Predicting, understanding and visualizing fire dynamics with neural networks

by **Larissa Saad**

Machine Learning techniques have introduced many improvements to advance our understanding of fire regime dynamics since process-based fire models are exhibiting different behavior when predicting future trends [1]. Neural networks have achieved great accuracy with fire modeling, however, challenges arise with unbalanced time series. This research investigates LSTM neural networks, which are designed for sequence modeling, to explore their ability to predict fire occurrence. Furthermore, this research focuses on exploring current machine learning interpretation and visualization techniques and their ability to characterize local and global feature importance, map feature importance spatial distribution and depict predictor-response relationships and feature interactions.

Fire Predictors

Fire occurrence depends on the existence of an ignitions source, availability of fuel and suitable weather conditions. For weather conditions, the maximum temperature (tmax), precipitation (pre), wind speed (wind), Diurnal Temperature Range (DTR) and the Nesterov Index (NI) were used (Data source: CRU JRA V2.0 [2]). For fuel presence, fraction of Absorbed Photosynthetically Activity (fAPAR) was obtained from MODIS data. Fire ignitions are obtained from the Global Fire Atlas [4]. The research is conducted for a small area in western Africa (Fig. 1).

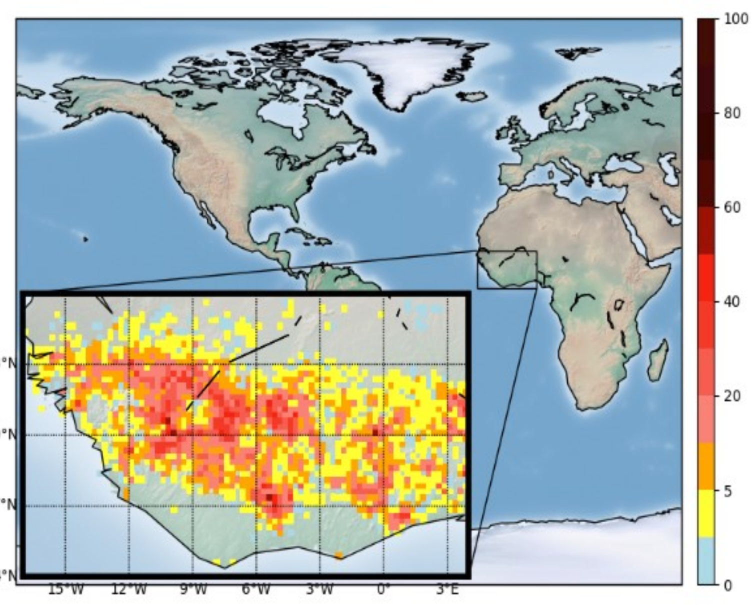

Figure 1: Study area with a sample of ignition count for one month

Methodology

All datasets were aggregated to monthly time steps and resampled to 0.25 deg latitude x0.25 deg longitude grid. Data pre-processing involved filling the missing values, removing correlated variables and data enhancement by applying the log transformation to mitigate data skewness. The chosen methodology is based on training one LSTM for each pixel. To prepare the data for LSTM, each pixel was structured as a multivariate time series then split into train and test sets. Then, the neural network architecture was selected by conducting multiple experiments to optimally determine LSTM hyperparameters. The chosen architecture is a vanilla LSTM with one hidden layer which takes the previous twelve time steps to make a prediction. This architecture is then used to predict one year in advance (Fig. 2).

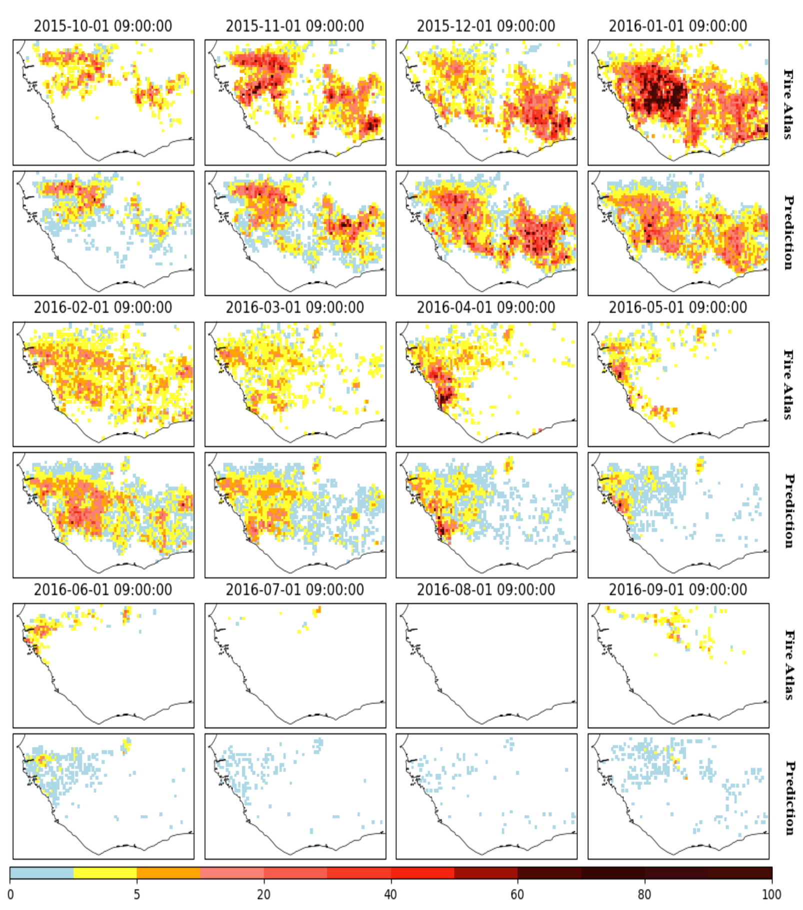

Figure 2: Comparison between the results of LSTM and Fire Atlas data for one year prediction

Visualization of LSTM-based neural networks

To understand LSTM behavior, three interpretation techniques were investigated. Permutation feature importance gave an overview of the most important variables for the entire study area (Fig. 3). Using variance-based feature importance [4], the spatial distribution of each feature was mapped (Fig. 4). SHAP [5] summary plots gave more details and depicted feature importance for each precedent time step in three sub-regions (north, middle and south) (Fig. 5).

To visualize LSTM inner relationships and interactions, SHAP dependence plots were used for feature-output relationships (Fig. 6). For feature interactions, a 3D extension of SHAP dependence plot with added color visual variable was found to be the best visualization technique (Fig. 7).

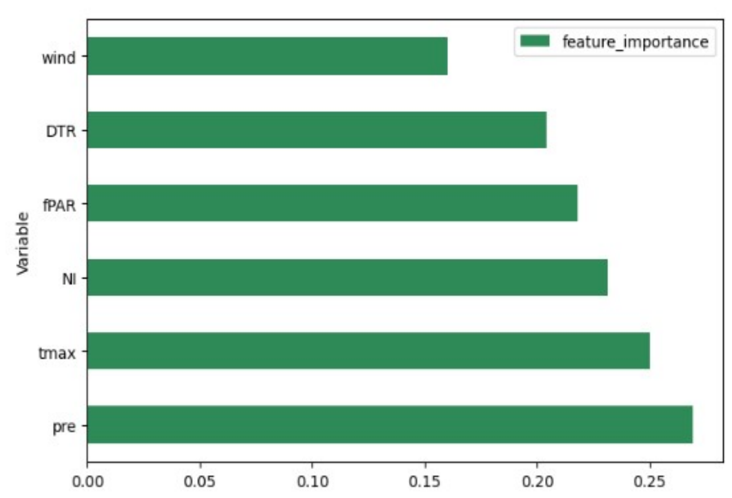

Figure 3: Overall feature importance

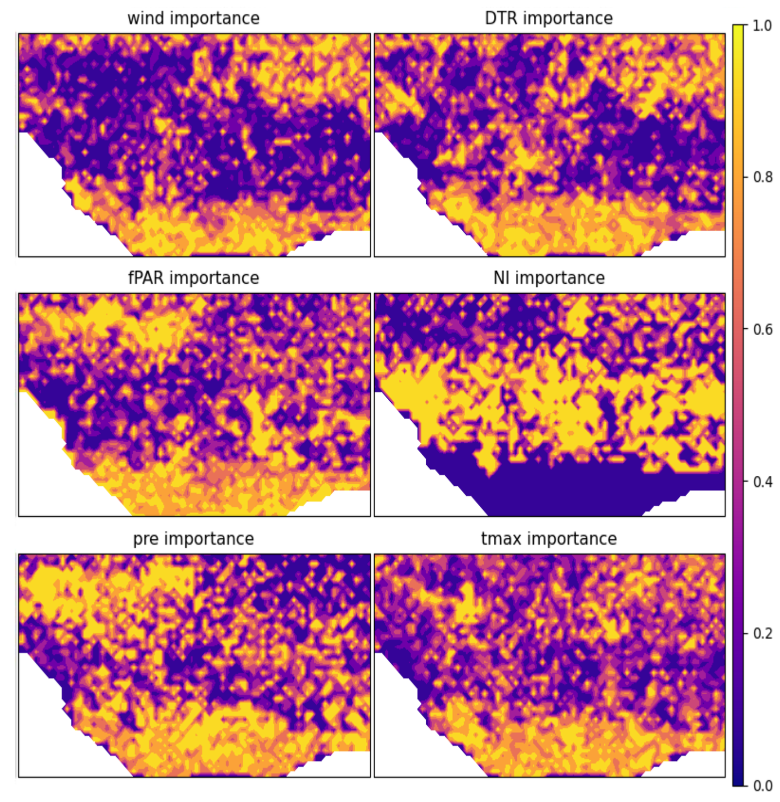

Figure 4: Spatial distribution of feature importance

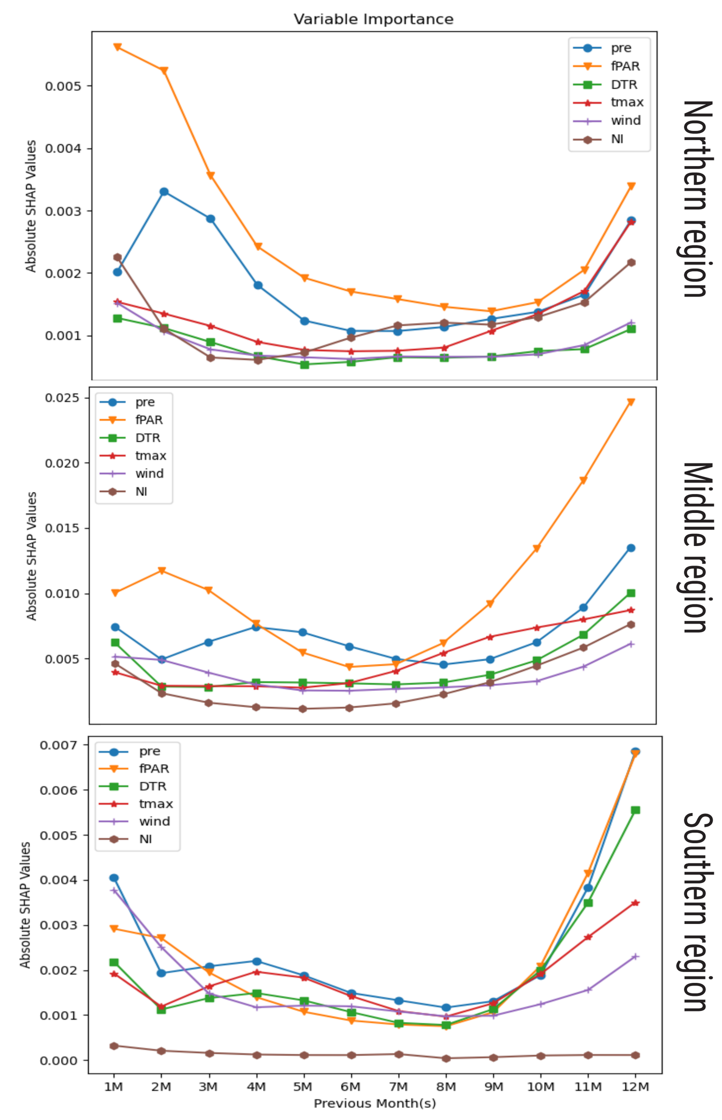

Figure 5: feature importance for the precedent twelve time steps

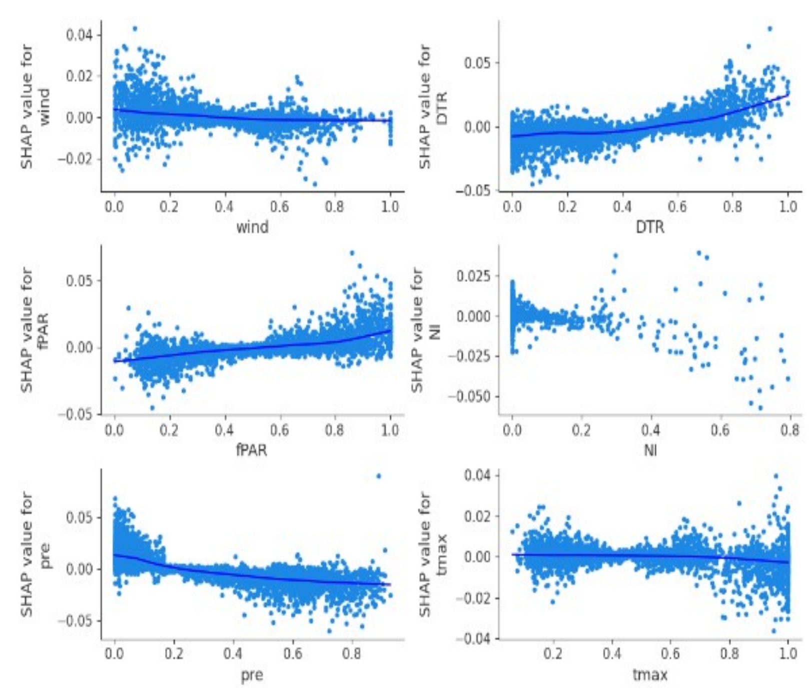

Figure 6: Predictor-response relationships

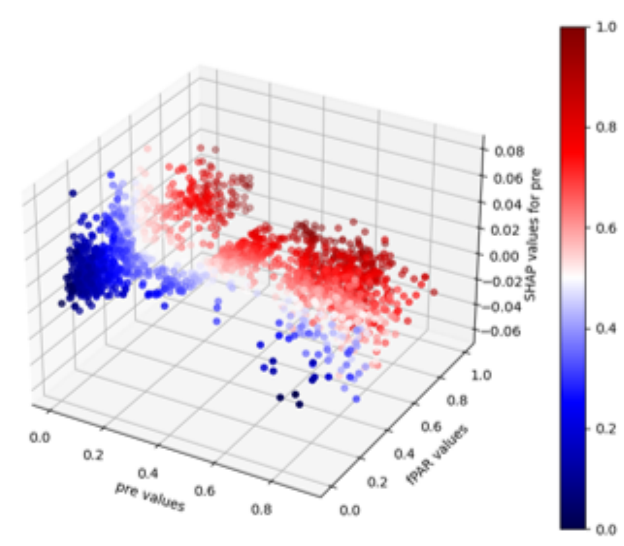

Figure 7: pre-fAPAR interaction plot

Conclusions:

The pixel-based LSTM was able to capture the seasonal and spatial varieties with RMSE value computed at 3.333. However, it underestimated the high values of ignitions during the peak of fire season. For interpreting pixel-based LSTM, no general approach was able to visualize local and general feature importance. The opportunities and limitations depend on the purpose of the visualization. Visualization techniques have contributed to a better understanding of the machine learning model and presented useful insights for further developments.

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Machine learning, LSTM, fire ignitions, interpretability, data visualization

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