## An investigation of ionospheric forecasting using TIE-GCM and EnKF

Scott M. Rabidoux<sup>\*</sup>, Roy S. Calfas, and Thomas L. Gaussiran II Applied Research Laboratories, The University of Texas at Austin, Austin, Texas 78758

The characterization and forecasting of ionospheric electron density is an important area of research due to the ionosphere's impact on positioning, navigation, and communication systems. In recent years, a number of physics-based ionospheric models (e.g. TIE-GCM, CTIPe, SAMI3) have been used in ensemble Kalman filter algorithms to try to characterize and forecast various ionospheric properties. Few studies, however, look at using these types of models to forecast ionospheric electron density more than an hour into the future. For this work, we created a forecasting model that uses the Thermosphere Ionosphere Electrodynamic General Circulation Model (TIE-GCM) with an ensemble adjustment Kalman filter (EAKF) algorithm [Anderson, 2003] to forecast ionospheric electron density. We present results from experiments that investigate our model's ability to predict vertical TEC measurements up to four hours into the future, as well as highlight the effects of some key implementation decisions on the performance of physics-based EnKF models.

In the experiments presented here,  $1^{\circ} \times 1^{\circ}$  grids of vertical TEC observations (available via the Madrigal database) are assimilated into the EnKF, and the forecasted vTEC measurements are scored against the same dataset. In each experiment, vTEC observations are assimilated every hour, and a 4-hour forecast is produced after each assimilation. Using this approach, we can observe how 1-, 2-, 3-, and 4-hour forecasts perform thoughout the entire assimilation period. Additional results presented in this work showcase the importance of certain implementation decisions, such as 1) choosing between using a  $2.5^{\circ} \times 2.5^{\circ}$  grid or a  $5^{\circ} \times 5^{\circ}$  grid in TIE-GCM, 2) using covariance inflation to maintain ensemble spread, and 3) updating external driver values along with state variables with each assimilation of data.