Adjusting the Ratio of Geomagnetic Storm Days to Quiet Days for Enhanced Ionospheric TEC Prediction: A Deep Learning approach

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The ionospheric Total Electron Content (TEC) is a critical parameter for the accuracy of satellite communication and navigation systems. Geomagnetic storms, primarily driven by solar activities, introduce significant variability in the ionosphere, posing substantial challenges to TEC prediction. Traditional models often fail to capture the complex dynamics introduced by these irregular events, leading to inaccuracies in TEC forecasting. This study aims to enhance the predictive accuracy of deep learning models for TEC by adjusting the ratio of geomagnetic storm days to quiet days in the training dataset.

Our approach utilizes an innovative deep learning framework, specifically the Convolutional Long Short-Term Memory (ConvLSTM) network, as proposed by Jeong et al. (2024). This model is adept at capturing spatial-temporal relationships, making it particularly suitable for TEC prediction. Additionally, we employ TEC maps reconstructed from the Deep Convolutional Generative Adversarial Network - Poisson Blending (DCGAN-PB) model (Jeong et al. (2022)), which provides enhanced data quality for training purposes.

By systematically adjusting the ratio of storm to quiet days in our training dataset, we aim to investigate how the model's predictive accuracy responds to different levels of storm representation. This method allows us to assess the model's ability to generalize and perform under various ionospheric conditions, a crucial aspect often overlooked in traditional approaches. Our findings suggest that a balanced representation of storm and quiet days in the dataset significantly improves the model's ability to accurately predict TEC during geomagnetic disturbances.

Furthermore, our research delves into the impact of dataset composition on model performance. We demonstrate that a carefully curated dataset, which accurately reflects the real-world distribution of geomagnetic storm occurrences, is essential for developing more reliable ionospheric prediction models. This study not only contributes to the field of ionospheric science but also provides valuable insights into the optimal training strategies for deep learning models in atmospheric and space weather forecasting.

In conclusion, our research underscores the importance of dataset composition in enhancing the performance of deep learning models for TEC prediction. The use of advanced deep learning techniques, such as ConvLSTM and DCGAN-PB, combined with strategic dataset management, paves the way for significant improvements in the accuracy of ionospheric TEC forecasts, especially during geomagnetic storm conditions.

Reference

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