Assessing Uncertainties of Mass Dimensional Relations Derived from Imaging Probes Using Machine Learning

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Mass-dimensional (*m*-*D*) relations are critical constraints for remote sensing retrievals and microphysics modeling of ice-phase precipitation. However, these relations are typically derived from limited ground-based or airborne particle-imaging-probe observations. Because "true" per-particle mass and dimension are difficult to measure in situ, the uncertainties inherent in these relations remain poorly characterized. This study evaluates these uncertainties by leveraging a database of physically realistic, synthetic three-dimensional ice structures with known *m*, *D*, and other physical properties. By simulating imagery across various viewing angles, we assess how probe configurations influence the estimation of *m* and *D*. Machine-learning models trained on these synthetic data reveal that, while the accuracies of both *m* and *D* scale with the number of views, the benefit for mass estimation plateaus after three viewing angles. Furthermore, validation against an independent particle collection shows that mass estimates are highly sensitive to the *m*-*D* range of the training data. These findings highlight the need for broader training datasets to accurately quantify *m*-*D* uncertainty and to improve ice-phase precipitation remote sensing and modeling.