An investigation into wildfire fuel moisture content: dead or alive

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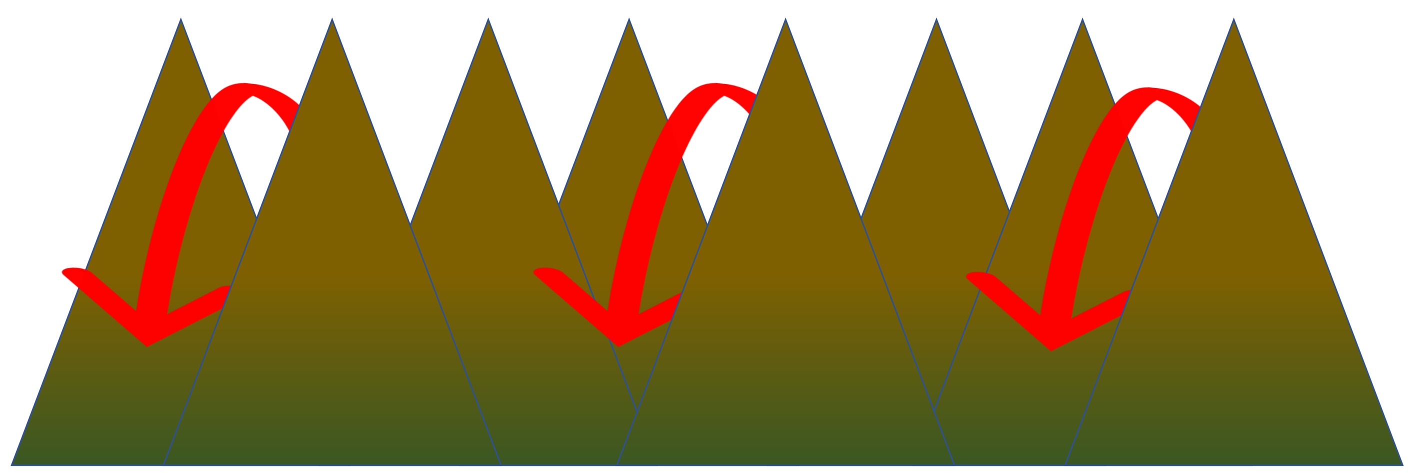
Abstract

Understanding wildfire dynamics requires comprehension of meteorology, climate, ecology, combustion, and complex topography. The interactions between these factors alter the amount of water within vegetation, also known as fuel moisture content (FMC), thus affecting the flammability. Better prediction of FMC can help communities increase their resilience and can help wildfire behavior analysts model fire spread. In this study, we create a machine learning model to predict live FMC. Our predictors include meteorological outputs from a 32-year Weather Research and Forecasting (WRF) Model climatology, Landsat observations, and static topography data. Our predictands consist of ten thousand in-situ FMC observations, spanning eight chaparral species, from the National Fuel Moisture Database. Lag correlation analysis is performed to determine the strongest relationship between predictors and predictands before running the random forest model. Dead FMC is being calculated using semi-empirical equations adapted from the Nelson dead fuel model. After successful live and dead FMC models are created, a historical, gridded dataset of FMC will be constructed. FMC variations will then be connected with different weather and climate events, as well as different wildfire behavior case studies. This moderate resolution modeling of FMC can also be used to better inform resilience efforts in the region of interest, such as Santa Barbara County's Regional Wildfire Mitigation Program (RWMP).



Application

Downslope windstorms, known as Sundowners, combined with flammable chaparral ecosystems and human spread into the wildland urban interface (WUI), cause significant wildfire danger to the populated regions of Santa Barbara County's south coast.

The Santa Barbara County Fire Safe Council is implementing a novel Regional Wildfire Mitigation Program (RWMP) aimed at holistically increasing wildfire resilience in three domains: community, landscape, built.

Dead Fuel Moisture (DFM)

This work is currently led by Katie Vick, UCSB Earth Science undergraduate. Dead fuels are classified into different size classes. The US National Fire Danger Rating System uses the nomenclature: 1-, 10-, 100-, and 1000-hr fuels, which corresponds to the amount of time that two thirds of the mass of the fuel equilibrates with atmospheric moisture levels.

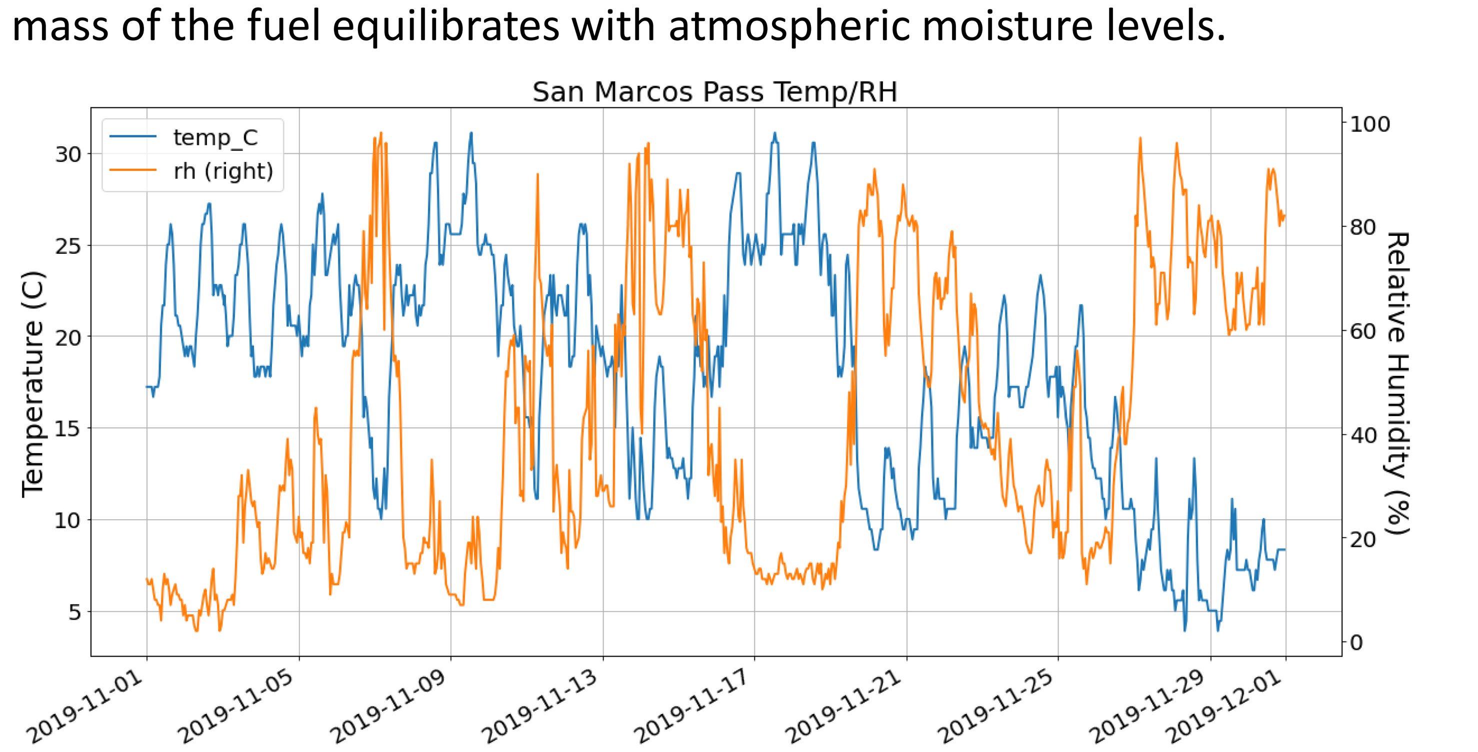


Figure 1. Temperature and relative humidity time series at a weather station near the November 25, 2019, Cave Fire ignition. The biggest driver of DFM changes involves vapor exchange with the surrounding air.

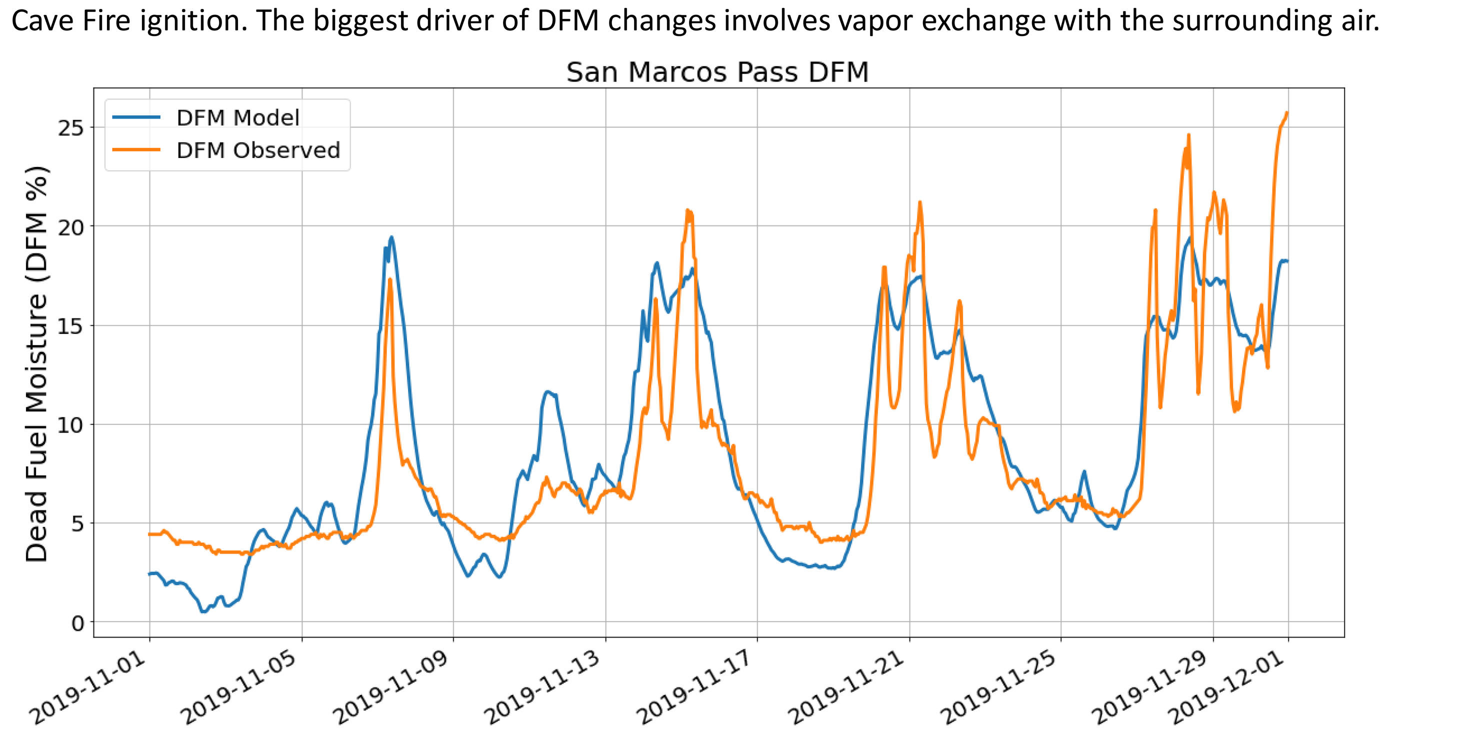


Figure 2. The RAWS from Fig. 1 also observes 10-hr DFM. We have been testing different semi-empirical methods for calculating the 10-hr DFM. This figure shows the method used in Nieto (2009), which is a variation of the Nelson (1984) model. It is based on calculating an equilibrium moisture content (EMC), as seen below.

$$\mathrm{EMC} = \frac{100}{B} \ln\left(\frac{-RT}{M \exp A} \ln \frac{\mathrm{RH}}{100}\right)$$

R = Universal gas constant
M = molecular weight of water
A/B = fuel type specific parameters
T = Temperature (K)
RH = Relative Humidity (%)

Live Fuel Moisture (LFM)

Live fuel moisture behaves differently than DFM, due to soil-plant-water dynamics. The LFM response time to changes in atmospheric conditions is longer than DFM and varies amongst vegetation type. Many fire agencies collect vegetation samples to help determine wildfire danger. The samples are immediately weighed, then dried, and weighed again to determine LFM. LFM significantly alters how hot, fast, and far a wildfire will burn, and it has a strong influence on when fire season begins and ends in any given location.

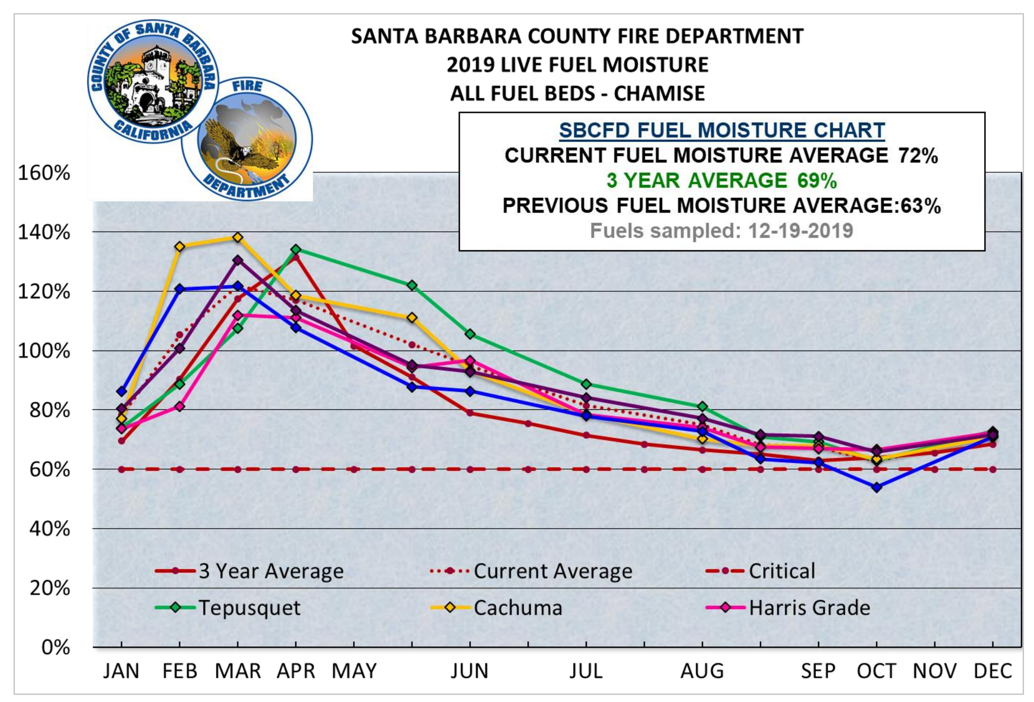


Figure 3. Chamise LFM samples taken throughout Santa Barbara County during 2019. LFM levels were on the rise, and above the critical 60% threshold when the November 25, 2019, Cave Fire ignited.

Data and Methods

We are building a machine learning model using predictors from Landsat, the Weather Research and Forecasting (WRF) model, and LANDFIRE. Predictands come from National Fuel Moisture Database LFM samples.

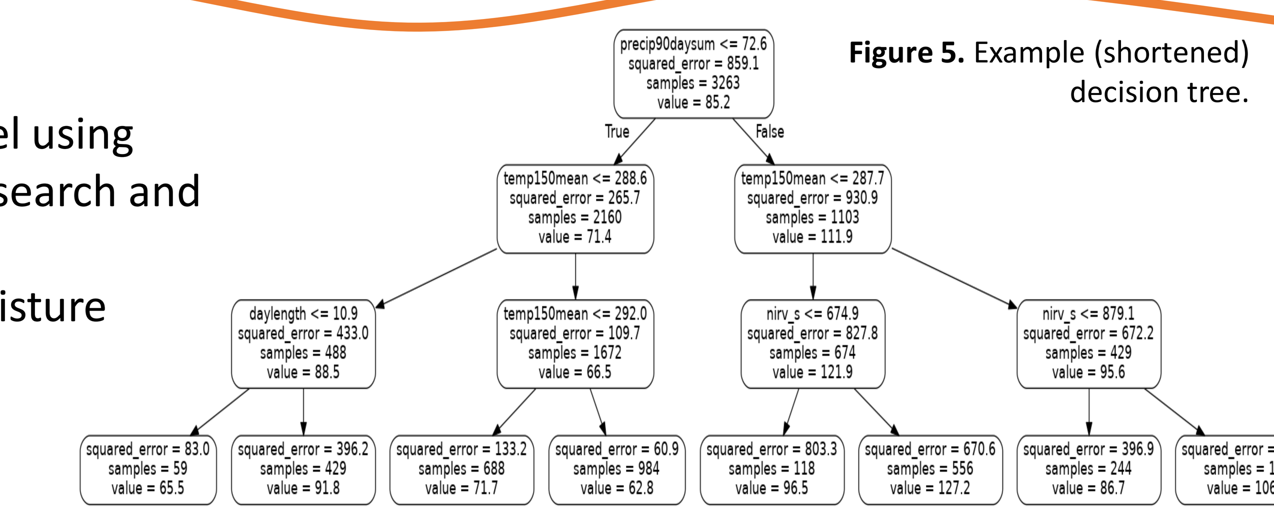


Figure 5. Example (shortened) decision tree.

Figure 4. LFM observation locations throughout our current domain. There are 30 locations, with 10,397 observations of 8 different species.

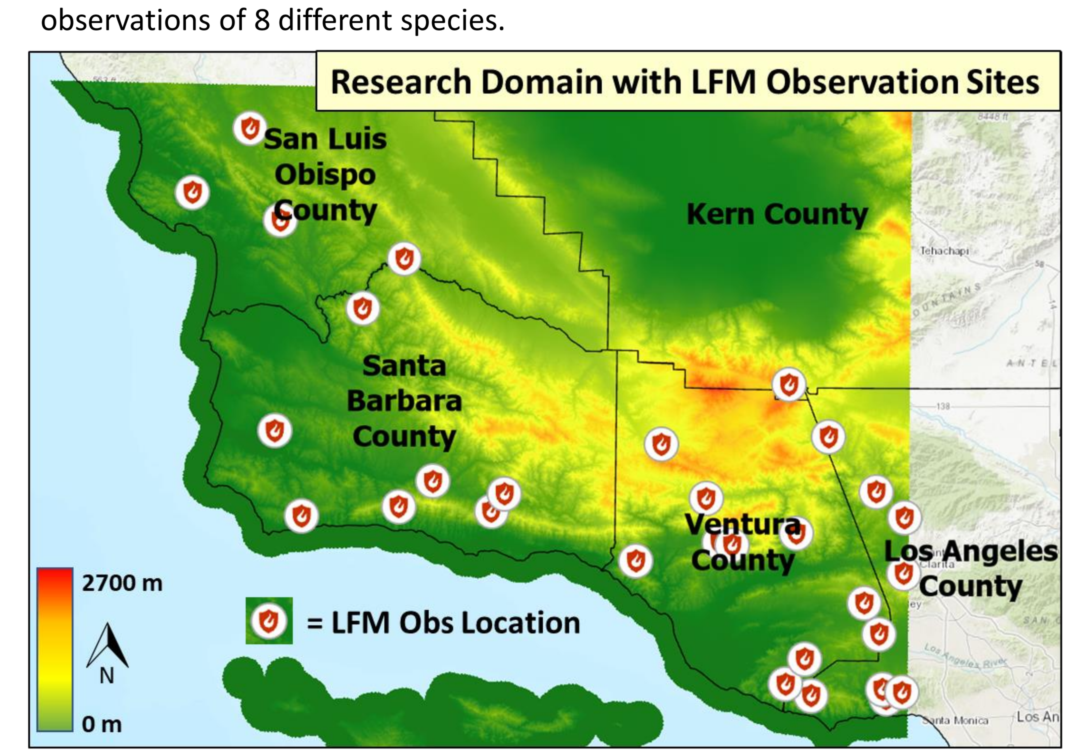


Table 1. Predictor variables are calculated at each of the LFM observation sites. The combination of numerical weather modeling variables and remote sensing variables incorporates environmental and vegetation conditions.

WRF variables		Raster vars
3-day max temp mean	90-day mean temp	Elevation
7-day max temp mean	150-day mean temp	Slope
7-day min RH mean	150-day mean RH	Aspect
3-day total precip	150-day incoming radiation	NDVI
7-day total precip	30-day wind speed	NDMI
Daily evapotranspiration	30-day mean VPD	NIRV
Daily AWD (e-p)	30-day total precip	
Day Length	90-day total precip	
7-day mean soil moisture		
Pressure		

Current results – 10 Random forest models were run, one with all species combined, as well as one for each individual species. Before the model run, k-fold cross validation was performed to determine the number of decision trees that minimized mean absolute error. The all-species model did not perform well, which was expected, due to the reasoning shown in Fig 7. Next steps include using potential evapotranspiration as a dry-down predictor, additional predictor analysis, and testing other machine learning methods.

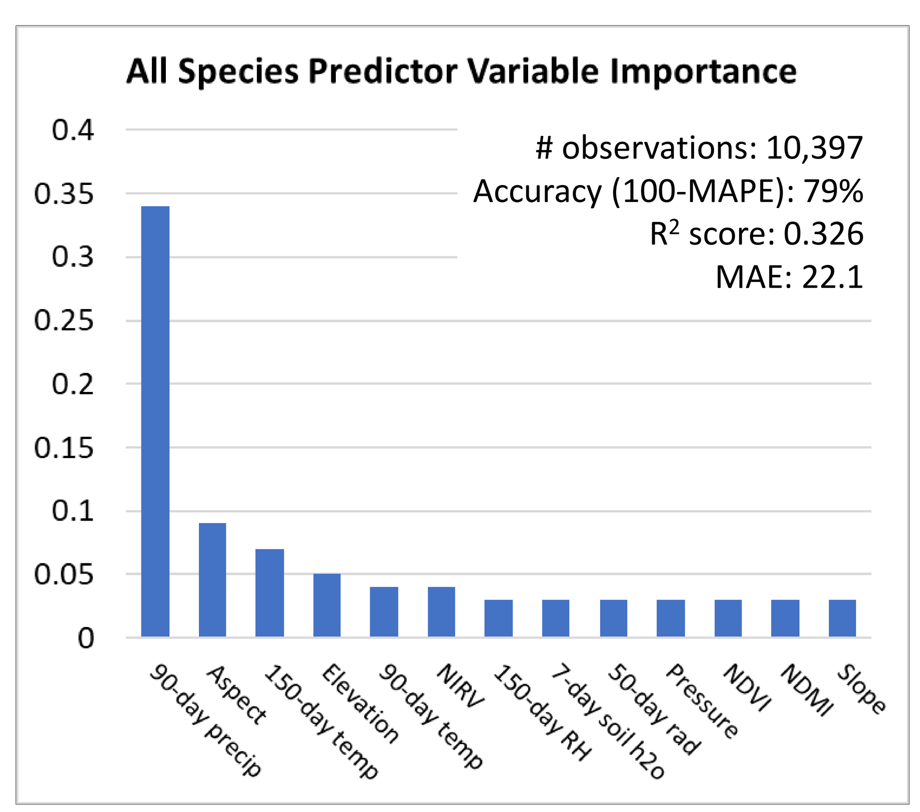


Figure 6. The random forest model that included all species did not perform well (see inset results) due to LFM variation between species (see Fig. 7). 90-day accumulated precipitation had the highest importance, which measures the decrease in incorrect classification likelihood when that variable is chosen to split a decision tree node.

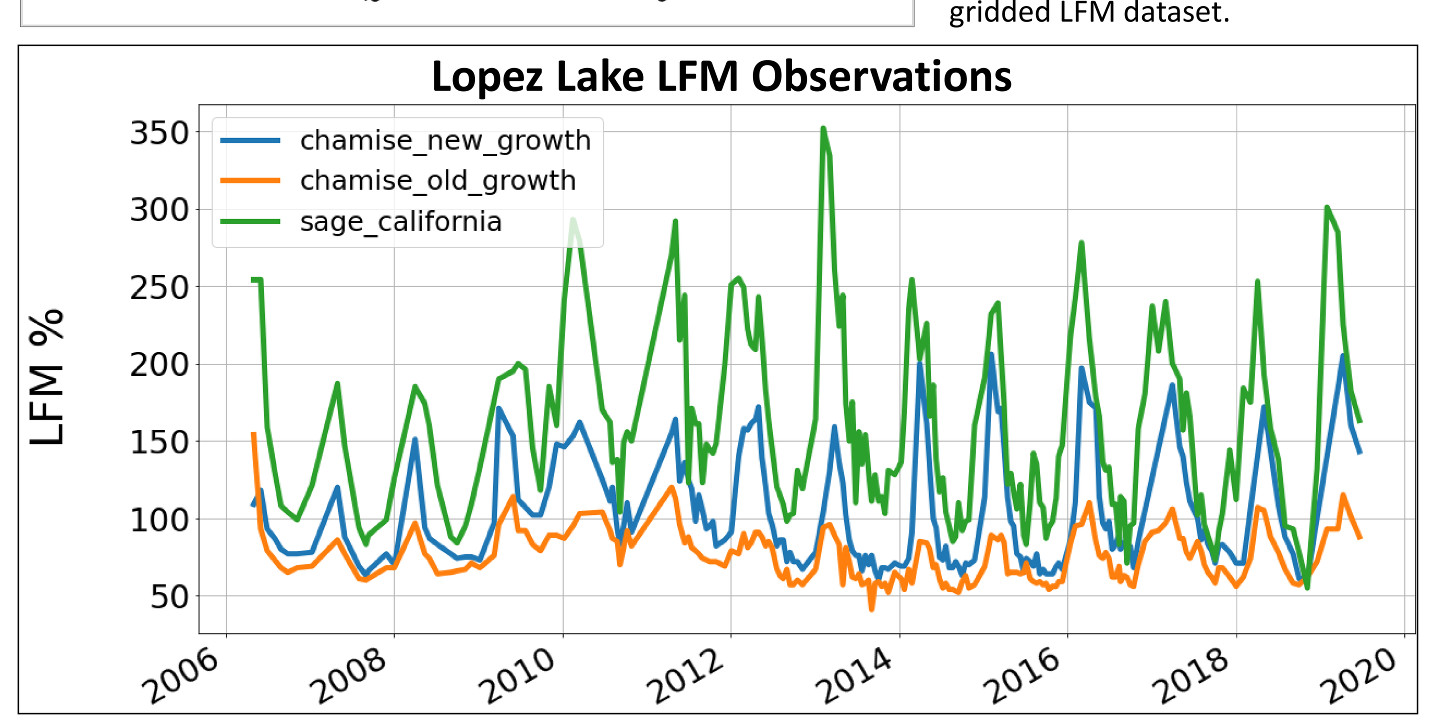


Figure 7. LFM observations of chamise, old growth chamise, and California sage at Lopez Lake. The differences between the samples makes it difficult to create a gridded LFM dataset.

Figure 8. The chamise random forest model performed much better than the all-species model (see inset results). The same predictor variables were used, but the top 6 variable importance values are shown here. Five out of the six variables all follow a seasonal cycle, just like LFM.

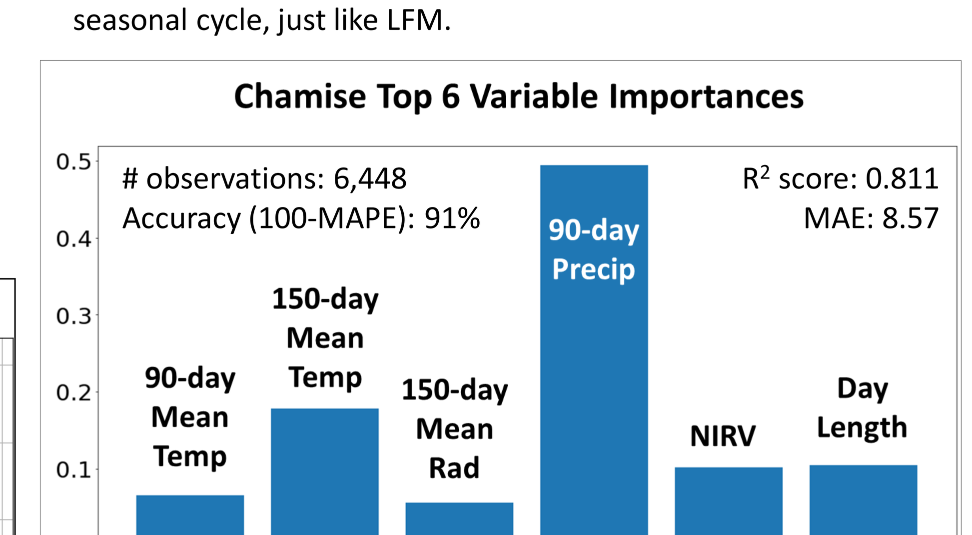
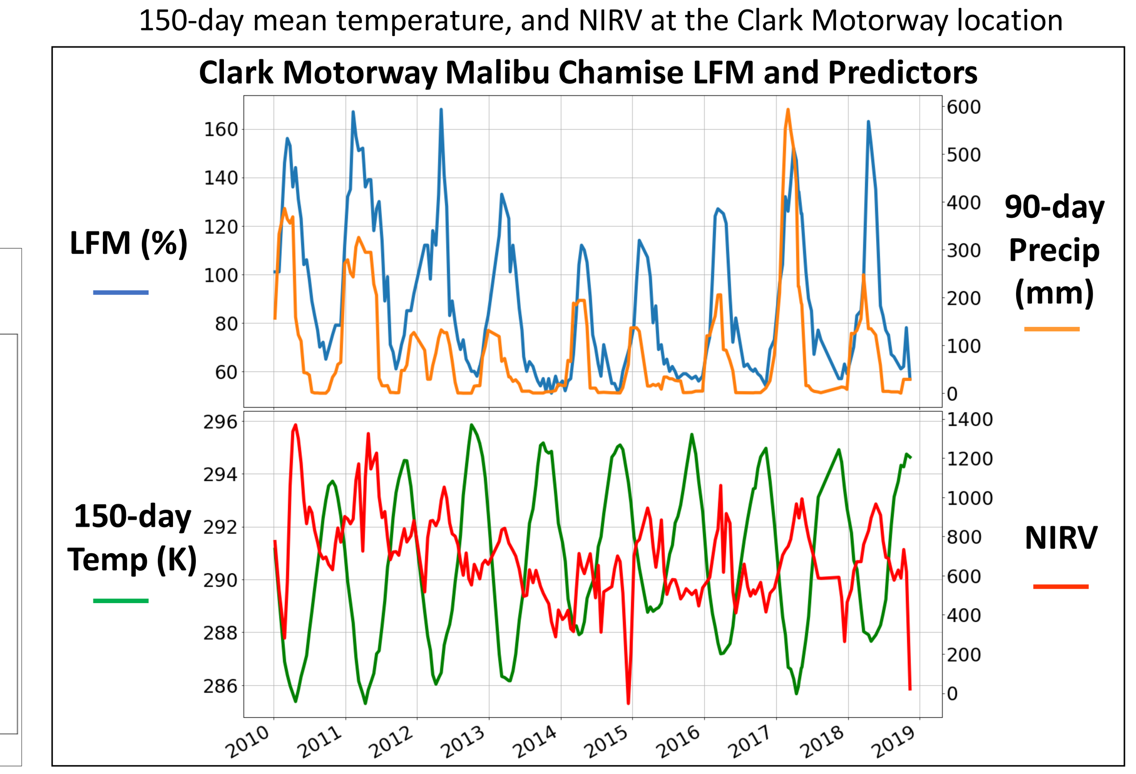


Figure 9. Observed chamise LFM, 90-day accumulated precipitation, 150-day mean temperature, and NIRV at the Clark Motorway location



References/Acknowledgments

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