Hybrid Ensemble-Variational Data Assimilation of the Ionosphere-Thermosphere System

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The ionosphere and thermosphere form a tightly coupled system, referred to jointly as the I-T system, that plays a crucial role in space weather and satellite operations. This presentation introduces recent advancements in I-T modeling using a hybrid ensemble-variational data assimilation approach. Traditional variational approaches can solve non-linear cost functions when combining observations and model data, and ensemble approaches allow for using non-parameterized covariance derived from an ensemble of models. By combining the statistical advantages of ensembles with variational techniques, the hybrid approach provides improved insights into I-T coupling and uncertainty-informed predictions of both ionospheric and thermospheric parameters.

Our data assimilation system ingests a diverse set of ionospheric and thermospheric observations, including satellite ephemerides, Total Electron Content (TEC) from GNSS ground and radio occultation satellite receivers, and ionosonde measurements. These observations are assimilated into a physics-based background model of the I-T system, where updates can be propagated between the ionosphere and thermosphere. We present the methods used to build and tune this data assimilation system, including how correlations observed in ensemble runs of the background model inform the covariance matrix used in data assimilation. We also present results from a case study of the Gannon superstorm of May 2024, demonstrating the model's ability to improve predictions of electron and neutral density through leave-one-out analyses. Additionally, we showcase the application of this technique to Space Domain Awareness (SDA) scenarios, including enhanced orbital prediction accuracy as compared to other drag models and multiple-object conjunction assessment using uncertainty provided from the ensemble outputs.