Applying Machine Learning Techniques to Forecasting Fire Behavior

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1- Key Points

- High resolution hourly fire radiative power (FRP) predictions enable forecasting of emissions from wildfires several days in advance so that they can be implemented in air quality forecasting simulations (such as RAP-Chem)
- Ability to predict the temporal evolution amplitude and phase of the FRP diurnal cycle.
- Grid free high resolution FRP allows the prediction of associated variables useful in emissions predictions such as FRP Fractionated by land use/fuel type.

2- Motivation

- Fast FRP prediction enables the forecasting of emissions from wildfires at least 24 hours in advance so they can be used in air quality forecasting.
- AIFire has the potential to be used not only in air quality forecast models but also in applications such as plume rise parameterization, FRP-based emissions estimations and in helping to derive FRP diurnal climatologies when the number of FRP samples from satellites are not sufficient to derive the diurnal climatologies.
- High temporal and spatial resolution FRP models allows not only the prediction of future fire behavior and emissions. It also allows the building of robust relationships between carbon monoxide (CO) and FRP to quantify CO emissions on large wildfires.

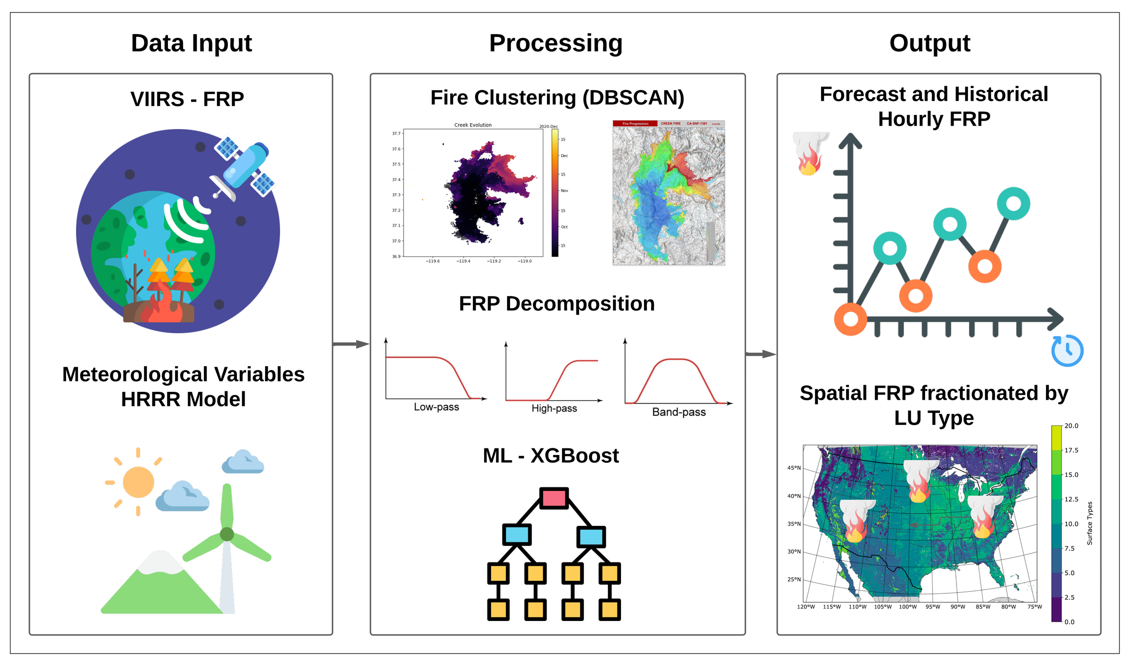


Figure 1: FRP is obtained from satellite data and combined with meteorological variables from forecast models. Fires pixels are clustered. Meteorological time series are represented by a FRP weighted average over the whole fire. The FRP is interpolated temporally and decomposed into three demodulated time series. XGBoost is trained to predict these time series. Output from XGBoost is recombined and an hourly FRP prediction is obtained. The original fire pixels can then be used to generate FRP fractionated by LU type.

3- AIFire Main Flowchart

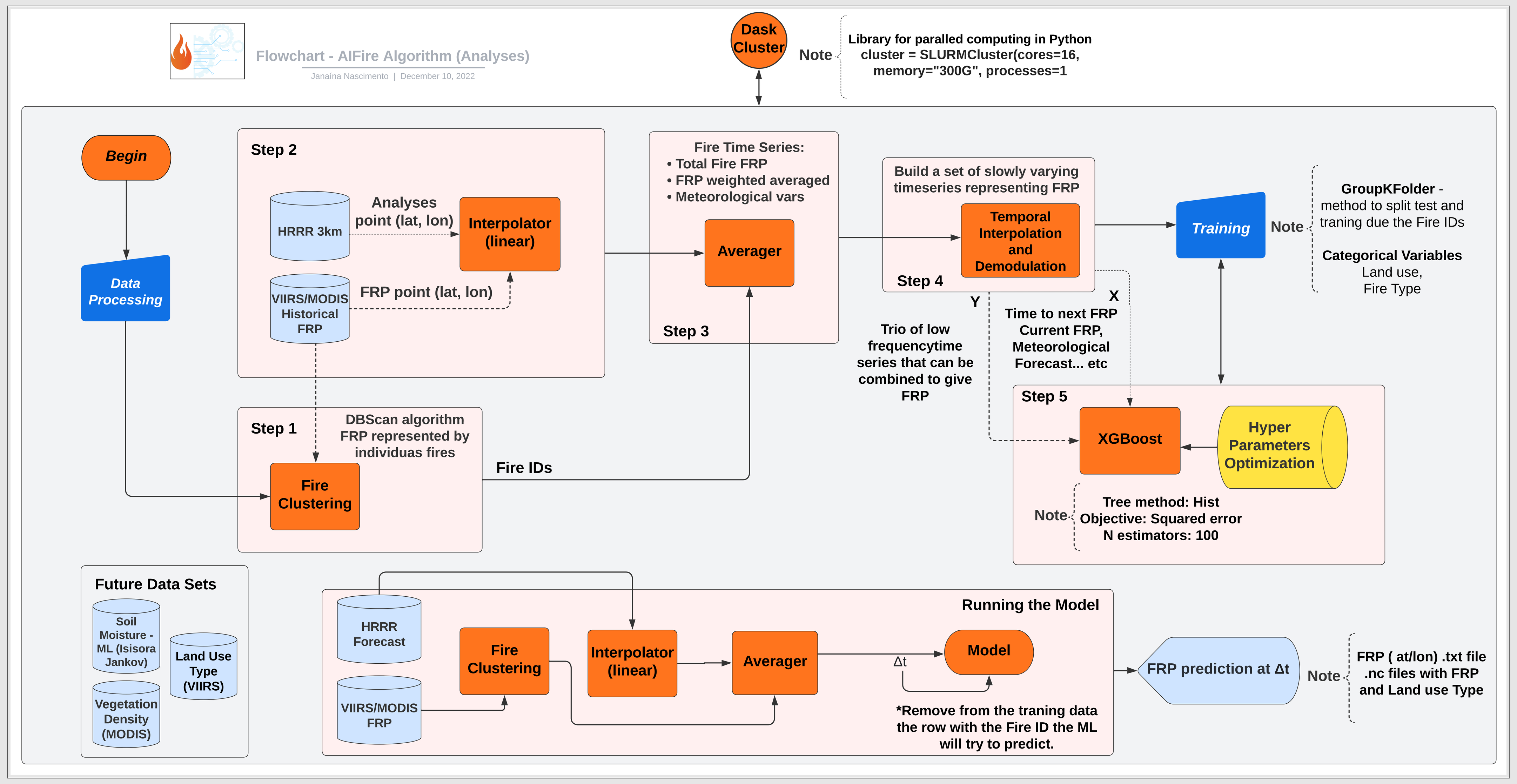
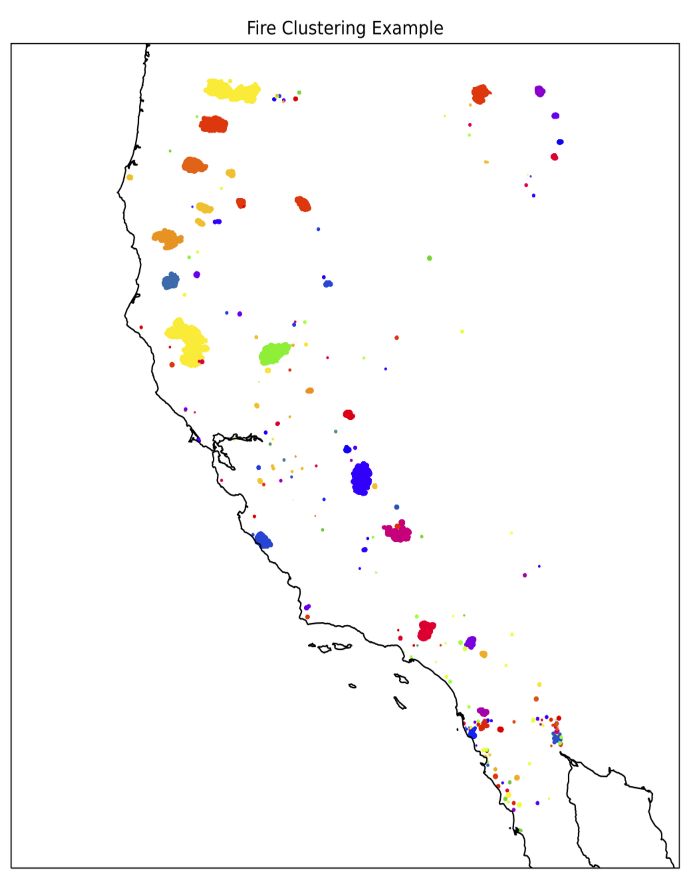


Figure 2: Flowchart demonstration the main steps to predict the hourly FRP. The workflow shows the steps for both training and running the AIFire algorithm as well as some implementation details.

4- Fire Clusterization

Figure 3: Clustering of fires in California during Sept 2022. Colors represent different fire clusters



Fire Clustering is accomplished with DBSCAN (Density-Based Spatial Clustering of Applications with Noise) running on the three variables separating the fires, lat/lon and time. Lat/lon and Time are not in the same Cartesian space so time is transformed by multiplying it by an empirical constant with units of deg/hours. Once we have the fire clusters we can make a single time series (sum of FRP in space) of the specific fire and try to extrapolate it. Variables defined over the fire area (eg wind speed) are also transformed into single time series by performing FRP weighted averages. Other, higher moments (standard deviation, etc) may also be transformed into time series.

5- AIFire FRP Evaluation compared with RAVE, VIIRS Satellite and RAP-Chem

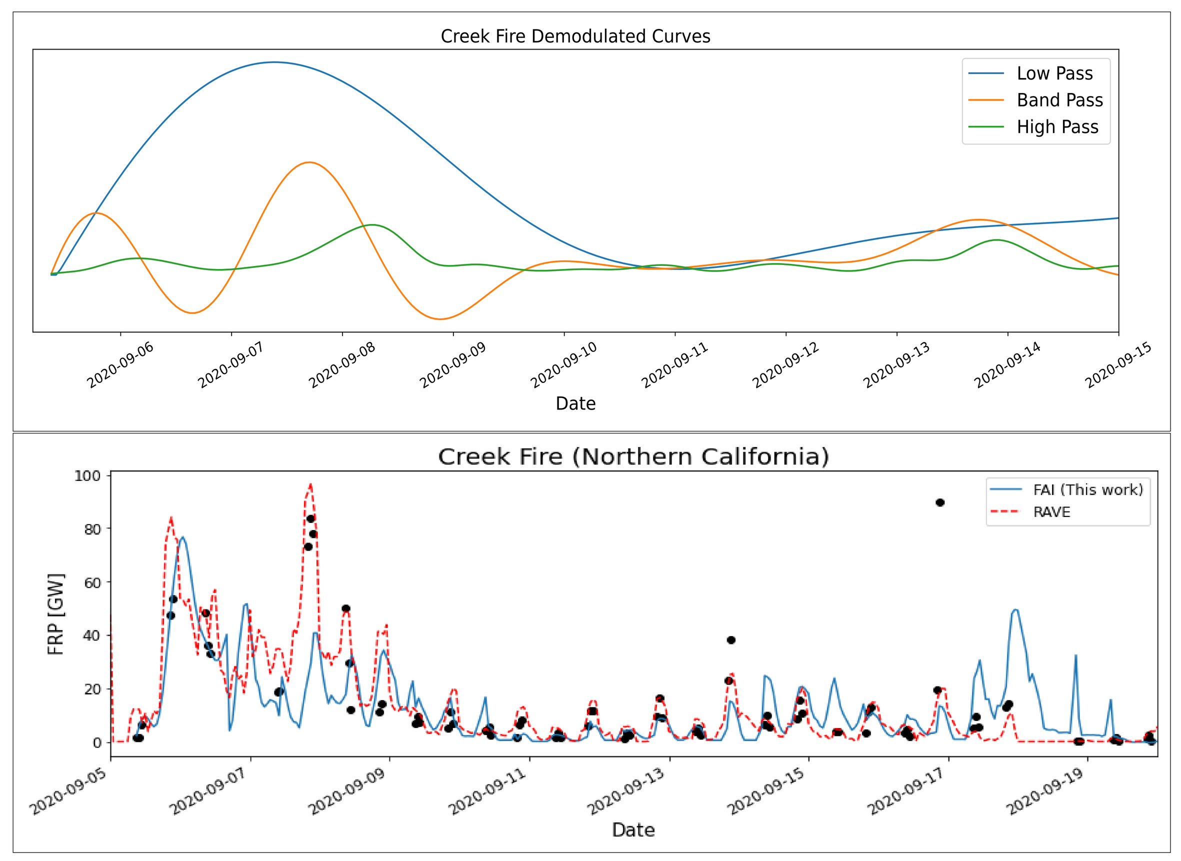


Figure 4: Top: Decomposed FRP timeseries. Bottom: FRP from VIIRS, direct reconstruction of the above plot, Regional ABI and VIIRS fire Emissions (RAVE) [Li, Fangjun et al., 2022], and the average of 24 hour forecasts given by our machine learning approach, which predicts the above 3 curves that are reconstructed into a single FRP.

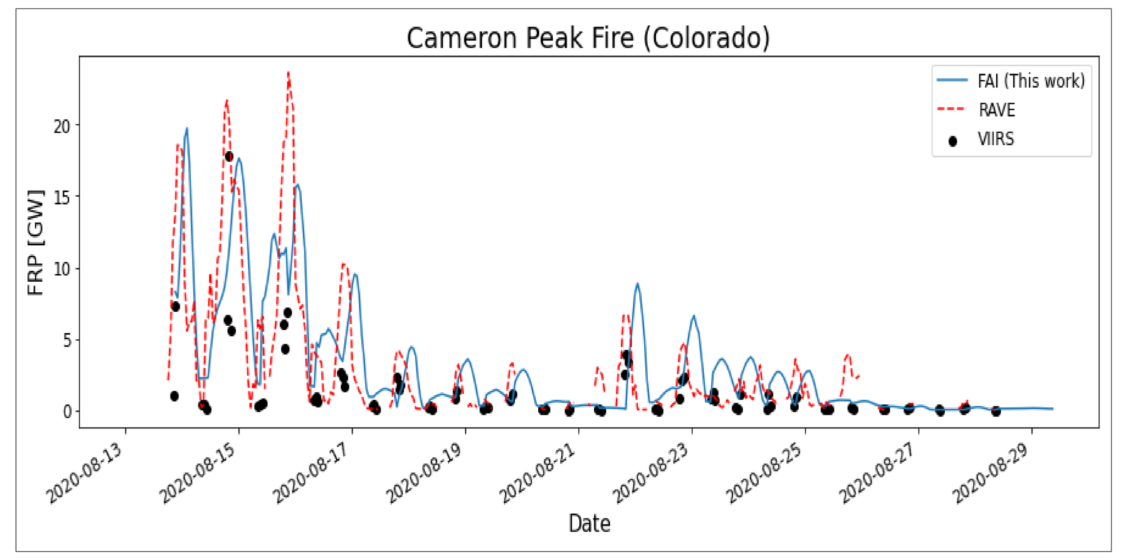


Figure 5: Same as fig. 4 bottom but with the Cameron Peak Fire (Fall 2020). The ML approach shows good agreement with RAVE FRP. VIIRS data is lower than both RAVE and AIFire because of cloud cover.

7- Model Analysis

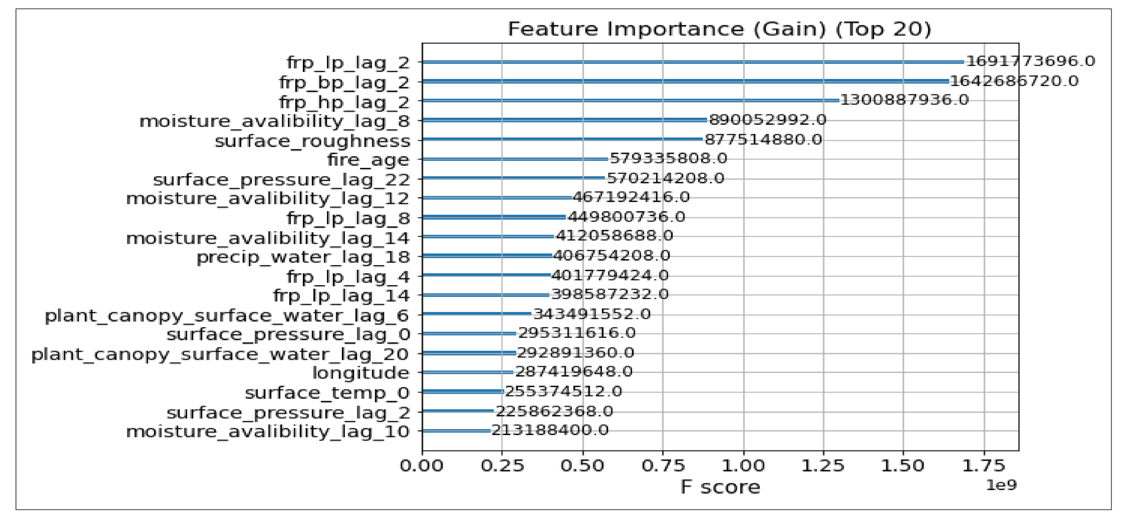


Figure 6: The relative influence of predictive variables on FRP. The delay between the input variables and forecast time is indicated by the lag postfix. The 'frp_lp', 'frp_bp' and 'frp_hp' variables refer to the lines in figure 4a.

The lack of meteorological variables in the top features is likely because our encoding scheme isn't representing the meteorological variables as time series properly. We evaluated model performance with cross validation using a group shuffle split scheme. We found: Mean Absolute Percentage Error: **13.6%**; Root Mean Square Error: **1310.44 (MW)**; Median Absolute Error: **7.5 (MW).**

Future Plans

- Include the AIFire model in RAP-Chem to see how it impacts PROC use and emissions forecasts.
- Use soil moisture data coming from in situ observations (U.S. Climate Reference Network - USCRN) and fuel data from the Fuel Characteristic Classification System.
- Fraction FRP by sub-pixel size land use type to further improve emissions forecasts.
- Fire shape/area prediction with principal component analysis (PCA).