Estimation of Fuel Moisture Content Based on MODIS Satellite Observations Using Machine Learning

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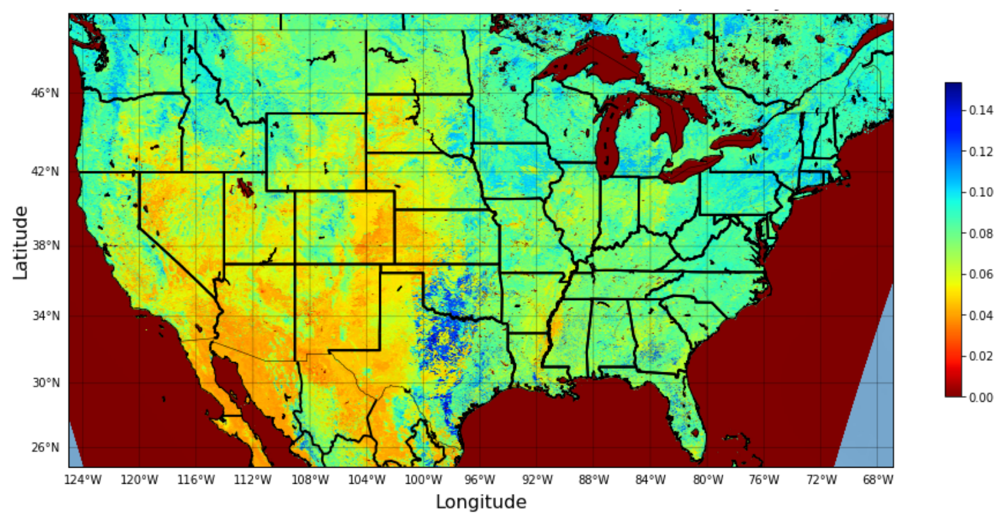


NASA Ames, June 12, 2019

NASA AIST-16-0079

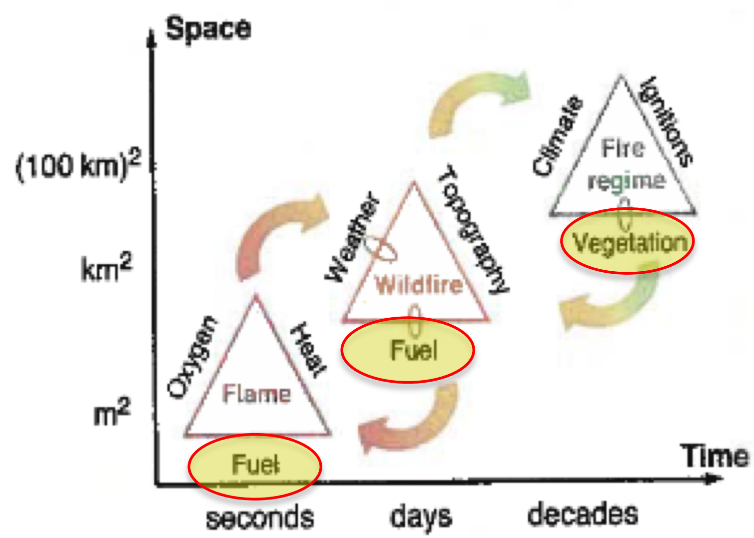
Fuel moisture content (FMC) is an essential parameter in forecasting wildland fire spread

- Decision support systems for wildland fire behavior are essential for effective and efficient wildland fire risk assessment and firefighting.
- Wildland fire prediction system is an important component of a decision support system for wildland fire behavior.
- For accurate prediction of wildland fire spread accurate information about fuels is essential.
- Rate of spread of wildland fires displays significant sensitivity to fuel moisture content.
- This 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

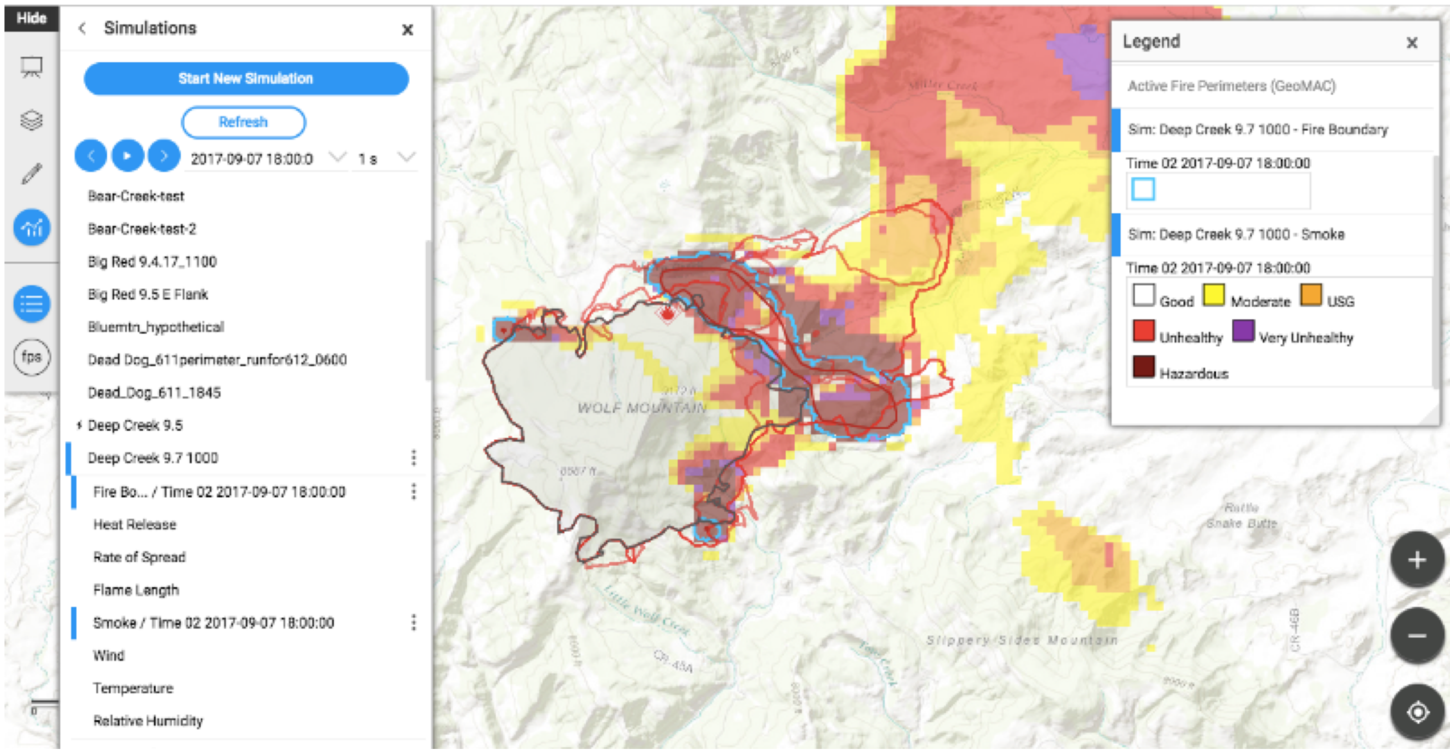
The goals of the project are:

- 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.



NCAR is developing a coupled operational wildland fire prediction system for Colorado

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



https://www.colorado.gov/pacific/dfpc/co-wims-colorado-wildfire-information-management-system

An operational coupled atmosphere wildland fire behavior prediction system requires high-resolution, frequently updated fuel moisture content dataset

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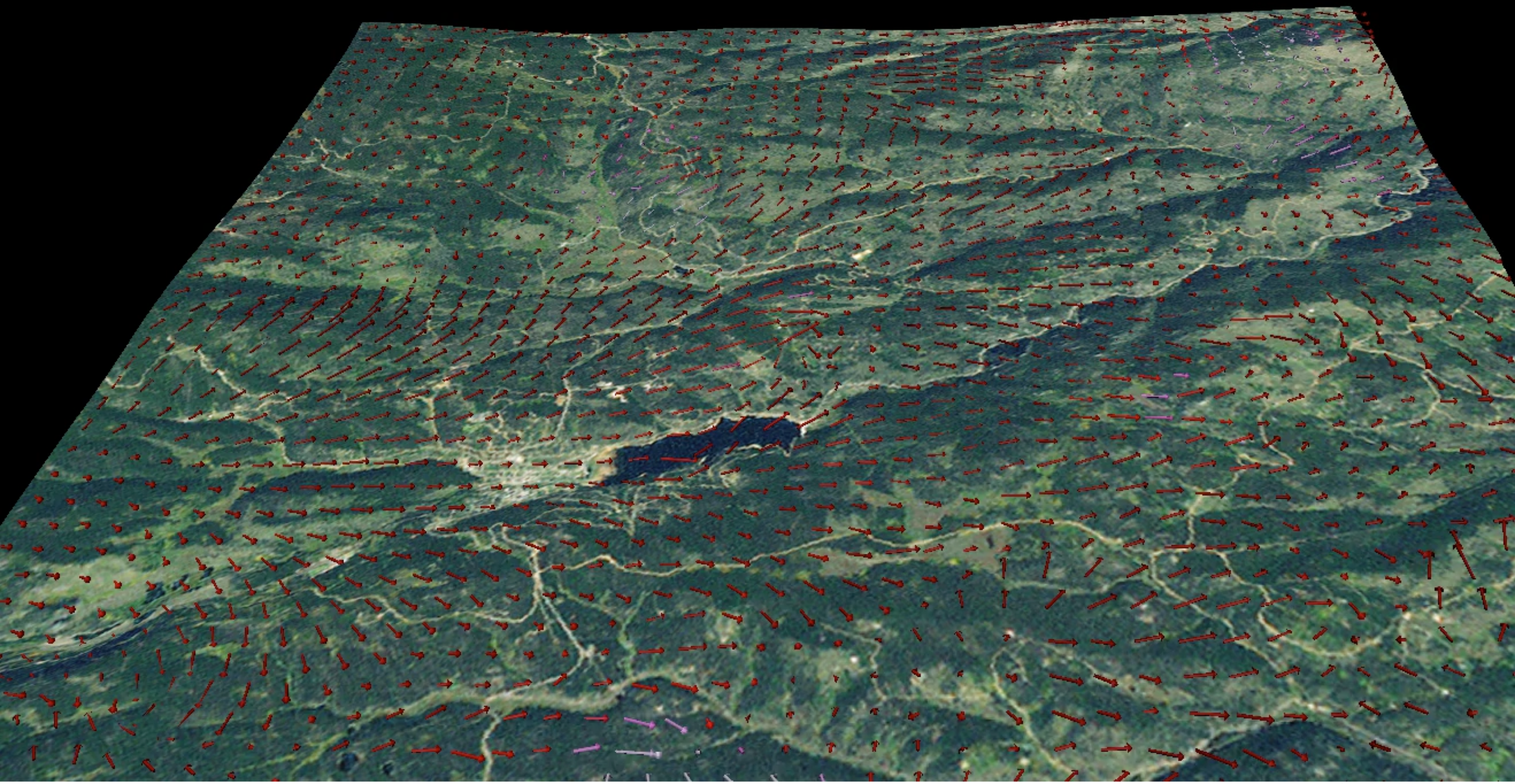
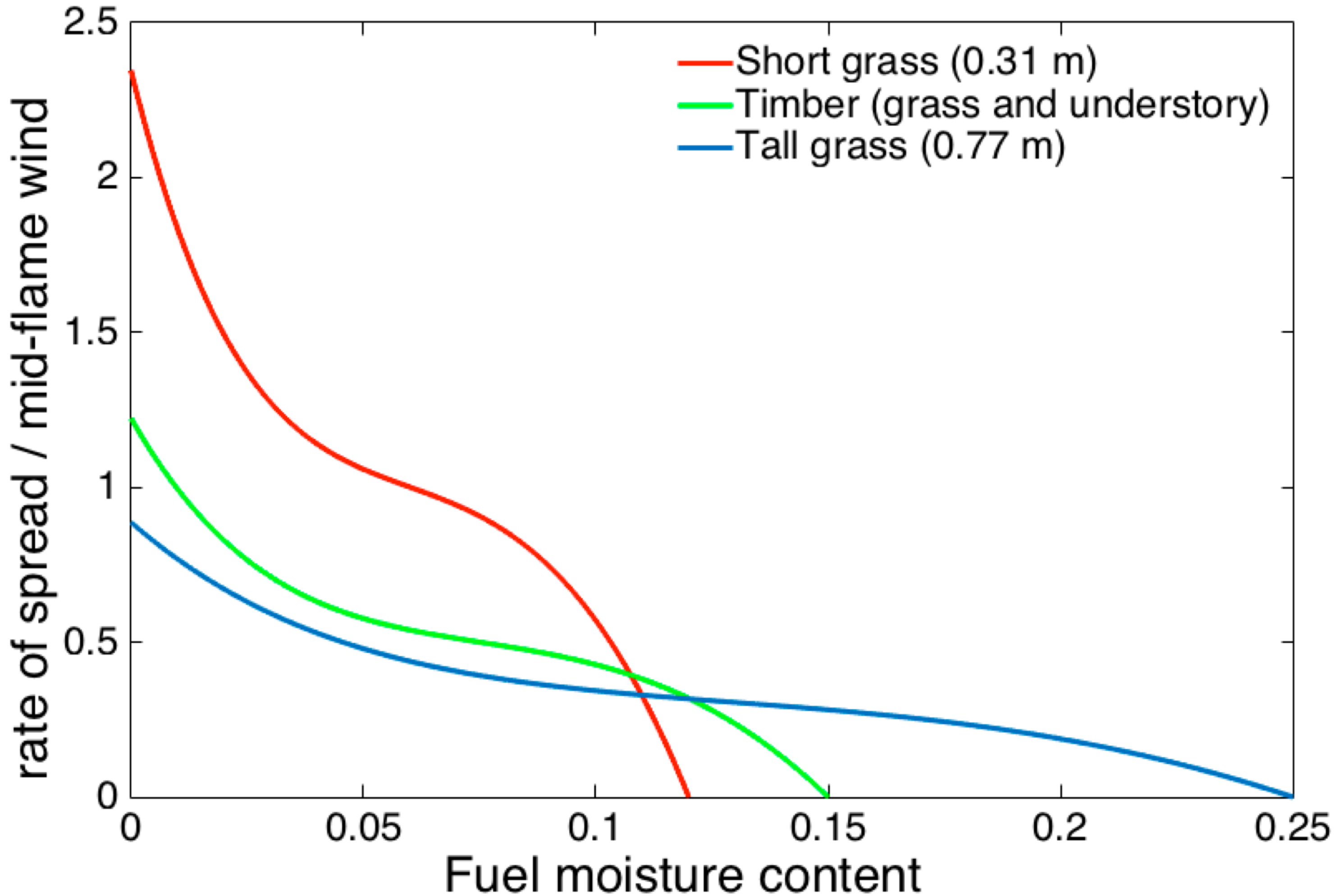
Last Chance fire, Nederland, CO, July 9, 2016



Dimensionless rate of spread as a function of FMC



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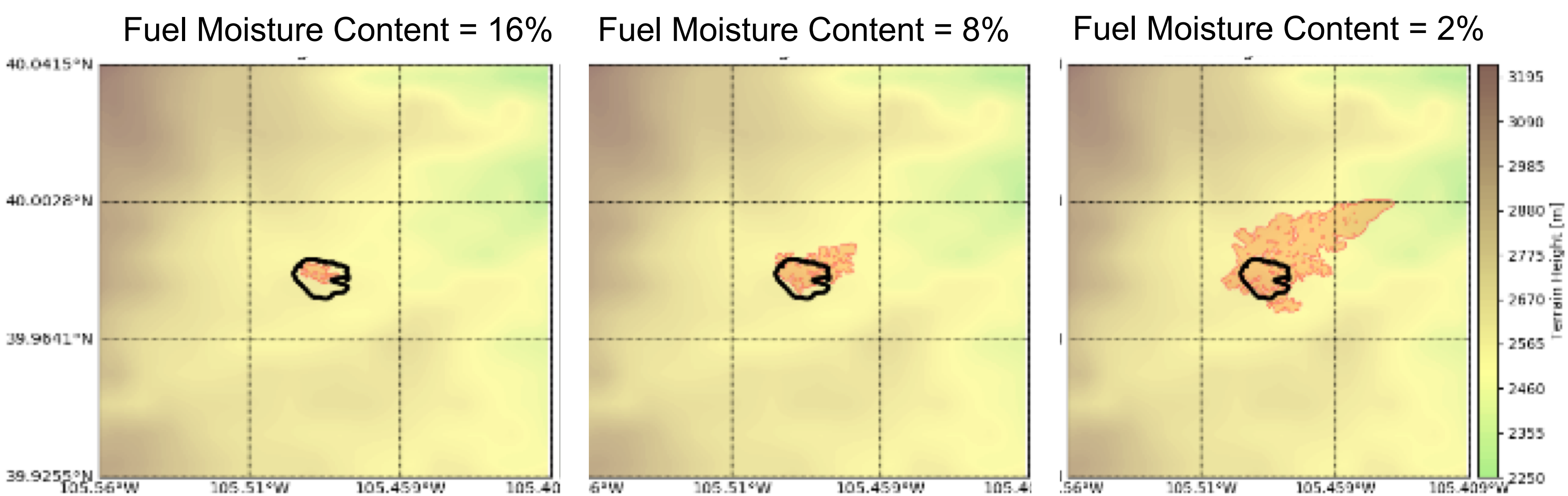
Wildland fire spread model displays significant sensitivity to the dead FMC

Simulation of Cold Springs fire near Nederland, Colorado, in 2016

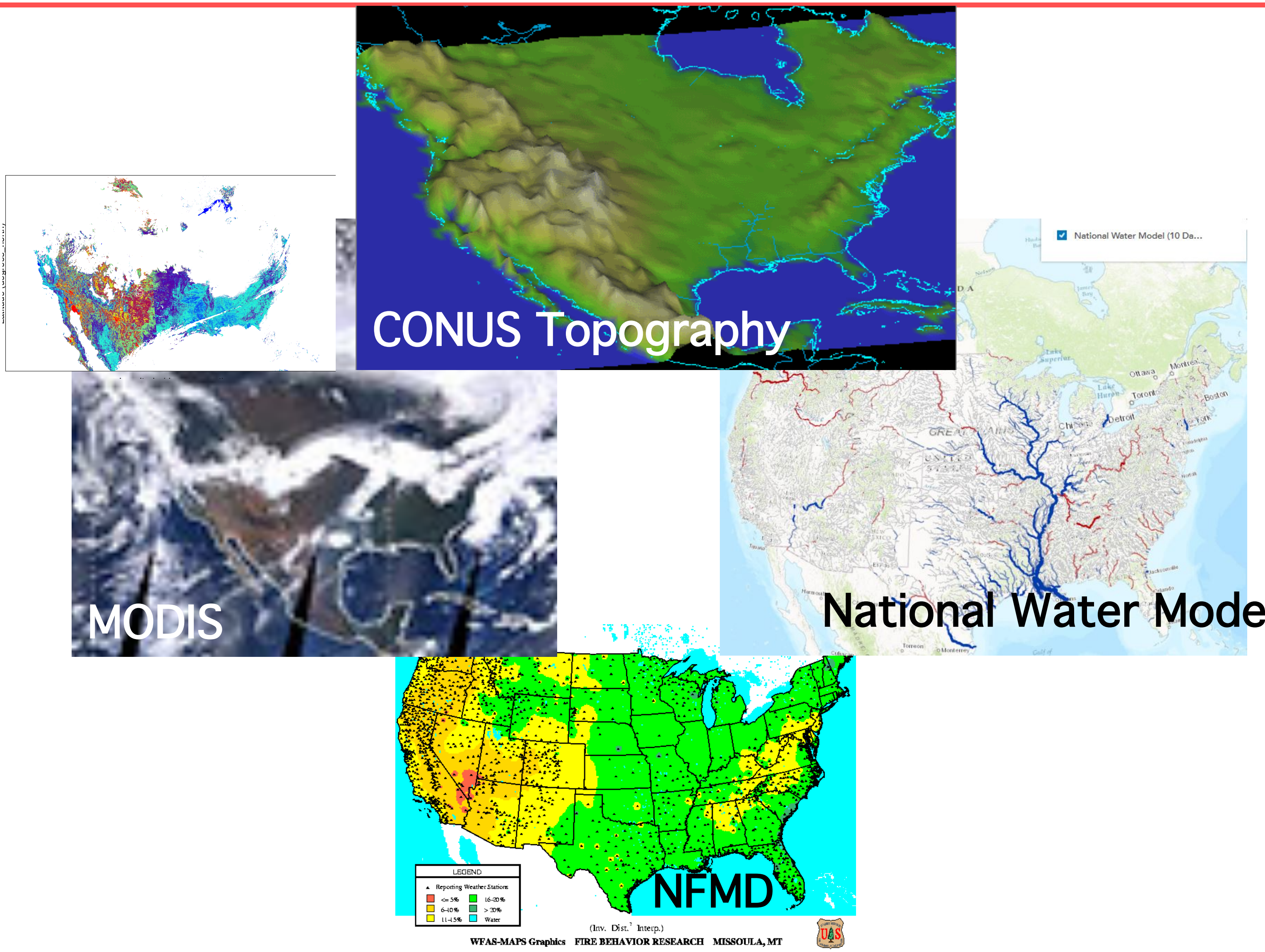


Wildland fire simulations using Rothermel (1972) fire spread model display significant sensitivity to fuel moisture content (FMC). Simulations with different prescribed dead FMC result in significant differences in burn area.

For operational applications there is a need for a gridded fuel moisture content dataset

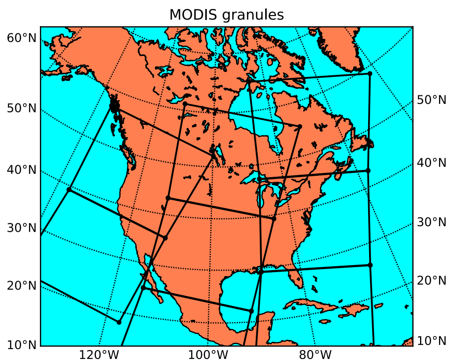
- Wildland fire rate of spread depends on the FMC
- Accurate information about FMC is essential for more accurate wildland fire spread prediction
- The National Fuel Moisture Database provides FMC based on *in situ* surface observations of dead FMC using Remote Automated Weather Stations (RAWS) and manual sampling of live FMC
- Interpolating observations from relatively sparse RAWS can result in large errors when applied to an operational system
- We are developing a dynamic, gridded FMC data set that can be assimilated in real-time in an operational system

MODIS data, National Water Model and topography are combined with surface data



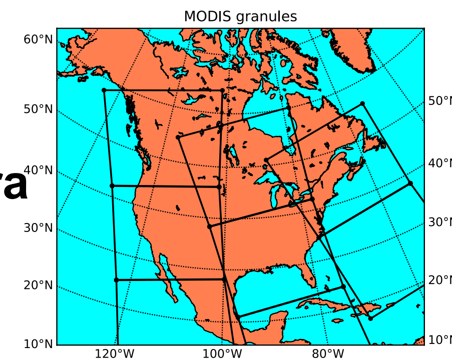
MODIS observations are processed to create CONUS maps of reflectances

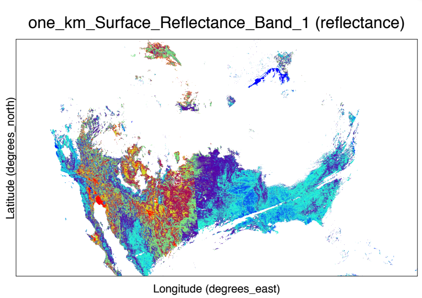
MODIS Aqua and Terra granules are separately mapped onto a 1 km CONUS grid that corresponds to the refined High Resolution Rapid Refresh (HRRR) forecasting system grid and which will be used to estimate FMC.



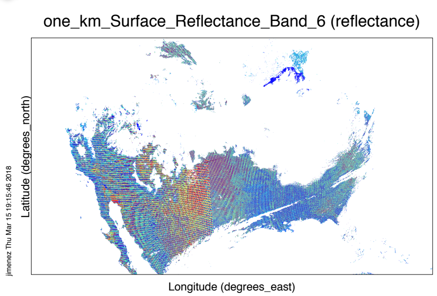
Aqua

Terra

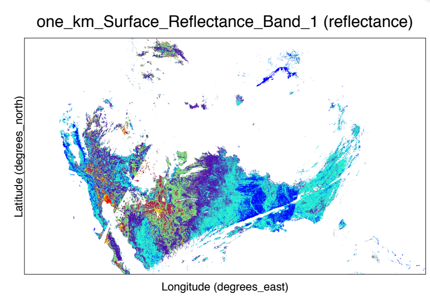




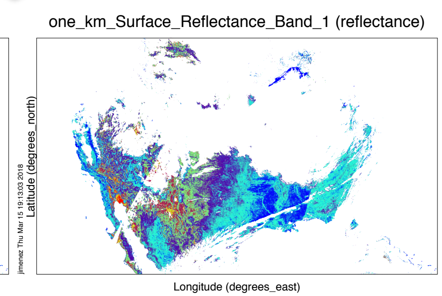
Range of one_km_Surface_Reflectance_Band_1: 121.161 to 3197.97 reflectance
Range of Longitude: 0 to 0 degrees_east
Range of Latitude: 0 to 0 degrees_north
Frame 178 in File modis-fmc.nc-aqua



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



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



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

We have explored using vegetation indices as predictors in machine learning models

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)

The primary use of these bands is to identify boundaries and properties of land, clouds, and aerosols in addition to **Band 7 (2105 – 2155 nm)**

Normalized Difference Vegetation Index (NDVI)
NDVI = (Band 2 – Band 1) / (Band 1 + Band 2)

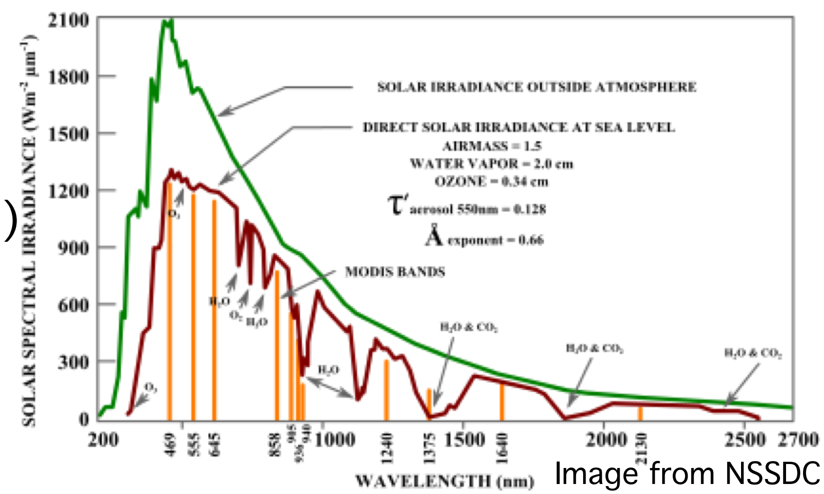


Image from NSSDC

Normalized Difference Water Index (NDWI)
NDWI = (Band 2 – Band 5) / (Band 2 + Band 5)

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

Visible Atmospherically Resistant Index (VARI)
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)]

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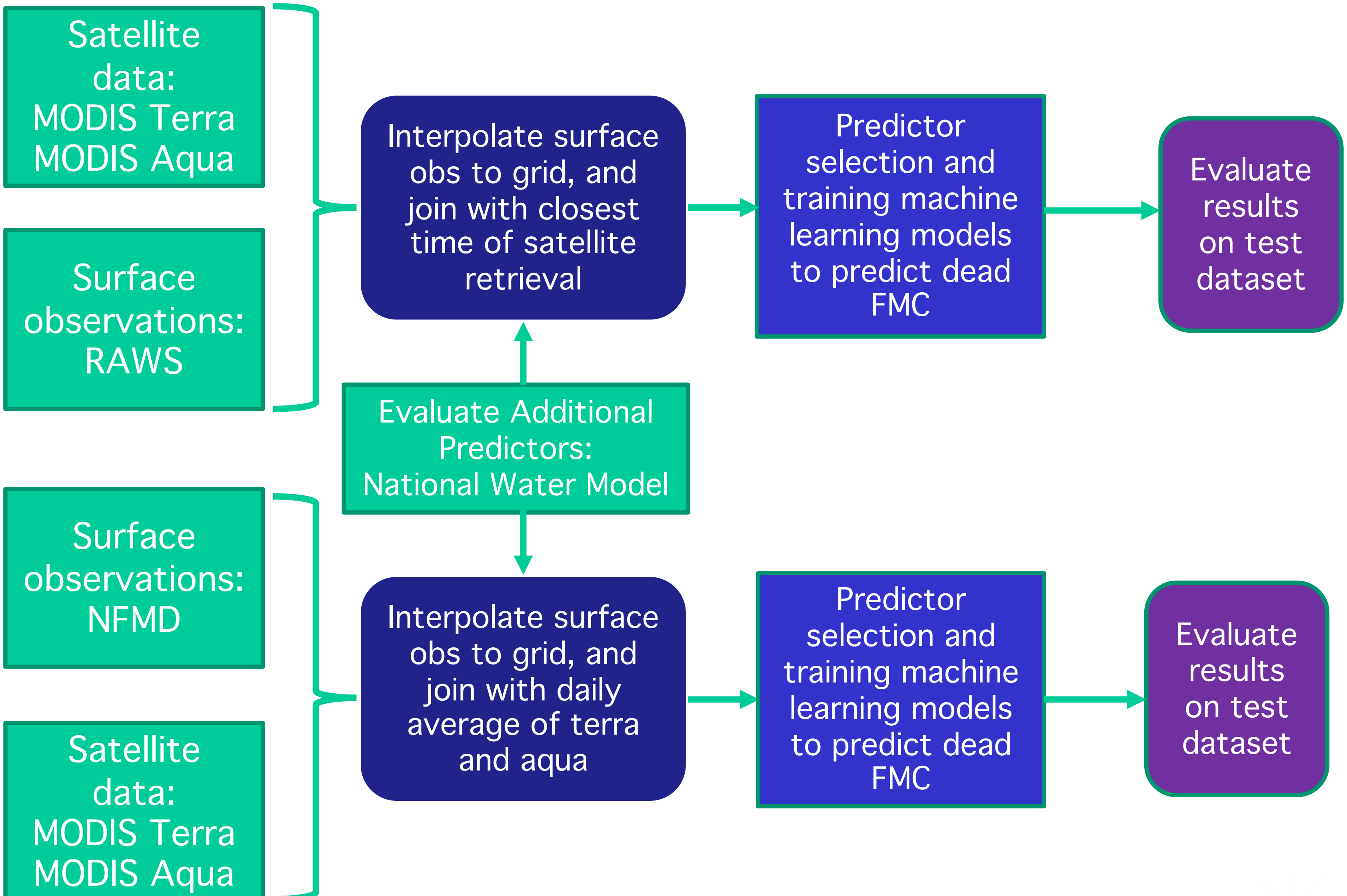
Schematic diagram of the FMC prediction system



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Machine learning models are first developed based on observations in Colorado

Initially we have focused on the data for Colorado:

- MODIS, RAWS, NFMD for 2016

Satellite observations within 2.5 km for surface observations are used to train machine learning model

Dead FMC:

- Measurements are hourly so we are using the nearest MODIS data to the time of the surface observation (i.e. 11AM surface observation would use 10:30AM Modis Terra satellite data)

Live FMC:

- Available measurements are daily so we are using an average of the MODIS Terra (10:30AM) and Modis Aqua (1:30PM) as best estimate of vegetation indices during time of surface observation

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We have compared several machine learning algorithms

Random Forest produces lowest average error

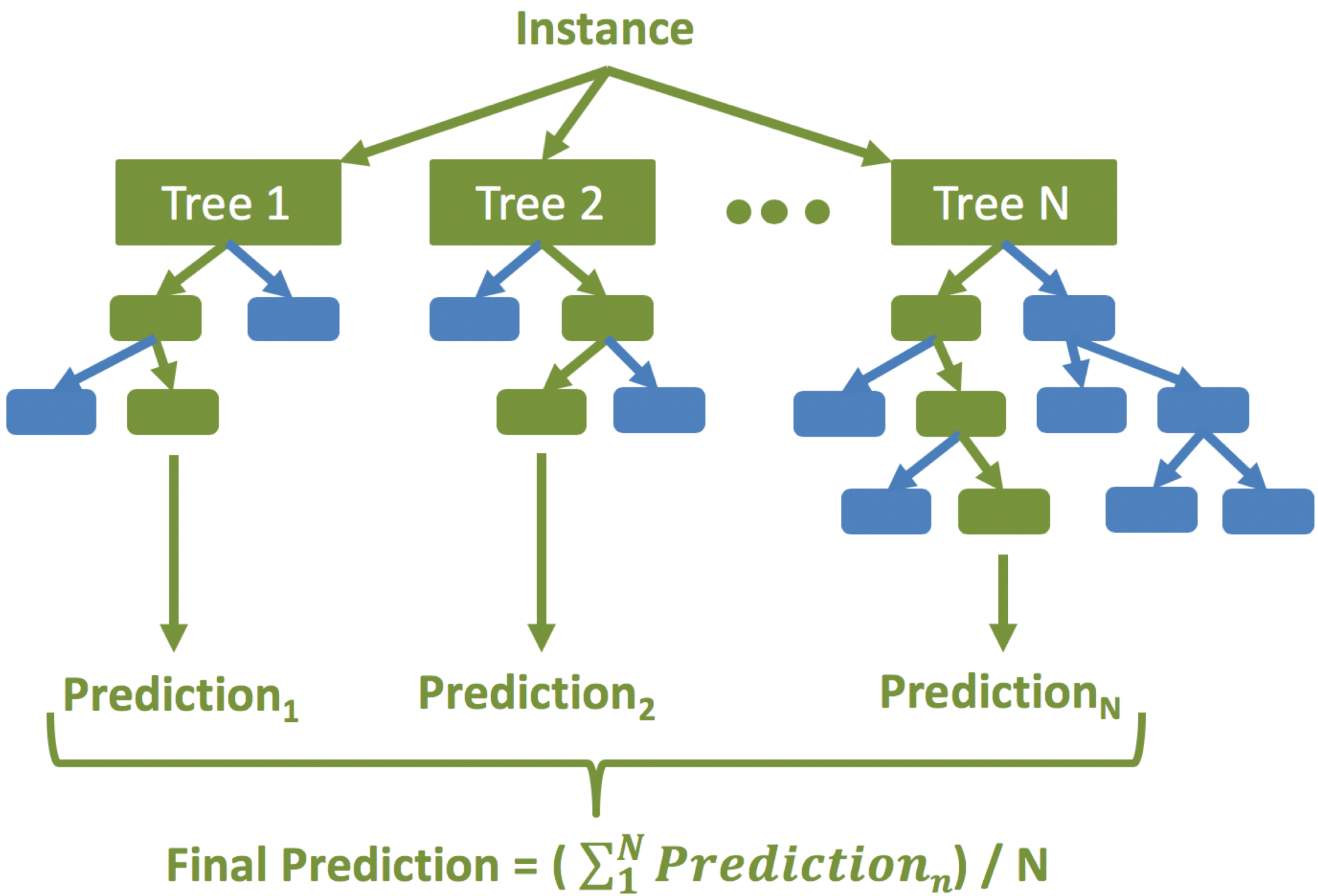
- Configuration has 500 trees,
  - minimum samples per split and per leaf = 100

	Aqua MAE %		Terra MAE %	
Method	Training	Testing	Training	Testing
MLR	2.36	2.36	3.27	3.25
ANN	1.97	1.94	2.67	2.65
GBR	1.40	1.73	1.97	2.33
RF	1.39	1.69	1.94	2.28

RF – Random Forest
GBR – Gradient Boosted Regression
ANN – Artificial Neural Network
MLR – Multiple Liner Regression

- Aqua test dataset mean dead FMC = 8.12
- Aqua test dataset standard deviation dead FMC = 3.33
- Terra test dataset mean dead FMC = 6.43
- Terra test dataset standard deviation dead FMC = 2.92

Schematic diagram for the Random Forest machine learning algorithm



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Weights assigned to predictors by machine learning model indicate their importance

Land surface temperature (LST) , elevation, accumulated evapotranspiration, slope, and bands 7, 5, 2, 1, 3, and 6

Variable (CONUS, Aqua)	Importance %
Land Surface Temperature	43
Elevation	16
Band 7	5
Acc. Evapotranspiration	5
WE-Slope	5
SN-Slope	5
Band 5	4
Band 2	3
Soil Saturation All Layers	3
Band 1	2
Band 3	2
Land Use Category	2
East Region	2
Band 4	1
Band 6	1

Variable (CONUS, Terra)	Importance %
Land Surface Temperature	42
Elevation	16
Band 7	6
Accumulated Evapotranspiration	5
WE-Slope	4
SN-Slope	4
East Region	4
Band 2	3
Soil Saturation All Layers	3
Band 1	2
Band 3	2
Band 4	2
Band 5	2
Band 6	2
Land Use Category	2

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Machine learning algorithms were applied to estimation of live fuel moisture

- Multiple Linear Regression produces lowest
- Gradient Boosted Regression overfits the data

	Aqua MAE %		Terra MAE %	
Method	Training	Testing	Training	Testing
MLR	29.58	29.55	28.71	29.43
ANN	26.51	26.64	25.86	26.90
GBR	13.11	22.61	11.68	21.55
RF	20.62	23.58	19.47	23.52

RF – Random Forest
ANN – Artificial Neural Network
GBR – Gradient Boosted Regression
MLR – Multiple Liner Regression

- Aqua test dataset mean LFMC = 64.91
- Aqua test dataset standard deviation LFMC = 26.57
- Terra test dataset mean LFMC = 76.61
- Terra test dataset standard deviation LFMC = 34.56

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For live FMC, elevation, band 2, LST, and evapotranspiration are important predictors

Variable (CONUS, Aqua)	Importance %
Elevation	24
Band 2	11
Acc. Evapotranspiration	10
Land Surface Temperature	9
WE-Slope	8
Band 5	5
Band 7	5
Soil Saturation All Layers	5
NS-Slope	5
Land Use Category	5
Band 1	4
Band 3	2
Band 4	2
Band 6	2

Variable (CONUS, Terra)	Importance %
Elevation	26
Band 2	11
Soil Saturation All Layers	7
Acc. Evapotranspiration	7
Land Surface Temperature	7
SN-Slope	6
Band 5	5
Band 6	5
WE-Slope	5
Land Use Category	5
Band 1	4
Band 7	4
Band 3	3
Band 4	2

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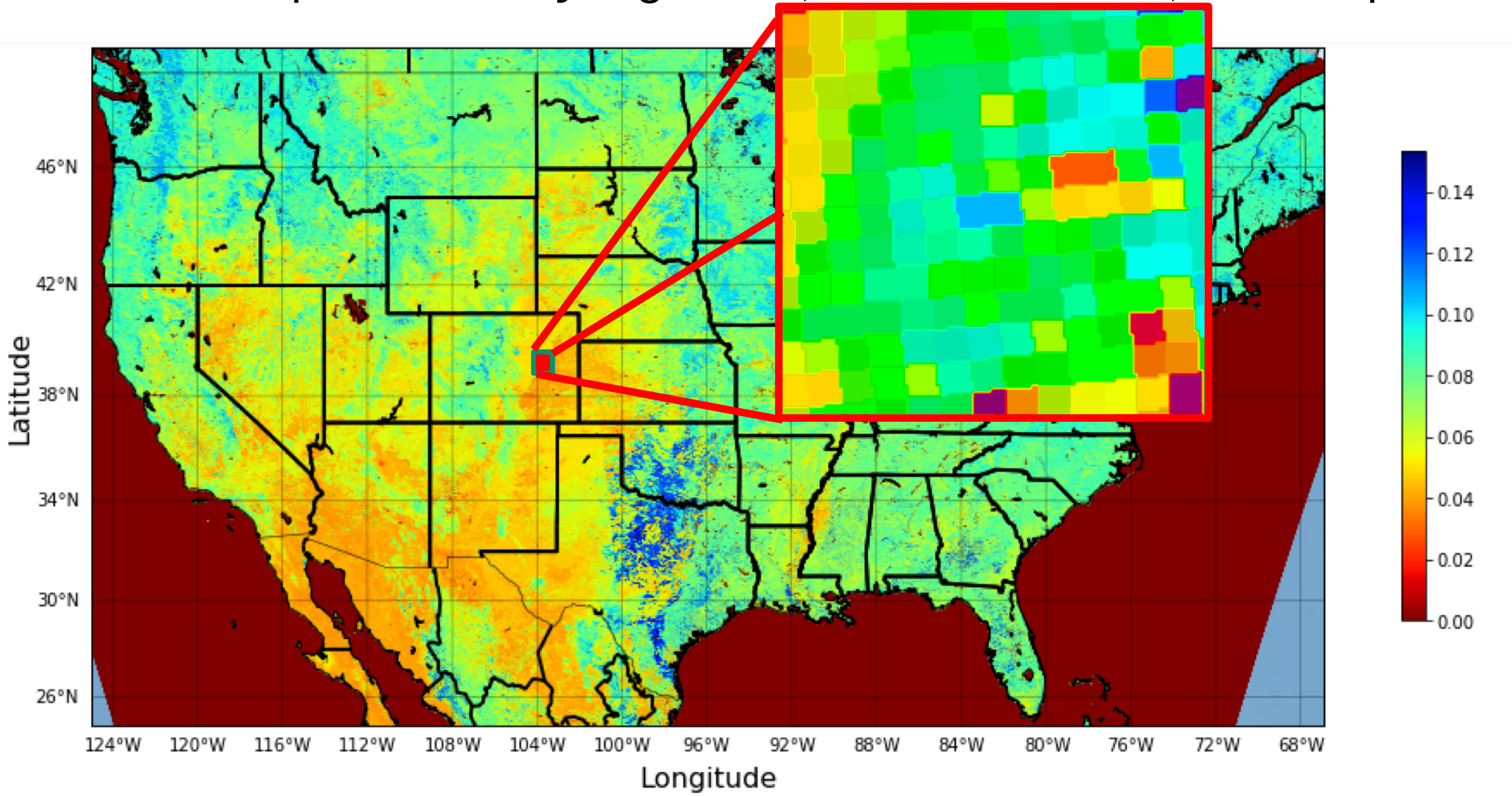
CONUS 1 km gridded dead fuel moisture map

We use machine learning methodology to combine MODIS Aqua and Terra satellite observations, National Water Model output, and terrain data with surface observations and estimate dead and live fuel moisture content (FMC) over CONUS and produce daily a gridded, 1 km resolution, FMC map.



9 July 2016 – the day of Cold Spring Fire in Colorado

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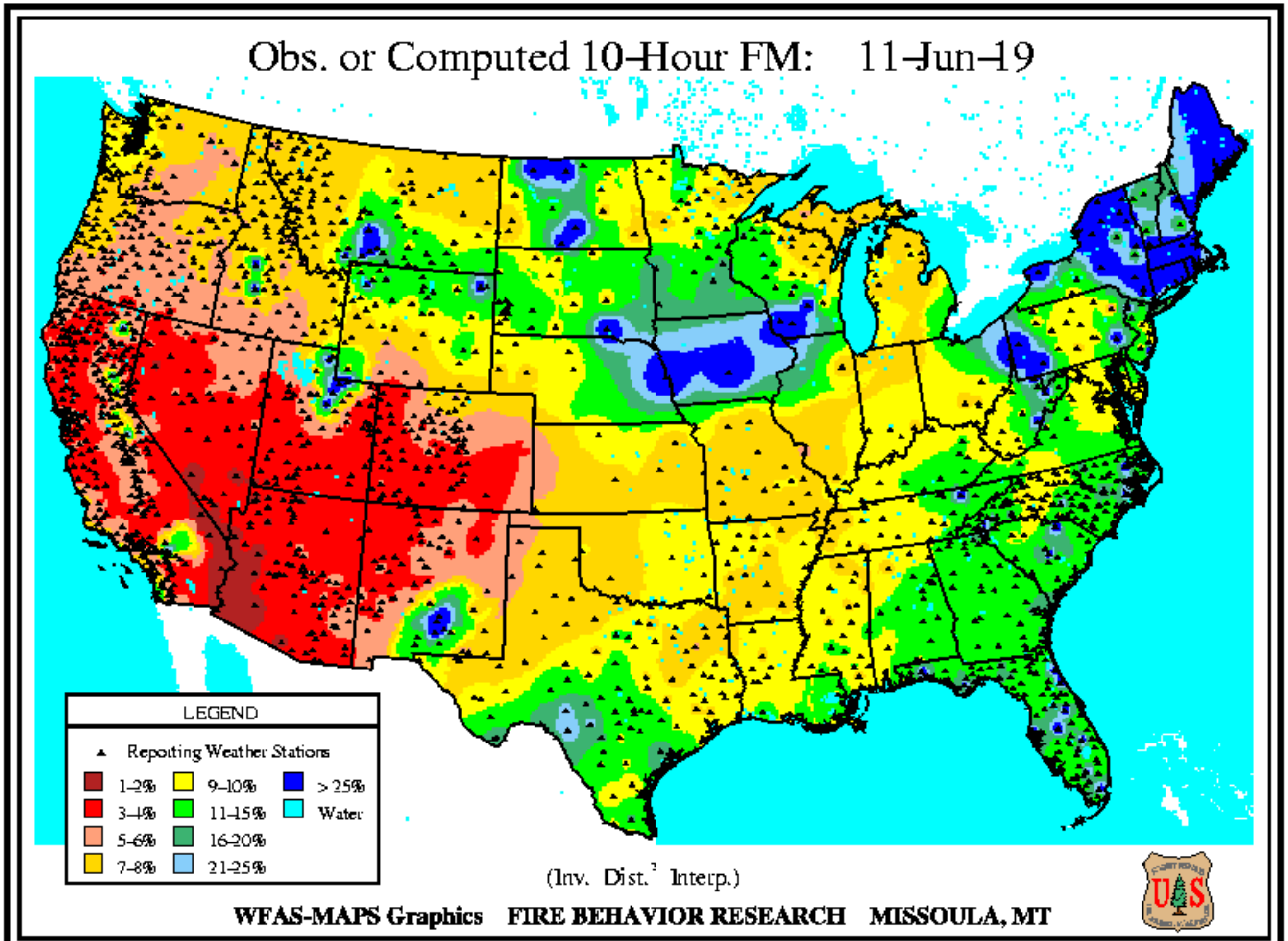
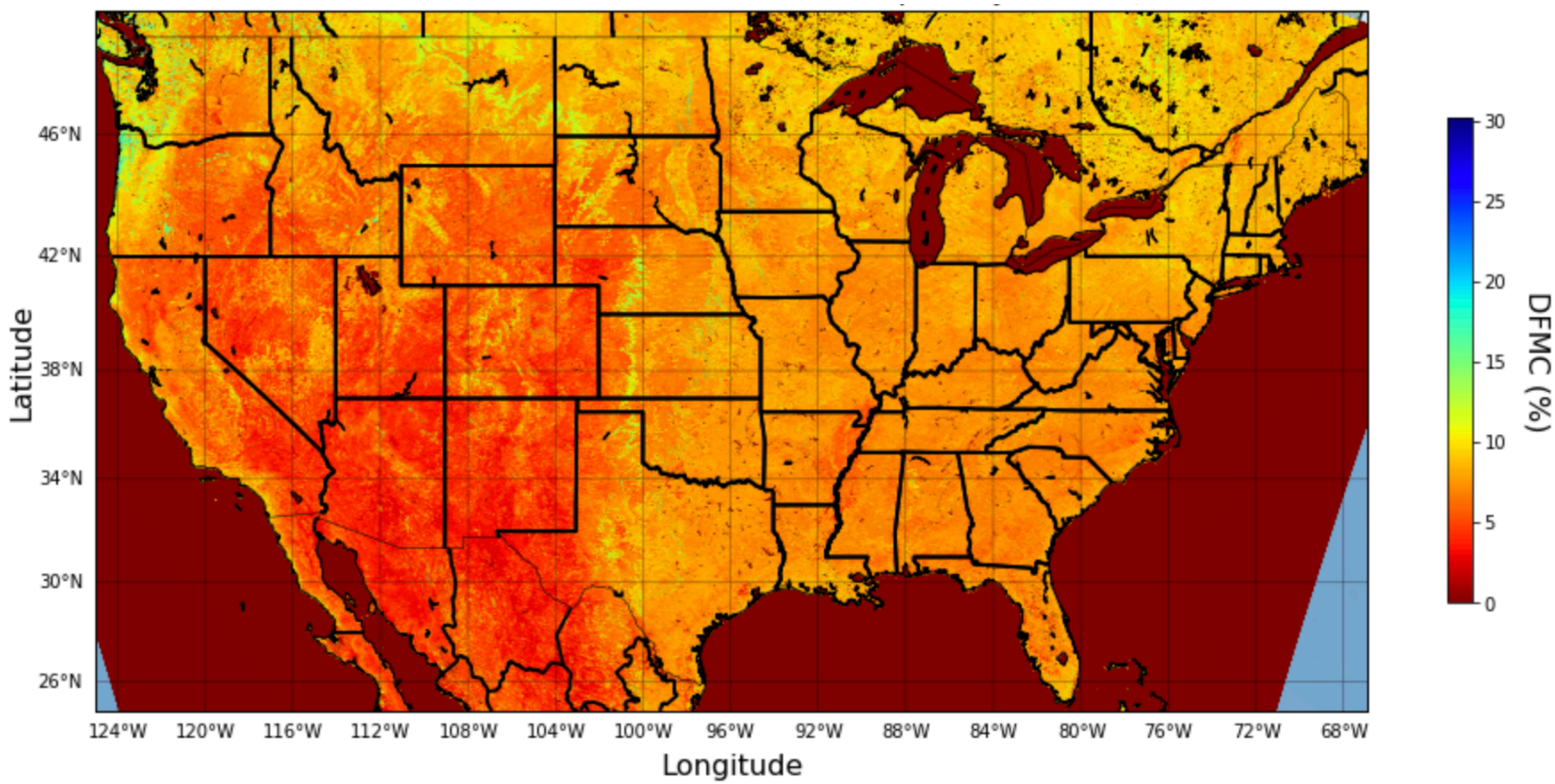
Comparison of the new 1 km dead FMC map with the map based on surface observations

There are about 2000 remote automatic weather stations distributed over CONUS



CONUS 1 km gridded dead fuel moisture map for June 11, 2019

Live FMC is sampled manually relatively infrequently and at a limited number of locations, particularly on the east of US.



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CONUS 1 km gridded live fuel moisture map for June 11, 2019

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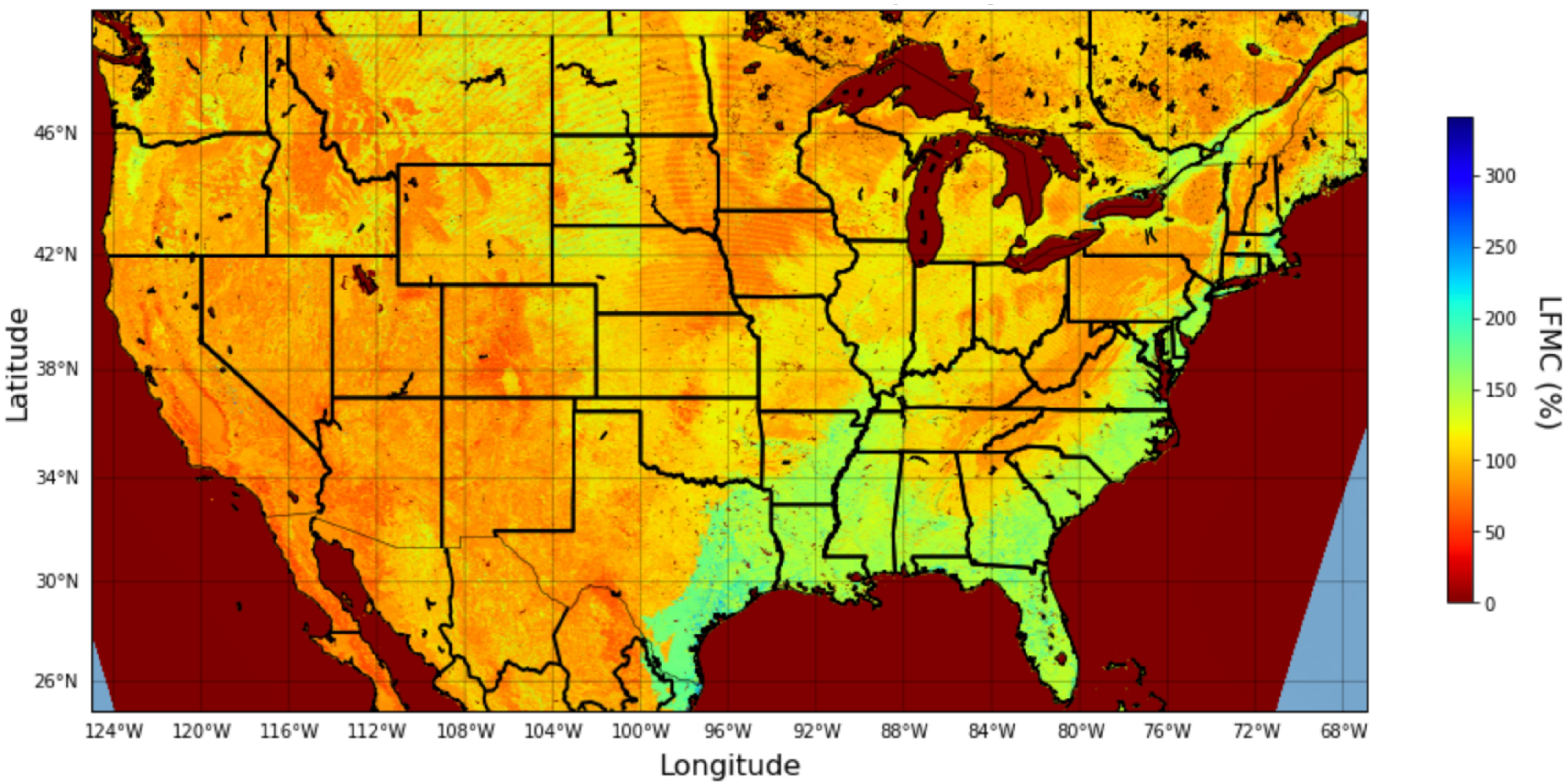

Summary

- Predictors for FMC consist of MODIS LST and reflectances, output from the National Water Model and terrain data
- Random Forest machine learning algorithm is most effective for development of a machine learning model for estimation of FMC
- Predictors with most significant importance are: land surface temperature, elevation, slope, accumulated evapotranspiration, and reflectance bands, particularly bands 7 (dead FMC) and 2 (live FMC)
- From the National Water Model the most important predictor is accumulated evapotranspiration
- We have implemented the Random Forest base machine learning models for dead and live FMC for CONUS
- Machine learning model is being implemented in a real-time system

Remaining Work

Machine learning models were developed and all the satellite and model data are processed daily for use in machine learning models

Complete implementation of the machine learning model in a real-time system

Continue assessment of the 1 km CONUS FMC dataset

Make daily CONUS maps of the dead and live FMC available through NCAR's Research Data Archive (https://rda.ucar.edu/datasets/ds084.1)

QUESTIONS?

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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 liv