32nd URSI GASS, Montreal, 19-26 August 2017

# The Space Weather Forecast Testbed (SWFT): Forecast Tools for Upper Atmosphere Space Weather

Anthony J. Mannucci*[(1)], Chunming Wang[(2)], Xing Meng[(1)], Olga P. Verkhoglyadova[(1)], Bruce T. Tsurutani[(1)],
Gary I. Rosen[(2)] and Surja Sharma[(3)]
(1) Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, USA
(2) University of Southern California, Los Angeles, CA, USA
(3) University of Maryland, College Park, MD, USA

## 1. Introduction

We will describe a combination of modeling and data analysis techniques being developed as a part of the NASA and NSF partnership for Collaborative Space Weather Modeling to develop a capability for forecasting anomalies in the Earth's ionosphere. We are in the process of delivering this capability, the Space Weather Forecast Testbed (SWFT), to NASA's Community Coordinated Modeling Center (CCMC) for community use. The testbed is the beginning of an effort to build a platform for the community to deposit relevant data, algorithm and validation results to improve forecast skills.

## 2. Approach

Ionospheric space weather can be defined as the development of "anomalous" conditions caused by disruptions in the interplanetary plasma environment near Earth. Identification of such anomalies is usually made by comparing the condition of the ionosphere a few days before and after the disturbances. Previous analyses of solar and interplanetary data have shown that significant disturbances in these data do not lead to obvious anomalies in the ionosphere. This indicates that there may be multiple connections between interplanetary events and ionosphere anomalies, and the relationship among these may be highly complex. This is particularly true when generalizing the concept of space weather to include ionospheric anomalies caused by coupling from below.

Advances in data mining techniques have shown considerable promise at characterizing the presence of anomalies in large quantities of data, as well as in extracting previously unknown quantitative connections between large data sets. In the past three years, our team has developed techniques to systematically identify anomalous conditions in the Earth's ionosphere from a historical archive of several years of observationally based data. We have performed regression analyses to characterize relationships between ionospheric anomalies, the solar wind and other space weather observations. Our analyses show that a forecast technique based on data mining for ionosphere anomalies can be constructed using currently available data. New data sets and algorithms can be incorporated to assess forecasting scenarios that are not now included.

Our initial data set for representing the condition of the ionosphere is the data driven Global Ionosphere Maps (GIM) produced daily over that past 20 years by the Jet Propulsion Laboratory. A GIM provides a map of Vertical Total Electron Content (VTEC) over the globe at one-degree latitude and one-degree longitude resolution for each 15 minutes. For solar observations, we use post-processed observations such as solar wind velocity, ion density, temperature, magnetic field, the F10.7 and sunspot indices. Geomagnetic indices such as Dst, Ap, Kp are incorporated. Community listings of space weather events are used for validation.

As part of this testbed, we are populating a database of first-principles coupled thermosphere-ionosphere model runs, using models currently supported at the CCMC, that are run in a partial "forecast mode". As currently defined, forecast mode model runs use measured solar wind inputs. However, an algorithm calculates a future solar F10.7 index based on past data. The F10.7 algorithm could be the basis of a forecast a few days in advance. We similarly compute, for model input, a hemispheric power (HP) index and geomagnetic indices, based solely on solar wind parameters. Such algorithms prepares us for a transition to purely forecasted model inputs once solar wind forecasts are the basis for upper atmosphere forecasts.

Our algorithms are based on unsupervised anomaly identification. We rely on a collection of measures, or metrics in mathematical terms, to represent the degree of difference between two GIMs. These metrics are also applicable to output from first-principle model runs. We augment these metrics with algorithms for "forecast variables", a type of metric designed to provide insight into the physical processes causing anomalies under geomagnetic storm conditions. Our results indicate that advanced data mining techniques have the potential to produce statistically reliable forecasts for ionosphere anomalies based on solar and space observations.