Deriving Fire Radiative Power (FRP) with Weather Model Variables and Satellite FRP using Random Forest (RF) Models

Christina Kumler[1,2], Ravan Ahmadov[1,2], Jebb Stewart[2]

Christina.E.Kumler@noaa.gov

[1]Cooperative Institute for Atmospheric Research in Environmental Sciences, [2]NOAA Earth System Research Laboratory

Each year, wildfires and smoke have substantial health and financial impacts. They pose an immediate danger to towns, livelihood, and more. If under favoring conditions, they can spread quickly. Wildfire smoke is also an increasing problem with more fires contributing smoke into the upper levels of the atmosphere. Smoke can have immediate and longer-term affects on people as well as as aerosol concentration and/or weather. Satellites can detect the intensity, or FRP, from a fire but sometimes miss measurements due to different factors such as sensor blocking or sensor frequency. Improving FRP modeling is important for applications such as smoke modeling.

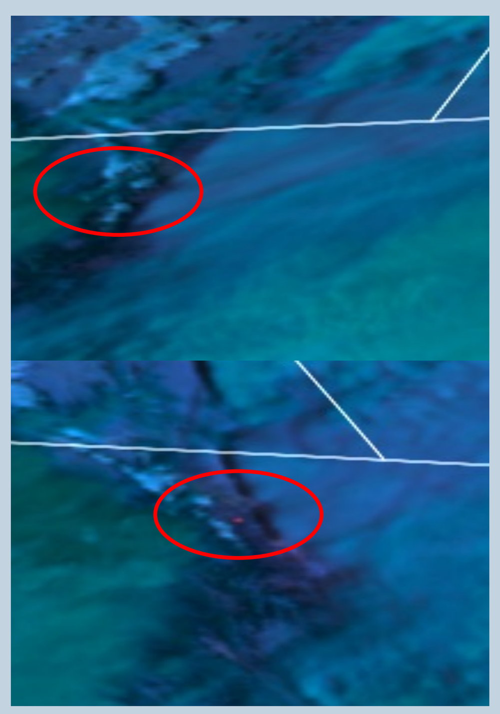


Figure 1: Fire product from GOES East (top) and GOES west (bottom) from Kruger Rock Fire Nov 16 2021 show cloud and/or smoke blocking have impacts on FRP detection. Images both taken at 19:30 UTC. GOES East does not show a sign of FRP and GOES west does.

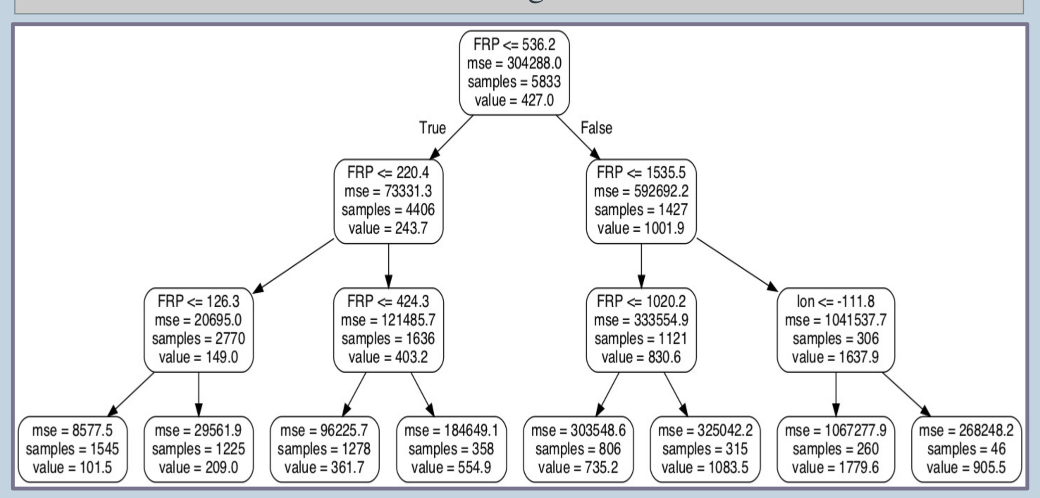
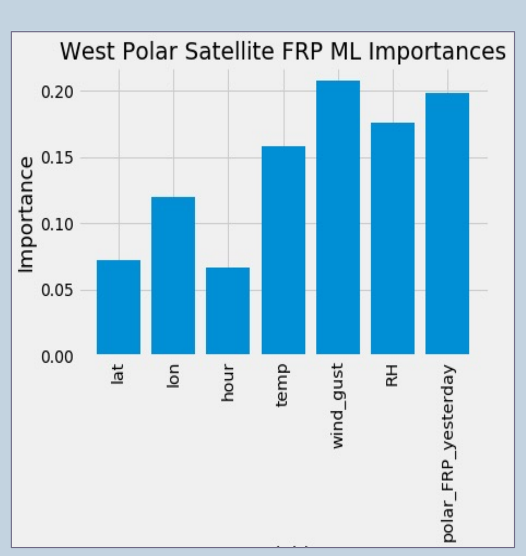


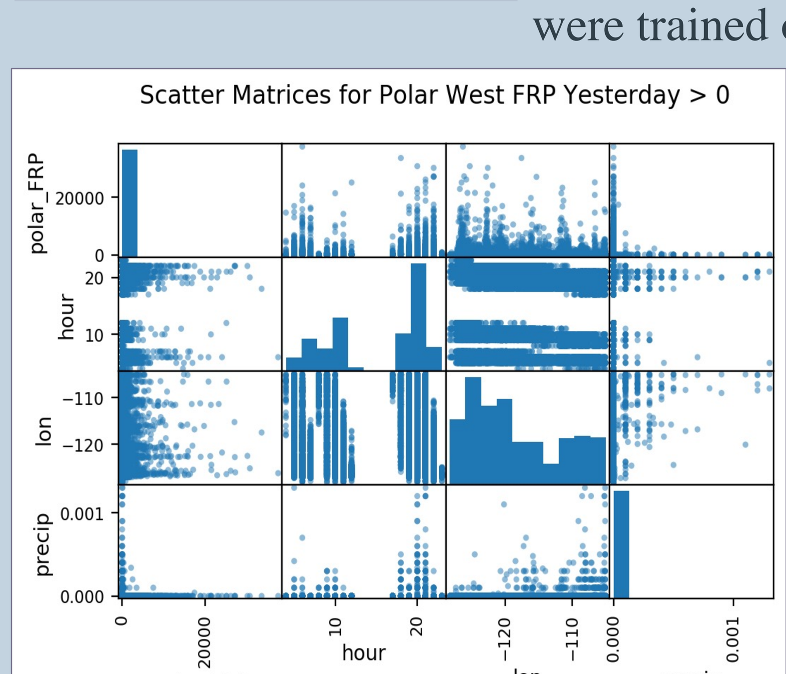
Figure 2: An example of a (shallow) tree from within the random forest model.

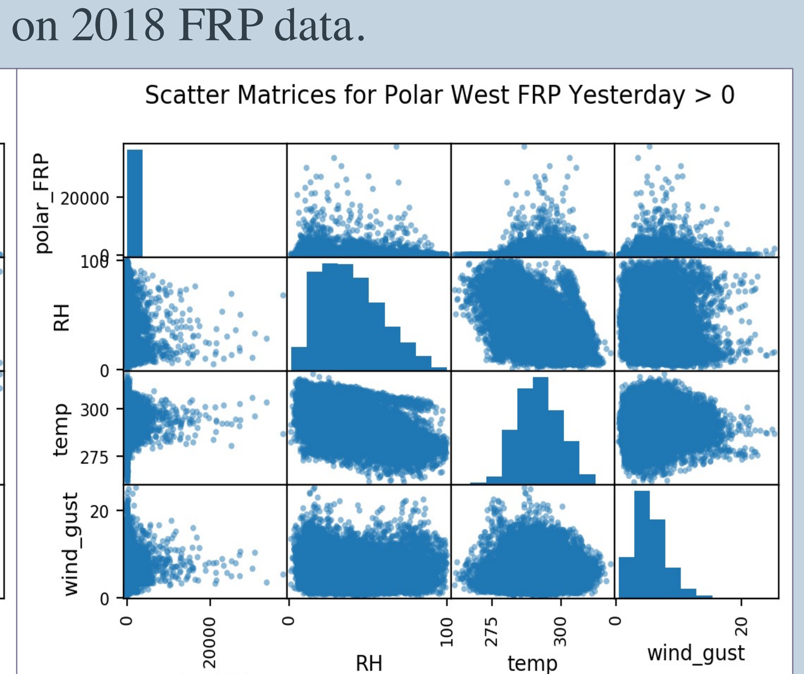
Random Forest Model for Fire Radiative Power (FRP):

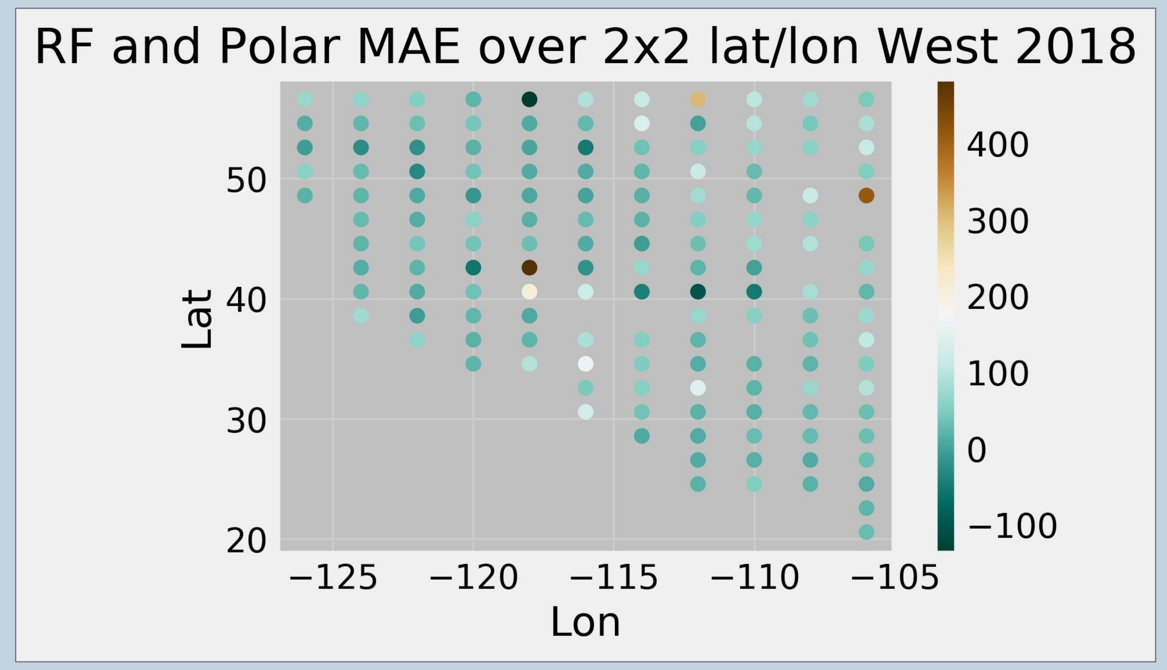
Polar WEST:		GOES WEST:	
Training Features Shape:	(26026, 7)	Training Features Shape:	(113870, 7)
Testing Features Shape:	(11154, 7)	Testing Features Shape:	(48802, 7)
MAE for RF:	242	MAE for RF:	65.9
MAE for HRRR:	388.52	MAE for HRRR:	184.93



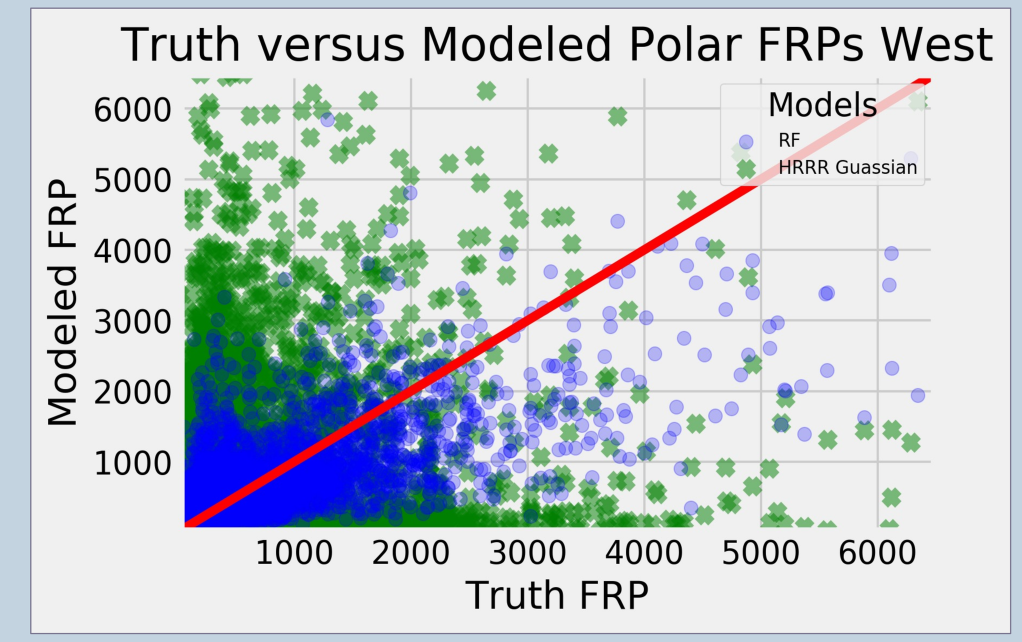
RF models make input importance analysis easy compared to other machine learning methods. Through this, precipitation was found to be an unimportant variable, likely due to its infrequency in the dataset, as was vegetation type. They were not included in these particular RF models. There are relationships between FRP and time of day, however no variable is completely dependent upon another. There is a slight bias to time of day in the polar models given the orbit. Satellite-type-specific models were trained on 2018 FRP data.

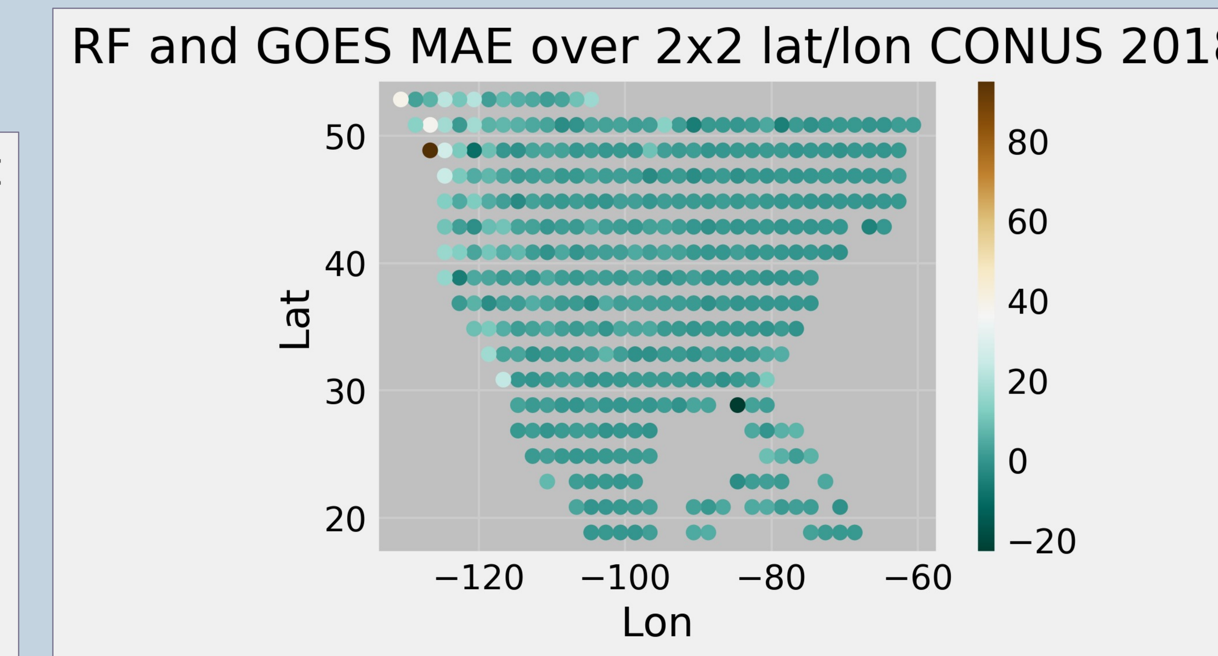




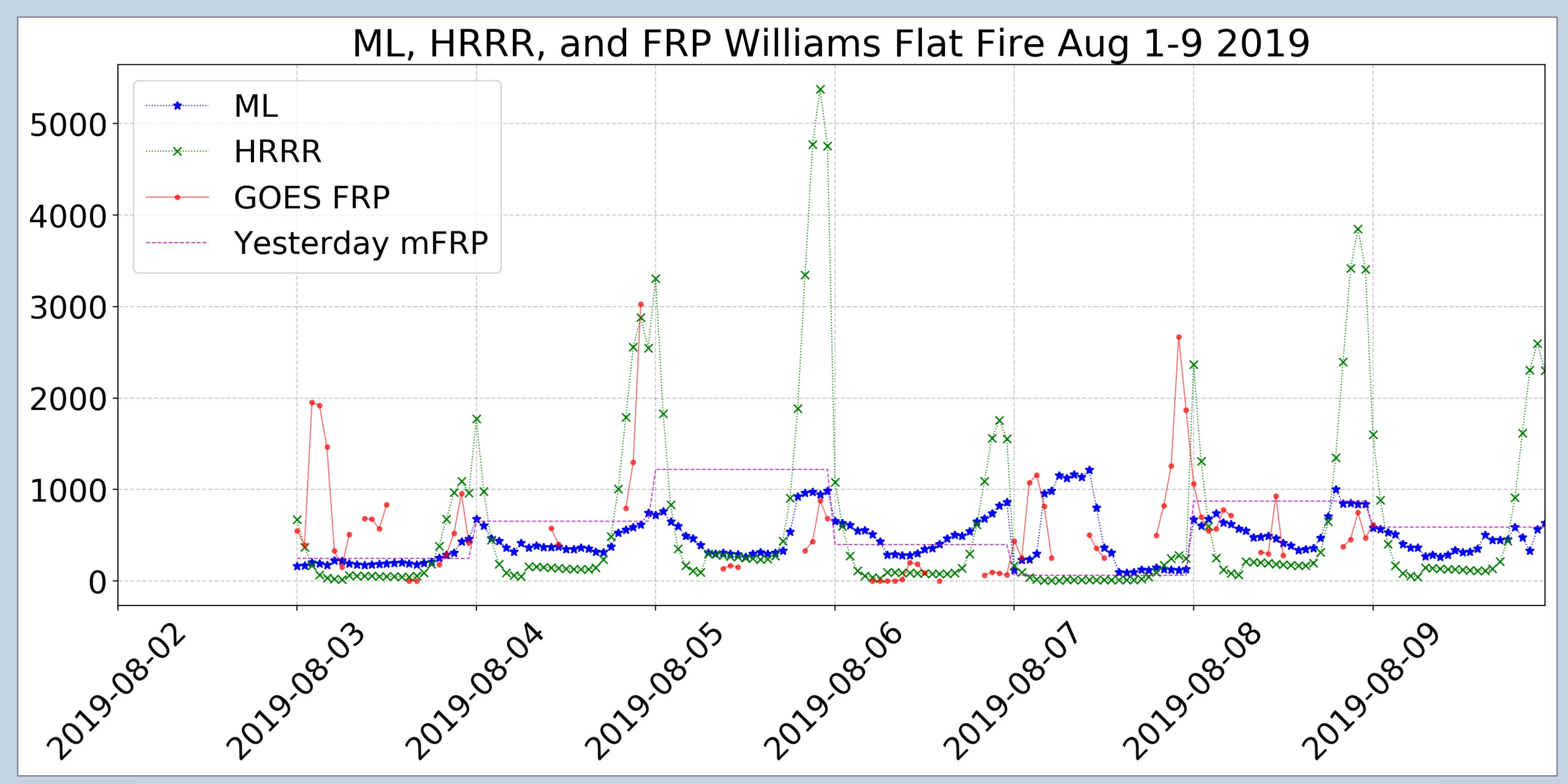


Model Analysis:

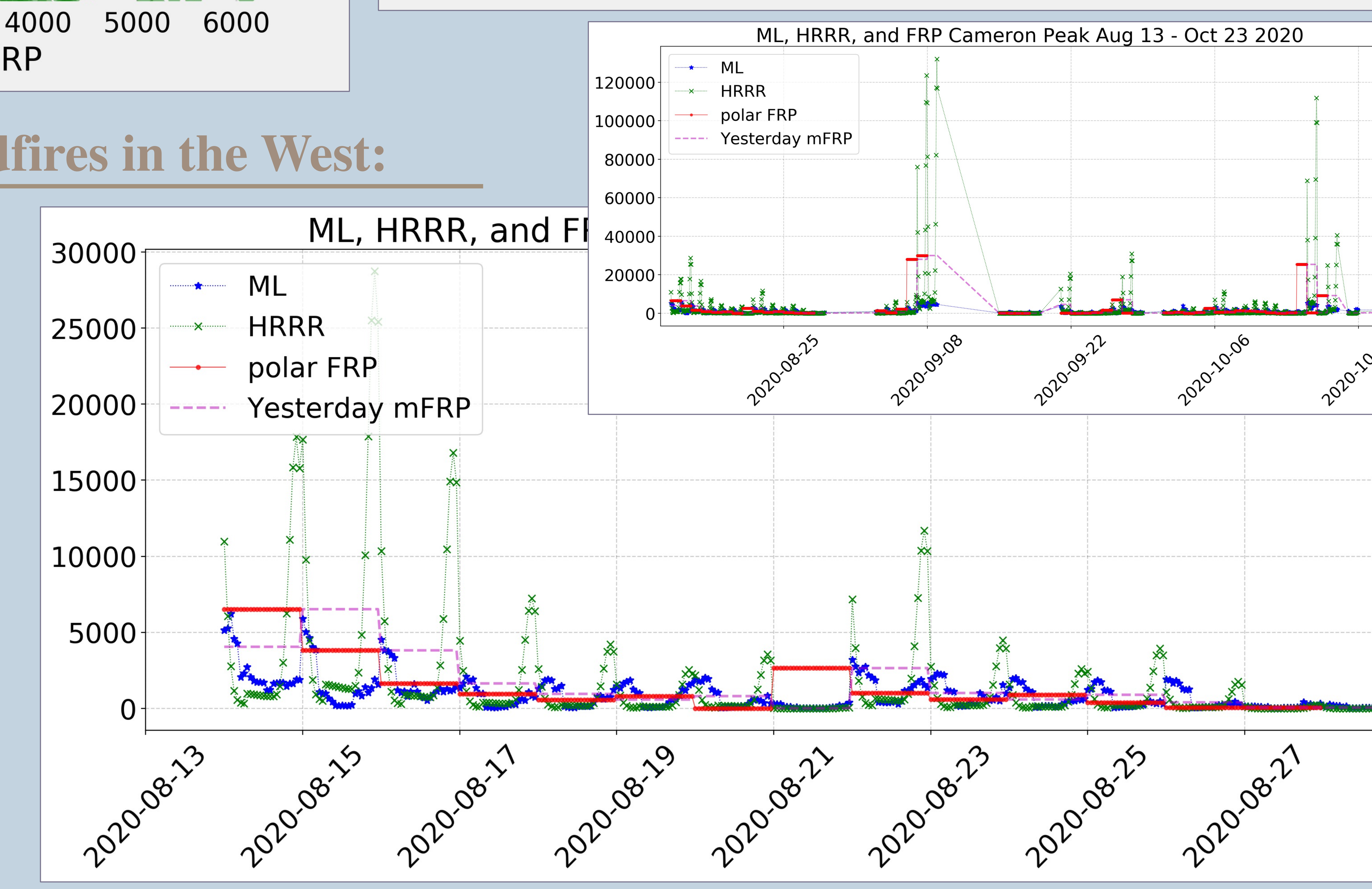




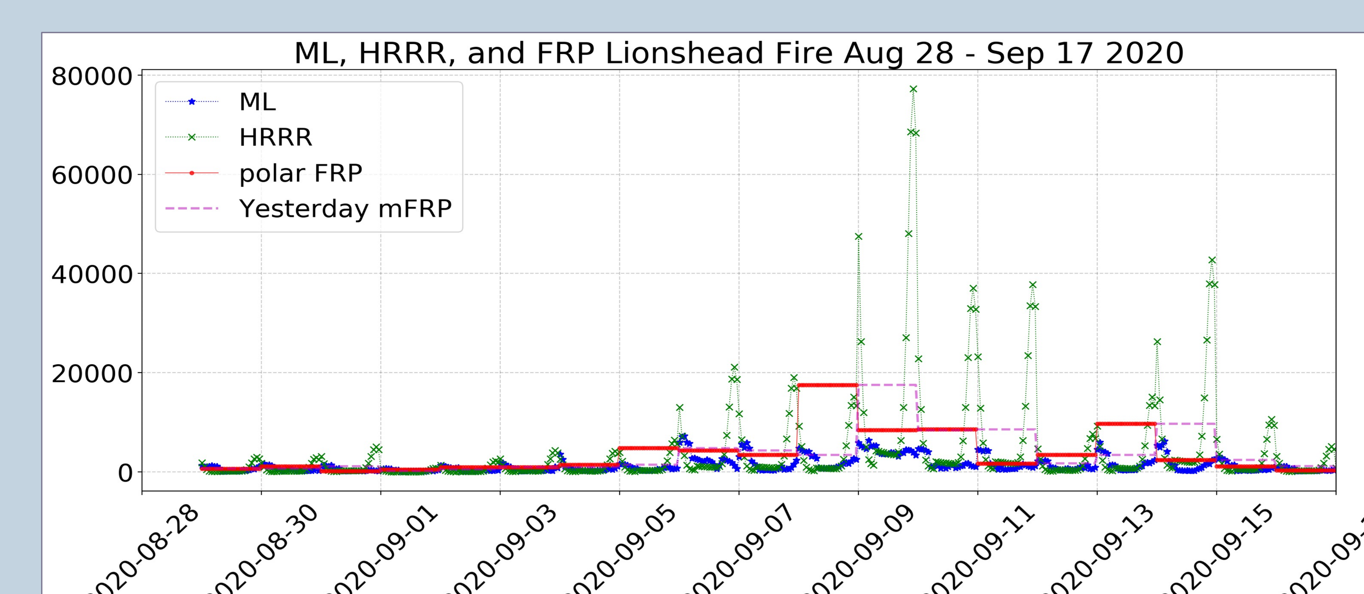
Case studies for Wildfires in the West:



Williams Flat Fire, Washington:
Mean Absolute Error for FRP RF: ***467.22***
Mean Absolute Error for FRP HRRR Gaussian Curve: ***870.34***
Mean Absolute Error for FRP RF at hourly points: ***429.46***
Mean Absolute Error for FRP HRRR Gaussian Curve at hourly points: ***743.5***



Cameron Peak Fire, Colorado:
Mean Absolute Error for FRP RF: ***2360.87***
Mean Absolute Error for FRP HRRR Gaussian Curve: ***3565.99***



Lionshead Peak Fire, Colorado:
Mean Absolute Error for FRP RF: ***3828.21***
Mean Absolute Error for FRP HRRR Gaussian Curve: ***6314.11***

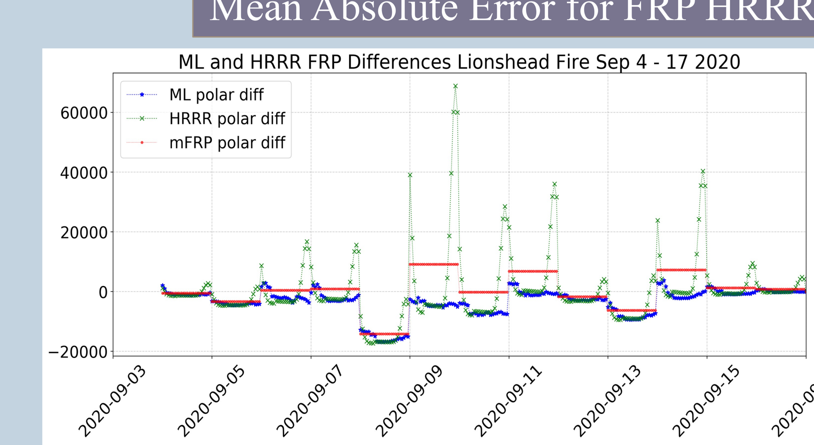


Figure 3: This difference plot shows how when FRP is at it strongest in this fire, the HRRR persistence model overestimates the FRP substantially. Typically, the FRP is underestimated by both methods the day after a large increase in mean intensity and then can be overestimated the next day.

Conclusions:

Two RF models were designed to use yesterday's mean FRP from either (1) polar orbiting or (2) geostationary satellites. Additionally, two RF models were trained over either (1) the entire conus or (2) west of the -105 longitude part of the CONUS domain to build models more fit to wildfire FRP modeling. The RF models all performed better than the current HRRR persistence method overall. The RF model is more bounded, so there are fewer extreme modeled FRP values as a consequence, the models tended to under estimate the FRP values.

One restriction to FRP modeling is the dependency on a non-zero FRP mean value from the day before. In future models, we are looking to model based on a rolling 24-hour average FRP product to help with modeling gaps and lags in new FRP information. Additionally, looking at a way to combine both GOES and polar orbiting satellite FRPs into one input FRP value to train RF models on a combined product could help with missing data gaps as well. Experimental RF models trained with rolling 24-hour average FRP inputs as well as a "both" product outperform the shown models, however the input data is not yet ready for real-time applications.

Additionally, a new fire weather index variable has been created in the lab, see Eric James, and it is our goal to train new RF models with this input, precipitation, and mean FRP as well as train over a larger time period which includes both 2018-2019. 2019 was a smaller fire year but we have quality controlled GOES FRP measurements.