature change in the level between middle level (800-850 hPa) than the lower level (900-950 hPa) -> show higher temperature change in the higher level (800-850 hPa) than the lower level (900-950 hPa).

Response: Corrected.

(6) Line 22: for the first time we -> for the first time, we

Response: Corrected.

(7) Lines 56-58: The key questions include … -> There are two key questions. The first one is what are the behaviors of ... and the second one is how these behaviors affect air quality ...

Response: Corrected.

(8) Line 59: understanding of winter air pollution -> understanding winter air pollution

Response: Corrected.

(9) Line 62: local residents -> residents

Response: Corrected.

(10) Line 69: conditions -> conditions'

Response: Corrected.

(11) Line 77: Our study is expected to -> We expect our study to

Response: Corrected.

(12) Line 91: since -> on

Response: Corrected.

(13) Line 113: can be used to evaluate -> can evaluate

Response: Corrected.

(14) Line 190: showed -> shown

Response: Corrected.

(15) Line 237: playing key role -> playing a key role

Response: Corrected.

References

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