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Reduced order emulation for operationalizing physics-based models in space weather

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Complex dynamical systems with a very large number of degrees of freedom are ubiquitous across domains. Terrestrial weather prediction relies on models of such complex systems that require large computational resources. These predictions are nudged by a large volume of spatiotemporal measurements through data assimilation since the chaotic dynamic system is highly sensitive to initial conditions. Enabled by the measurements and reanalysis datasets, emulators developed with AI/ML are garnering significant attention in terrestrial weather applications.

Space Weather, a sister domain of terrestrial weather, is no exception to this paradigm. Space Weather is the combined study of the Sun, the solar wind, and the geospace environment that can influence technological systems and endanger human life and health. Known impacts of space weather include radiation exposure for astronauts and civil aviation passengers and flight crew, damage to electric power grids, navigation/communication degradation, satellite charging and damage, and satellite operations. While there are great number of similarities between the two sister domains, there are challenges that are unique to space weather that limit the use of physics-based models in operations.

The primary challenge is the highly restricted spatiotemporal and imbalanced (storm v/s quiescent) nature of the measurements which poses challenges in data assimilation and reanalysis. Additionally, multiple space weather impacts involve requirements and integration with system of operations that involve additional processing steps whereby the computational cost limits use and application. For example, models of the thermosphere are desired to be deployed on resource constrained satellite platforms for orbit determination and prediction to avoid collisions in space.

Combining physics-based modeling, machine learning, and uncertainty quantification, we have been working on developing reduced order probabilistic emulators (ROPEs) for operationalizing physics-based ionosphere-thermosphere models. The ROPEs provide an approximate ~10,000x speed-up over full physics-based models, uncertainty estimates with predictions and simplify data assimilation. This talk will provide an overview of the developments and discuss potential for wider applications.