Investigating the Sensitivity of Ionospheric Plasma Drift to the Neutral Wind Profile observed by ICON

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Introduction

- The Earth's ionosphere is the upper layer of our atmosphere - the border between us and outer space. It is constantly changing due to the Sun's energy ionizing various particles, but it does not follow the daily cycle of the Sun consistently.
- There is ionospheric variability present that can be attributed to winds in the thermosphere. (Figure 1)[1]
- The aim of this investigation is to understand how the changes in these upper atmospheric winds cause fluctuations in the in situ plasma densities of the ionosphere.

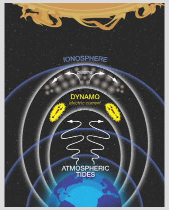


Fig 1: Showcases how the in situ plasma density in the ionosphere is influenced by thermospheric winds ('tides'). Source: NASA Goddard's Scientific Visualization Studio

Data and Methods

For this analysis, the data from the ICON mission's Ion Velocity Meter (IVM) and Michelson Interferometer for Global High-resolution Thermospheric Imaging (MIGHTI) was utilized.

- IVM measures the plasma densities and drifts. [2]
- MIGHTI data contains the horizontal neutral wind profiles from the altitude range of 90-300 km. For this analysis, the zonal winds were utilized. [2]
- The data is taken from only the "perfect" magnetic conjunctions at equatorial crossing. (Figure 2)

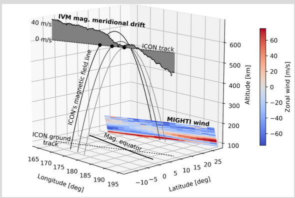


Fig 2: This diagram shows how ICON takes measurements of the MIGHTI horizontal wind profiles and the in situ ion drifts. Adapted from Immel et al. (2021)

Data Filtering

- The IVM data is filtered by using quality flags, and only considering later local times (hours 11-16).
- The MIGHTI data consists of 84 different altitude profiles spread through the range, and 80 of these are used for the analysis (alts 2-82).

Linear Regression Modeling

- Using the zonal wind profiles and Python's SKLearn, the data is split into training and test sets to create a linear regression model predictor that generates a predicted meridional ion drift profile based on the zonal winds.
- Due to overfitting, a dimensionality reduction methodology (principal component analysis) is used to increase model efficiency (Figures 3,4).

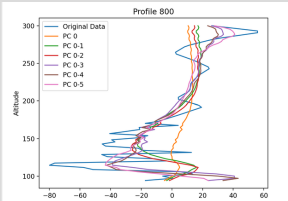
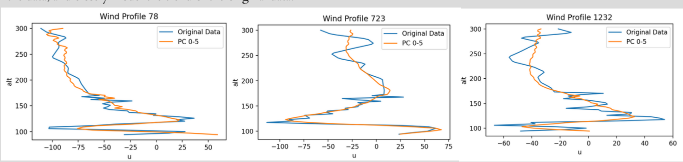


Fig 3:: Principal Component Analysis- the original wind profiles are 'reduced' into 'weights' (linear combination of specific features from the dataset). The plot showcases how utilizing the first 5 features (out of 80) generates the reduced profiles and represents their variability relatively effectively.

Fig 4 : Principal Component Analysis-these plots exemplify how the first five principal components from the PCA begin to recreate the variability in the data, and closely model the trend of the original data.



Change in Meridional Drift Predictor

- After developing a strong understanding of how PCA works, this is further utilized to create a linear regression model to predict the change in the meridional drift from the change in the zonal winds.
- To isolate day-to-day variability from other kinds of variability (seasonal, longitudinal, etc.), a change in time interval was defined such that it yields the change of the wind at nearly the same place and local time, separated by almost 1 day (24-24.15 hours).
- When the PCA is applied, a number of components needs to be selected. This is the number of features that will be used in the linear regression model to optimize the bias-variance tradeoff and ensure there is no overfitting/underfitting (Figures 5,6).

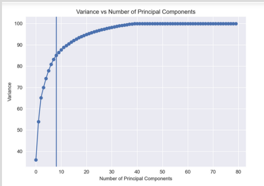
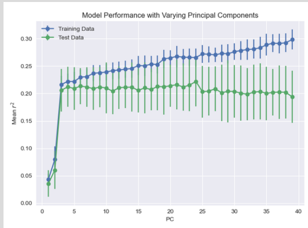


Fig 5: Principal Component Selection
The plot showcases the number of features (the number of principal components- which are the 80 altitude profiles) versus their contribution to the variance. If all 80 features are used, the model encapsulates 100% of the variance. In this case, the 8th principal component is used to capture 85.66% of the variance.

Fig 6: Principal Component Linear Regression Model Performance
This plot validates the choice of the principal component number. As we can see from the r^2 value, (which is a metric of how well the changes in zonal winds are able to capture the variance in the meridional drifts) for both the train and test set, after the 8th component, the model's performance only slightly increases for the test set. The error bars were determined by using multiple randomized train test splits, and determining the standard deviation of the r^2 value.



- The r^2 value was used to evaluate the model performance on both the training and test sets. They seem to quantitatively match the Immel et al. [2021], conclusions that were made that the found correlations of r ~ 0.47 to 0.56, which is consistent with the r^2 from this model of ~ 0.2. [1]

Comparative Study: Conductivity Weighted Winds

- Immel et al. [2021] utilized a different dimensionality-reduction approach, using a conductivity model to reduce the entire neutral wind profile to two features, the Hall and Pedersen conductivity weighted winds (CWW). [1]
- To create a comparison between the PCA-based linear regression model, a weighted-wind model was created. For this model, the mean of the wind was taken over the crossings, and once again, the change in this mean in the 1-day interval was determined.
- To evaluate the performance of these models multiple randomized train test splits were used. Then, finding the r^2 value of each one of these model instances led to the mean and standard deviation being determined. (Figure 7)

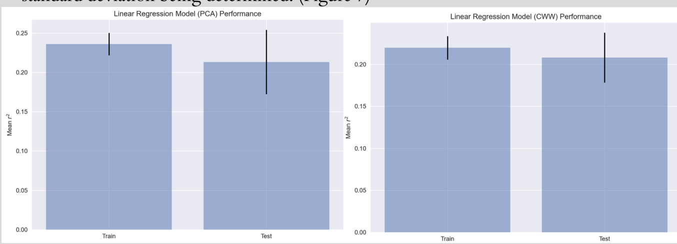


Fig 7: Performance of the Linear Regression Models
This plot shows the mean r^2 value of a randomized run of 100 train-test splits. As shown, the train sets outperform the test consistently, and the PCA model and Weighted-Winds model seem to have similar outcomes for the mean r^2.

Conclusions

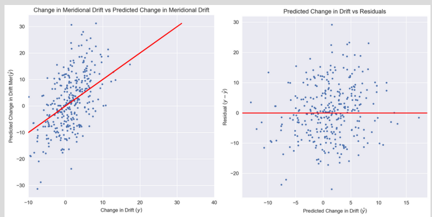


Fig 8: Linear Regression Model: Prediction results

- The plot on the left showcases how the change in predicted meridional drifts correlates with the actual change in measured values from the IVM data. As shown in the plot, there is a positive correlation between the predictions and the actual values, and overall the model seems effective in this regard.
- The plot on the right showcases the residuals (the difference between the measured changes in meridional drifts from the IVM data and the predictions made using the changes in zonal winds) vs the predicted drifts. There is no clear trend in the data, and it is clustered around the x-axis, further showing that a linear regression model can be used effectively.

- A dimensionality-reduced principal component regression model can be used to effectively create a predictor for the meridional ion drifts using the zonal winds.
- The performance of the PCA model is comparable to that of one that utilizes the Hall and Pedersen conductivity-weighted winds- without making any assumptions about the conductivity, while the conductivity-weighted wind (CWW) approach does need to assume a conductivity profile.

Sensitivity Profiles

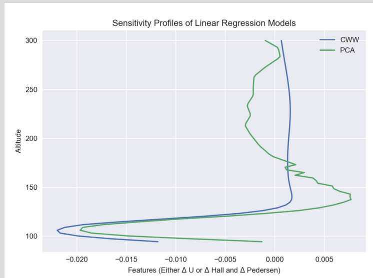


Fig 9: Sensitivity Profiles
The plot showcases the dependence of the linear regression model on the features from the PCA components and the Hall and Pederson winds. Both models have 'weightage' profiles that follow a similar trend throughout all of the selected altitude zonal wind profiles.

Linear regression can be modeled by an equation, and the coefficients (or 'weights') in this equation are what build up the sensitivity profile (as shown in Figure 9).

$$\Delta v = c_0 * \Delta u_0 + c_1 * \Delta u_1 + ...$$

Ongoing Work

- For this study, only the zonal neutral wind profiles were utilized. Adding on the meridional winds may provide additional insights into correlations between the winds and the meridional ion drifts.
- The PCA procedure's efficiency increases when the datasets it is being used upon are scaled and centered- so a methodology to scale this data could be used to improve model performance.
- A similar analysis could be run on the ion density data to understand how the changes in the densities are related to the change in the winds.
- The PCA component profiles hold information that is correlated to other factors that influence the meridional drifts (e.g. local time), and investigating these could generate a better understanding of the ion drifts.

References

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2. Immel, T. J., England, S. L., Mende, S. B., Heelis, R. A., Englert, C. R., Edelstein, J., Frey, H. U., Korpela, E. J., Taylor, E. R., Craig, W. W., Harris, S. E., Bester, M., Bust, G. S., Crowley, G., Forbes, J. M., Gérard, J.-C., Harlander, J. M., Huba, J. D., Hubert, B., … Sirk, M. M. (2017). The Ionospheric Connection Explorer Mission: Mission Goals and Design. Space Science Reviews, 214(1). https://doi.org/10.1007/s11214-017-0449-2

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