

Uncertainty Quantification of the Ionosphere-Thermosphere with WAM-IPE

Weijia Zhan¹ (weijia.zhan@colorado.edu), Alireza Doostan¹, Eric Sutton¹, Tzu-Wei Fang²
 1. University of Colorado Boulder
 2. NOAA Space Weather Prediction Center

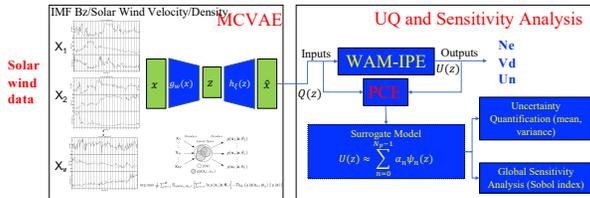
1. Abstract

One of the most frequent space weather events in the ionosphere-thermosphere (IT) system, equatorial and low latitude ionospheric irregularities can have a significant effect on radio transmission in the ionosphere. In order to narrow down the input parameters and identify the most crucial external drivers, it is necessary to quantify the uncertainty in the IT system.

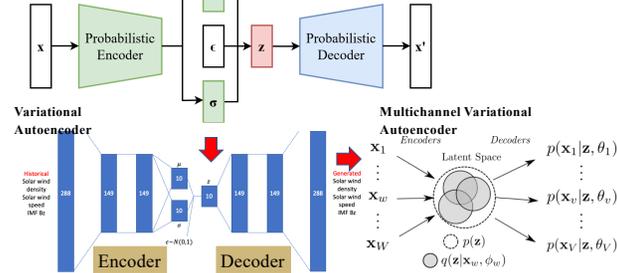
In this study, the uncertainties of the IT conditions simulated by the Whole Atmosphere Model-Ionosphere Plasmasphere Electrodynamics (WAM-IPE) for **different solar wind drivers** are estimated. Using an advanced multichannel variational autoencoder (MCVAE), the historical solar wind density, velocity, and interplanetary magnetic field (IMF) data are gathered to generate synthetic data for driving the model. We drive WAM-IPE and produce an ensemble of simulations using the synthetic solar wind parameters. Then, polynomial chaos expansion (PCE) is used to approximate the quantities of interest (QoI) and to estimate the statistical metrics of the QoI based on the expansion coefficients. Using the PCE-based UQ and Sobol index, we find that (1) while the UT variation of solar wind drivers causes greater uncertainty during nighttime, the average state of IT system could modify the uncertainty and lead to the spatial distributions; (2) the polarity of IMF Bz plays dominant role in the uncertainty.

2. Methodology

2.1 Workflow



2.2 MCVAE



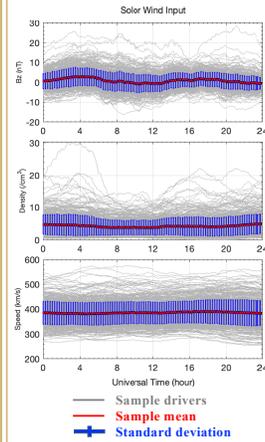
2.3 PCE-based UQ and sensitivity analysis

$$u \approx \hat{u}(x, t, z) = \sum_{i=0}^{N_p-1} \alpha_i(x, t) \psi_i(z)$$

ψ_i denote polynomials (Hermit in this study) and α_n denote expansion coefficients. $N_p = \binom{d+p}{p}$ is the number of expansion factors. The statistical metrics of interest can be obtained directly from the coefficients. The mean and variance can be obtained by $E[u] \approx E[\hat{u}] = \alpha_0$, and $V[u] \approx V[\hat{u}] = \sum_{i=1}^{N_p-1} \alpha_i^2$. First order Sobol index: $S_k = \sum_{i \in I_k} \alpha_i^2 / V[u]$, $I_k = \{i \in N_0^d; i_k > 0, i_{m \neq k} = 0\}$. Total effect Sobol index: $S_k^* = \sum_{i \in I_k^*} \alpha_i^2 / V[u]$, $I_k^* = \{i \in N_0^d; i_k > 0\}$ (used in this study)

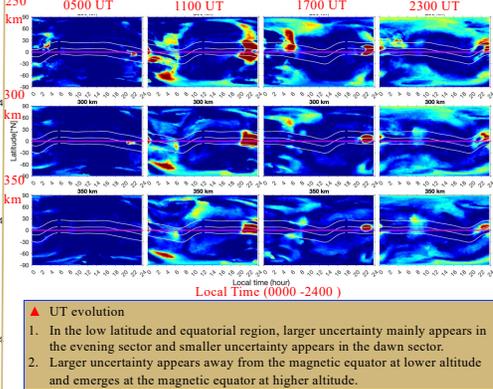
3. Results and Discussion

3.1 Solar wind input

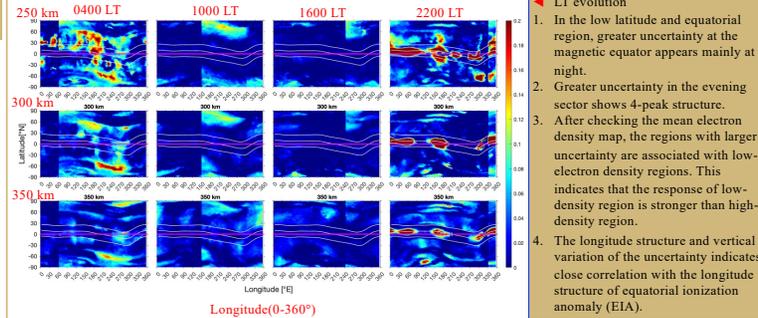


3.2 Uncertainty

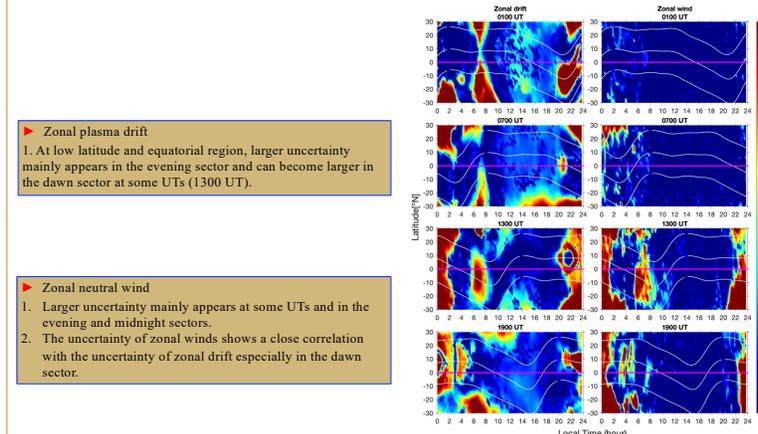
3.2.1 Universal time evolution of uncertainty (Ne)



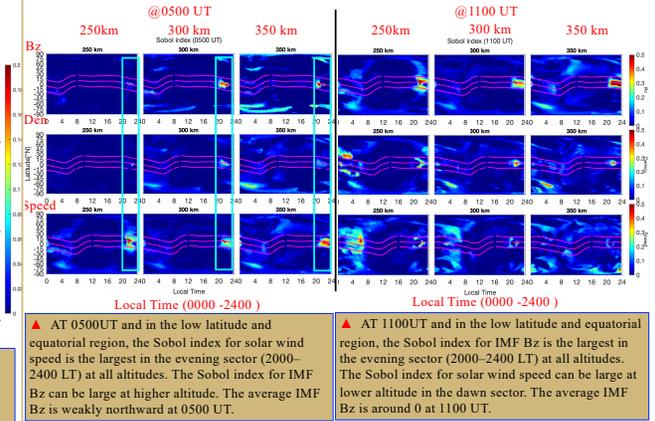
3.2.2 Local time evolution of uncertainty (Ne)



3.2.3 Universal time evolution of uncertainties (Vd_zonal, Un_zonal@300 km)



3.3 Global sensitivity analysis (std(Ne)*Sobol index)



4. Conclusion

- The solar wind produces the most electron density uncertainty in the low-latitude and equatorial ionospheres, with higher values typically appearing in the evening sector.
- The greater electron density uncertainty in the evening sector emerges away from the magnetic equator at lower altitudes, whereas it emerges at higher altitudes.
- The uncertainty in electron density at specific local periods in the nighttime sector demonstrates longitude dependency with four peaks, indicating a strong association with the EIA's longitude structure.
- The UT and LT evolutions of electron density uncertainty reveal a strong correlation with the equatorial ionization anomaly, with more uncertainty appearing in regions with lower electron densities.
- The uncertainty of the zonal neutral wind at 300 km is considerably higher between dawn and dusk for several UTs.
- For some UTs, the zonal plasma drift uncertainty increases in the dawn and dusk sectors and has a substantial relationship with the zonal wind uncertainty.
- The sensitivity analysis indicates that IMF Bz polarity play a dominant role in the variability. When IMF Bz is northward, the solar wind could be important to the variability of low latitude ionosphere, otherwise IMF Bz is the dominant factor.

References

- Antelmi et al., Proceedings of the 36 th International Conference on Machine Learning, Long Beach, California, PMLR 97, 2019.
- Fang, T.-W., Fuller-Rowell, T., Yudin, V., Matsuo, T., & Viereck, R. (2018). Journal of Geophysical Research: Space Physics, 123.
- VAE: https://en.wikipedia.org/wiki/Variational_autoencoder.
- Hadigol, M., Maute, K., & Doostan, A. (2015). Journal of Power Sources, 300, 507-524.

Acknowledgment

The works by WZ, AD, ES, and TWF are supported through National Science Foundation (NSF) SWQU AGS 2028032. We would like to acknowledge high-performance computing support from Cheyenne (doi:10.5065/D6RX99HX) provided by NCAR's Computational and Information Systems Laboratory, sponsored by the National Science Foundation.