**Reviewer #2 – Overview Response**

We thank Reviewer #2 for the thoughtful and forward-looking review, which emphasized the broader atmospheric and methodological implications of our study. The reviewer’s insights prompted us to clarify how semi-supervised learning extends supervised approaches in SPMS classification, to provide additional detail on the PALMS dataset provenance and experimental setup, and to discuss more explicitly the applicability of our framework to future field measurements. In response, we expanded the Data and Methods section to specify chamber conditions and data sources, detailed how labeled and unlabeled spectra were combined, and explained the composition of the unlabeled pool. The revised Discussion now connects the modest numerical improvements in model metrics to their scientific importance for identifying compositionally rare particle types—such as soot, feldspars, and bioaerosols—that drive radiative and microphysical processes. We also clarified the limits of semi-supervised learning in discovering new aerosol classes, added discussion of planned field validation, and noted that all source code will be made publicly available. We greatly appreciate the reviewer’s constructive guidance, which helped us strengthen the paper’s methodological rigor, atmospheric relevance, and long-term research significance.

**Reviewer #2 Summary Response: This paper investigated the performance of semi-supervised learning approaches in the automated classification of atmospheric aerosols from SPMS data. By leveraging unlabeled data, semi-supervised learning can enhance the model's generalization performance and mitigate the risk of overfitting. This study demonstrates the significant potential of semi-supervised learning and advanced machine learning architectures in improving aerosol classification. However, the new methods have not been tested using field data, limiting its potential implications. It can be recommended for publication after the following comments are addressed.**

**Specific comments:**

**1. Lines 118-120: The authors stated that a supervised learning approach cannot identify aerosol types absent from the training data. How did the semi-supervised learning method resolve this problem? It would be helpful to show the performance of both methods when aerosol types are absent from the training data.**

**Author Response.** We thank the reviewer for this important clarification. Semi-supervised learning does not generate new aerosol categories; rather, it enhances feature generalization by incorporating unlabeled spectra during training. This broadens the decision boundaries learned by the model and mitigates overfitting to limited labeled examples. We have revised Section 2.3 to clarify this distinction and now explicitly note that semi-supervised “methods improve classification robustness for boundary and minority classes but cannot identify truly novel aerosol types.”

We included: “Although semi-supervised learning cannot discover entirely new aerosol classes, it improves generalization for spectra lying near class boundaries or under-represented types. By incorporating unlabeled data through consistency regularization and pseudo-labeling, the model learns broader spectral manifolds and reduces overfitting to specific training clusters.” In the Introduction section and: “Semi-supervised methods improve classification robustness for boundary and minority classes but cannot identify truly novel aerosol types.” In the Methods section.

**2. Lines 142-150: It is unclear how the PALMS data were collected. Are these data obtained during chamber experiments? Details on the experimental procedures should be given. The model performance should also be tested for field data that is more complex.**

**Author Response.** We appreciate this comment and have revised the Methods section to specify that the PALMS dataset was collected during controlled laboratory and chamber experiments involving reference aerosol standards. Each particle type was atomized and sampled individually under reproducible conditions. We also acknowledge that the models have not yet been tested on field data and have added a statement outlining future work to evaluate performance on ambient atmospheric measurements, which typically exhibit greater compositional complexity.

The following sentence was added to the Data Methods section: “The dataset was obtained from PALMS measurements conducted during controlled laboratory and chamber experiments, where reference aerosols of known composition (e.g., Na-feldspar, K-feldspar, soot, biological, and secondary organic aerosol surrogates) were atomized and introduced into the PALMS inlet under dry conditions. Each particle’s time-of-flight was recorded concurrently as a proxy for aerodynamic diameter. Although the dataset represents controlled compositions rather than ambient mixtures, it provides a benchmark for algorithm validation prior to deployment on field measurements.”

**3. Lines 158-160: Were these unlabeled mass spectra collected for a mixture of different aerosol types? Did these data include inorganic aerosols?**

**Author Response.** We thank the reviewer for requesting clarification. The unlabeled dataset consists of spectra collected from mixed aerosol batches containing both inorganic and organic species. These unlabeled data were used to emulate realistic field-like variability and to support semi-supervised learning of generalized spectral features. Corresponding clarifications have been added in the Data Methods section.

The following: “The unlabeled dataset (14 478 spectra) comprises mixed aerosol batches that include both inorganic (e.g., mineral dust, sulfate, nitrate) and organic particles (e.g., secondary organics, biological material). These data were intentionally aggregated without type-level annotation to emulate real-world measurement conditions where composition is unknown.” Was incorporated in the Data Methods section.

**4. It will be helpful if the source code is open to the public.**

**Author Response**

We agree with the reviewer that open access to source code is essential for reproducibility. The full preprocessing and model-training pipeline has been archived on GitHub / Zenodo (link to be included upon final acceptance). A “Code and Data Availability” statement has been added at the end of the manuscript.