Estimations of fuel moisture content for improved wildland fire spread prediction

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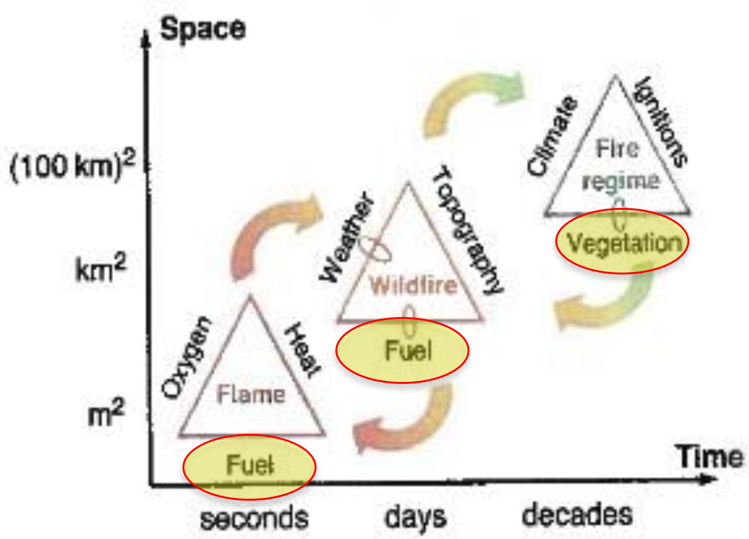
Fuel moisture content (FMC) is an essential parameter in forecasting wildland fire spread

- Decision support systems for wildland fire behavior are essential for effective and efficient wildland fire risk assessment and firefighting.
- Together with the Center of Excellence for Advanced Technology Aerial Firefighting in Rifle, Colorado we are developing a wildland fire prediction system for the State of Colorado.
- The wildland fire prediction system is based on the National Center of Atmospheric Research's Coupled Atmosphere Wildland Fire Environment (CAWFE) model, and the Weather Research and Forecasting – Fire (WRF-Fire) model.
- The project supports Applied Science Program goals to deliver near-term uses of Earth observations by building capabilities for applying Earth science data to improving disaster response and ecosystem management related to wildfire prediction and thus deliver societal benefits.

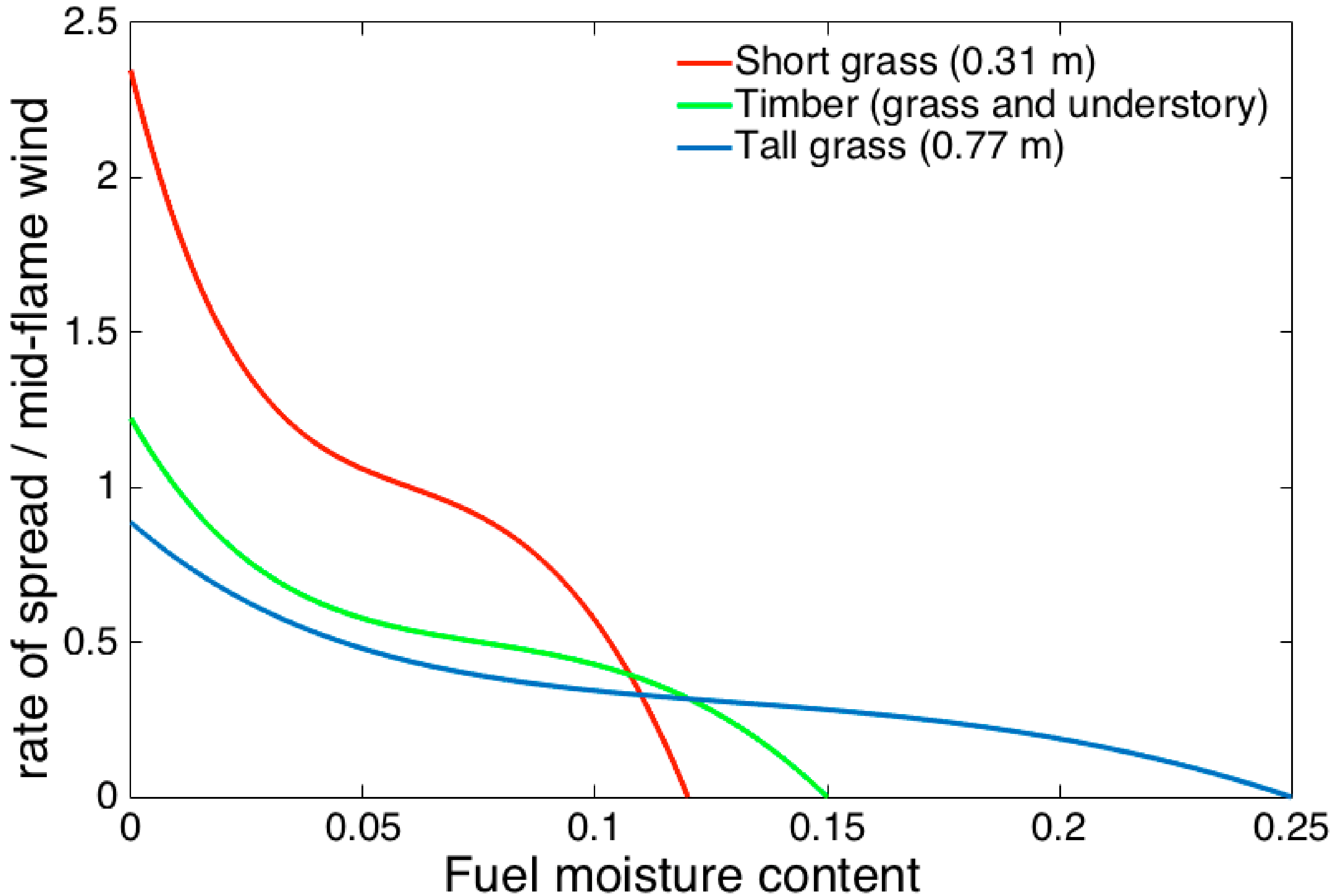
Objective is to develop a real time gridded fuel moisture content data set over CONUS

The goals of the project are:

- Develop, implement, and demonstrate dynamic, real-time FMC database in WRF-Fire coupled atmosphere wildland fire prediction model (a component of CO-FPS).
- Achieve more accurate accounting for live and dead FMC that will result in more realistic, dynamic representation of fuel heterogeneity and in improved accuracy of wildland fire spread prediction.
- Assess the effectiveness of the coupled atmosphere wildland fire spread prediction model accounting for the FMC using observations of wildland fires over Colorado.



Dimensionless rate of spread as a function of FMC



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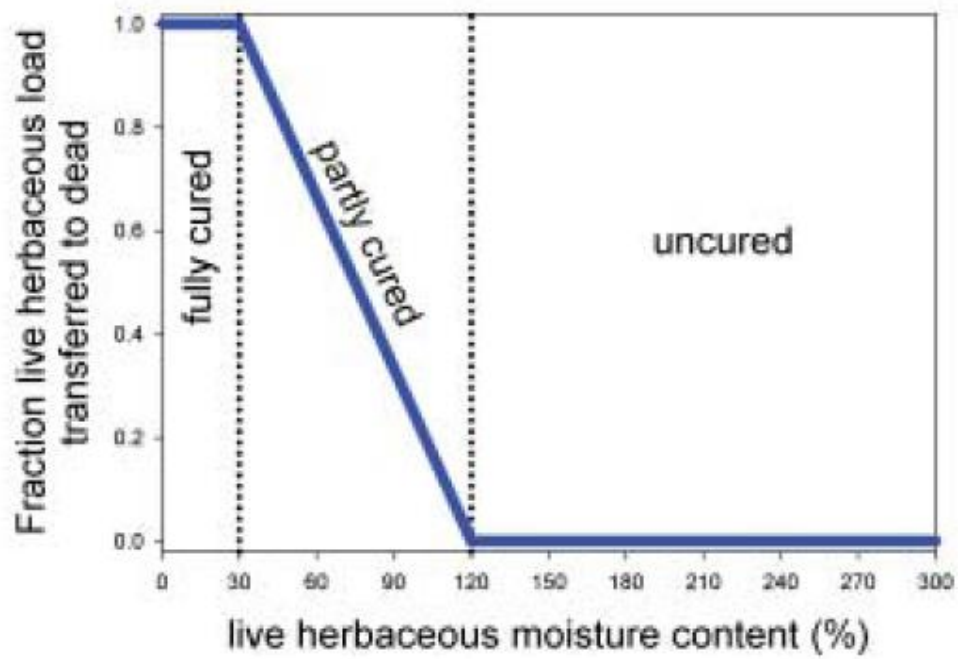
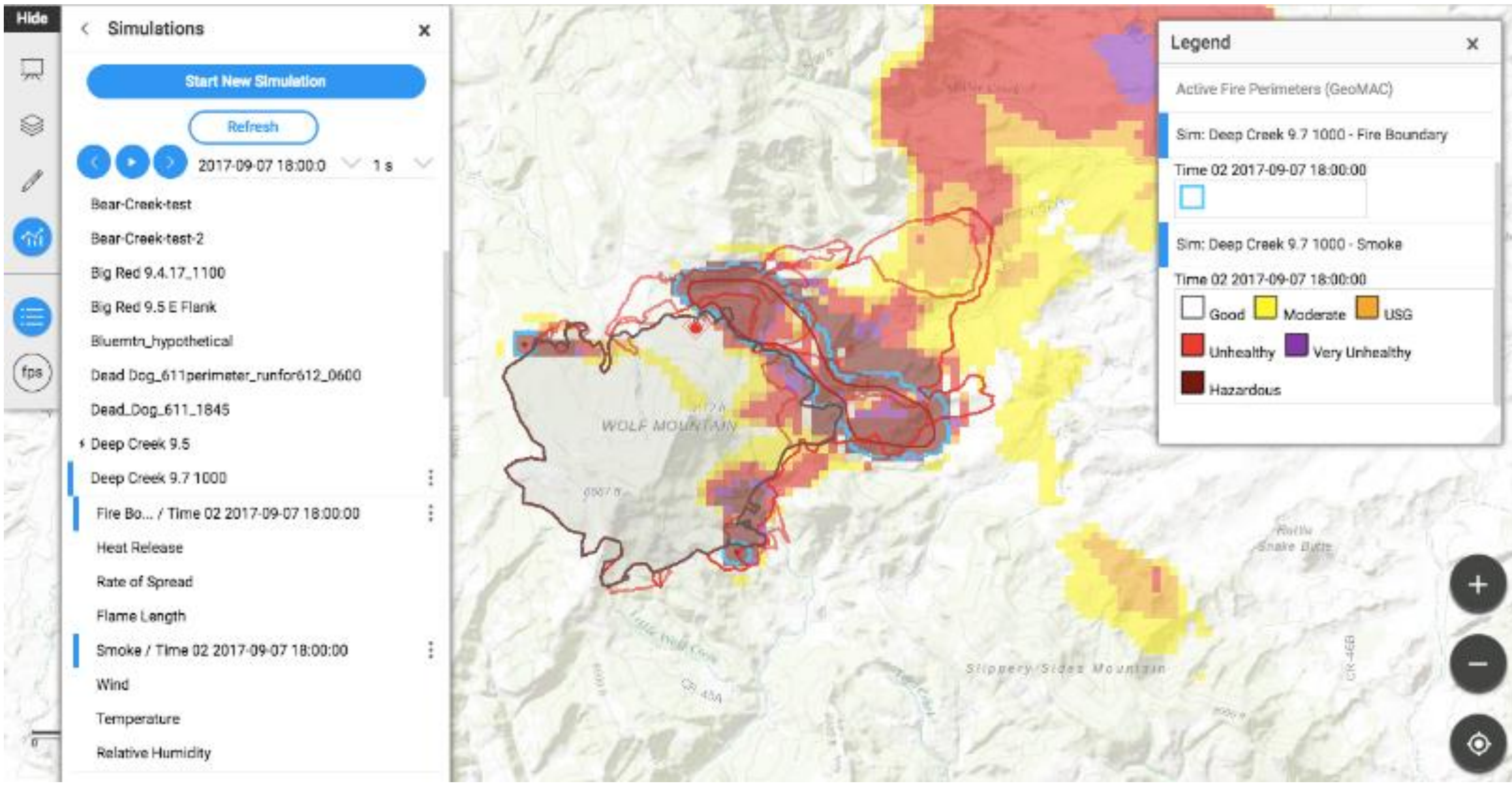
Scott and Burgan's Fuel Model

- Scott and Burgan's "Dynamic" Fuel Model (2005) eliminates the assumption that the fuel is uniformly dry.
- Instead "live herbaceous load is transferred to dead as a function of the live herbaceous moisture content."
- The use of a curing coefficient allows more realistic modeling of fire behaviors in live fuels.

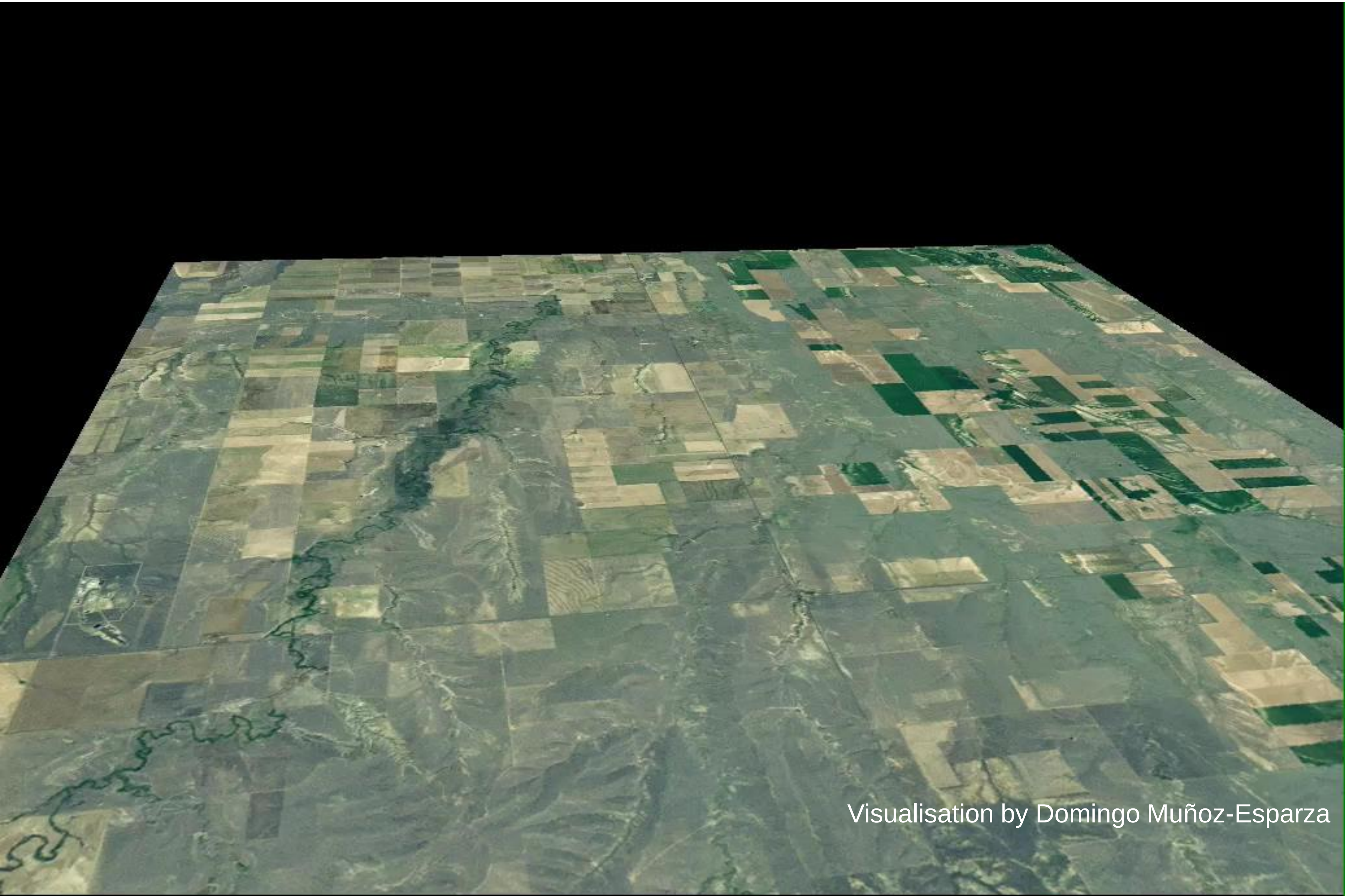


Colorado Fire Predictions System (CO-FPS)

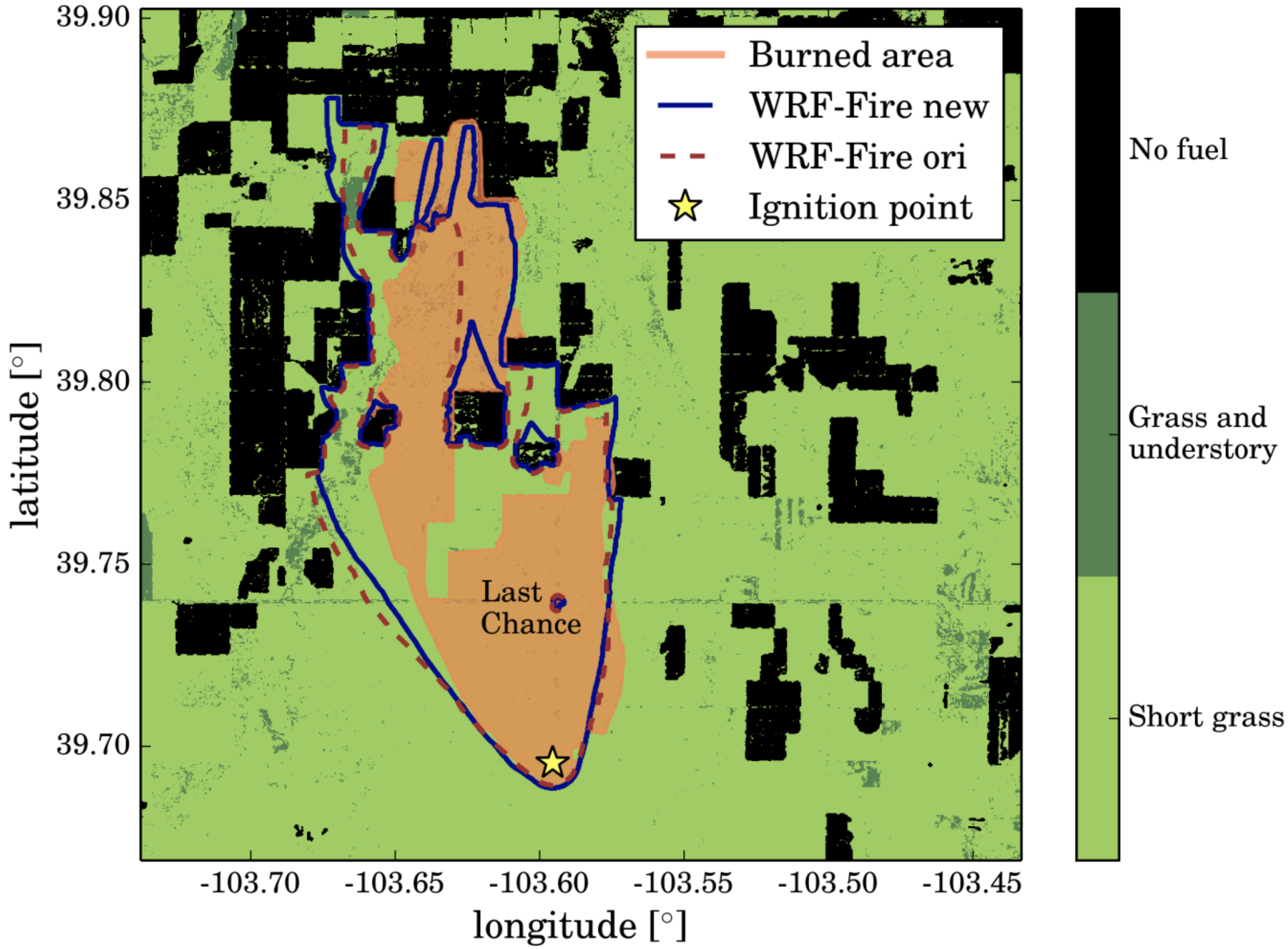
Colorado Fire Prediction System (CO-FPS) can be accessed through Colorado Wildfire Information Management System (CO-WIMS)



WRF-Fire Simulation of Last Chance Fire Colorado 2012



Last Chance, Colorado, fire in 2012 was successfully simulated using WRF-Fire



Muñoz-Esparza, Kosović, Jimenez, and Coen, JAMES 2018

https://doi.org/10.1002/2017MS001108

We have processed surface and satellite observations and model output for use in machine learning

We have collected historical (2016-2017) data and we are collecting real time data

MODIS Terra and Aqua satellite instruments: vegetation indices and measured reflectances from the remote sensing

Remote Automatic Weather Station (RAWS) and WFAS: surface observations

Fuel Type from Landfire

National Fuel Moisture Database

NWP: WRF-Hydro or HRRR

We have processed surface and satellite observations and model output for use in machine learning

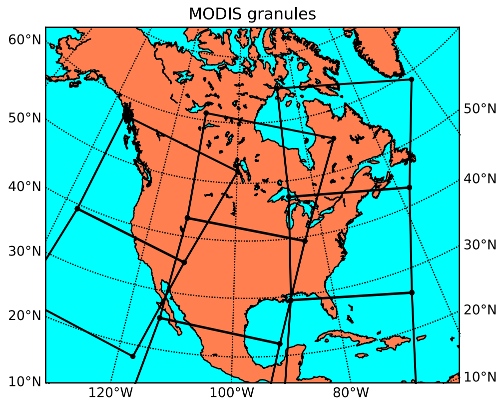
- The data were quality controlled, satellite data were projected onto a 1 km CONUS grid, and all the data were converted to the netCDF format.
- The data are in general of good quality and therefore suitable for effective use in machine learning algorithms.
- Using reflectances we have computed the following vegetation indices: GVMI, NDVI, NDWI, PMI, and VARI.

- We have selected 11 wildland fires observed during fire season 2016 in Colorado as test cases for the new FMC data set.
- We carried out simulations of selected wildland fires using constant FMC, these simulations will represent a baseline for the assessment of the new FMC data set.

Aqua and Terra granules are mapped onto a one-kilometer CONUS grid

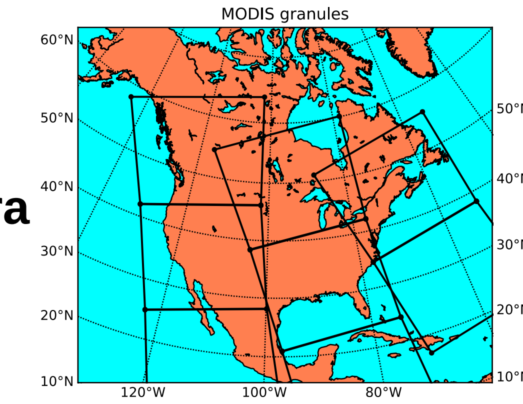
Processing of MODIS (Aqua and Terra) Granules

MODIS Aqua and Terra granules are separately mapped onto a 1 km CONUS grid that corresponds to the refined High Resolution Rapid Refresh (HRRR) forecasting system grid and which will be used to estimate FMC.

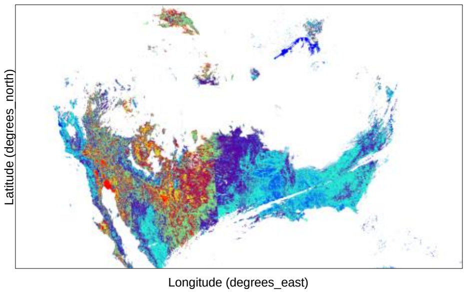


Aqua

Terra

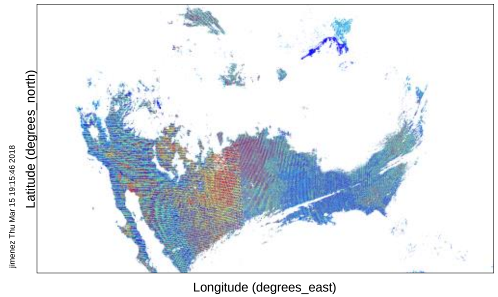


one_km_Surface_Reflectance_Band_1 (reflectance)



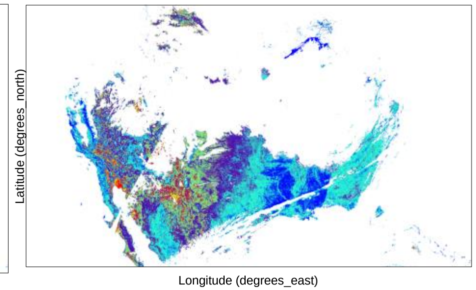
Range of one_km_Surface_Reflectance_Band_1: 121.161 to 3197.97 reflectance
Range of Longitude: 0 to 0 degrees_east
Range of Latitude: 0 to 0 degrees_north
Frame 178 in File modis-fmc.nc-aqua

one_km_Surface_Reflectance_Band_6 (reflectance)



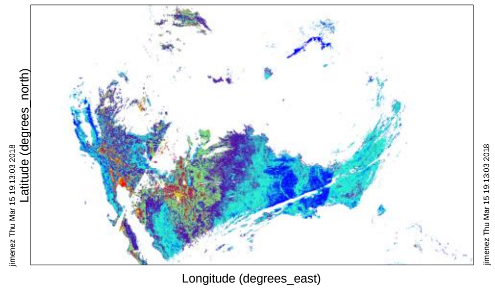
Range of one_km_Surface_Reflectance_Band_6: 1.52046 to 5020.76 reflectance
Range of Longitude: 0 to 0 degrees_east
Range of Latitude: 0 to 0 degrees_north
Frame 178 in File modis-fmc.nc-aqua

one_km_Surface_Reflectance_Band_1 (reflectance)



Range of one_km_Surface_Reflectance_Band_1: 200.024 to 3689.34 reflectance
Range of Longitude: 0 to 0 degrees_east
Range of Latitude: 0 to 0 degrees_north
Frame 194 in File modis-fmc.nc-terra

one_km_Surface_Reflectance_Band_1 (reflectance)



Range of one_km_Surface_Reflectance_Band_1: 200.024 to 3689.34 reflectance
Range of Longitude: 0 to 0 degrees_east
Range of Latitude: 0 to 0 degrees_north
Frame 194 in File modis-fmc.nc-terra

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Various Relevant indices are computed using reflectance bands

Vegetation Indices

Vegetation indices are based upon 6 of the MODIS bands

Band 1 (620-670 nm), 2 (841-876 nm), 3 (459-479nm), 4 (545-565 nm), 5 (1230-1250 nm), and 6 (1628-1652 nm)

NDVI (Normalized Difference Vegetation Index)

NDVI = (Band 2 – Band 1) / (Band 1 + Band 2)

NDWI (Normalized Difference Water Index)

NDWI = (Band 2 – Band 5) / (Band 2 + Band 5)

PMI (Perpendicular Moisture Index)

PMI = -0.73 (Band 5 – (0.94 Band 2) – 0.028)

VARI (Visible Atmospherically Resistant Index)

VARI = (Band 4 – Band 1) / (Band 4 + Band 1 – Band 3)

GVMI (Global Vegetation Moisture Index)

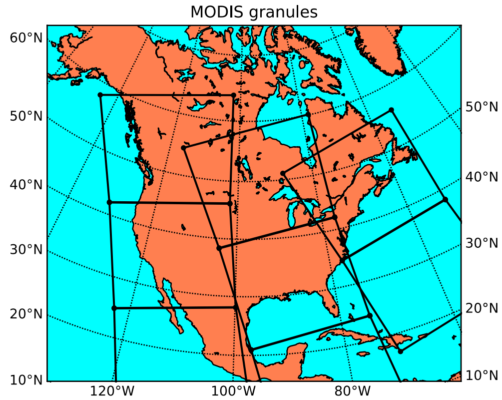
GVMI = (0.1 + Band 2) –(0.02 + Band 6) / (0.1 +Band 2) +(0.02 +Band 6)

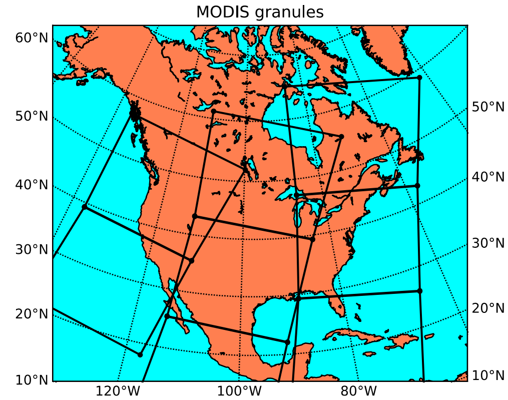
Vegetation indices are computed using reflectances and mapped onto a one-kilometer CONUS grid

Computing Vegetation Indices Using MODIS Reflectances

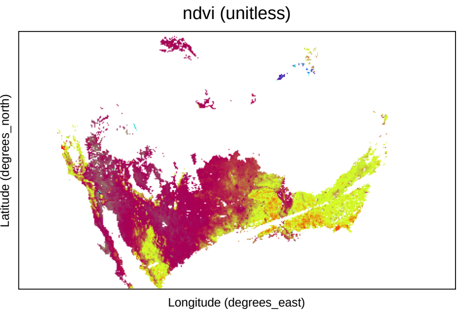
Vegetation indices are computed directly from Aqua and Terra reflectance granules.

Terra

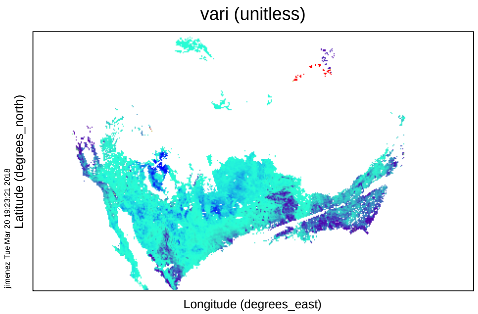




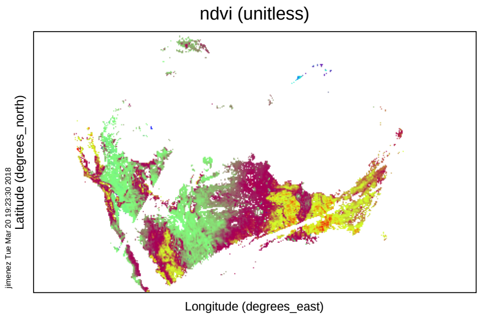
Aqua



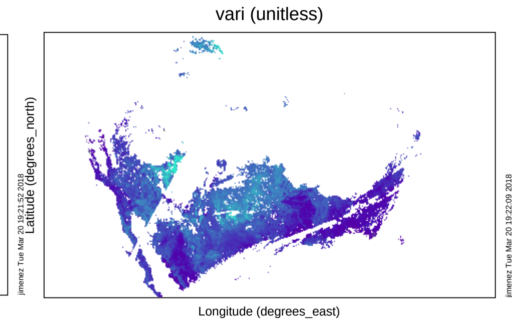
Range of ndvi: -1 to 0.81537 unitless
Range of Longitude: 0 to 0 degrees_east
Range of Latitude: 0 to 0 degrees_north
Frame 178 in File modis-fmc.nc-aqua



Range of vari: -0.380573 to 0.856777 unitless
Range of Longitude: 0 to 0 degrees_east
Range of Latitude: 0 to 0 degrees_north
Frame 178 in File modis-fmc.nc-aqua



Range of ndvi: -0.581194 to 0.830318 unitless
Range of Longitude: 0 to 0 degrees_east
Range of Latitude: 0 to 0 degrees_north
Frame 178 in File modis-fmc.nc-terra



Range of vari: -0.929276 to 1.80771 unitless
Range of Longitude: 0 to 0 degrees_east
Range of Latitude: 0 to 0 degrees_north
Frame 178 in File modis-fmc.nc-terra

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Linear fits of NFMD live FMC data to the MODIS bands 1 – 6 data are not significant to 2σ.

Data is for Colorado in 2016.

Band1
No

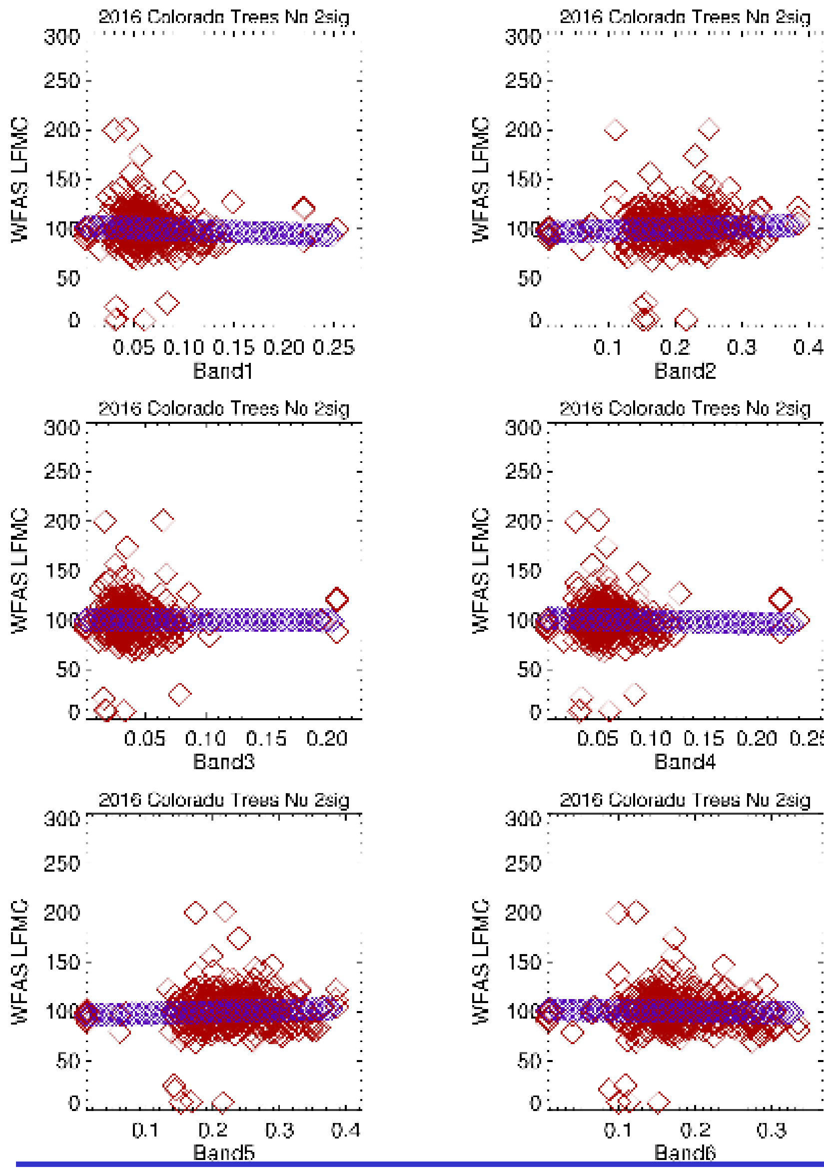
Band2
No

Band3
No

Band4
No

Band5
No

Band6
No



Band data is Not Significant To 2σ

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Linear fits of live FMC data to the MODIS derived NDVI, GVMI, and VARI spectral indices are significant to 2σ

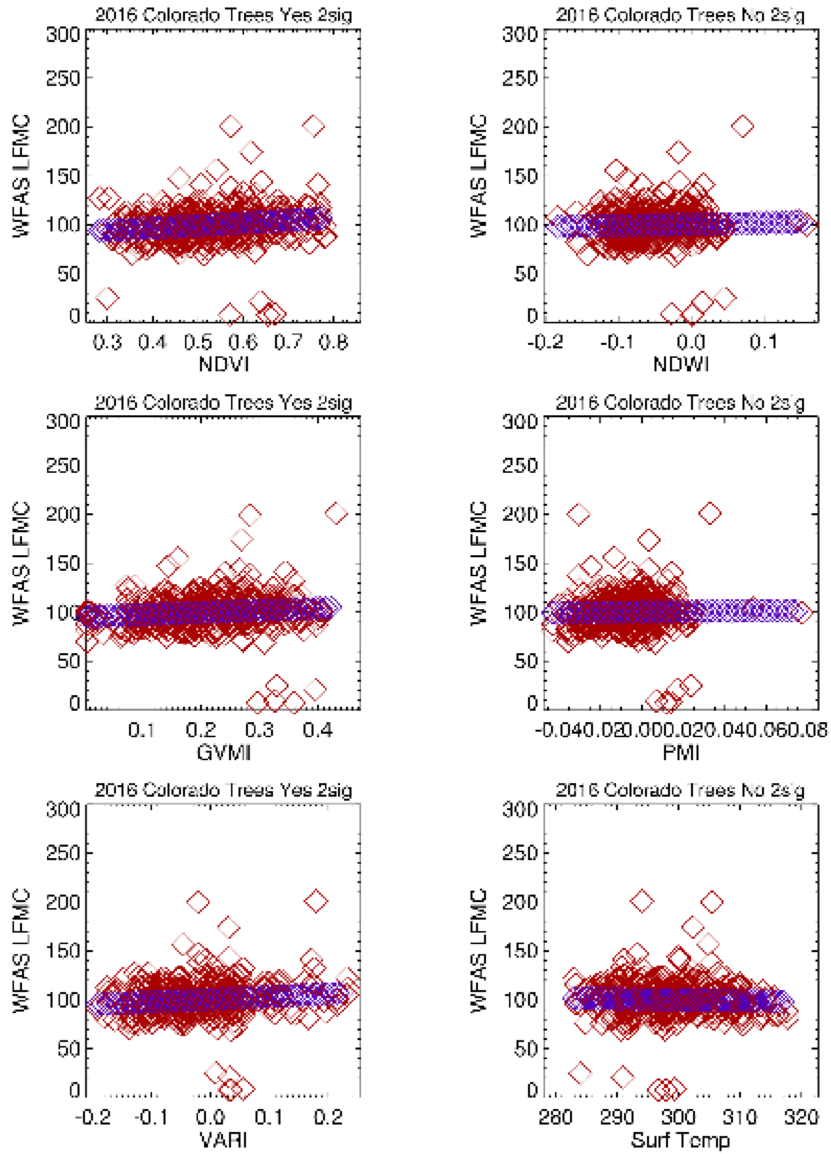
Data is for Colorado in 2016.

NDVI
Yes, 2σ

GVMI
Yes, 2σ

VARI
Yes, 2σ

Significant
to 2σ



NDWI
no

PMI
no

Surface
Temp
no

Not Significant
to 2σ

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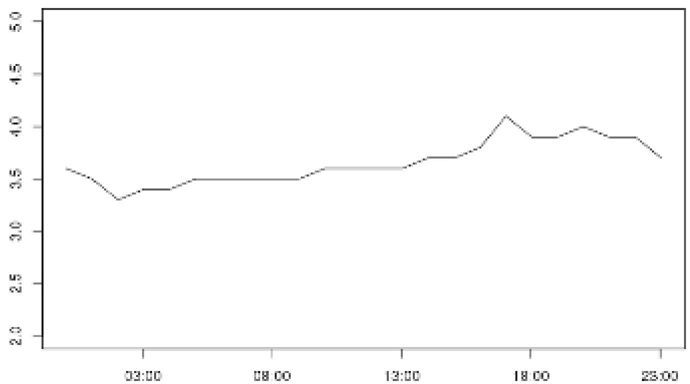
In some cases there is significant diurnal dependence of dead FMC – likely related to precipitation

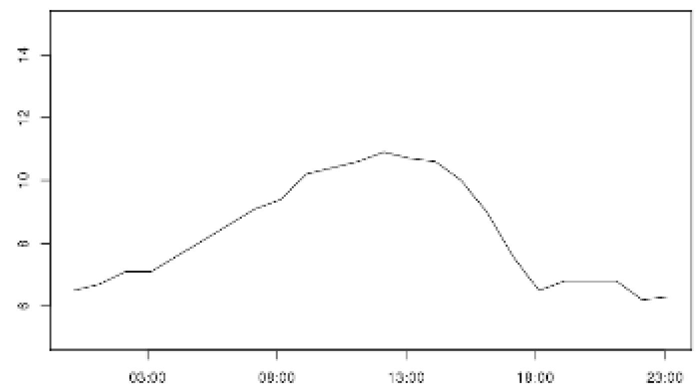
Diurnal Variability of the Dead FMC

At some locations at different times of a year the dead FMC may exhibit significant diurnal variability. In general higher dead FMC is observed during nighttime.

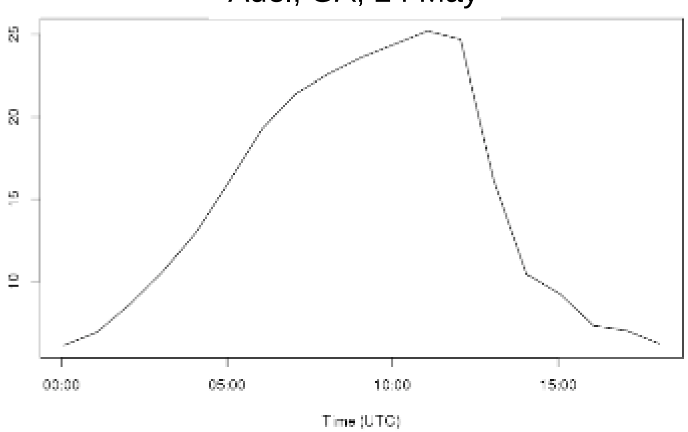
Metcalf Gap, CA, 15 August



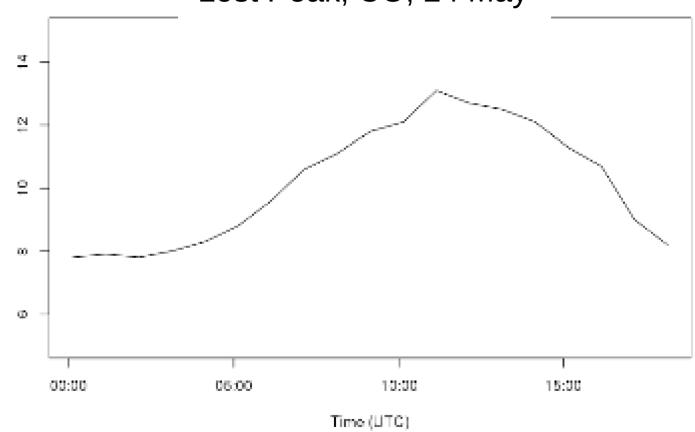
Lost Peak, CO, 15 August



Adel, GA, 24 May



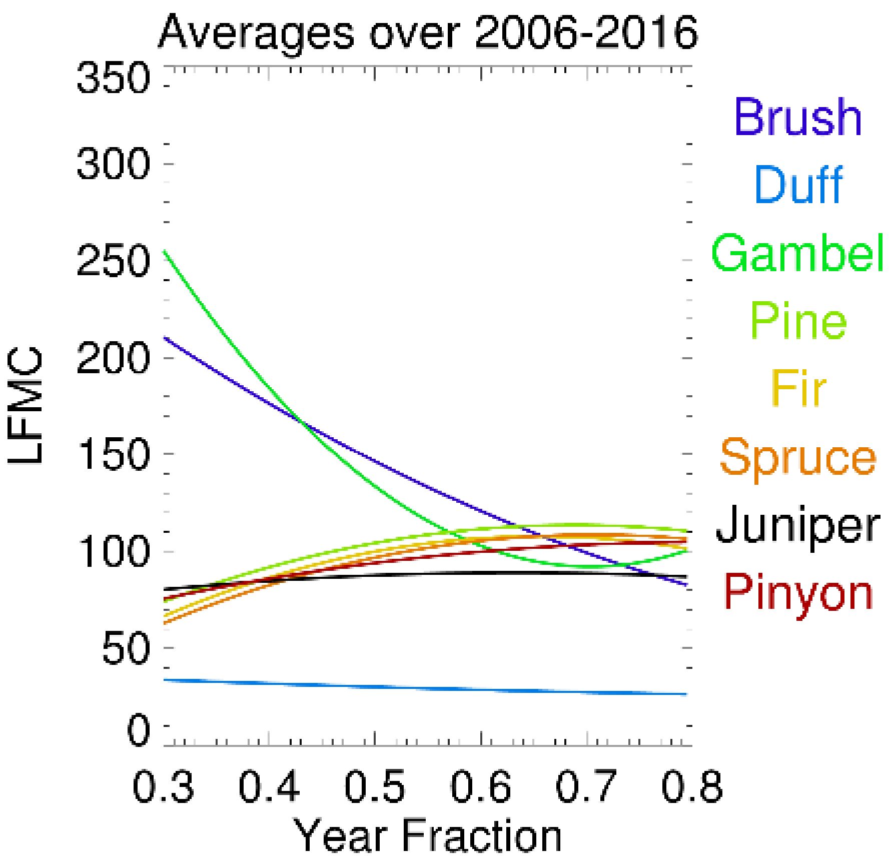
Lost Peak, CO, 24 May



Some live fuels show significant annual/seasonal variability of their FMC

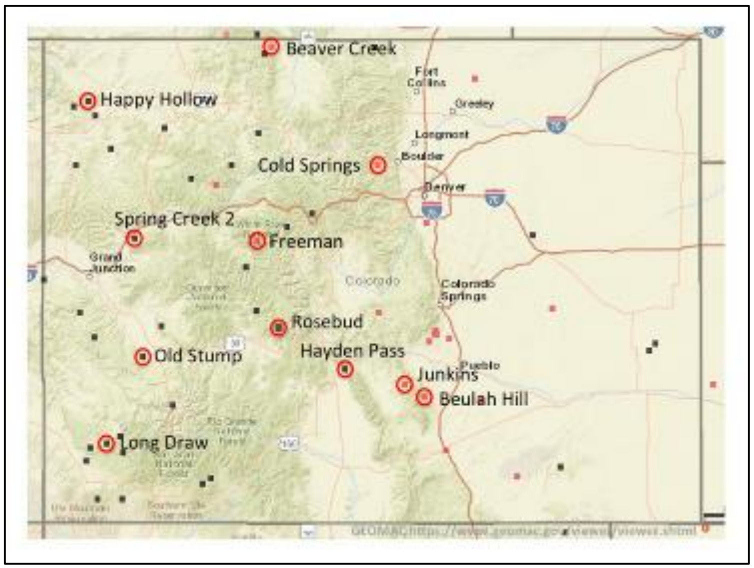
FMC for Certain Fuels Exhibits Significant Seasonal Dependence

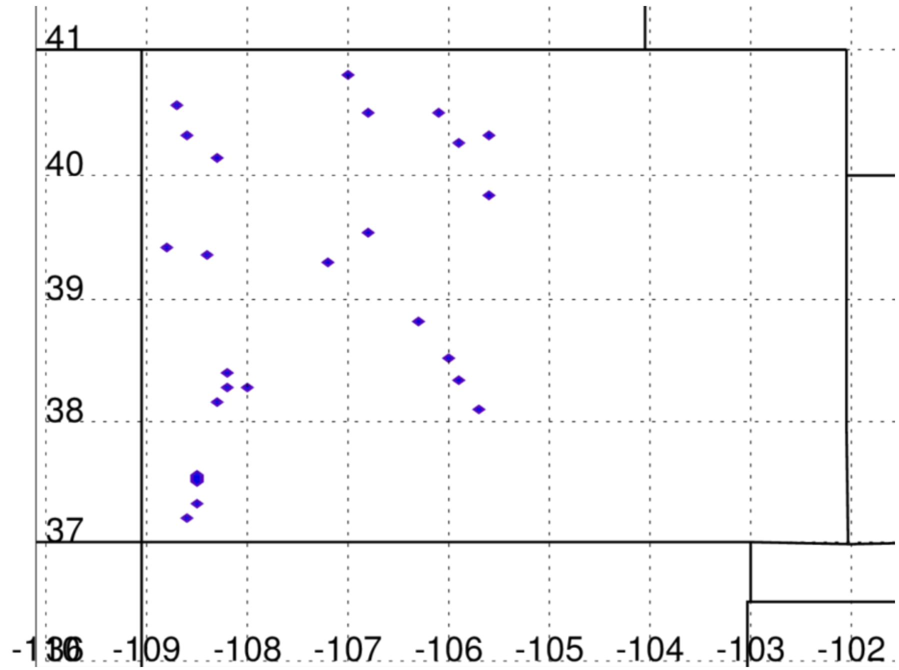
Analysis of live Colorado FMC from NFMD shows that some fuels exhibit significant annual variability, while others do not. This means that Julian day will be a predictor for some fuels (e.g., brush) and not for other fuels (e.g. Juniper).



Selected Colorado Wildfires Observed During 2016

We have baseline simulations of 11 wildfires that were observed in Colorado during fire season 2016. These fires will be used to assess the performance of the newly developed fuel moisture content dataset (product).



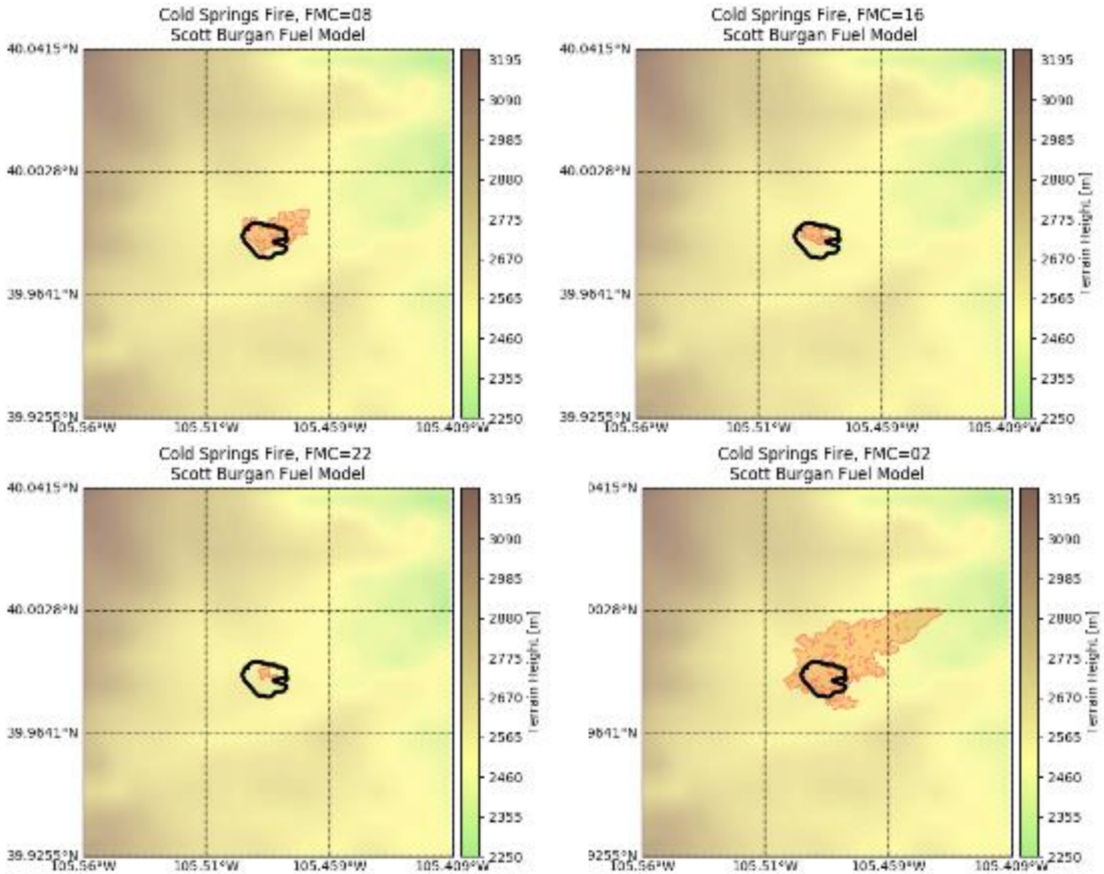


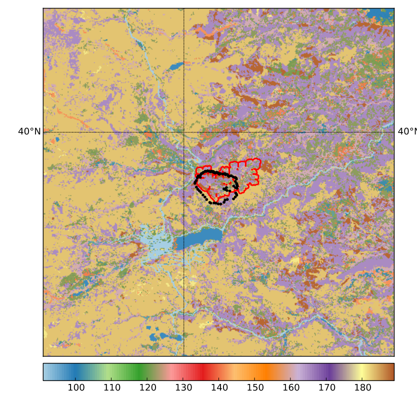
Selected NFMD Sites

Wildland fire rate of spread model (Rothermel, 1972) displays significant sensitivity to dead FMC

Simulation of Cold Springs Fire Near Nederland, Colorado, in 2016

Simulations with different prescribed dead FMC result in significant differences in burn area.





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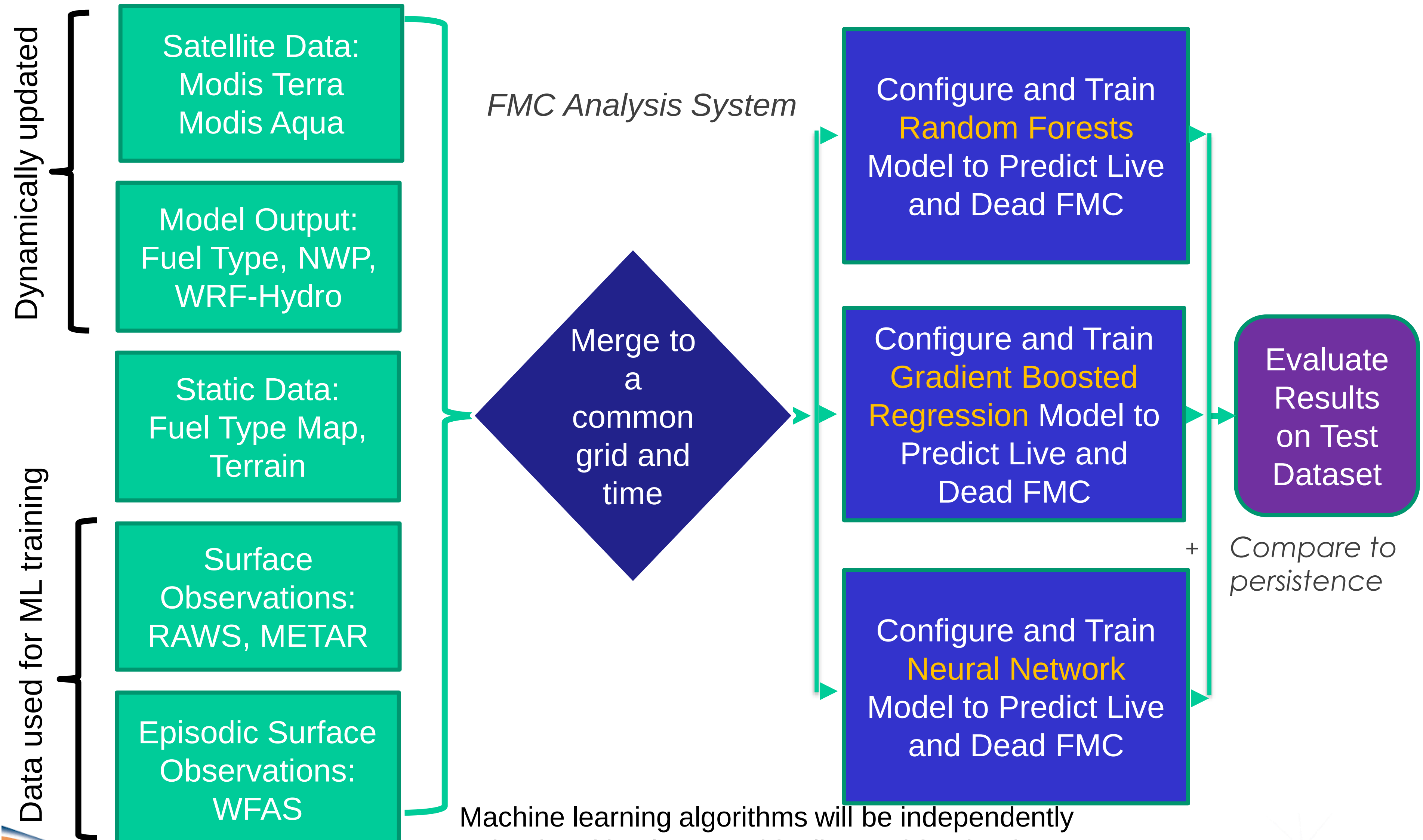
FMC data processing system design



Machine learning algorithms will be independently trained and implemented for live and for dead FMC

Ongoing work

Step 1: Subset data for Colorado

- MODIS, RAWS, WFAS

Step 2: Interpolate Live and Dead FMC to grid

- Most recent RAWS and WFAS observations prior to MODIS obs
- For RAWS, will start with 10:00AM observations for 10:30AM Modis file, but may need to use 9AM observations depending on processing time
- Include previous observation of FMC as baseline persistence forecast
- Include elevation, latitude/longitude as predictors
- Create separate datasets for Live and Dead FMC since Live is 24-hr and Dead is 1-hr

Future steps

Step 3: Make initial FMC predictions using Machine Learning, Random Forests, Gradient Boosted Regression, and Neural Netowr algorithms

- **Begin feature selection for surface weather observations**
- **Determine if additional derived variables could be used based on importance of feature selection (i.e. 168-hr accumulated precipitation, max or min temps, etc.)**

Step 4: Evaluate WRF-Hydro, HRRR model output, or METAR data as predictors

Future steps

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Step 4: Evaluate WRF-Hydro, HRRR model output, or METAR data as predictors

Step 5: Train selected machine learning algorithm

Step 6: Implement real time system for FMC data

Step 7: Evaluate real time FMC data set in comparison to baseline wildland fire simulations

Questions?

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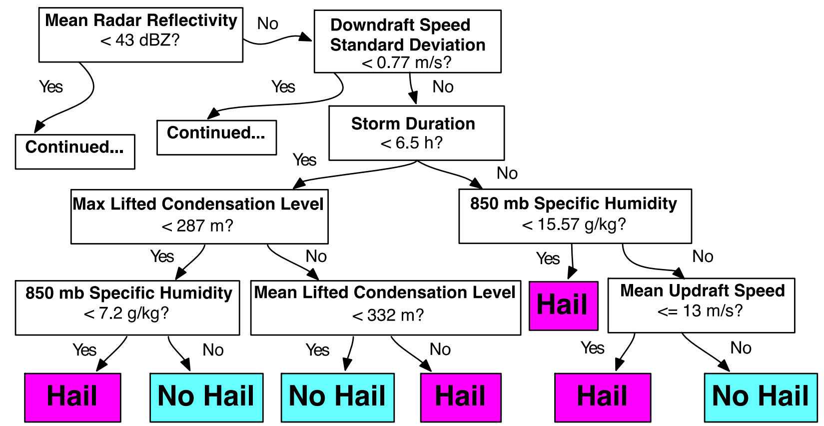
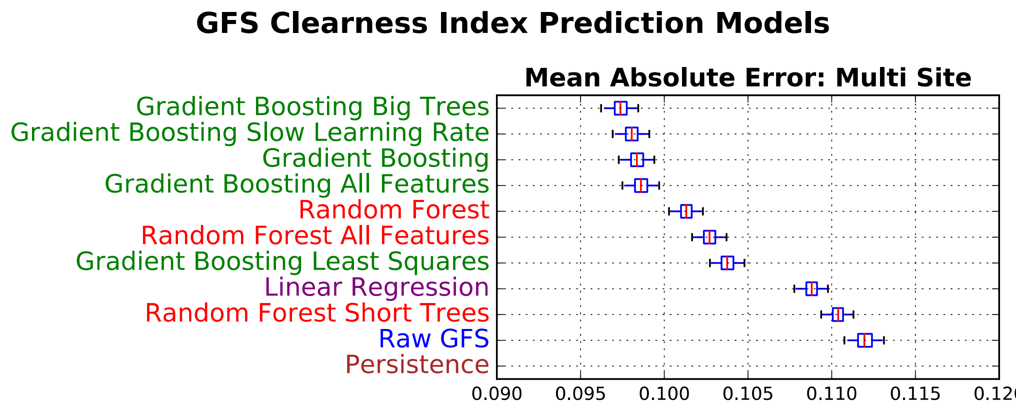
Machine Learning Overview

- **Machine learning**: mathematical models that discover patterns in large datasets and use those patterns to make predictions
- **Decision trees**: machine learning model that identifies similar hierarchical sub-regions and applies a separate prediction to each region
- **Random forests**: ensembles of decision trees with resampled training data for each tree and random selection of features for tree growing
- **Gradient boosting**: additive ensemble of decision trees that minimizes errors from cumulative prediction of previous trees
- **General experience:**
  - Random forests produce accurate, robust predictions and are easy to train.
  - Gradient boosting predictions are sometimes more accurate but require more tuning to get the best results.



Example of a decision tree (McGovern et al. 2017).



Comparison of machine learning models for gridded solar energy forecasting (Gagne et al. 2017).

Data Integration

Predictor Selection

MODIS

- Optimal combination of indices vs measured reflectances

RAWS

- Predictor selection of surface weather observations
- Additional derived predictors?

WFAS

- Predictor selection of additional surface observations

Fuel Type

- Determine value of fuel type or derivation of histogram as predictor

NWP

- WRF-Hydro or HRRR
- Predictor selection of relevant model output

METAR

- Predictor selection of METAR surface obs
- Comparison to RAWS predictor value

Live and Dead Fuel Moisture Content

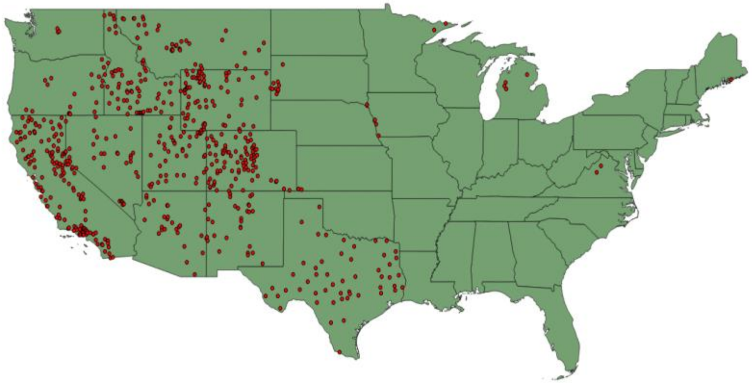
Predictand Metadata

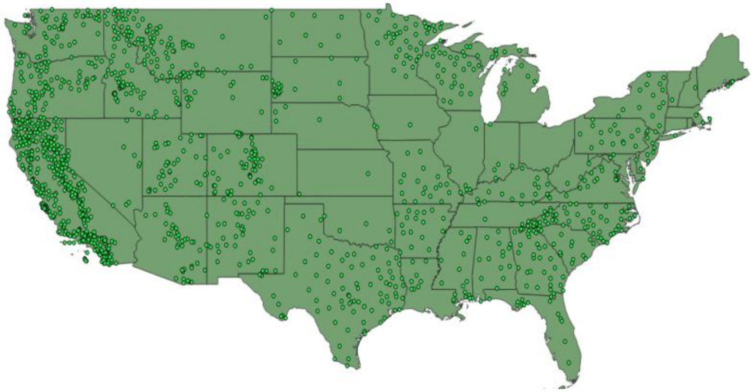
Live Fuel Moisture Content

- *Source: WFAS*
- *Temporal Resolution: Daily*
- *Data Format: netCDF format*
- *Period of Record: 2016*
- *Number of Obs Sites: 638*

Dead Fuel Moisture Content

- *Source: RAWS*
- *Temporal Resolution: Hourly*
- *Data Format: netCDF format*
- *Period of Record: 5/9/2016 1900 to 12/19/2016 1300*
- *Number of Obs Sites: 1229*





MODIS

Data Analysis

MODIS Terra / Aqua

- *Source: MODIS*
- *Temporal Resolution: Daily*
- *Data Format: netCDF*
- *Period of Record: 2016 May-October*
- *Spatial Resolution:1-km (0.015 degrees lat/lon)*

- *Misc Tech Notes:*
  - *zy2016d205.dump has file contents on /d1/NASA-FMC/modis2016*
  - *MODIS mod09(1km surface reflectance), mod35 (cloudmask) and mod11 (surface temperature) data. If the cloudmask says that the pixel is cloudy (or if there is sunglint, night data, water, ..) then the pixel is not used*

Available Predictors

NDVI
NDWI
GVMI
PMI
VARI
Dry Index
Surface Temperature
Ratio
Band 1
Band 2
Band 3
Band 4
Band 5
Band 6
Band 7

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Surface Observations

Available Predictors

RAWS

Dewpoint Temperature	Sky Cover Base Layer
Elevation	Sky Cover Cloud Fraction
Fuel Temperature	Snowfall Accumulation Rate
Precipitation Accumulation (1-min)	Soil Moisture Tension
Precipitation Accumulation (10-min)	Soil Moisture Percent
Precipitation Accumulation (3-hr)	Soil Temperature
Precipitation Accumulation (6-hr)	Solar Radiation
Precipitation Accumulation (12-hr)	Surface (Station) Air Pressure
Precipitation Accumulation (Time??)	Temperature
Precipitation Intensity	Visibility
Precipitation Rate	Wind Direction (10-m)
Precipitation Type	Wind Direction at Gust
Present Weather	Wind Direction at Gust (10-m)
Relative Humidity	Wind Gust
Sea Level Pressure	Wind Gust (10-m)
Wind Speed (10-m)	

WFAS

Day of Year
Elevation
"FracYear"
"VegStr"
"SiteFuel"

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WRF-Hydro and HRRR

WRF-Hydro

- *Source: NWM/NCAR*
- *Temporal Resolution: hourly*
- *Data Format: netCFD*
- *Period of Record: 2016, 2017, and ongoing*
- *Spatial Resolution: 1km*
- *Variables: soil moisture, soil saturation, evapotranspiration*

HRRR

- *Source: NCEP/NCAR*
- *Temporal Resolution: hourly*
- *Data Format: netCFD*
- *Period of Record: 2016, 2017, and ongoing*
- *Spatial Resolution: 3km*
- *Variables: surface temperature, relative humidity, wind speed*

Technical Development Overview
Rate of Spread Model

Semiempirical Rothermel (1972) rate of spread model is defined as

$$R = R_0(1 + \Phi_w + \Phi_s)$$

Empirical functions of terrain slope, Φ_s [dimensionless], and wind speed, Φ_w [dimensionless] are determined by varying wind speed and slope in a small flame experiments in a chamber.

The base rate of spread of the leading edge of the flaming front, R_0 [m s^{-1}], is a function of fuel properties in zero wind conditions on flat ground.

$$R_0 = \frac{I_R \xi}{\varrho_b \varepsilon Q_{ig}}$$

- ξ is the propagating flux ratio [dimensionless];
- ρ_b is the oven dry bulk density [kg m-3], the mass of fuel per cubic meter of fuel bed;
- ε is the effective heating number [dimensionless];

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Technical Development Overview

- Q_{ig} is the heat of preignition [J kg^{-1}], the amount of heat required to heat 1 kg of fuel to combustion temperature defined as

$$Q_{ig} = 250 + 1116FMC$$

- I_R is the reaction intensity [W m^{-2}], the rate of heat release per unit area per unit time in the fire

$$I_R = \Gamma' W_s h \eta_M \eta_S$$

Here, η_M and η_S are moisture and mineral content damping coefficients, respectively. Moisture damping coefficient is defined as

$$\eta_M = 1 - 2.59r_M + 5.11r_M^2 - 3.52r_M^3$$

Where r_M is defined as a ratio of *FMC* and moisture of extinction, M_x

$$r_M = \frac{FMC}{M_x}$$

Released Sensible Heat Is A Function of FMC

The sensible heat flux H_s [Wm^{-2}] released by the ground fire is calculated as

$$H_s = \frac{\Delta m}{\Delta t}(1 - B)h_c$$

The term *B* is related to the more commonly measured fuel moisture content, *FMC*, the mass of water per unit mass of dry fuel, by:

$$B = \frac{FMC}{1 + FMC}$$

where Δm [kg m-2] is the change in fuel load in the current time step, Δt [s], and h_c [J kg-1] is the heat of combustion for dry cellulose fuels (17.4 MJ kg-1).

Released Latent Heat Is A Function of FMC

- Combustion releases water absorbed by the fuel from its environment (FMC), which varies with ambient conditions for dead fuels and with the plant health and drought stress in live fuels.
- Combustion also releases water bound in cellulose, which is assumed to make up 56% of the biomass.
- The latent heat flux liberated by combustion is calculated based on the mass consumed in the current time step, the FMC for either dead or living fuel, and the water content of cellulosic fuels.
- The latent heat flux LE_s released by the surface fire is calculated as:

$$LE_s = \frac{\Delta m}{\Delta t}[B + 0.56(1 - B)]L_v$$

$$B = \frac{FMC}{1 + FMC}$$

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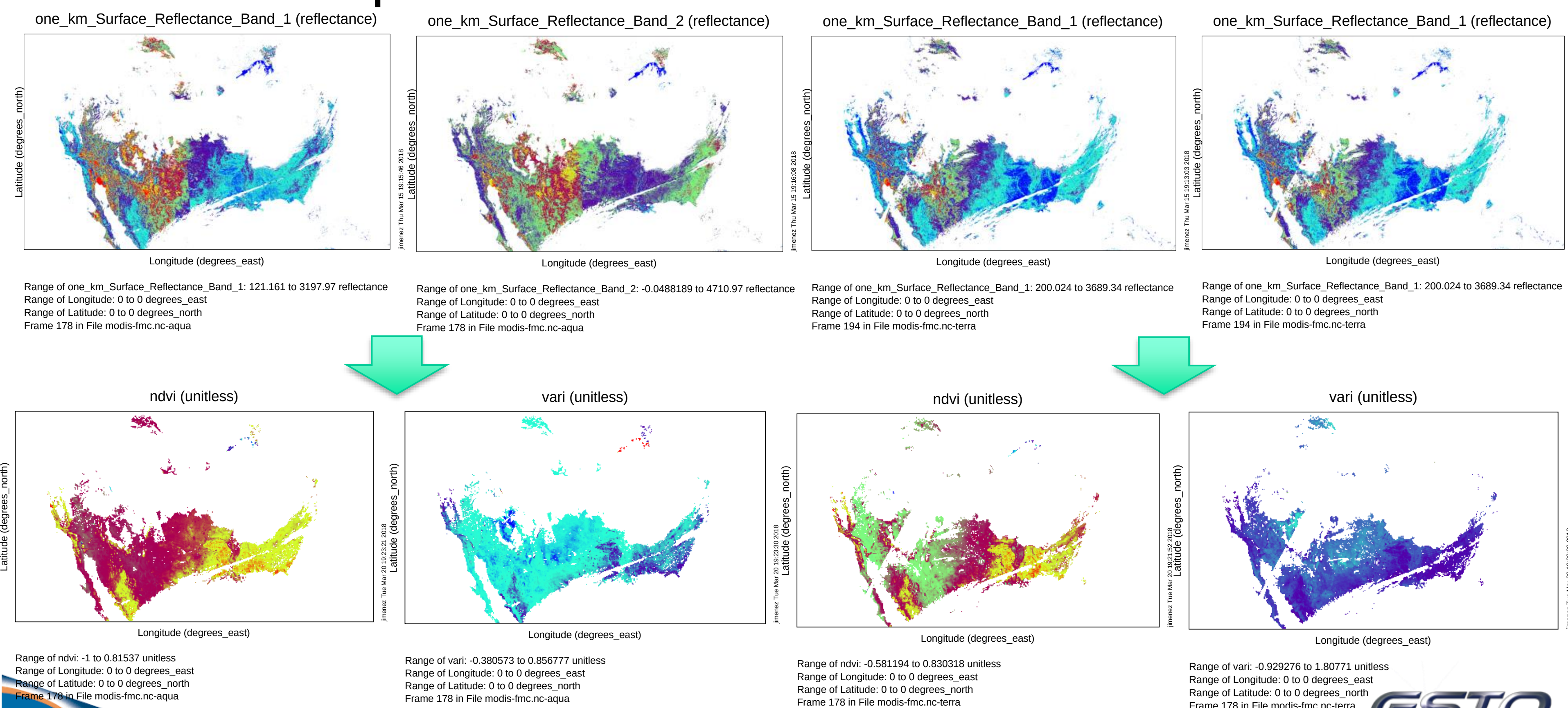
Vegetation indices are computed using reflectances already mapped onto a one-kilometer CONUS grid

Computing Vegetation Indices Using MODIS Reflectances

One possibility is to first map all the reflectances and then compute vegetation indices on 1 km CONUS grid. Analysis shows that this introduces a small error, compared to direct computation of vegetation indices

Aqua **Terra**



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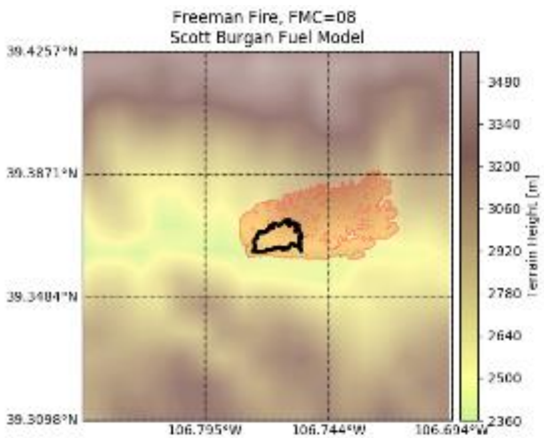
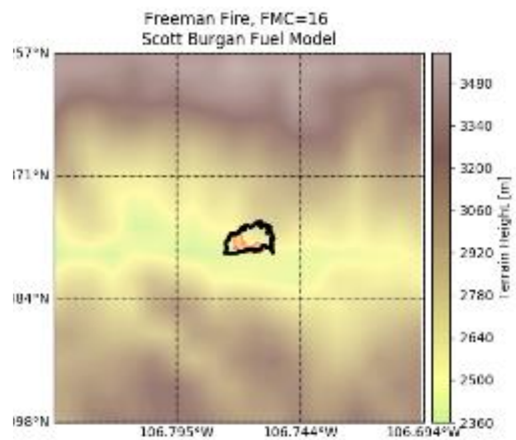
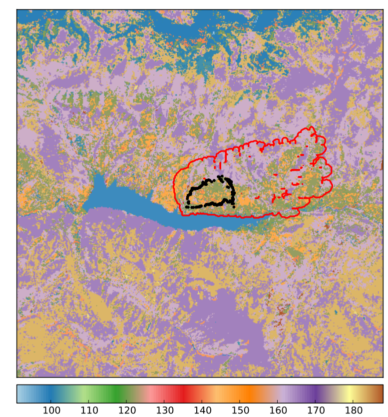
Wildland fire rate of spread model (Rothermel, 1972) displays significant sensitivity to dead FMC

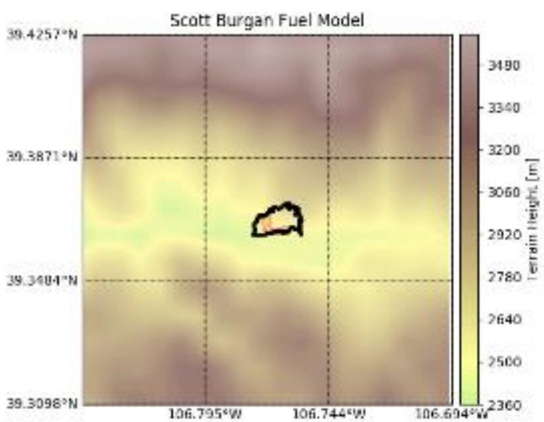
Simulation of Freeman Fire in Colorado in 2016

Simulations with different prescribed dead FMC result in significant differences in burn area.









The fire perimeter reached the domain boundary before the simulation with FMC = 2 % ended.

Analysis of availability and quality of RAWS data shows that there are sufficient data available

Analysis of RAWS Data

Majority of the RAWS are missing less than 5% of data.

Percent Missing	Number of Stations	Percent of Total Stations
>80%	8	0.5%
>50%	11	0.7%
>25%	27	1.7%
>5%	66	4.1%