

Estimating the SEP Flux for the Upcoming Solar Cycle 25 using LSTM Network

Mohamed Nedal, Kamen Kozarev

Institute of Astronomy of the Bulgarian
Academy of Sciences, Sofia, Bulgaria

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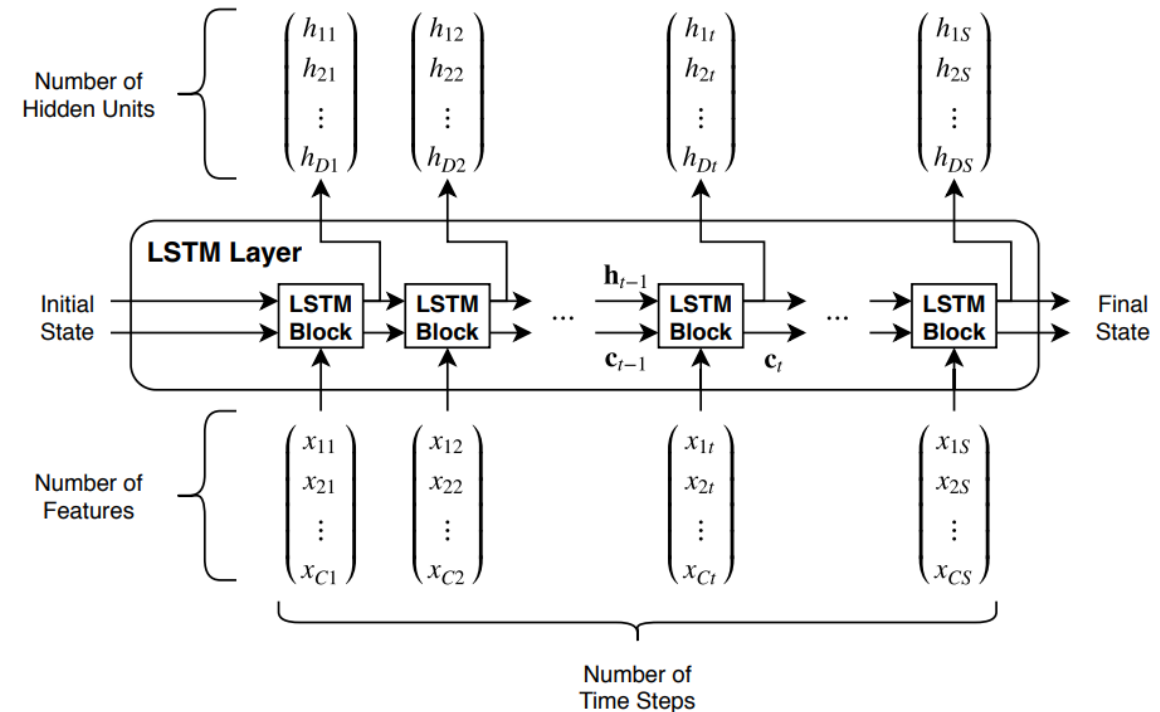
Introduction



- Solar energetic particles (SEP) are high-energy particles originating from the Sun, and they are composed of electrons, protons, and some heavy ions with energy ranging from a few tens of keV to several GeV
- All objects in space are electrically charged due to the constant exposure to the energetic solar particles that fill the space environment
- That continuous exposure to solar particle radiation leads to an accumulation of charges on the satellite's surface and the spacesuits of astronauts, which cause electrical discharges, malfunctioning, and radiation sickness in astronauts and increased risk of cancer
- Additionally, the highest energetic protons (>100 MeV) can enhance neutron count rates at ground levels through secondary radiation effects, which are known as Ground Level Enhancements (GLEs) which in turn cause problems to technology and biological systems on Earth
- Therefore, it is essential to study the SEPs and forecast their flux at the near-Earth orbit
- In this work, we implemented a forecasting model to predict the solar protons flux at 1AU during the entire solar cycle 25 using the Long Short-Term Memory (LSTM) neural network method

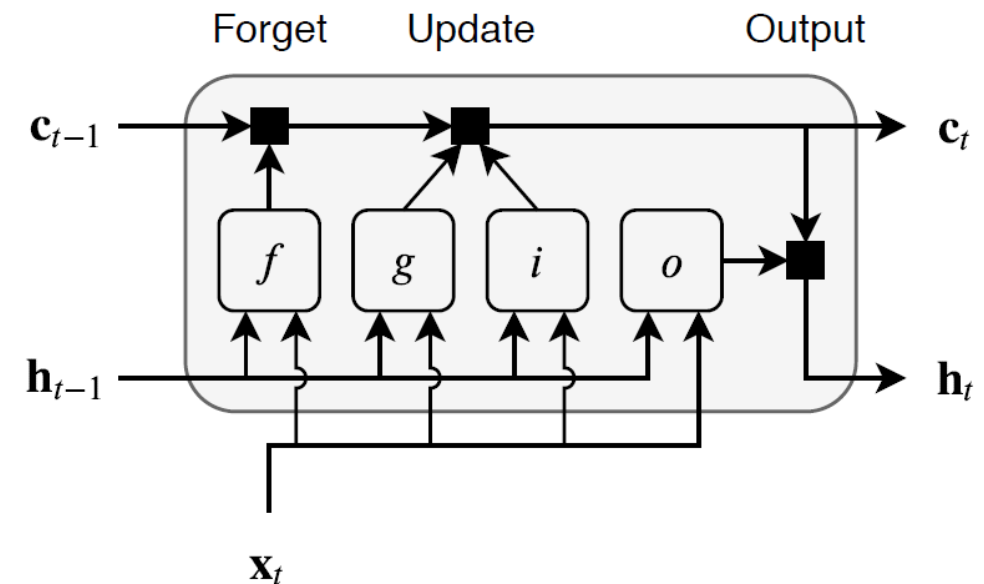
LSTM Network Model

- The LSTM networks are a subset of the Recurrent Neural Network (RNN) used in the field of deep learning
- LSTM networks address the contextual information of inputs by integrating a loop that allows information to flow from one time step to the next
- This is managed by learning when to remember and when to forget, through their forget gate weights
- This diagram shows the flow of a time series X with C features of length S through an LSTM layer
- Here, h_t and c_t denote the output (*also known as the hidden state*) and the cell state at time step t , respectively
- A common LSTM unit is composed of a cell, an input gate, an output gate and a forget gate



LSTM Network Model (cont'd)

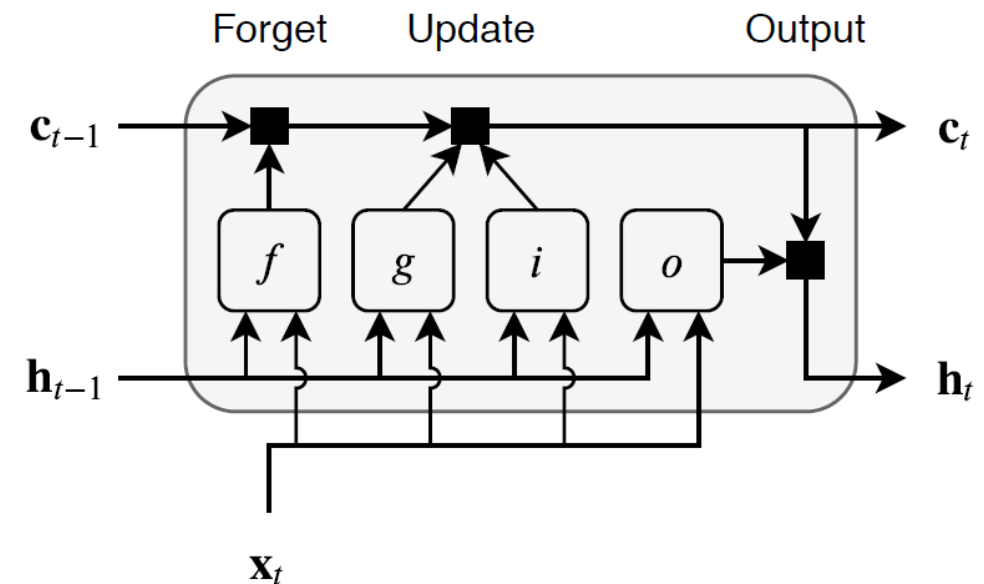
- The cell remembers values over the time steps and the three former gates adjust the information stream into and out of the cell
- This diagram shows the flow of data at time step t and highlights how the gates forget, update, and output the cell and hidden states
- Here, f , g , i , o are the forget gate, the cell candidate, the input gate, and the output gate, respectively
- We used 3 input features obtained from OMNI database (the absolute average interplanetary magnetic field – B_t , the solar wind flow speed – V_p , and the solar radio flux density – F10.7-index)
- The reason for choosing those 3 features is because the dynamics of the interplanetary medium and the solar activity degree influence the protons flux since they travel within the inner heliosphere



Credit: MathWorks

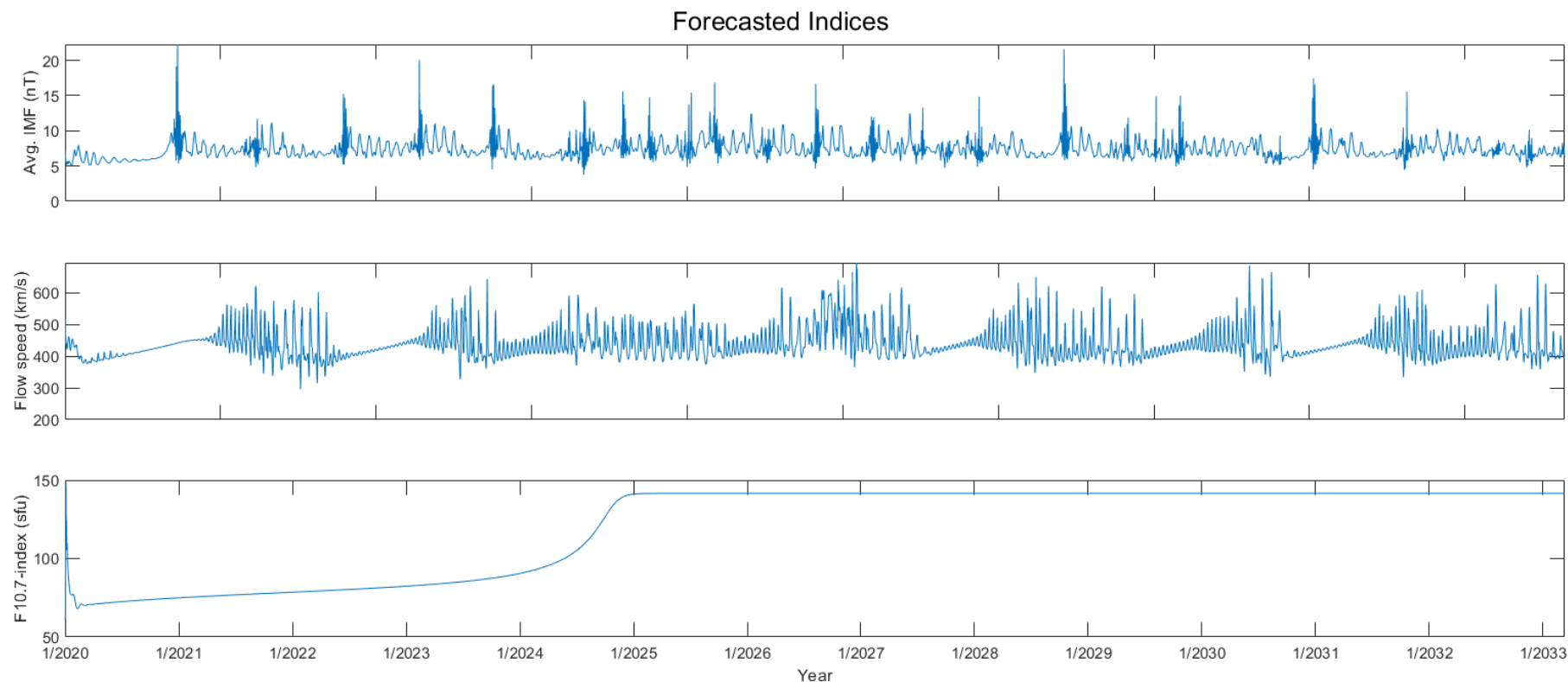
LSTM Network Model (cont'd)

- First, the data is split into 70% (from 1976 to 2006) for training the LSTM model and 30% (from 2006 to 2019) to validate and test the model's performance
- A univariate multi-step LSTM model is implemented to forecast each one of the 3 input features from 2020 to 2033
- Then, the 3 forecasted input features are used to forecast the integral proton flux by implementing a multivariate multi-step LSTM
- Finally, the model is used to forecast the integral protons flux in 3 energy channels (>10 MeV, >30 MeV, and >60 MeV) throughout the following 13 years (from 2020 to 2033)



Credit: MathWorks

Results



Train RMSE: 0.75 nT
Valid. RMSE: 1.019 nT
Testing RMSE: 3.44 nT

Train RMSE: 0.53 km s⁻¹
Valid. RMSE: 0.72 km s⁻¹
Testing RMSE: 113.95 km s⁻¹

Train RMSE: 0.13 sfu
Valid. RMSE: 40.01 sfu
Testing RMSE: 0.17 sfu

Fig. (1): the forecasted 3 inputs features from Jan 2020 to Jan 2033

Results (cont'd)

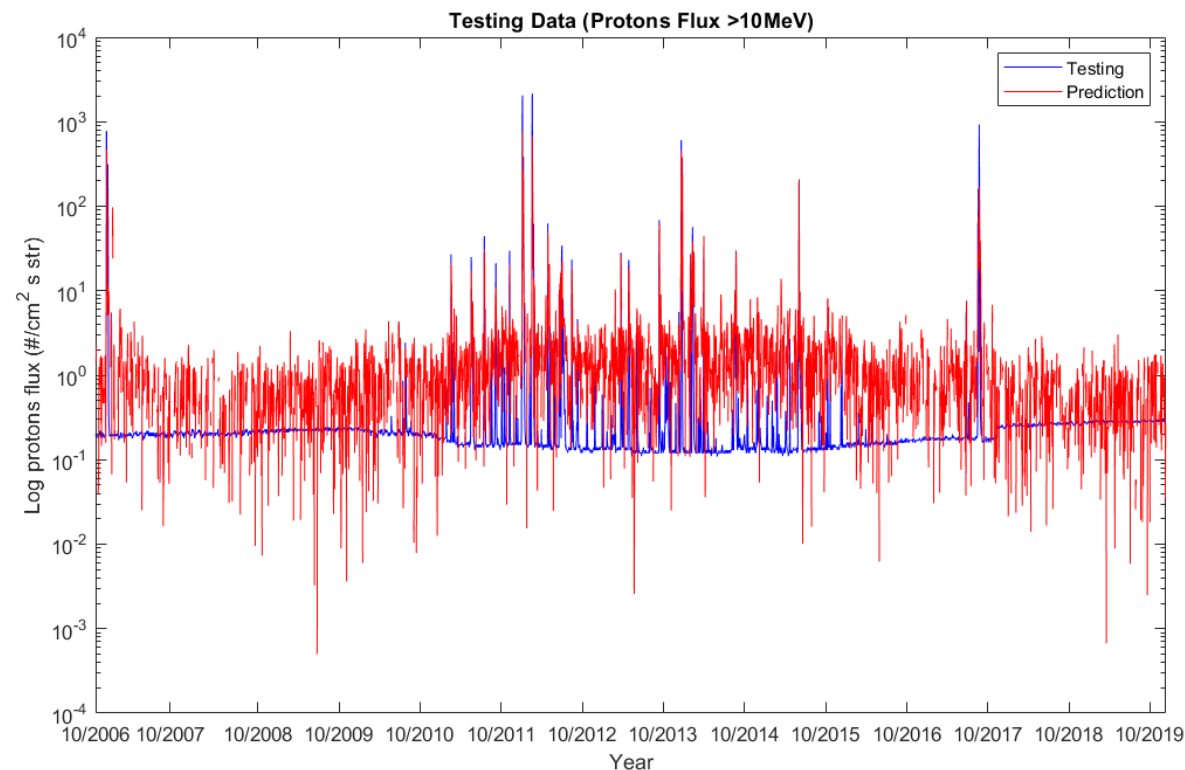
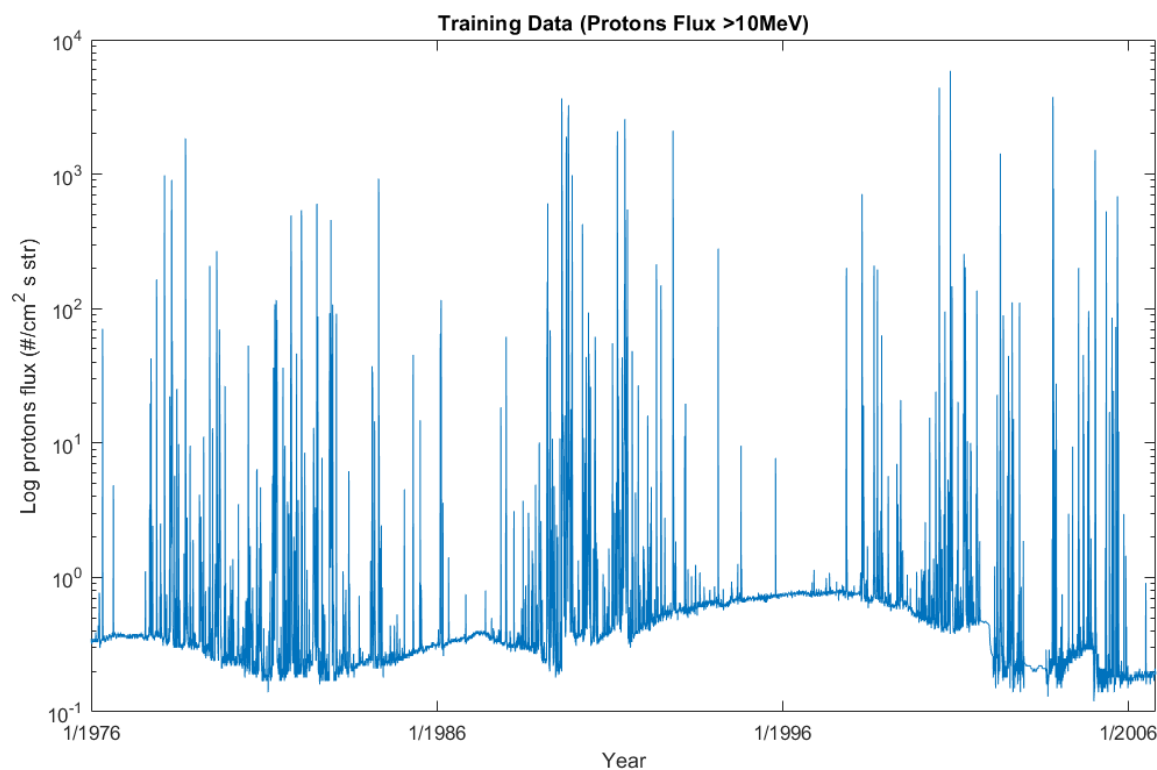
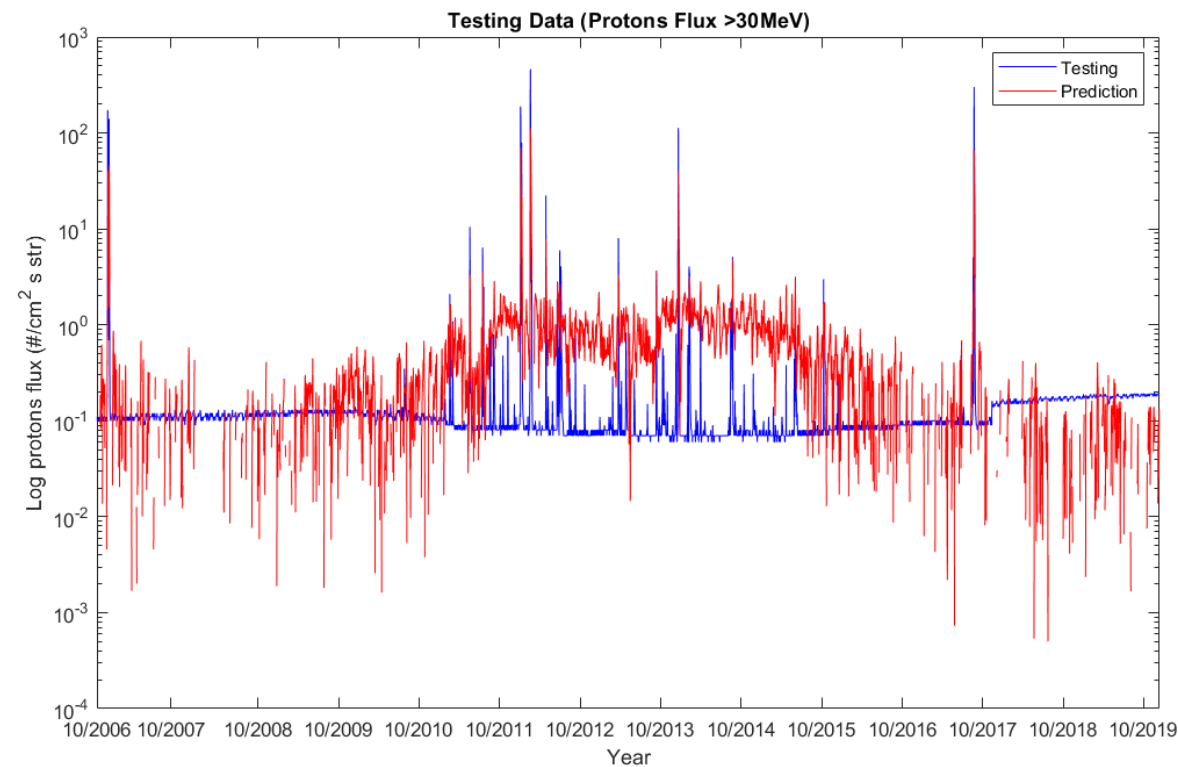
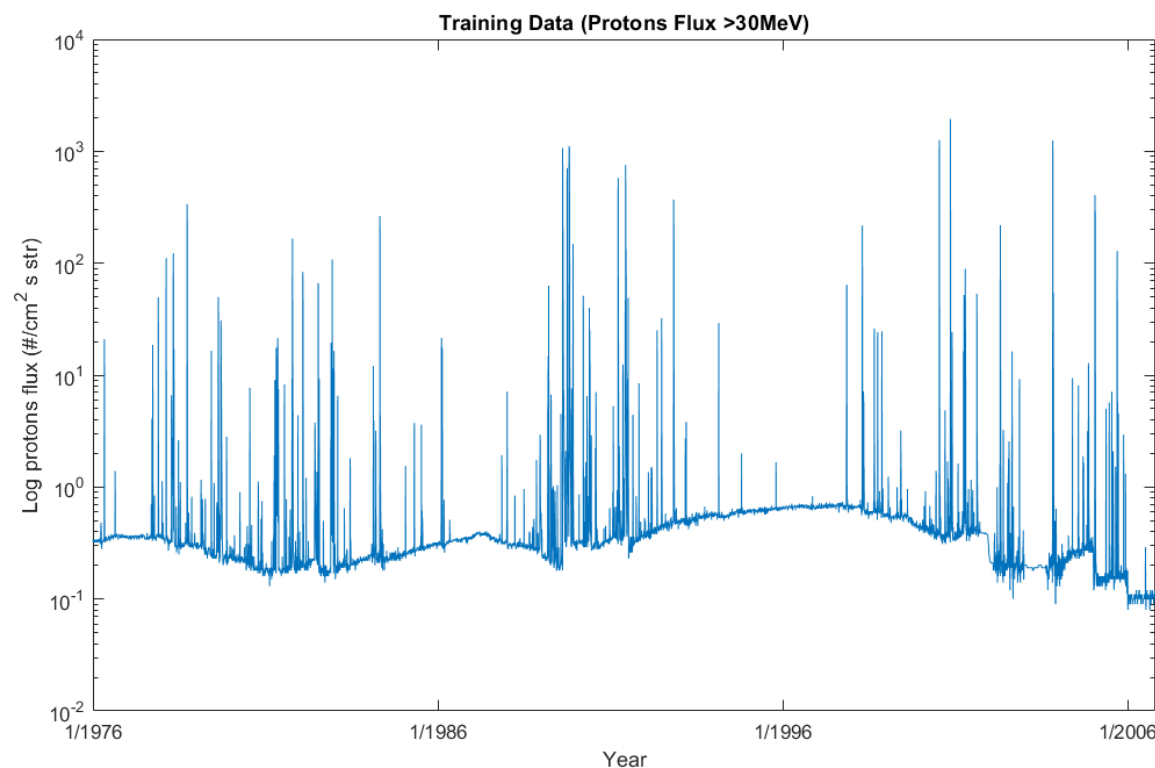


Fig. (2): (Right) the log-scale of the integral proton flux >10 MeV of the testing data (in blue) and the predicted data (in red) from Oct 2006 to Oct 2019. (Left) the training data of the integral proton flux >10 MeV from Jan 1976 to Jan 2006

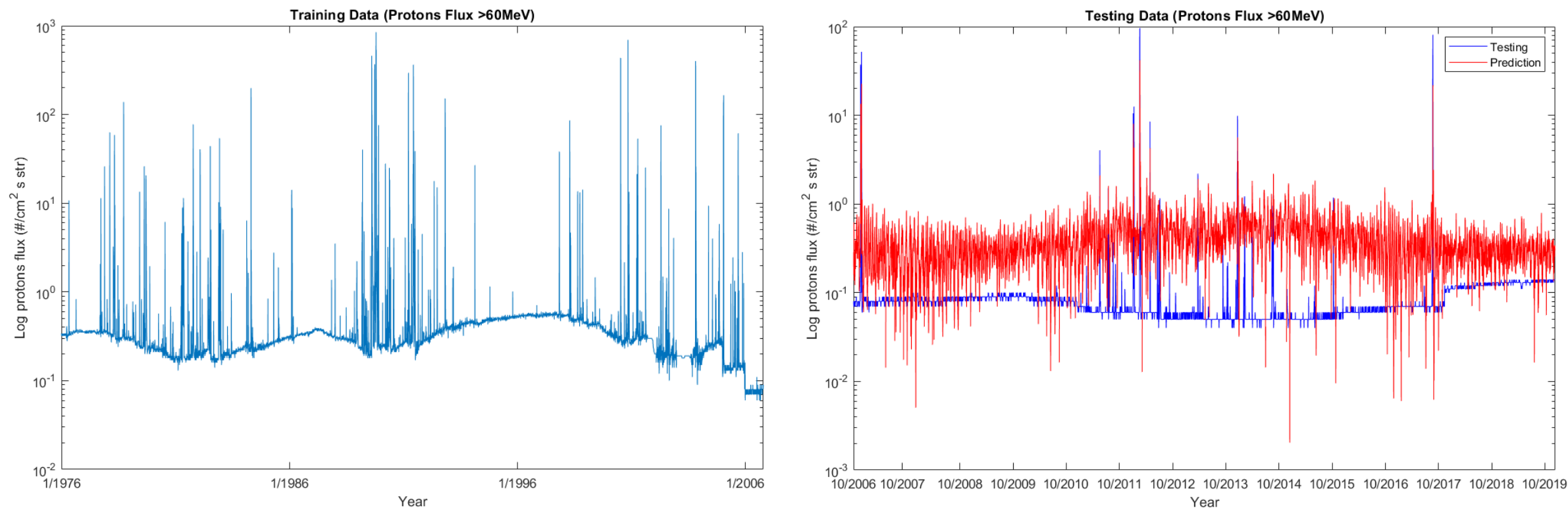
Results (cont'd)



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Fig. (3): (Right) the log-scale of the integral proton flux >30 MeV of the testing data (in blue) and the predicted data (in red) from Oct 2006 to Oct 2019. (Left) the training data of the integral proton flux >30 MeV from Jan 1976 to Jan 2006

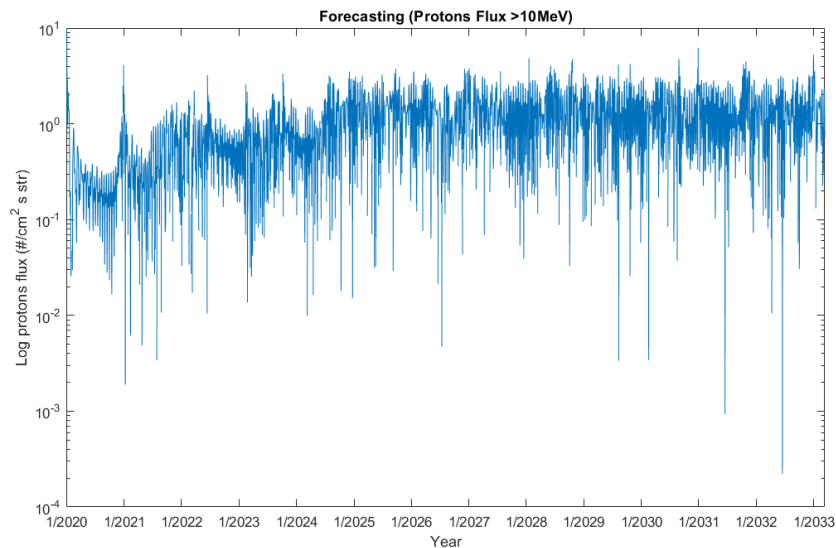
Results (cont'd)



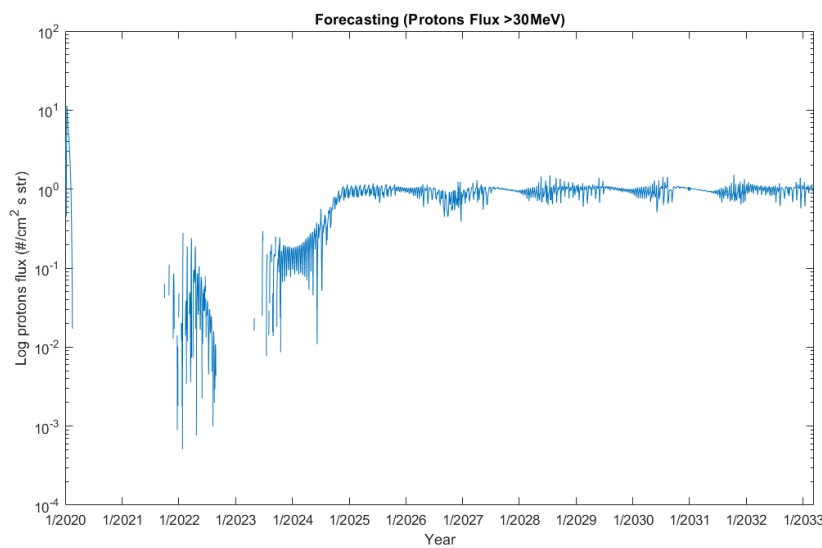
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Fig. (4): (Right) the log-scale of the integral proton flux >60 MeV of the testing data (in blue) and the predicted data (in red) from Oct 2006 to Oct 2019. (Left) the training data of the integral proton flux >60 MeV from Jan 1976 to Jan 2006

Results (cont'd)

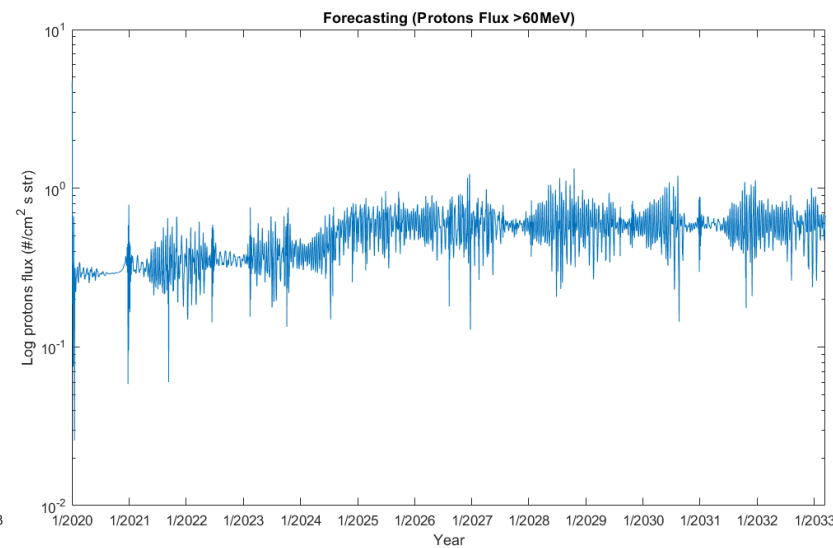


Train RMSE: 0.05000 pfu
Valid. RMSE: 0.03150 pfu
Testing RMSE: 53.85 pfu



Train RMSE: 0.05100 pfu
Valid RMSE: 0.01456 pfu
Testing RMSE: 10.47 pfu

1 pfu = particle/cm². str. s



Train RMSE: 0.0230 pfu
Valid RMSE: 0.0036 pfu
Testing RMSE: 2.39 pfu

EGU2020-16131 | ST4.1 Fig. (5): the log-scale of the forecasted integral proton flux >10 MeV (Let), >30 MeV (Center), and >60 MeV (Right) from Jan 2020 to Jan 2033. The raw forecasted data has no gaps and this is maybe due to the presence of very small values (~ zero) and how the log-scale deal with it

Conclusion



- We implemented a prediction model to forecast the protons flux, in 3 different energy channels, for the entire solar cycle 25 based on the data of the past 4 solar cycles and by using 3 input features that reflect the solar activity degree and the state of the interplanetary medium
- There is a lack of extreme SEP events in the forecasts, which implies that the solar cycle 25 may be weak
- The RMSE of prediction decreases at higher proton energies, which implies better forecasting at higher energies
- Although the model still needs more fine-tuning, it could predict the extreme events well
- The next step will be to working on the hourly averaged data (×24 more samples), adding more input features, and enhancing the hyper-parameters and the network structure



THANK YOU