Review result of “Urban-rural patterns and driving factors of particulate matter pollution decrease in eastern china” (egusphere-2025-2194)

Response to Reviewer #2:
reviewer’s comments are given in blue,
our responses are given in deep red.

Some of the content in the manuscript have been revised and updated.

We would like to thank the editor and reviewers for carefully reading the manuscript and providing detailed and constructive comments, which have helped a lot in improving the manuscript. We quote each comment below, followed by our response.

This Manuscript uses an Extreme Trees based machine learning model to identify the drivers in changes of urban and rural PM in China. This is a good effort, and the authors demonstrate reasonable applicability of their approach.

The authors are very grateful to the reviewers for their comments. We thank them for taking the time to review this manuscript and for their valuable suggestions, which have significantly improved the academic quality of this manuscript.

Following are key points that need to be addressed:

1. Since the authors use spatial - temporal datasets, why was LSTM and Convolutional Neural Networks not applied?

Thank you very much for your valuable suggestions. The main reason why LSTM and convolutional neural network (CNN) were not adopted to process spatio-temporal data is that the selection of models should be closely combined with the research objectives and data characteristics. The core objective of this study is to identify the driving factors of PM changes (such as human factors, meteorological conditions, etc.). Extreme tree models have significant advantages in feature importance analysis and nonlinear relationship modeling. They can directly quantify the contribution of each variable to PM changes (such as including the importance of permutation features, relative contribution, and Shapley value), while LSTM and CNN are more suitable for capturing complex temporal or spatial patterns. However, the support for feature interpretation of LSTM and CNN are relatively weak and there is no direct python that can be applied. In addition, extreme tree models can handle high-dimensional mixed data without complex sequence modeling. We believe that LSTM and CNN have great potential in spatio-temporal modeling and plan to explore their applications in subsequent research, such as handling more complex spatio-temporal dependencies based on the LSTM-CNN hybrid model. In conclusion, we employed an extreme tree model to achieve a high degree of match between the model selection and the research objective. In the future, we will further optimize the method in combination with the suggestions of the reviewers.

2. Figure 7: Explain the physical justification for why SHAP values for temperature are

negative in summer and positive in winter? Would these change between urban versus rural areas? For example, biogenic emissions might increase in summer at higher temperatures increasing secondary organic aerosol formation. In winter, reducing temperatures might increase demand for residential heating. Further discussions are needed here.

Thank you very much for your valuable suggestions. The phenomenon whereby the SHAP values for temperature in Figure 7 are negative in summer and positive in winter primarily stems from the SHAP value calculation method and the way in which temperature influences PM concentration. Firstly, SHAP values are calculated based on how a specific variable, such as air temperature, increases or decreases the average PM concentration. In other words, the SHAP value for temperature indicates its positive or negative impact on PM, reflecting how much the model-output PM concentration deviates from the average PM concentration value in either direction. Furthermore, research findings from several sources suggest that, in summer, rising temperatures may reduce PM levels through two mechanisms: enhancing photochemical reactions that generate ozone (O_3), which consumes some precursors, and promoting atmospheric dispersion that dilutes pollutants. This results in negative SHAP values. Conversely, in winter, low temperatures primarily increase PM concentrations by boosting coal-fired emissions due to heating demands, as well as creating poor dispersion conditions caused by temperature inversions. This leads to positive SHAP values. The two figures below show the SHAP values of various variables for PM in urban and rural areas, respectively. The impact of various variables, including temperature, on PM is primarily evident in urban areas, where the magnitude of the values and the rate of change are both higher than in rural areas.

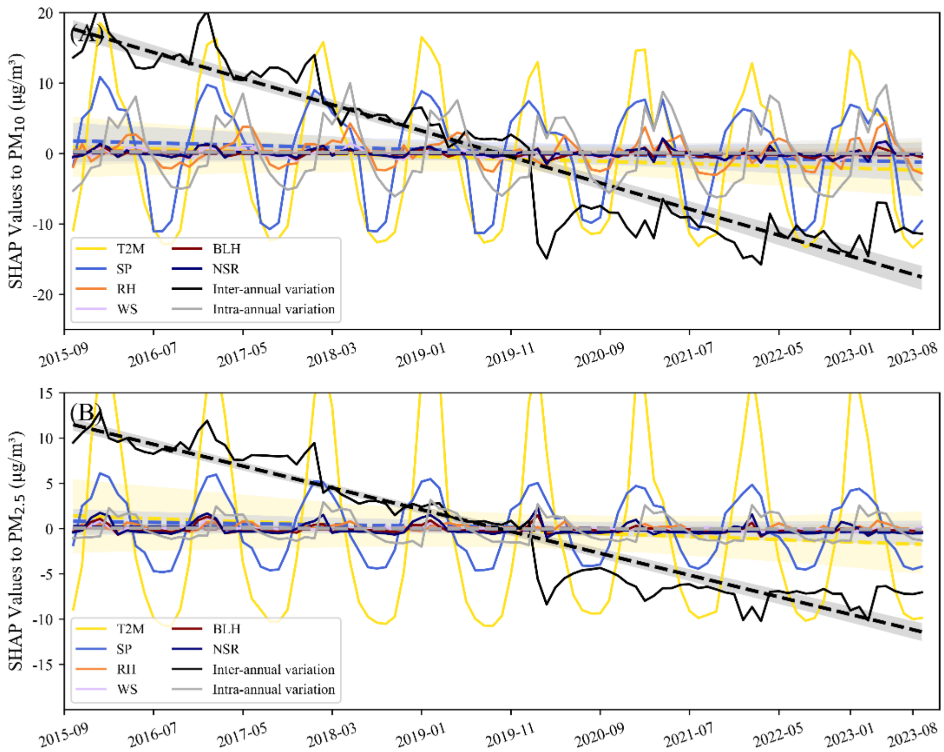

Figure S8. The SHAP values of each variable for PM in urban.

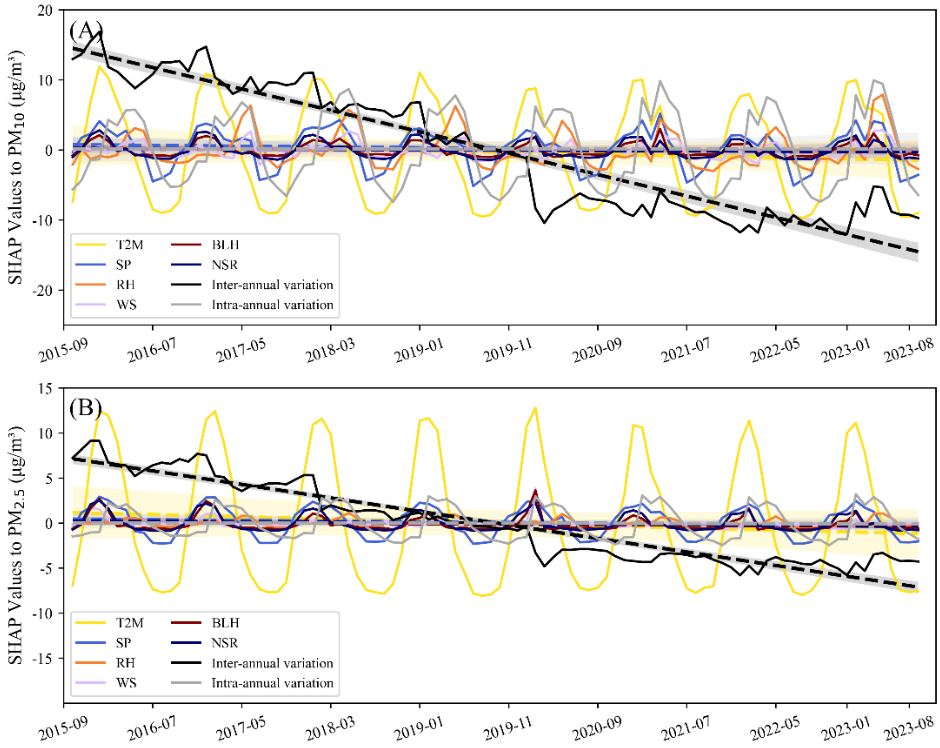

Figure S9. The SHAP values of each variable for PM in rural.

3. Figure 8 and related discussions: The figure is not clear. Discussions on lines 352-356 suggest different results for how interannual variations change between urban and rural areas using the 2 approaches: Relative contributions versus SHAP. Why are these different? Are SHAP values more reliable? The authors seem to just combine results from relative contribution and SHAP in their Abstract and Discussions. However, physical justification is needed to figure out what causes these differences.

Thank you very much for your suggestions. This study used relative contributions and SHAP values to explore the drivers of PM changes. However, the calculation methods for these two values differ. Relative contributions enable the results of each PM prediction to be broken down into bias and feature contributions. Each prediction can be presented as a simple sum of feature contributions, showing how features lead to a specific prediction. For a dataset with n features, each prediction is decomposed as follows: prediction = bias + feature_1_contribution + ... + feature_n_contribution. Here, 'bias' represents the model's inherent deviation, while 'feature_n_contribution' quantifies the magnitude of each variable's influence on the model output.

SHAP, based on the Shapley value from game theory, quantifies the positive or negative impact of each feature on the model prediction by calculating its average marginal contribution across all possible combinations of features. This method systematically eliminates interference from other features in order to assess the role of each feature in different combinations. Ultimately, it decomposes the model output into the independent contribution of each feature. For a dataset with n features, the SHAP value can be expressed as follows: prediction = mean + feature_1_contribution + ... + feature_n_contribution. Here, 'mean' is the average value of the PM time series and 'feature_n_contribution' is the feature SHAP value, representing the positive or negative impact of each variable on the model output and carrying a sign.

Thus, both relative contributions and SHAP values indicate the contribution of a variable within the model. The difference between them is that relative contributions break down each feature's contribution to a specific prediction, while SHAP values also show whether the feature's impact is positive or negative. As we clarified in the description of Figure 8, while the relative contribution suggests a significant contribution from interannual variability, the declining trend is not evident because it does not reveal that interannual variability has become a negative contributor to PM pollution. SHAP values, however, capture this distinction. The SHAP value changes for urban and rural areas shown in response to the second question demonstrate that the trend of lower SHAP values for interannual variability in urban regions is reasonable.

4. What about role of photochemistry? The authors include solar radiation, however, it does not show up as a key variable in SHAP interpretability analyses.

Thank you very much for your suggestion. First, we have corrected an error: we use the “net solar radiation at the surface” variable from ERA5 data to represent solar radiation, abbreviated as NSR in the text. However, in the previous version, this variable was incorrectly labeled as SSR in some figures. This has now been rectified. The current estimation model can be expressed as:

$$(PM_{10}, PM_{2.5}) = f\begin{pmatrix} TOAR_{1,2,3,4,6}, BLH, RH, SP, T2M, WD, WS, NSR, Height, LUCC, RK, \\ year, mon, doy, hour, lon, lat, SAA, SAZ, SOA, SOZ \end{pmatrix}$$

Then, in the SHAP interpretability analysis diagram (Figure 7), solar radiation is represented as NSR. Studies indicate that photochemical reactions play a significant role in the formation and transformation of fine particulate matter in the atmosphere through the “new particle formation effect” (Guo et al., 2020). Our SHAP analysis results also suggest that NSR influences PM and exhibits periodic variations.

5. Conclusions: Line 402-405: The authors rightfully acknowledge that anthropogenic influences are just represented by a time variable in their analyses. This is clearly insufficient. If possible, the authors should consider emissions, photochemistry (ozone, OH radicals, NOx, VOCs) etc. in their analyses.

Thank you very much for your suggestion. Time variables (year, month) effectively characterize cyclical patterns and long-term trends in human activity, serving as reliable proxy indicators in pollution analysis (Song et al., 2023). Monthly cycles directly reflect seasonal rhythms: winter heating spikes $PM_{2.5}$ and SO_2 levels (Liu et al., 2017), agricultural phases amplify ammonia emissions (Ma et al., 2025), and transportation peaks during holidays elevate NO_2 concentrations (Hua et al., 2021). Annual trends capture industrial evolution and policy impacts, such as the $PM_{2.5}$ reduction after implementing the "Air Pollution Prevention Action Plan" (Geng et al., 2024; Geng et al., 2021). As standardized, quantifiable metrics, time variables circumvent data limitations for complex activities (e.g., energy consumption, economic behaviors, urban sprawl), enable cross-regional comparisons without normalization, and reveal pollution responses to socioeconomic rhythms and policy efficacy (Dai et al., 2021; Shi et al., 2021). Furthermore, due to data limitations, it is extremely challenging to fully account for emissions and photochemical parameters (such as ozone, hydroxyl radicals, NOx, and VOCs). Therefore, we employed a time variable to simply represent human influence while applying meteorological normalization to PM data to eliminate the impact of sudden meteorological events, thereby ensuring the validity of our data analysis. In the future, we will explore methods for obtaining long-term emission and photochemical data for analysis to enhance the related research. We have added relevant explanations in Section 2.3 of the Methods section of the manuscript to explain the rationality of using time variables (year, month) as proxies for human activity.

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