This manuscript presents an innovative and practical approach to deriving black carbon (BC) mixing states using a machine learning (ML) framework, specifically LightGBM. The integration of SHAP analysis for interpretability and the application of the model to real-world data significantly enhance its relevance. The study is methodologically sound, with comprehensive results demonstrating the model's robustness and applicability. With previous comments addressed, further minor clarifications, particularly in defining particle categories and expanding on error analysis, will further enhance the paper's clarity and scientific rigor. Overall, this is a strong contribution to the field and can be published after minor revisions.

Specific comments:

1. Line 15-20: Briefly explain why LightGBM was chosen over other models like Random Forest or Neural Networks. Highlight its advantages for handling large datasets or nonlinear relationships.
2. Expand the discussion on how this method improves upon or complements existing techniques, such as the LEO fitting method or other machine learning approaches. For example, what specific challenges of previous methods (e.g., noise resistance, scalability) does this model overcome?
3. Although the study uses data from a single site, could the authors discuss the expected performance of the model in different environmental conditions or geographical regions? For example, how might differences in aerosol composition affect results?
4. Consider adding uncertainty quantification for model predictions. For instance, providing confidence intervals for particle size or optical property predictions would help assess reliability in practical applications.
5. The SHAP analysis identifies important features in the scattering and incandescence signals. However, the physical relevance of these features (e.g., why certain regions of the signal are more predictive) could be discussed more thoroughly.