Machine Learning-based Prediction of global TEC and High-latitude ROTI Maps

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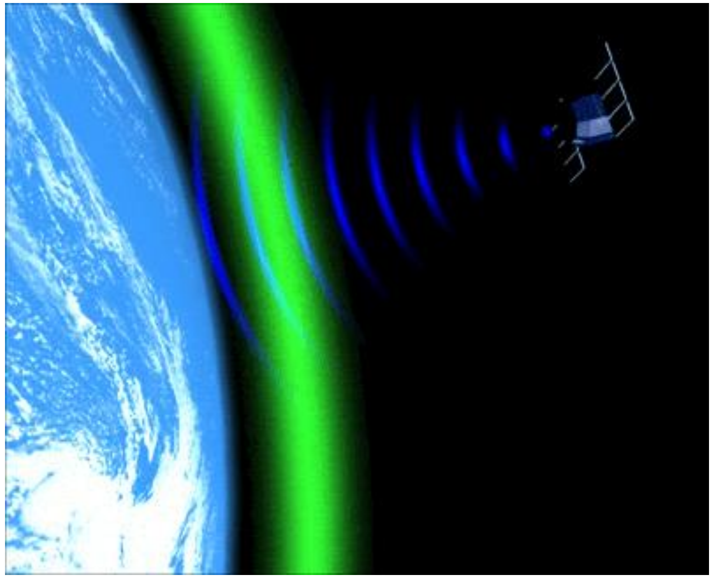
AGU FALL MEETING

SCIENCE is SOCIETY

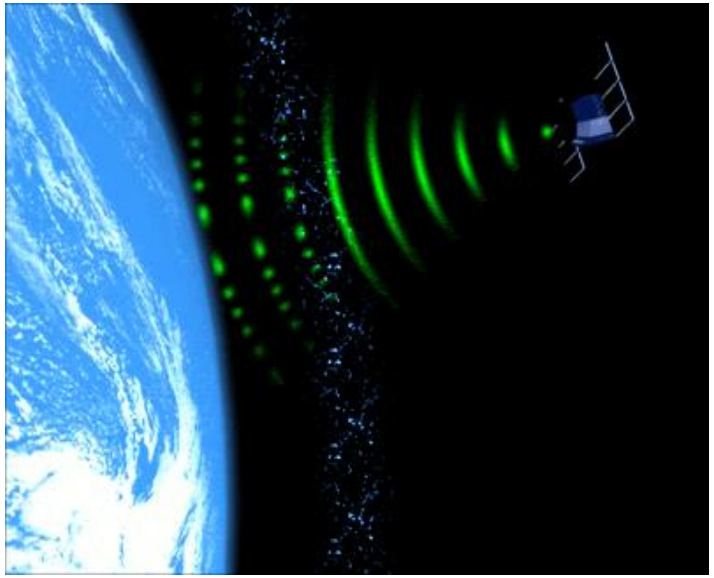
Outline

- Background & Motivation
- Machine Learning (ML) Prediction of Ionospheric Parameters
  - Predicted indicators: TEC & ROTI
  - ConvLSTM-based ML Algorithm
- Two Applications
  - Global ionospheric TEC Forecasting
  - High-latitude ROTI maps
- Conclusion and future work

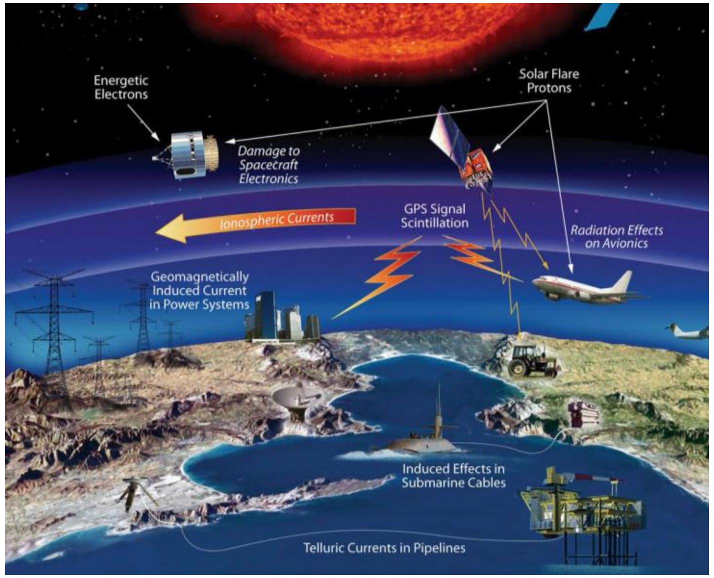
Background & Motivation



Ionosphere **TEC** Delay



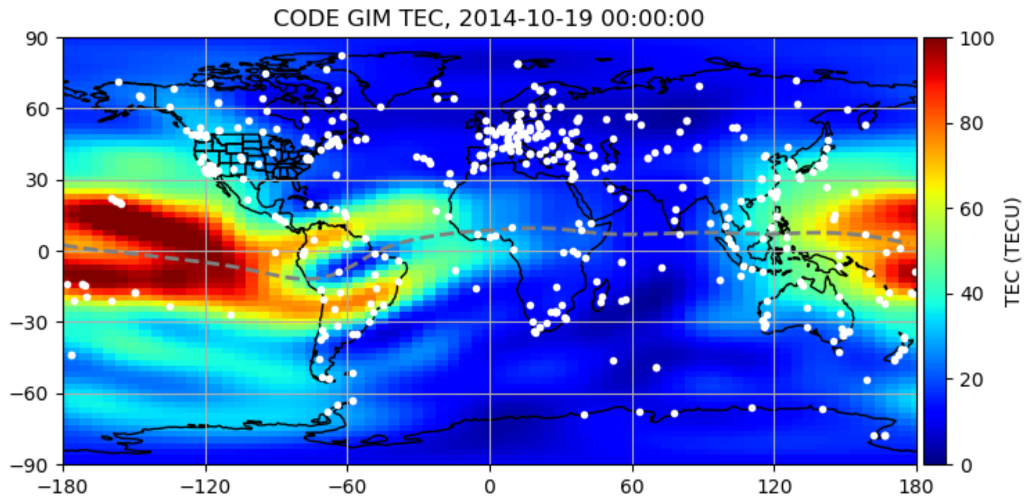
Irregularities/Scintillation: **ROTI**



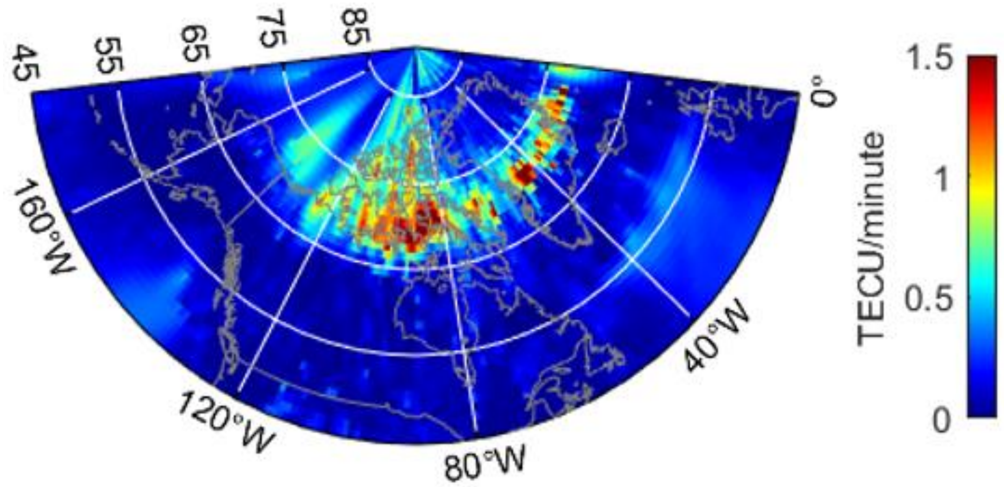
Space Weather Impacts

Predicted Indicators

- **Global Ionospheric Maps (GIM)**
  - Released by CODE ionospheric analysis center
  - Resolution: 1-hour interval, 2.5° by 5°
- **Regional ROTI Maps**:
  - Coverage: (45-90 N, 0-180 W)
  - Data Source: UNACO and CHAIN networks
  - Resolution: 10-minute interval, 1° by 1°



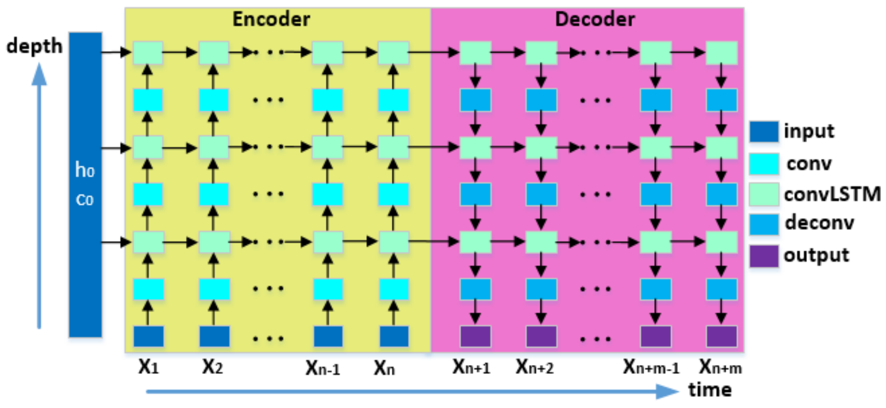
Global ionospheric TEC map



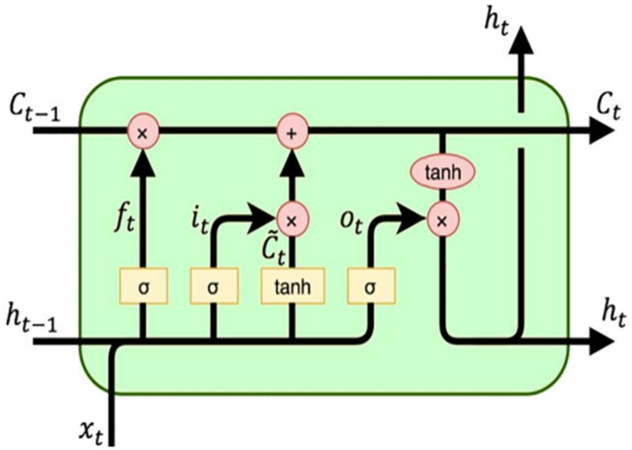
GNSS-derived ROTI map over North America

Machine Learning (ML) Algorithm: Architecture

- Input: feed n historical maps ($\boldsymbol{X_1, X_2, \ldots, X_{n-1}, X_n,}$);
- Output: predict m future maps ($\boldsymbol{X_{n+1}, X_{n+2}, \ldots, X_{n+m-1}, X_{n+m}}$)
- Encoder/Decoder Blocks
- Convolutional (conv) and deconvolutional (deconv) layers
- Core module: convolutional long short-term memory (ConvLSTM)



ConvLSTM-based machine learning architecture

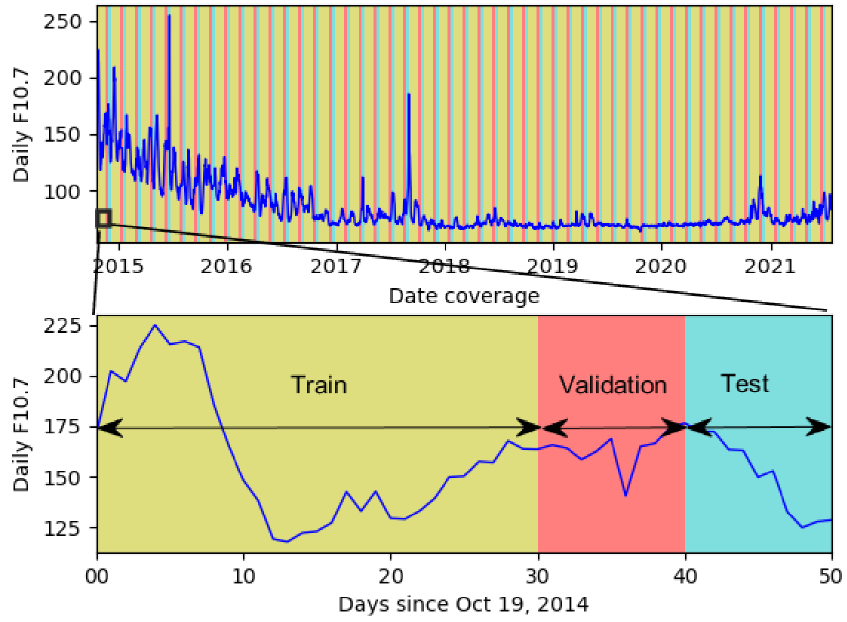


convLSTM module

Application I: Prediction of Daily Global Ionospheric TEC Maps

- **Global TEC maps description:** 1-hour interval; 2.5° by 5°; CODE analysis center
- Data division: solar activity levels are considered
- **Residual prediction:** $\hat{X}_t = TEC(t) - TEC(t-24)$
- **Input features:** 24 historical TEC maps
- **Output features:** 24 future TEC residual maps
- **Predicted TEC maps:** $\widehat{TEC}_t = \hat{X}_t + TEC(t-24)$

Data coverage	7 years: October 19, 2014 - July 21, 2021
Data division	Training (60%), validation (20%), and testing (20%). Data segmentation based on **solar activity levels.**
Lead time	24 hours with 1-hour interval

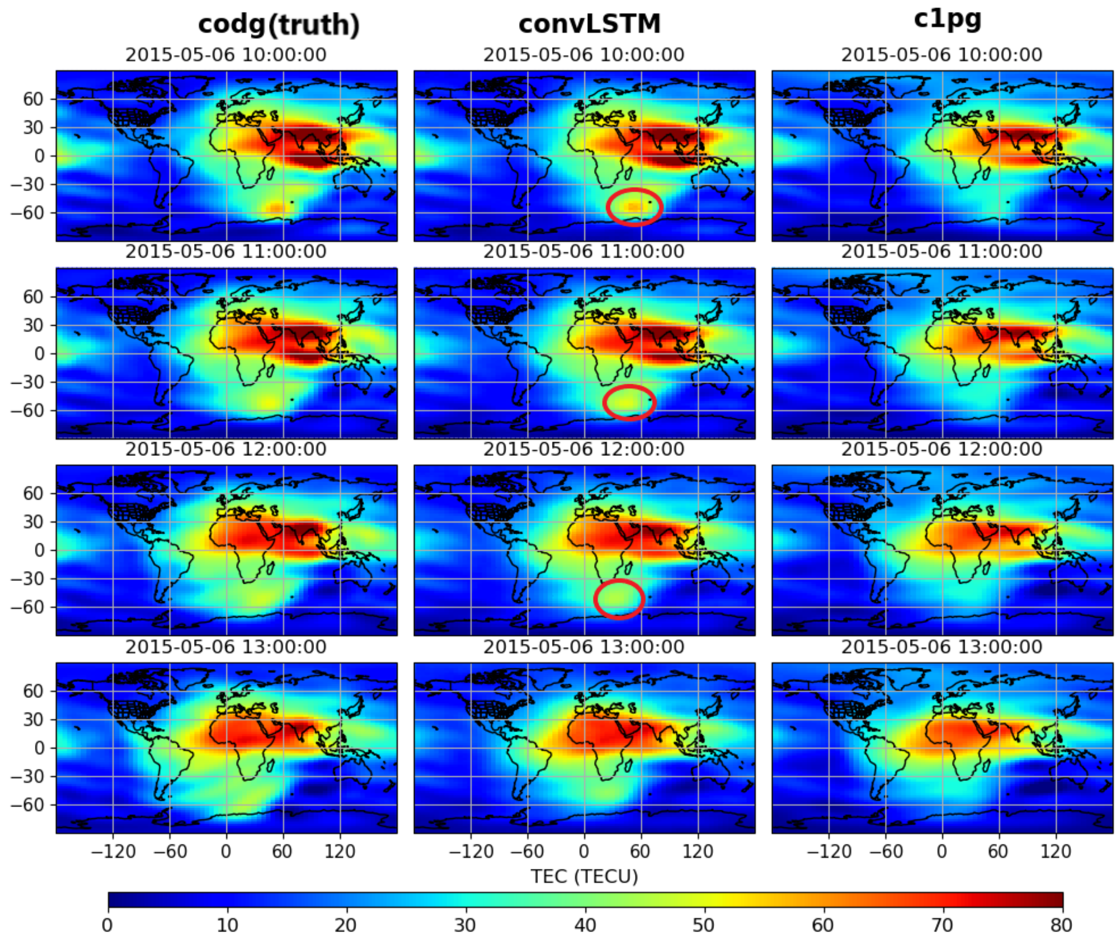


Application I: A qualitative case study

- **codg:** CODE's daily GIM, which is the ground truth
- **convLSTM:** ML algorithm developed in this study
- **c1pg:** CODE'S 1-day predicted GIM

➢ Large-scale ionosphere patterns, such as EIA crest, are well-preserved;

➢ TEC enhancement (see red circles) is well reproduced from the convLSTM while the c1pg fails to capture it.

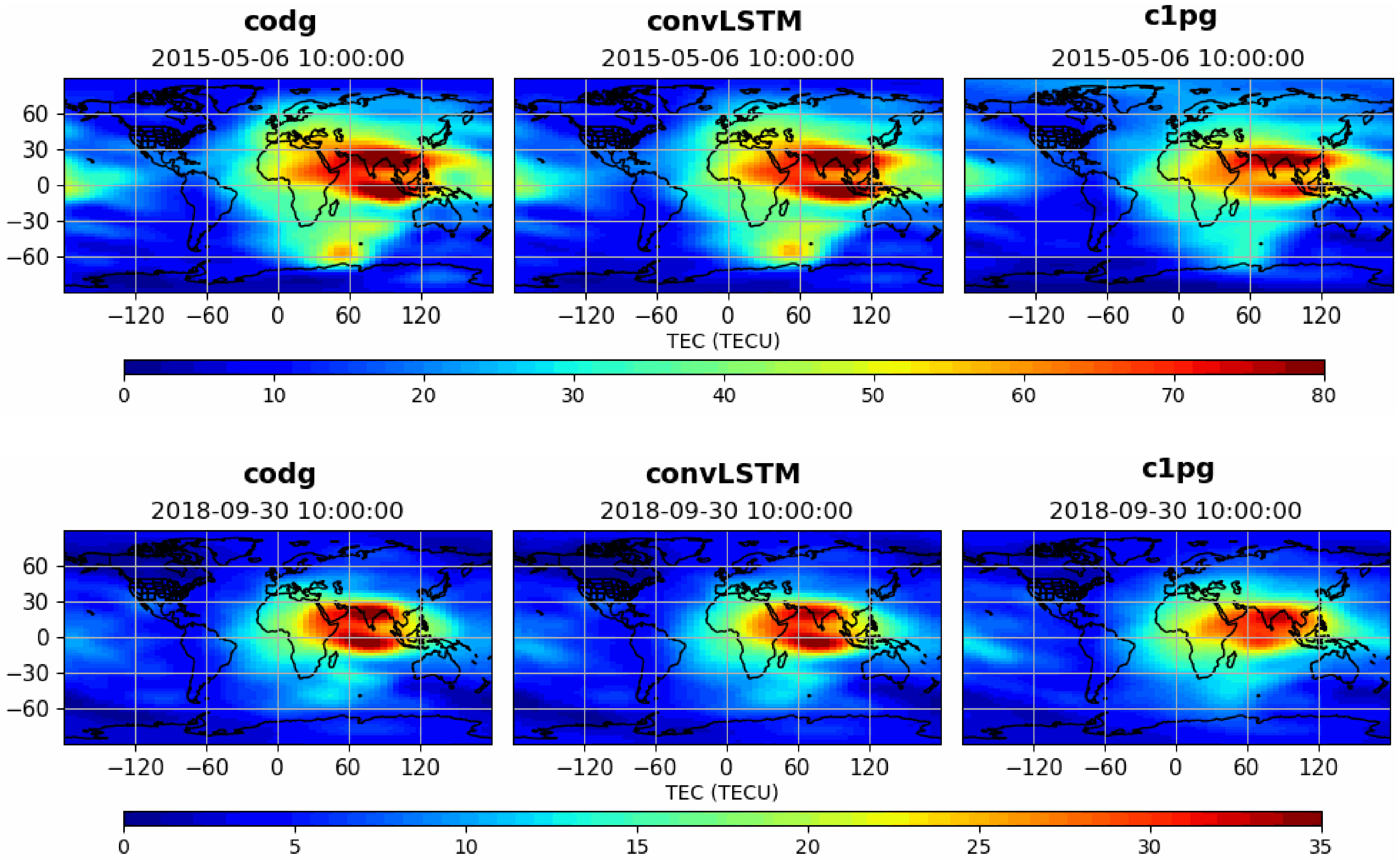


An example of the predicted global TEC maps with 1-hour interval during the main phase of one geomagnetic storm event (10:00-13:00 UT, May 6, 2015)

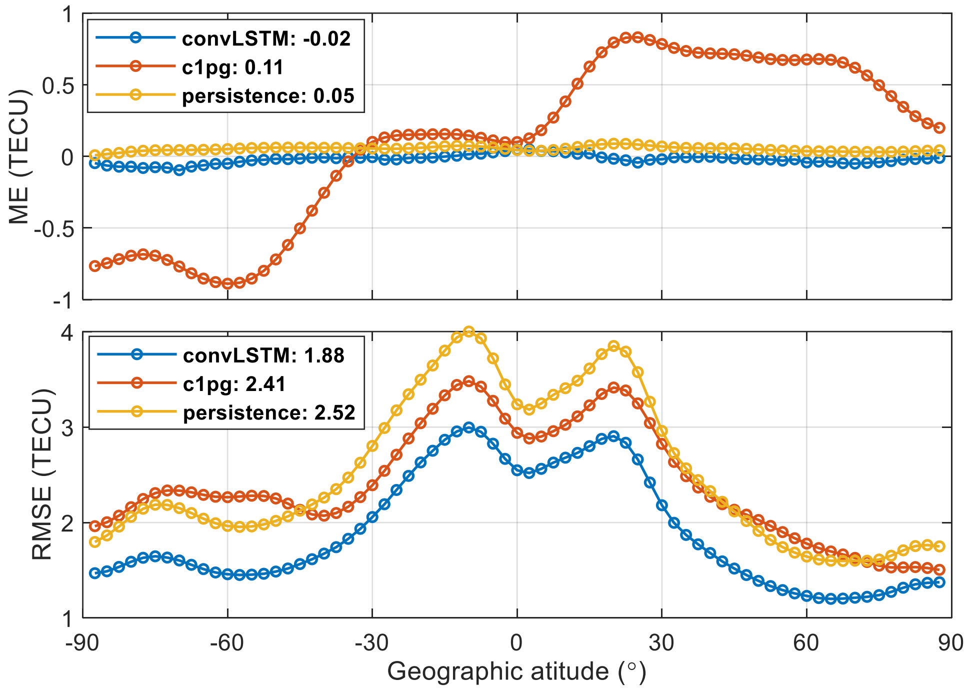
Application I: Predicted Global TEC Maps with Lead Time of 24 Hours

Storm time:

Quiet time:



Application I: Statistical Evaluation



Latitudinal ME and RMSE errors of three prediction models on the testing set.

- There are no systematic biases in the TEC maps predicted by convLSTM and the persistence model.
- The convLSTM shows an improved performance than other two models over various latitudes.
- RMSE errors shows obvious latitudinal dependence

Application II: Prediction of Storm-time High-latitude Irregularities

- **GNSS-derived ROTI maps description:**
  - Coverage: (45-90 N, 0-180 W)
  - Resolution: 10-minute interval, 1 by 1 degree
- **Data division:** training, validation and testing
- **Loss Function:** customed L_c , instead of conventional L_1 or L_2
- **Input features:** 12 historical ROTI maps (120 minutes)
- **Output features:** 6 future ROTI maps (60 minutes of lead time)

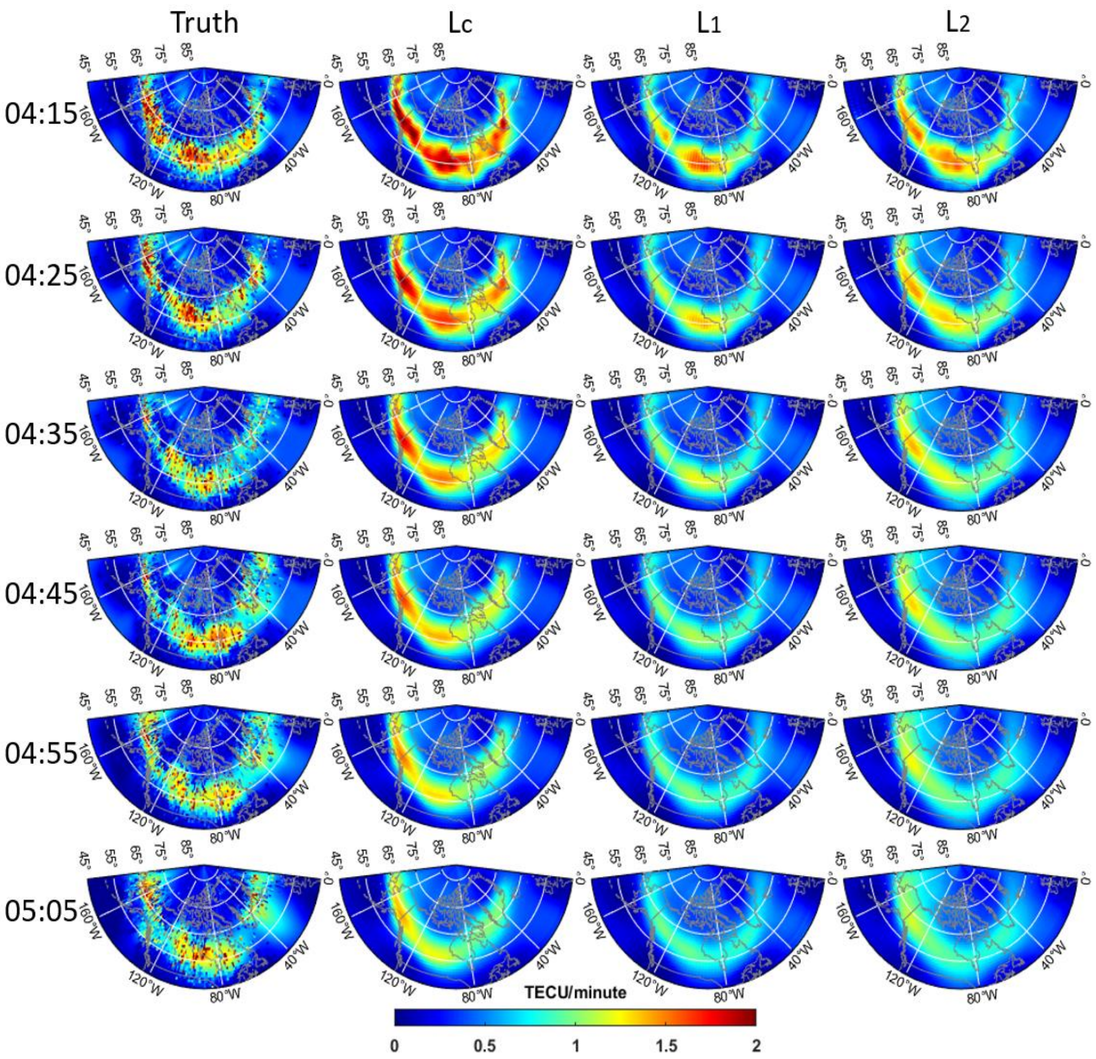
Data used	2015
Training (60%)	Jan 1-Aug 7
Validation (20%)	Aug 8-Oct 19
Testing (20%)	Oct 20-Dec 31

$$\begin{cases} L_c = \lambda_1 \cdot L_{w1} + \lambda_2 \cdot L_{w2} + \lambda_3 \cdot DP \\ L_{w1} = \frac{1}{N}\sum_{i=1}^{N} w_i \cdot |x_i - \hat{x}_i| \\ L_{w2} = \frac{1}{N}\sum_{i=1}^{N} w_i \cdot (x_i - \hat{x}_i)^2 \\ DP = max(|x_i - \hat{x}_i|) \end{cases} \qquad w_i = \begin{cases} 0.25, & x_i \le 0.25 \\ 0.9, & 0.25 < x_i \le 1 \\ 2.0, & 1 < x_i \le 2 \\ 3.0, & x_i > 2 \end{cases}$$

Customed Lc is designed to solve the problem caused by the imbalanced ROTI distribution

Application II: Prediction of Storm-time ROTI Maps

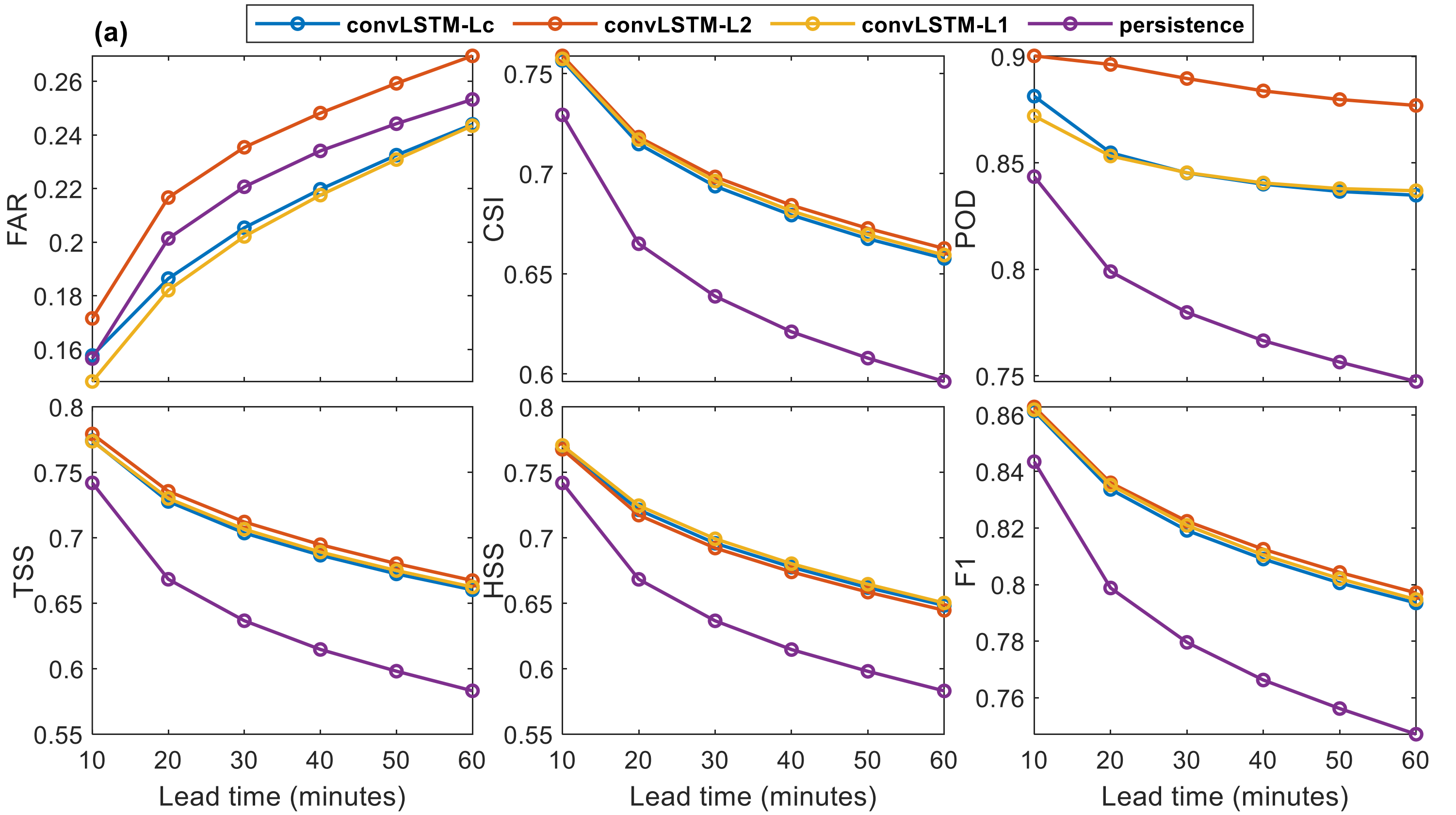
- **A predicted example**



Prediction example of ROTI maps over 6 prediction steps during the recovery phase (04:15-5:05 UT, December 21, 2015)

Application II: Prediction of Storm-time ROTI Maps

- **Statistical evaluation: weak** $(0.25 \le ROTI < 0.9)$

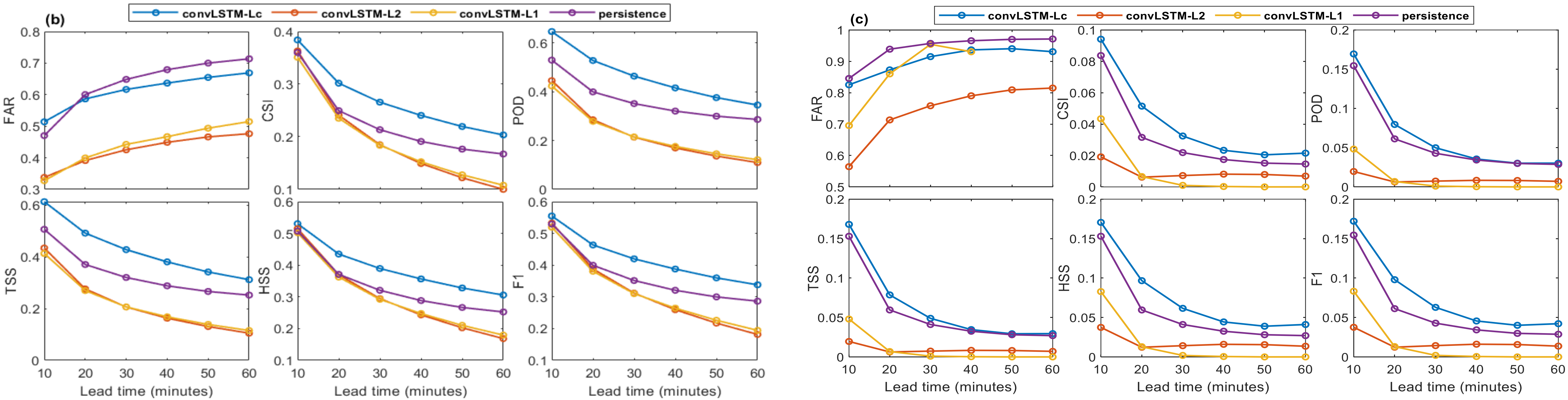


Prediction performance of convLSTM-Lc, convLSTM-L1, convLSTM-L2, and the persistence models under weak an ionospheric irregularity level

The convLSTM-Lc does not have an advantage in prediction of weak ionospheric irregularities when compared to convLSTM-L_1 and convLSTM-L_2 implementations.

Application II: Prediction of Storm-time ROTI Maps

- **Statistical evaluation: moderate** $(0.9 \le ROTI < 2)$ **and strong** $(ROT \ge 2)$



Prediction performance under moderate (b) and strong (c) ionospheric irregularity levels.

The convLSTM-Lc implementation shows better performance than those from convLSTM-L_1, convLSTM-L_2, and persistence models in predicting moderate and strong ionospheric irregularities for all lead times tested.

Conclusion

The convLSTM-based ML model to tackle two GNSS ionosphere applications.

- **ML + residual prediction:** prediction of daily global TEC maps. The developed model outperforms the c1pg and persistence model.
- **ML + Lc loss function:** prediction of high-latitude irregularities from GNSS-derived ROTI maps. The developed model outperforms the convLSTM-L1, convLSTM-L2 and persistence models.

Future Work

- Incorporate solar wind and geomagnetic activity measurements into the model with the goal of improving the prediction performance.

Liu, L., Morton, Y. J., and Liu, Y. (2021). Machine Learning Prediction of Storm-Time High-Latitude Ionospheric Irregularities From GNSS-Derived ROTI Maps. Geophysical Research Letters, 48(20), e2021GL095561.

Liu, L., Morton, Y. J., and Liu, Y. (2021). Machine Learning-based Prediction of Daily Global Ionospheric TEC Maps. **To be submitted.**

Acknowledgement

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- Global TEC maps are available from CODE analysis center.
- The GNSS data used for ROTI calculation are from UNAVCO and CHAIN networks.

Thank you!