NASA ENSCO THE UNIVERSITY OF ALABAMA IN HUNTSVILLE SPoRT NATIONAL WEATHER SERVICE FOREST SERVICE U.S. DEPARTMENT OF AGRICULTURE

Applying Antecedent Land Surface Conditions and Machine Learning to Wildfire Events and Seasonal Burn Prediction

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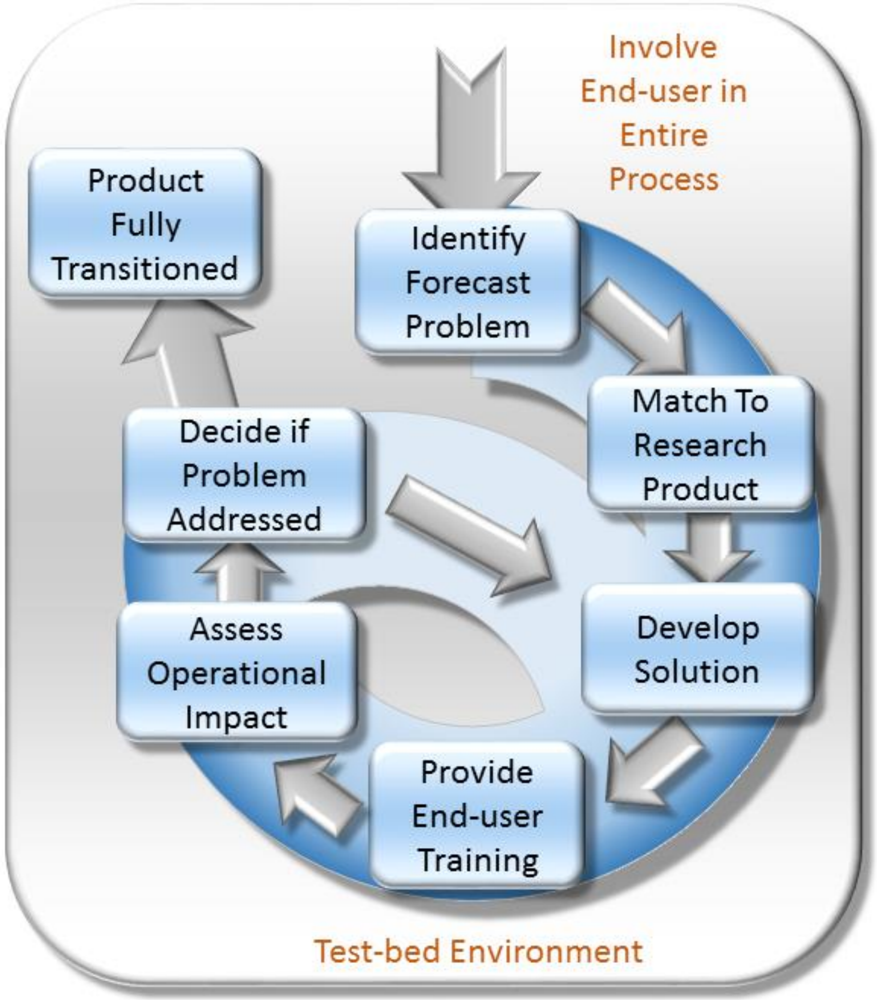
30 April 2019 *6th International Fire Behavior and Fuels Conference; Albuquerque, NM*

Deep Dive Session: 1040am

What is SPoRT?

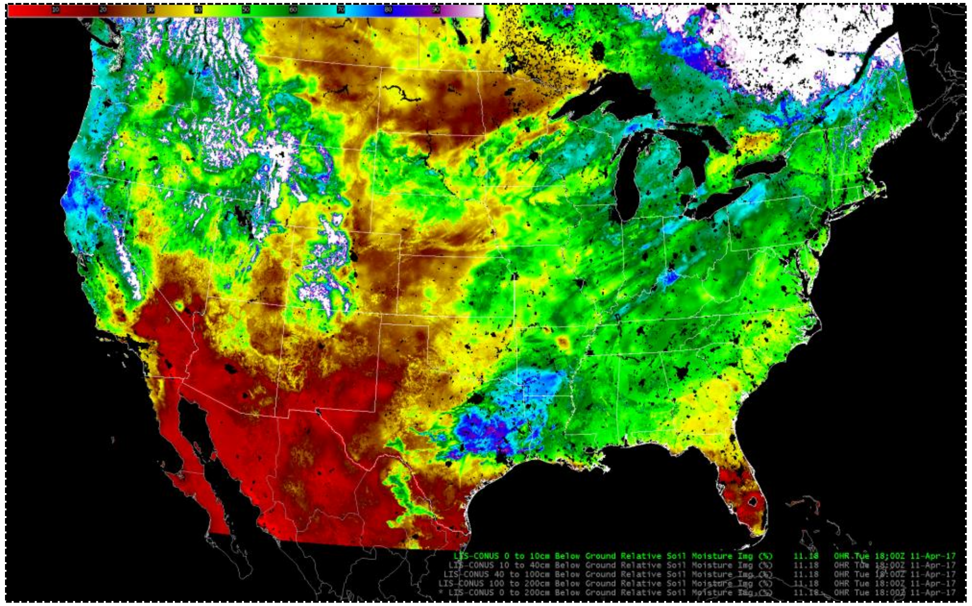
- Short-Term Prediction Research and Transition (SPoRT) Center
- Our main purpose is to transition experimental NASA datasets and products to operational end users
  - ✓ *Identify operational challenge*
  - ✓ *Determine how NASA data and products can aid in the decision making process.*

SPoRT
Short-term Prediction Research and Transition Center

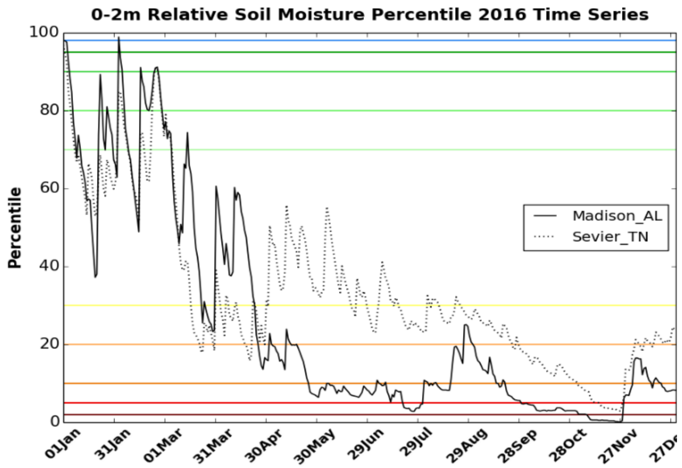


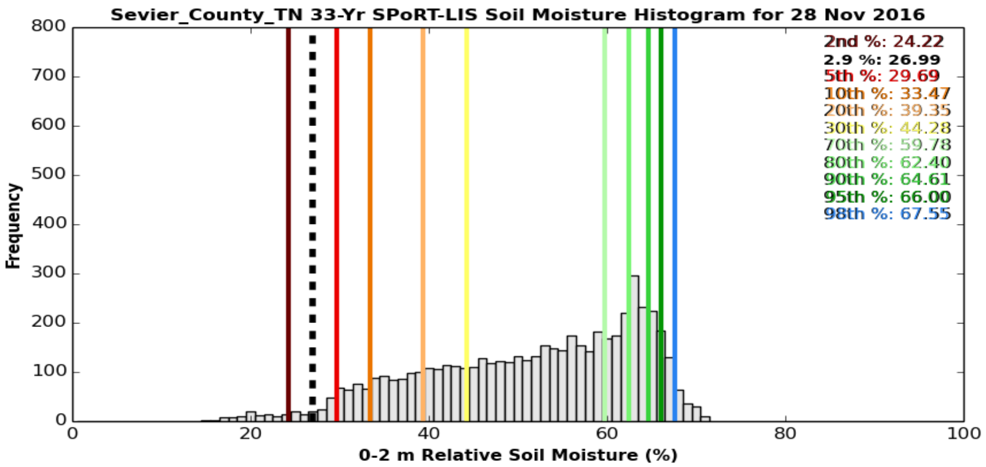
SPoRT-Land Information System (SPoRT-LIS)

- **Near real-time configuration of the NASA Land Information System**
- Covers the **full CONUS** at ~3-km resolution
- Hourly 0.125° NLDAS-2 analyses and precipitation from initialization up to t – 4 days, based on ~4 day latency of NLDAS-2 analyses in real-time
- Global Data Assimilation System (GDAS) analyses & short-term forecasts; **NCEP/NSSL Multi-Radar Multi-Sensor (MRMS) from t – 4 days to t_0**, based on ~6-9 hour latency of GDAS in real-time
- **Daily 1981-2013 soil moisture climatology and soil moisture percentiles**
- Incorporates daily real-time, global **VIIRS 4-km Green Vegetation Fraction (GVF)**
- Data available via web portal for WRF initialization, web graphics **and AWIPS II**



Soil Moisture degradation prior to Gatlinburg, TN wildfire (below)





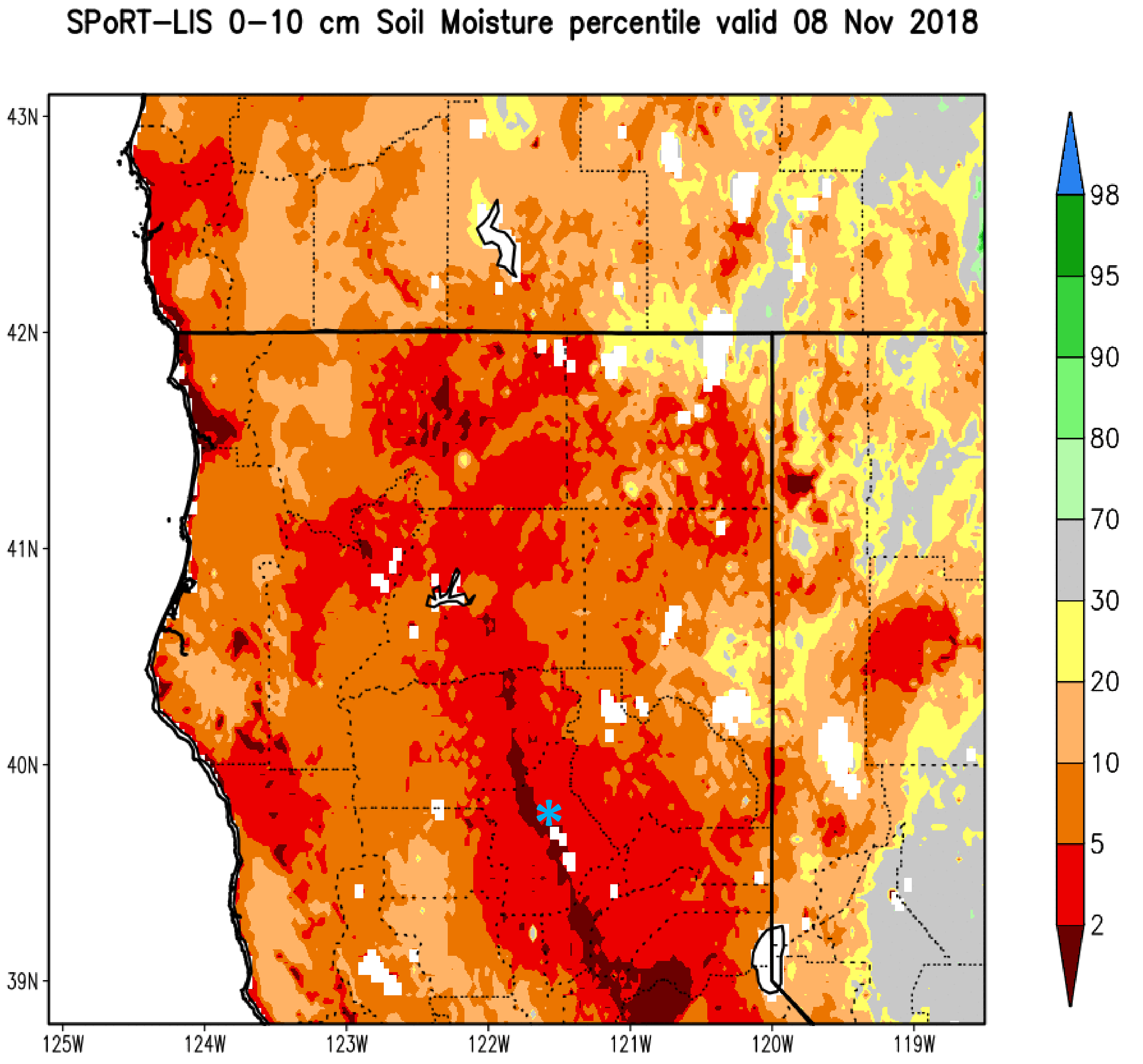
Recent Collaboration with the National Wildfire Coordinating Group (NWCG)

- SPoRT was tasked in 2018 to understand how the SPoRT-LIS can provide additional information for wildfire purposes.
- Primary focus was on soil moisture fields at various depths, green vegetation fraction, and seasonal changes in those variables that provide additional information to inform wildfire potential.
- Focus region: Pacific Northwest U.S. during 2015.
- Follow-on project to apply remote sensing and land surface modeling assets to better characterize wet vs. dry fuels in Western U.S.

SPoRT-LIS soil moisture analysis associated with deadly Camp, CA wildfire

Static soil moisture percentiles and percentile temporal change fields valid 8 Nov 2018

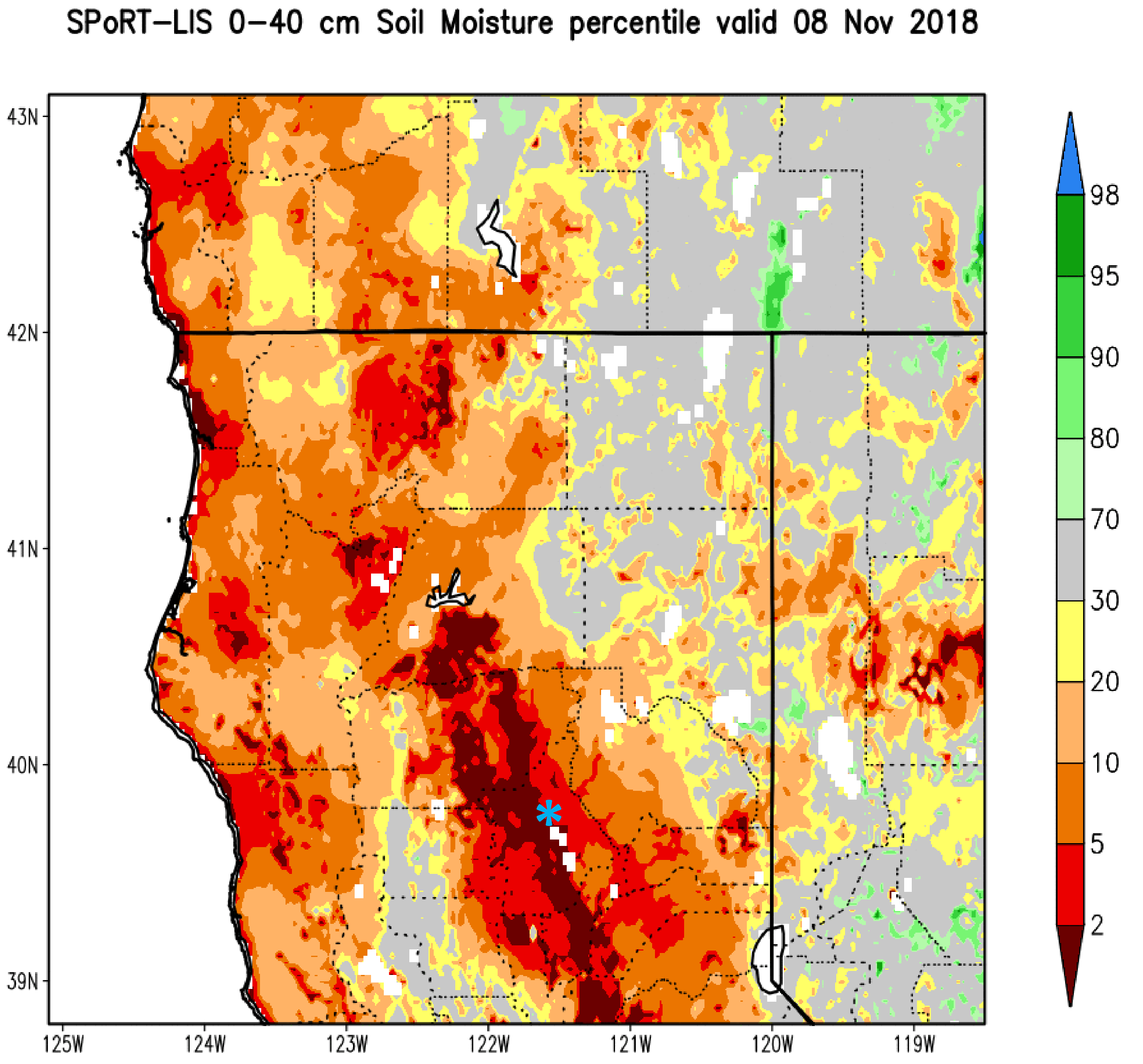
Top 10 cm soil moisture percentile valid on 8 Nov 2018



**Fairly uniform low percentiles, esp. in “stripe” along front range of Sierras

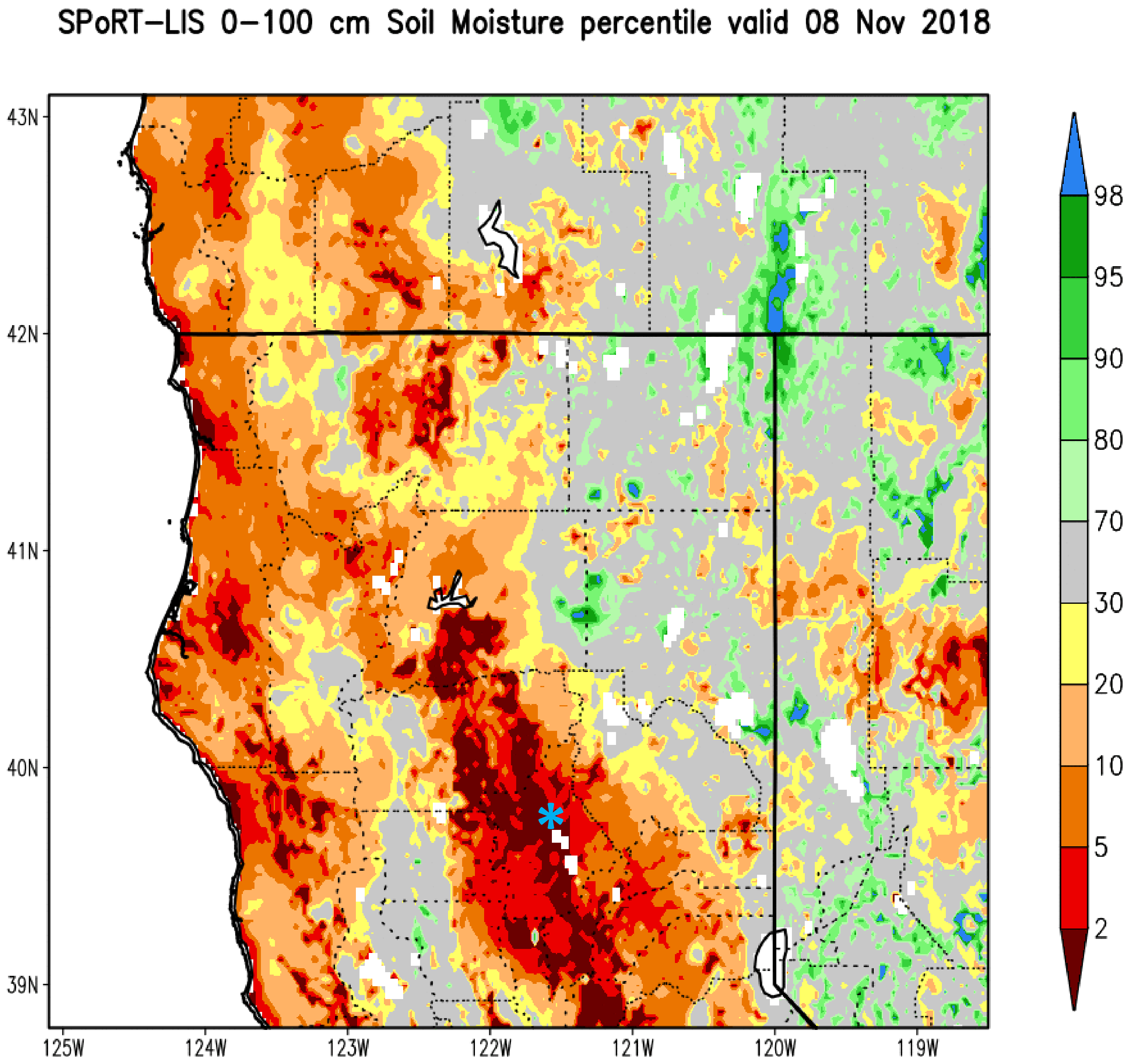
(Location of Paradise, CA given by blue asterisk)

Top 40 cm soil moisture percentile valid on 8 Nov 2018



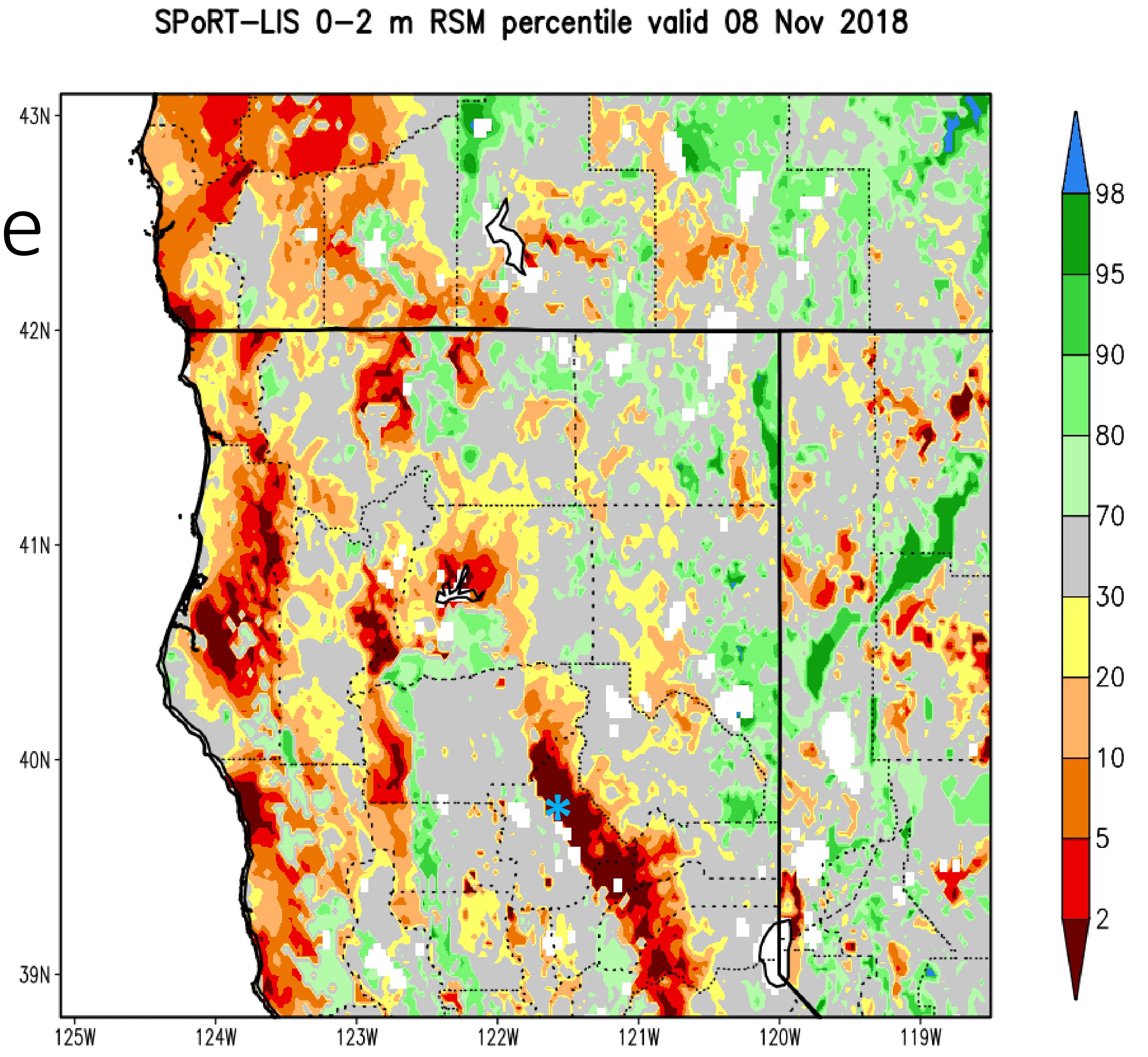
**Lowest percentiles a bit more concentrated on the eastern side of the valley to the Sierra foothills

Top 100 cm soil moisture percentile valid on 8 Nov 2018



**Lowest percentiles a bit more concentrated on the eastern side of the valley to the Sierra foothills

Total column (2 m) soil moisture percentile valid on 8 Nov 2018



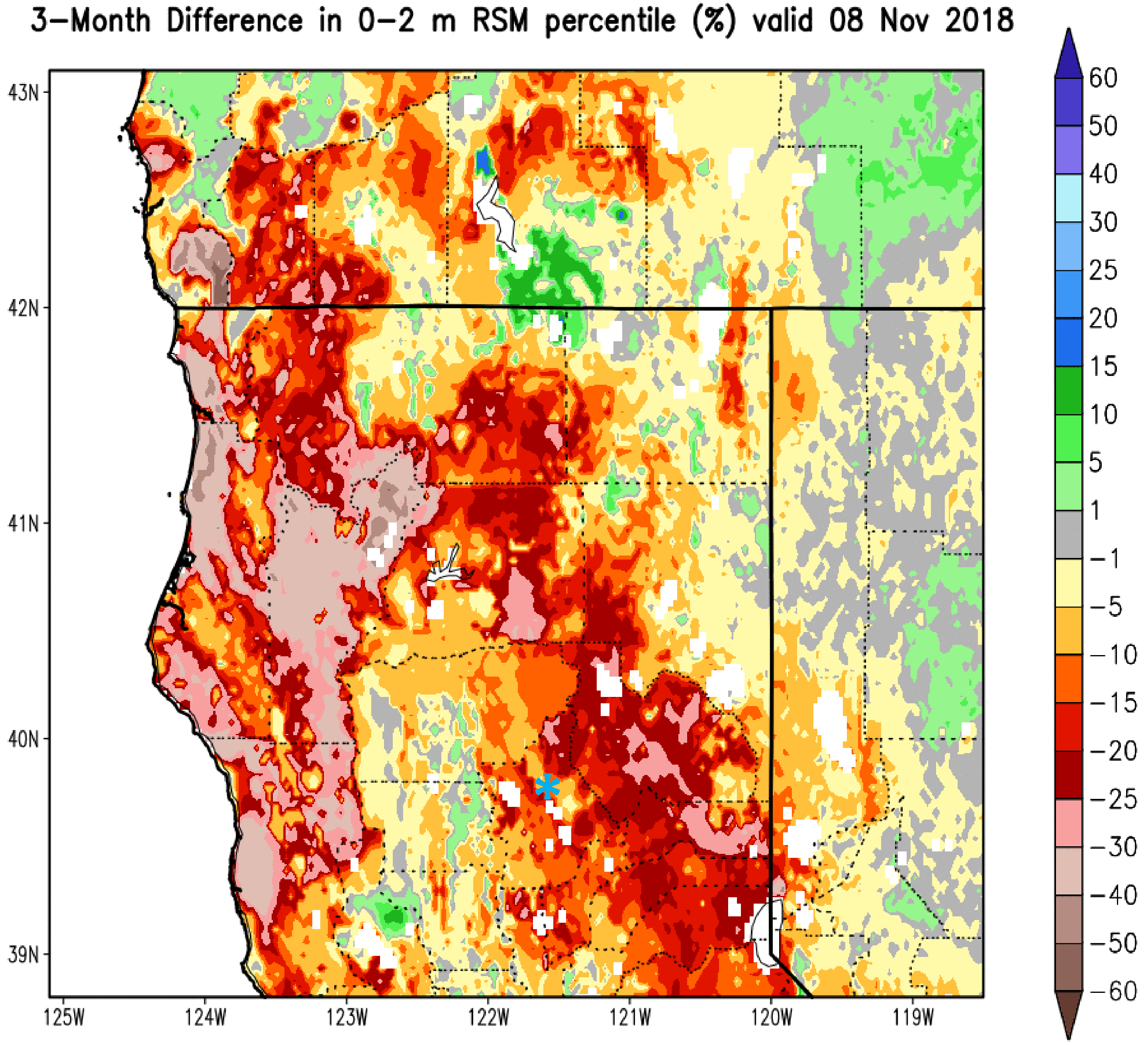
**Lowest percentiles concentrated along the Sierra foothills, and along NW CA/OR coastal range

<u>NOTE</u>: total column percentiles are currently derived from county-based, daily climatologies, as shown in slides 2-3.

Temporal change maps of 0-2 meter soil moisture percentiles

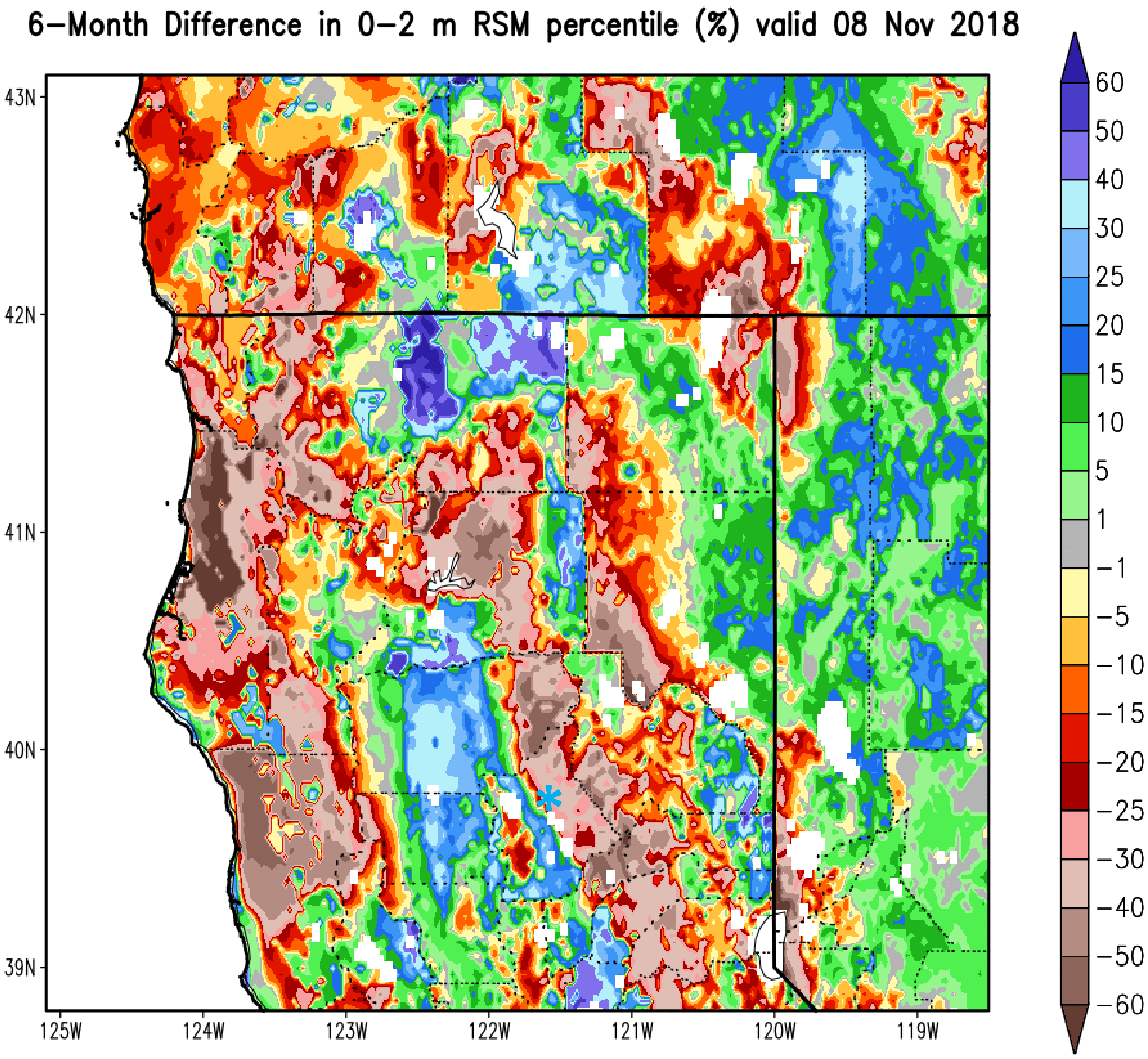
Percentile differences ranging from 7 days to 1 year

3-mon change in 0-2 meter soil moisture percentile ending 8 Nov 2018



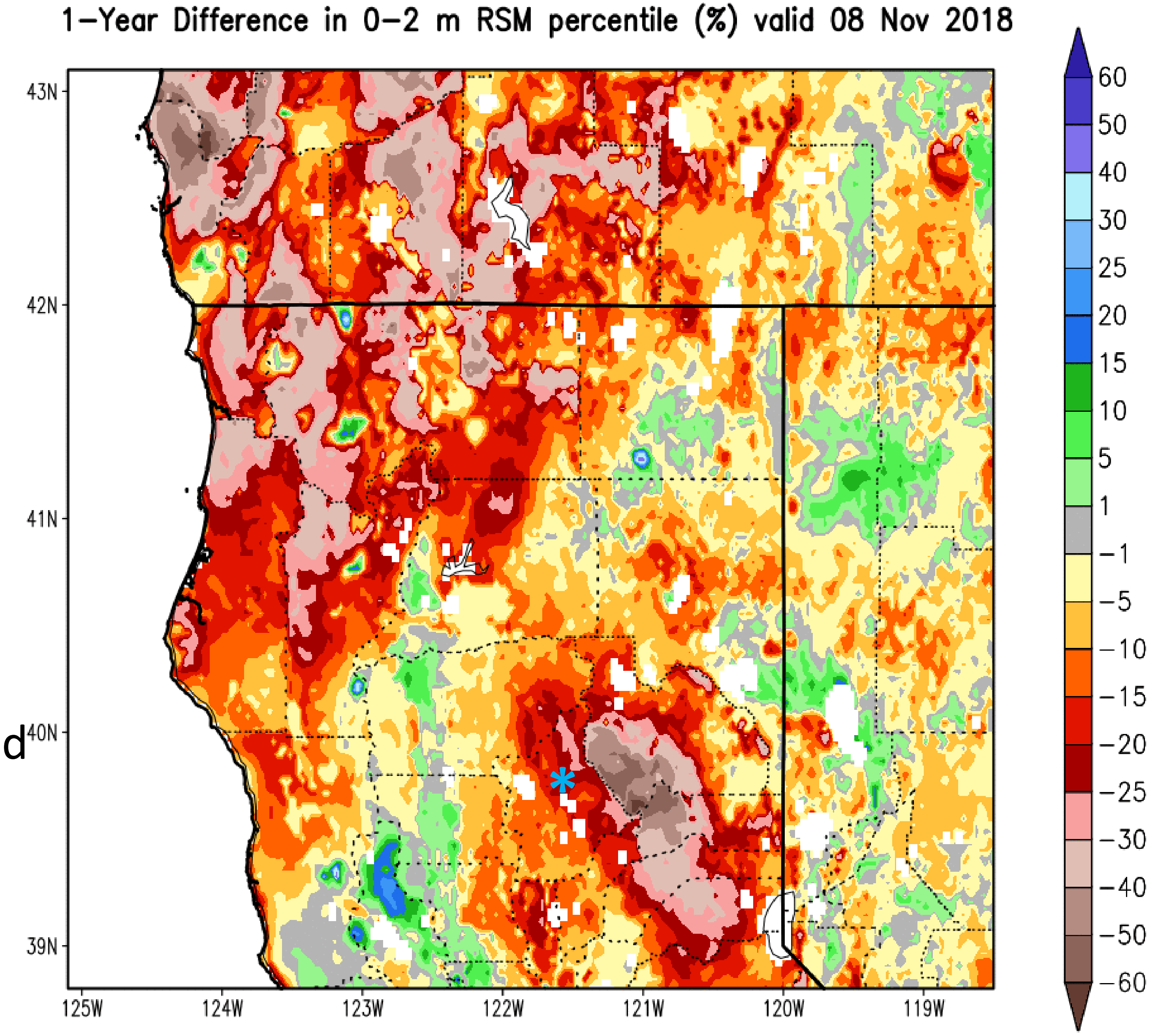
**Soil moisture percentile degradation most concentrated across NW coast/mountains and Sierras

6-mon change in 0-2 meter soil moisture percentile ending 8 Nov 2018



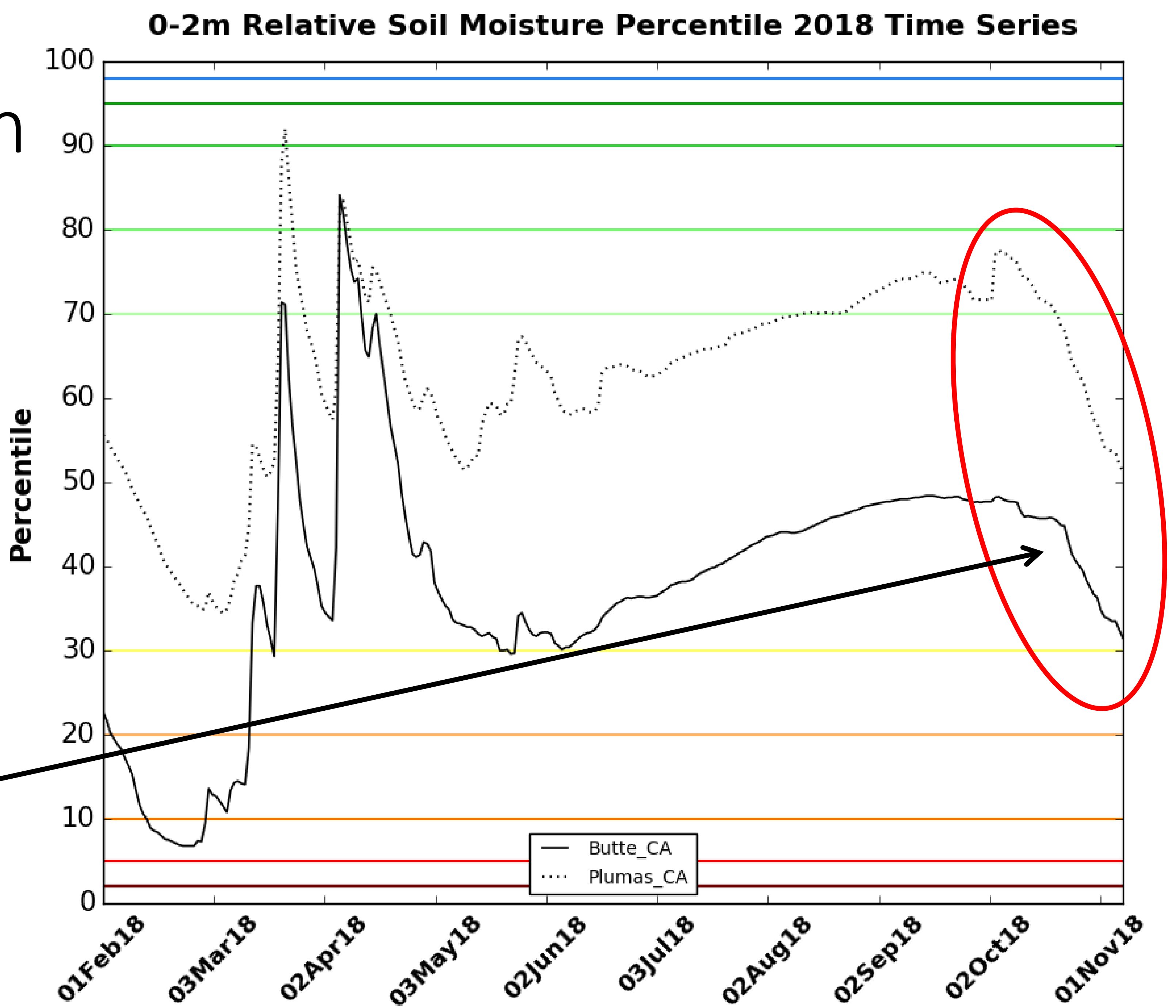
**Soil moisture percentile degradation particularly focused across coastal mountains and Sierra foothills

1-year change in 0-2 meter soil moisture percentile ending 8 Nov 2018



**Soil moisture percentile degradation across broad portion of NW California and Oregon, but also very focused in vicinity of Camp Fire and Sierras

Time Series of 0-2 meter total column soil moisture percentiles in Butte and Plumas counties

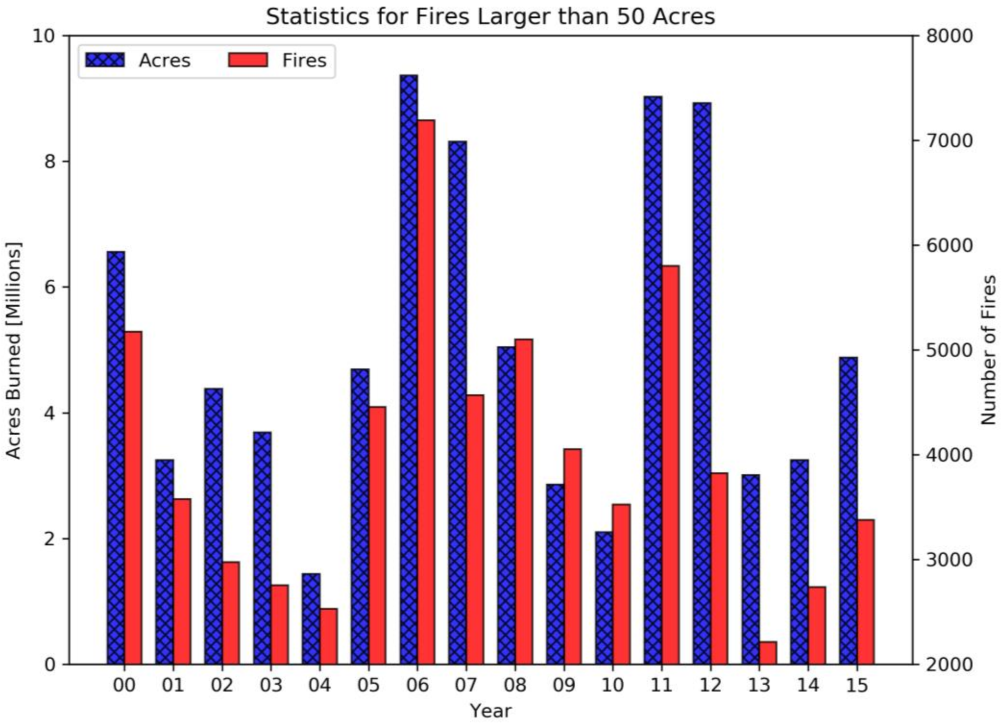


Notice rapid decline leading up to fire event

Wildfires: Machine Learning

- **Continual increases in the cost of fire suppression efforts has put a strain on the U.S. Forest Service's budget.**
  - Funds are diverted from wildfire risk mitigation to suppression activities.
  - Appropriate pro-active resource allocation could help reduce some of the cost.

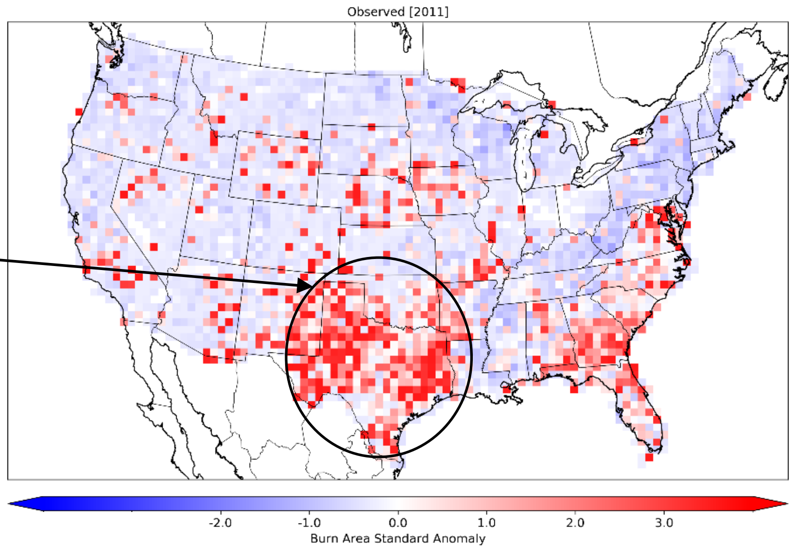
- **Yearly changes in fire activity is related to changes in both atmospheric and land surface conditions.**
  - Numerous amounts of available data related to fire potential (i.e. dead fuel moisture, soil moisture, precipitation, temperature, moisture, etc.)
  - Antecedent conditions provide an indication about potential fuel availability and dryness.



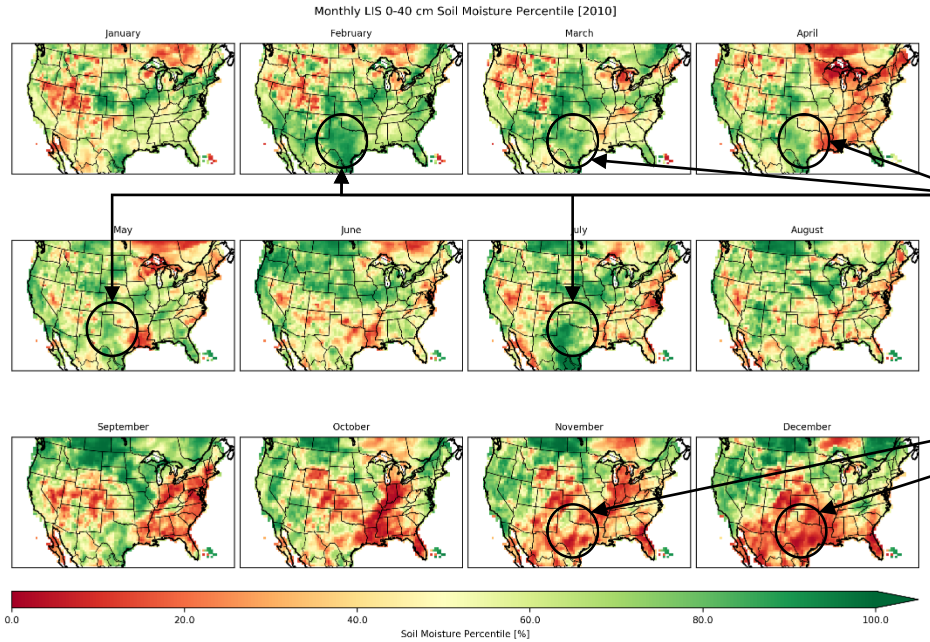
Yearly number of fires and acres burned across the CONUS domain. Indicates high year to year variability.

Antecedent Relationships

- **Standardized burn area anomaly for 2011 shows anomalous wildfire activity over much of Texas.**
- **SPoRT LIS 0 – 40 cm Soil Moisture percentile is high for much of the previous year (2010), especially over the growing season.**

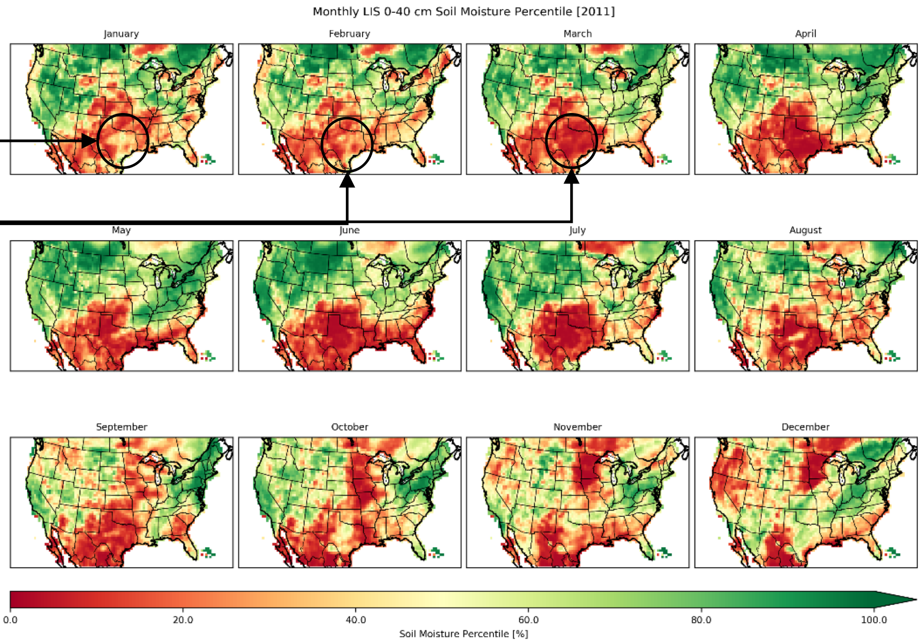


- **Drying then occurred from late fall 2010 and continued through 2011.**
- **High antecedent soil moisture during growing season can lead to a build up of fuel.**
- **Low soil moisture leading up to fire season continually dries the available fuel.**



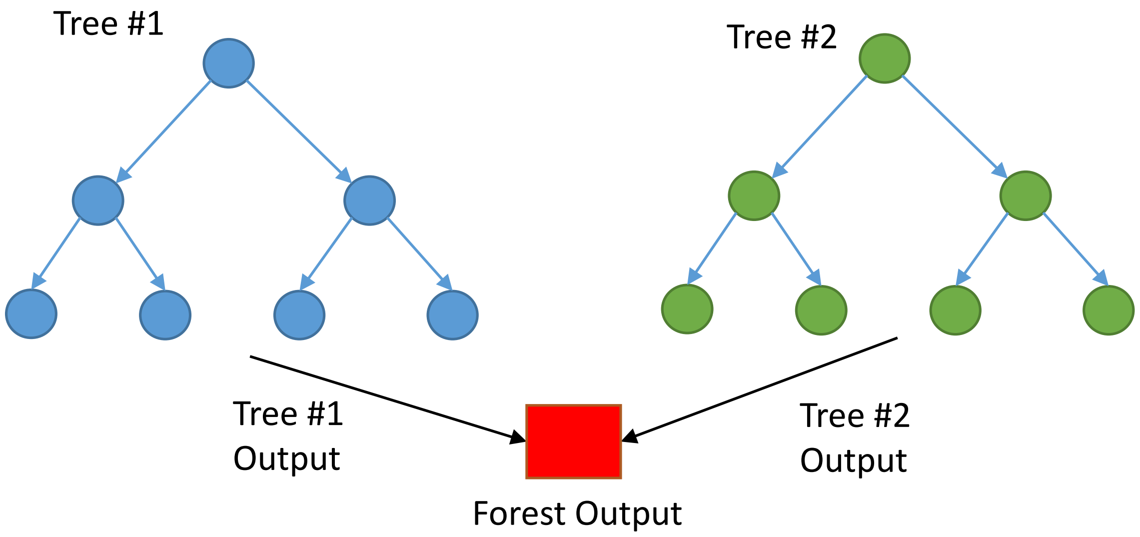
High antecedent (2010) soil moisture during growing season.

Low antecedent soil moisture during late Fall 2010 into early Spring 2011.

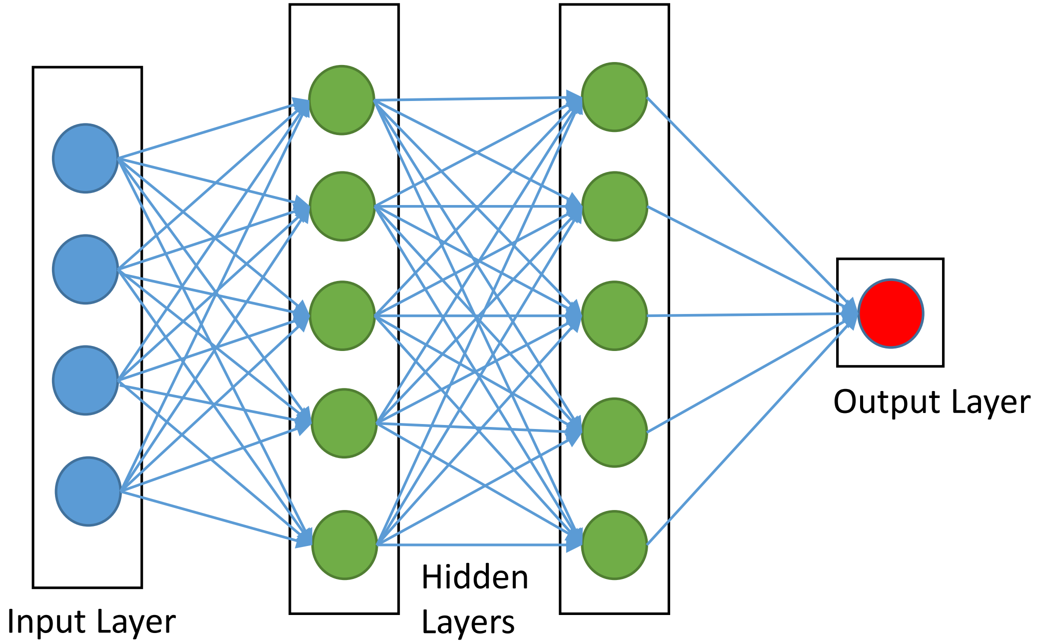


Machine Learning Methods

- Random Forest (RF)
  - Tries to create uncorrelated trees through random sampling of both the input data and features.
  - Splits are determined by minimizing the mean square error.

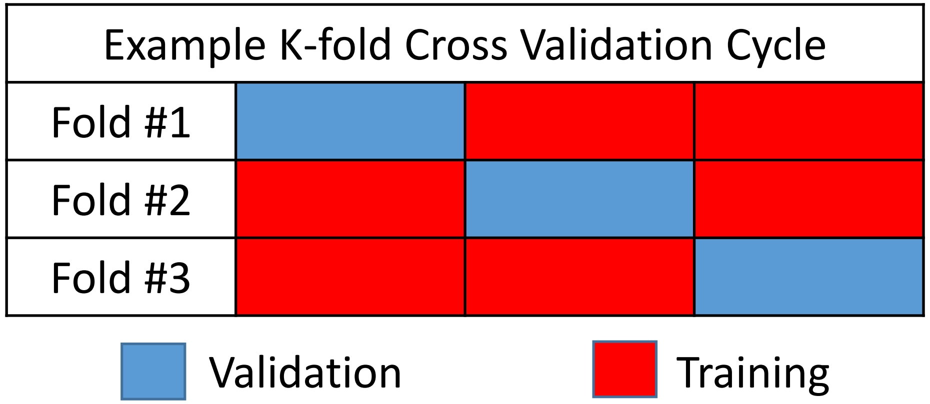


- Deep Neural Network (DNN)
  - Learn representations from the data through hierarchical layers.
  - Works by determining the weights which effectively map the inputs to their targets.



Model Configuration

- Hyperparameters were determined using K-fold cross validation.
  - For each K-fold, one year was held out for validation.
  - Produces a model that generalized to each year

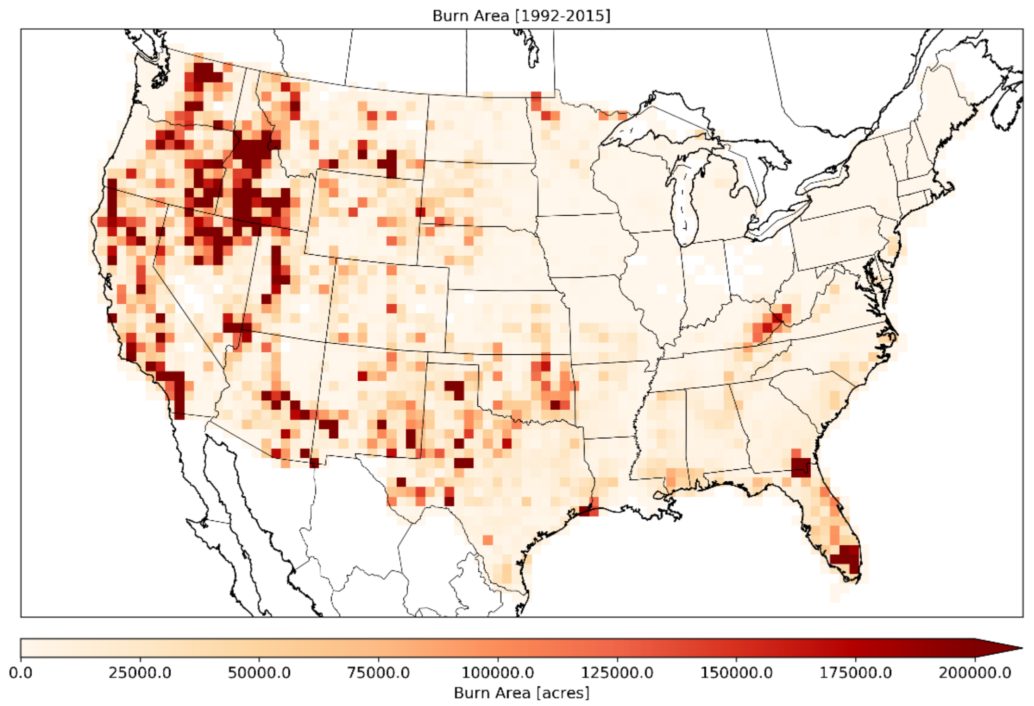


- Random Forest (scikit-learn)
  - Number of Trees: 500
  - Max Depth: 10
  - Max Features: log2

- Deep Neural Network (Keras)
  - 5 layers (4 hidden and 1 output)
  - 500 neurons in each hidden layer

Input Features

- ➢ Monthly average standard anomalies of each feature from the previous year through March of the current year were used.
  - Standard anomalies are used to account for the non-uniform nature of the input features and acres burned across the CONUS domain.
  - Allows for the use of a universal model for all pixels.
- ➢ The 4th edition Fire Program Analysis – Fire Occurrence Database (FPA-FOD) is used as the truth dataset (Short 2017).

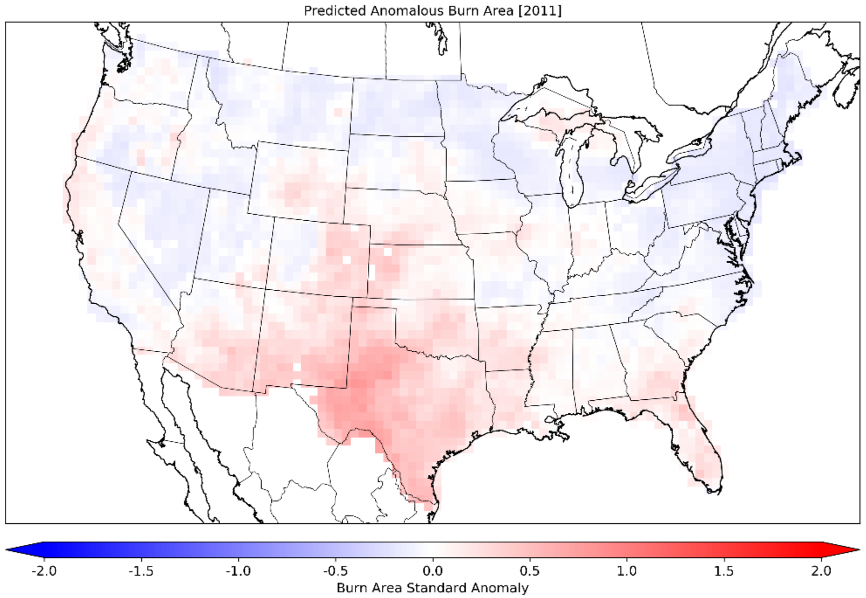


Input Features	
SPoRT LIS Volumetric Soil Moisture (0-10 cm, 0-40 cm, 0-100 cm)	SPoRT-LIS Soil Moisture Percentiles (0-10 cm, 0-40 cm, 0-100 cm)
Dead Fuel Moisture (100-hr and 1000-hr)	Precipitation
Daily Minimum and Maximum Temperature	Daily Mean Vapor Pressure Deficit
MODIS LAI/GVF	Energy Release Component
Potential Evapotranspiration	Evaporative stress index

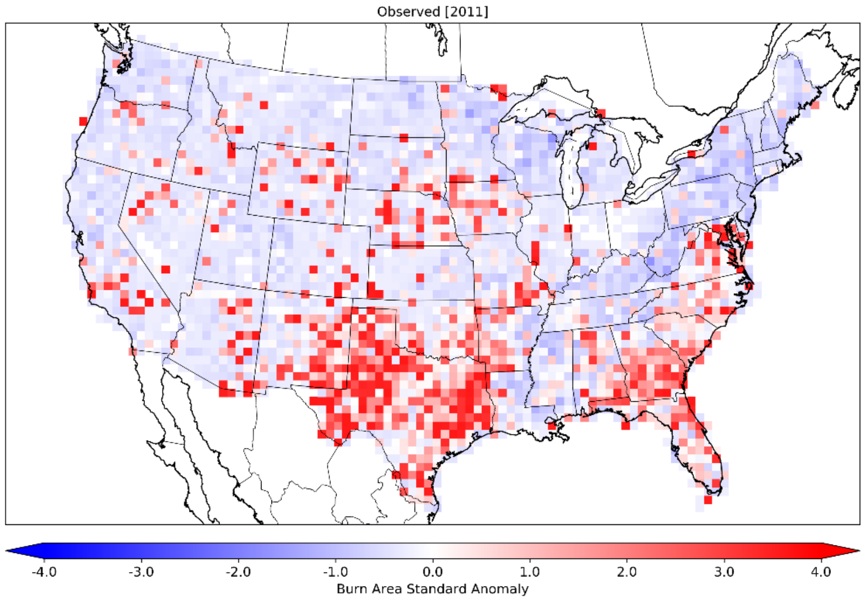
Preliminary Results

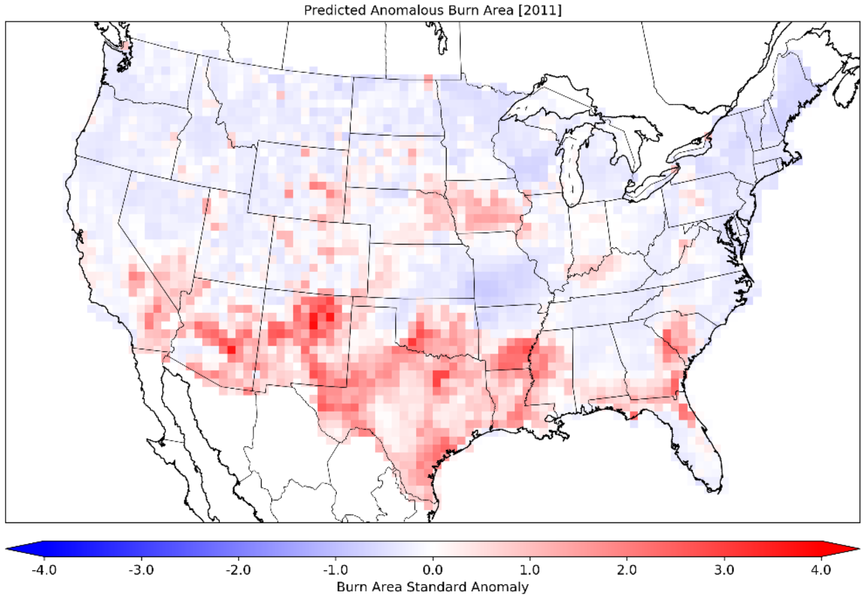
- The model predictions provide an indication of fire potential.
    - The model is reasonably able to capture general locations of yearly fire activity.
- RF predicted magnitudes tend to regress towards the mean.
- DNN predicted magnitudes are closer to the observations.

B) RF Prediction for 2011 (adjusted magnitude)



A) Observed Burn Area Standard Anomaly





C) DNN Prediction for 2011

Machine Learning Summary

- Both models (RF & DNN) show promise for predicting areas of high wildfire potential.
  - DNN shows greater potential for accurately predicting the appropriate anomalous magnitudes.

- Antecedent conditions are only one piece of the equation.
  - An ignition source is required which further complicates the model training and prediction.

- Currently do not account for in season changes.
  - Likely better at predicting early season wildfire potential as appose to late.

Machine Learning Future Work

- Produce probabilistic lightning initiated wildfire predictions.
  - Lightning initiated fires are more closely tied to the atmospheric/land surface conditions.
- Produce monthly to weekly outlooks.
  - Able to capture in-season changes.
- Explore using machine learning for fire spread characterization.

Presentation Summary and Future Efforts

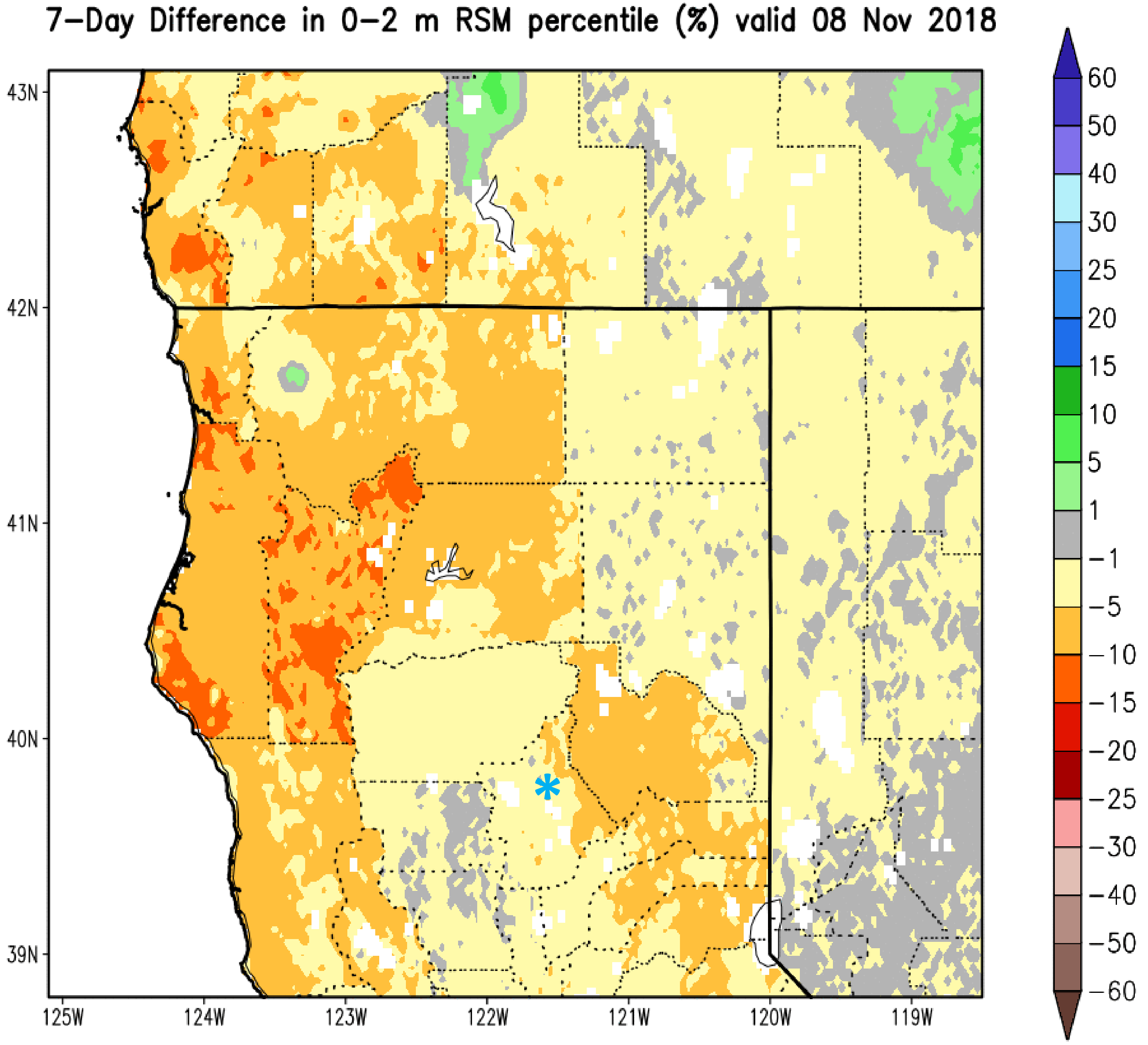
- Land surface evolution has connection to wildfire events
- Continue developing relationships between land-surface variables and wildfire seasonal events
- Refine machine-learning models and techniques to best predict wildfire seasonal behavior
- Characterization of wet/dry fuels in western U.S. (follow-on project)

NASA/SPoRT web:
https://weather.msfc.nasa.gov/sport/
Twitter: @NASA_SPoRT
Facebook: NASA.SPoRT

Acknowledgements: This research is funded by the National Wildfire Coordinating Group and Dr. Tsengdar Lee of NASA HQ

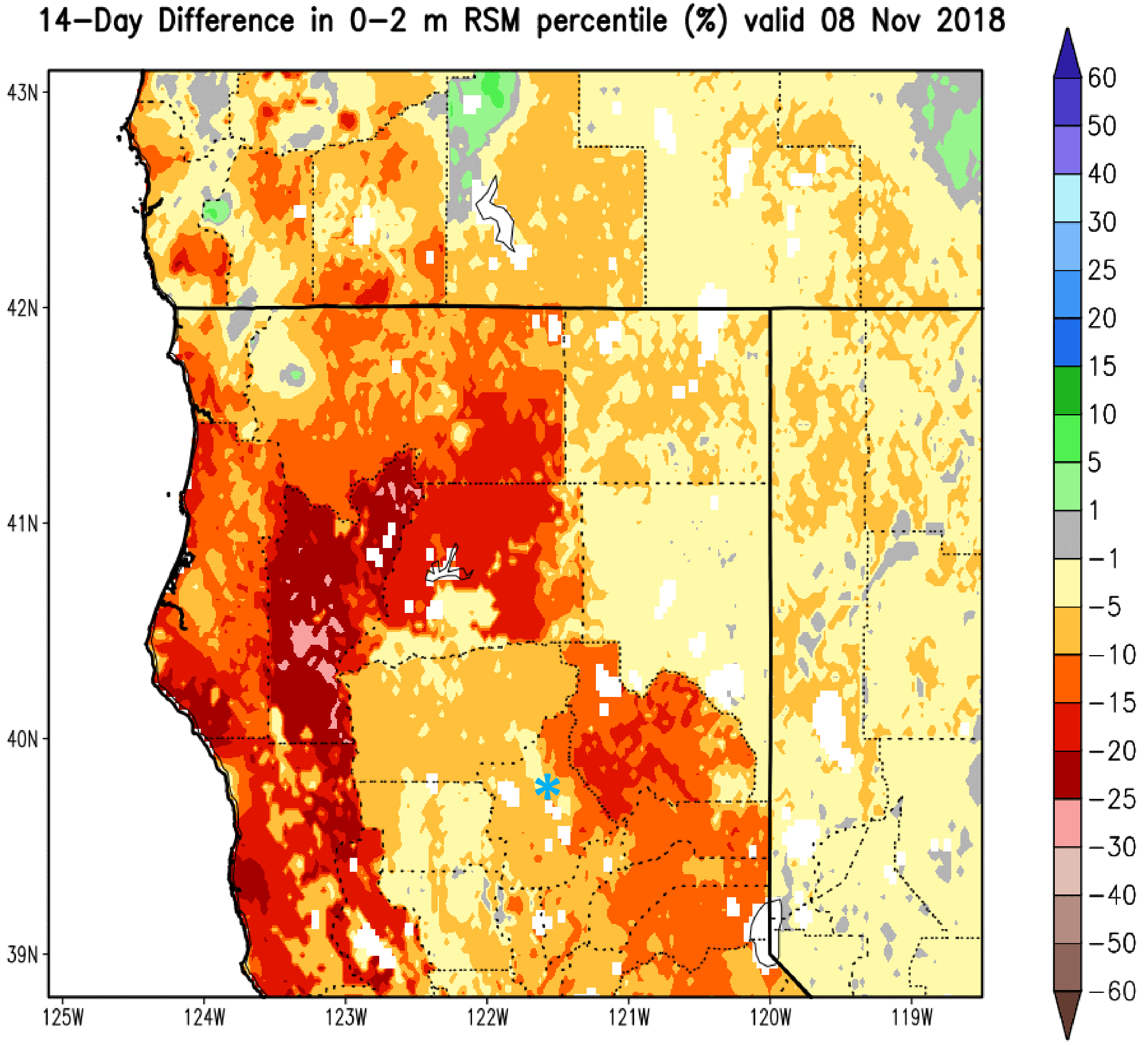
Backup Slides

7-day change in 0-2 meter soil moisture percentile ending 8 Nov 2018



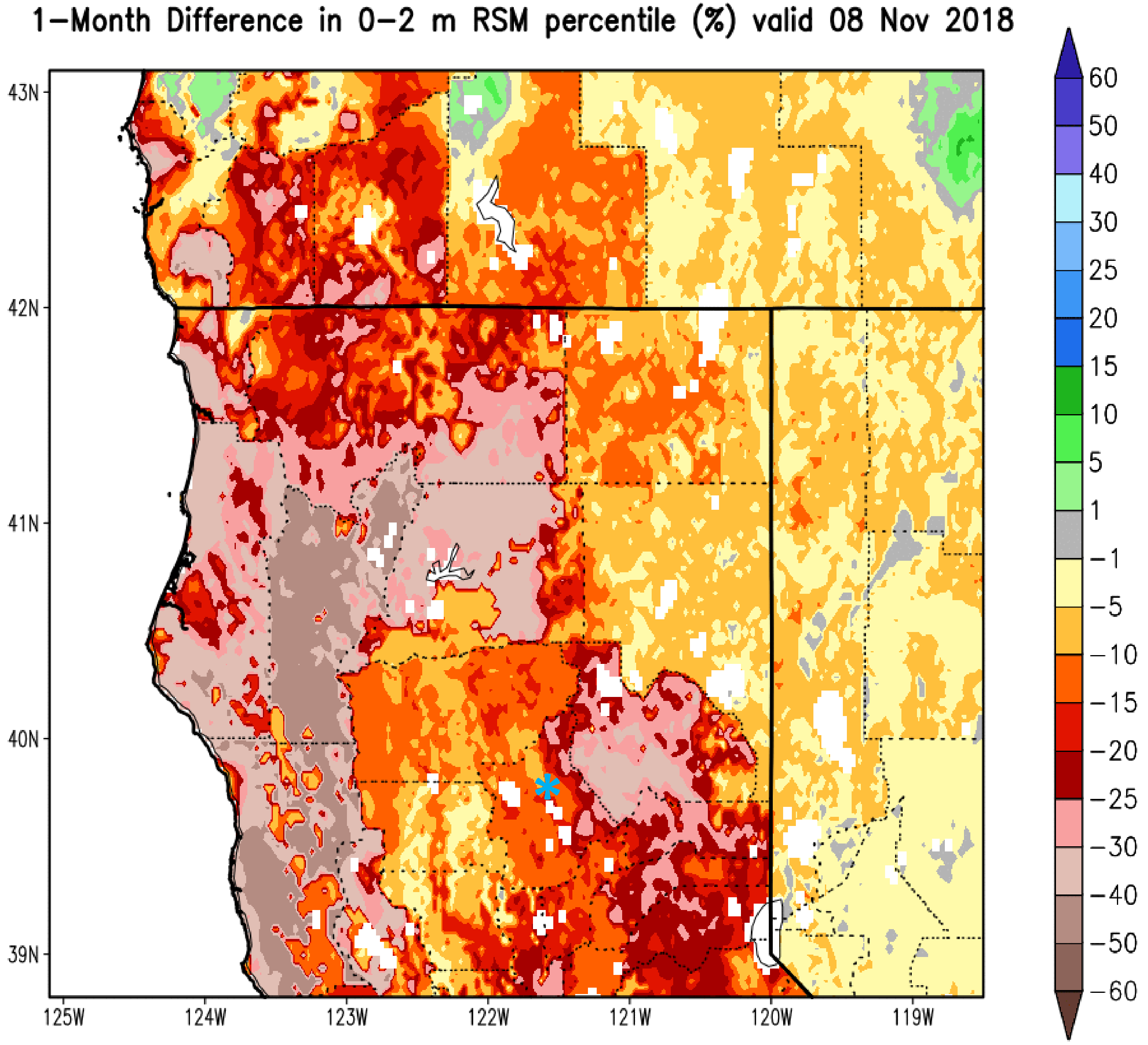
**Fairly uniform degradation in soil moisture percentile across NW California

14-day change in 0-2 meter soil moisture percentile ending 8 Nov 2018



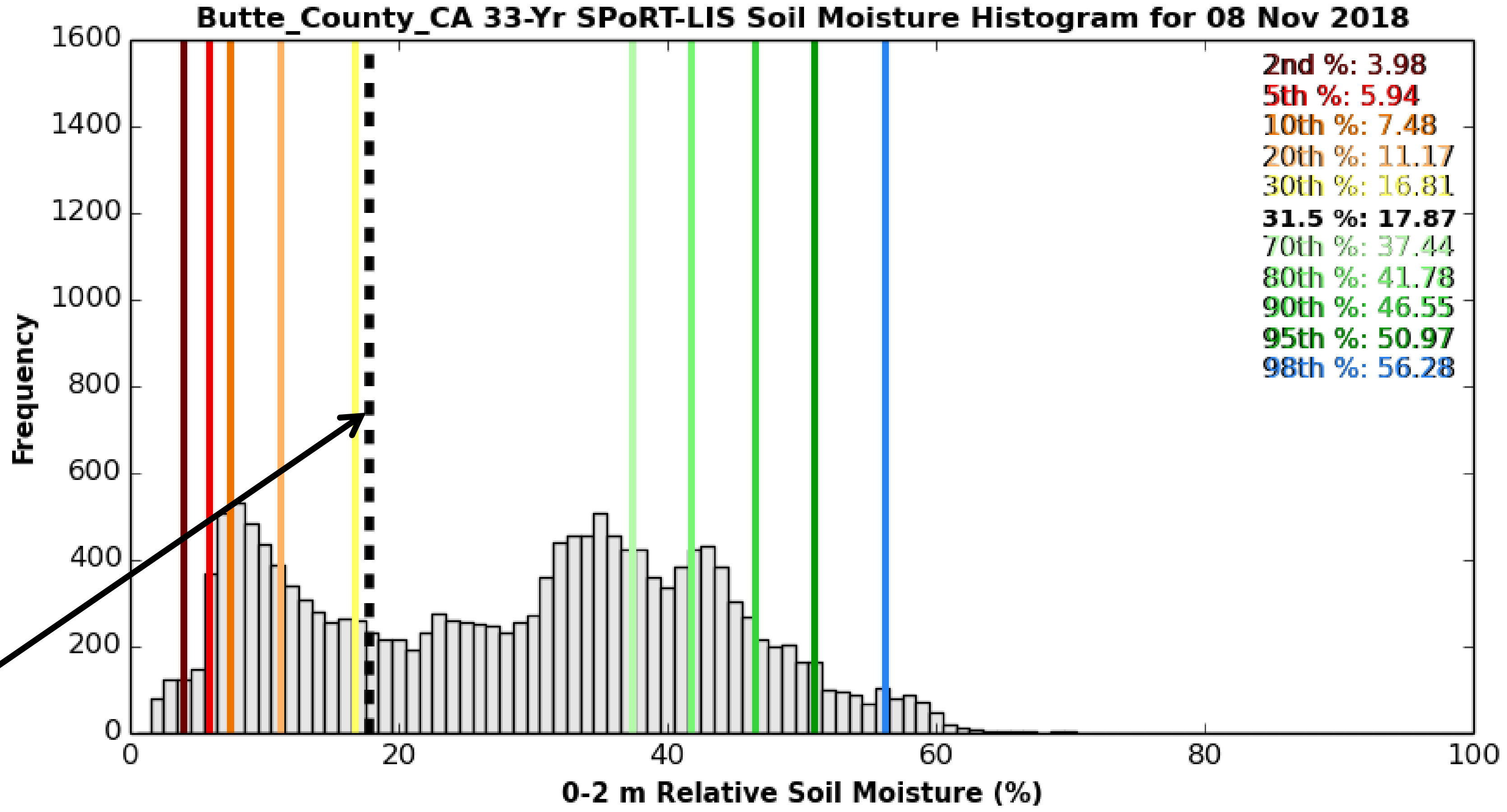
**Soil moisture percentile degradation most concentrated across NW coast/mountains and Sierras

1-mon change in 0-2 meter soil moisture percentile ending 8 Nov 2018



**Soil moisture percentile degradation most concentrated across NW coast/mountains and Sierras

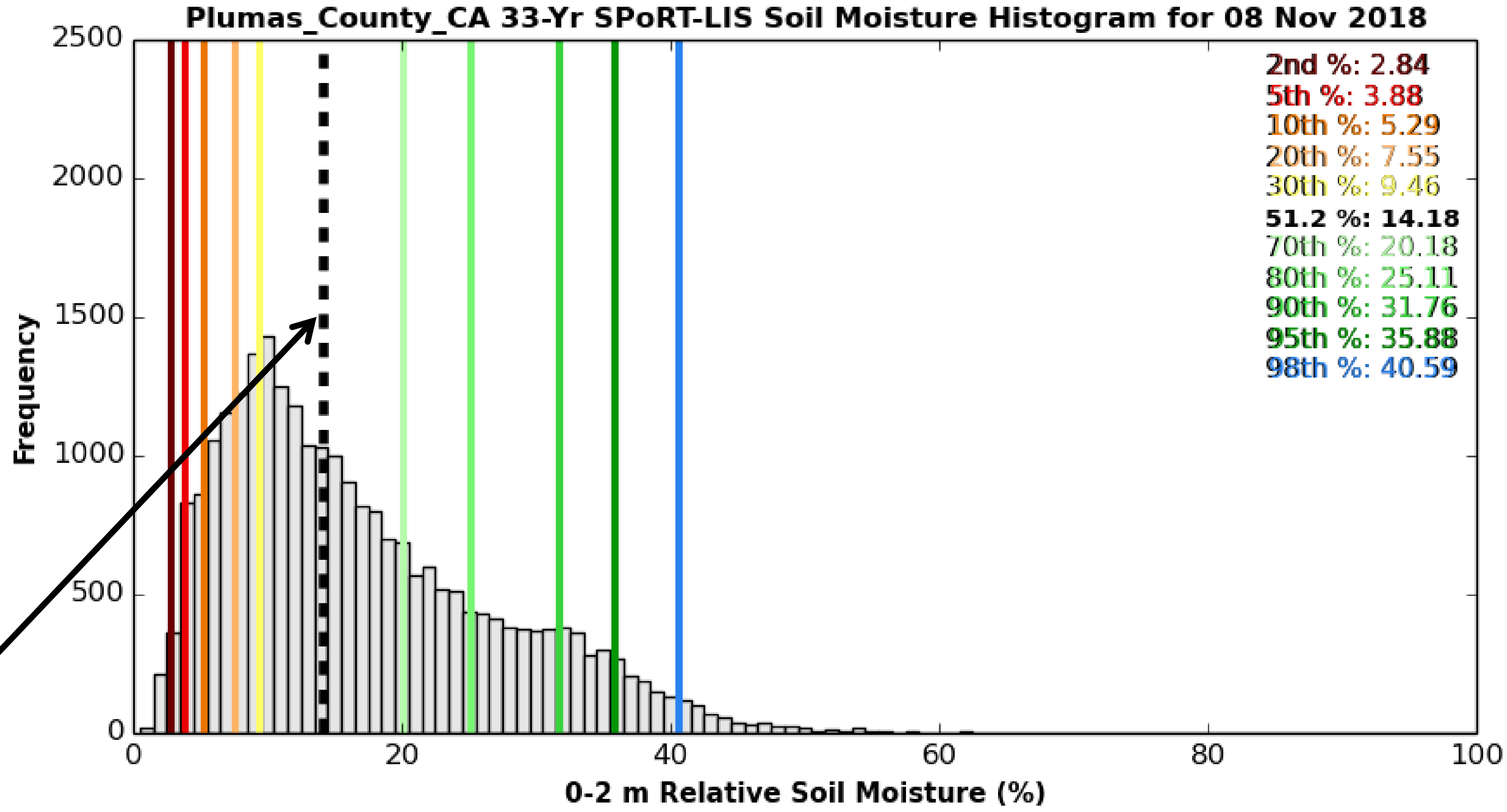
1981-2013 Histogram of 0-2 meter total column soil moisture: Butte County on 8 Nov 2018



Present-day percentile, averaged over all SPoRT-LIS grid points within County (black dashed line)

**Values are not all that compelling because county is quite large and significant heterogeneity exists in soil moisture distribution (forthcoming slides)

1981-2013 Histogram of 0-2 meter total column soil moisture: Plumas County on 8 Nov 2018

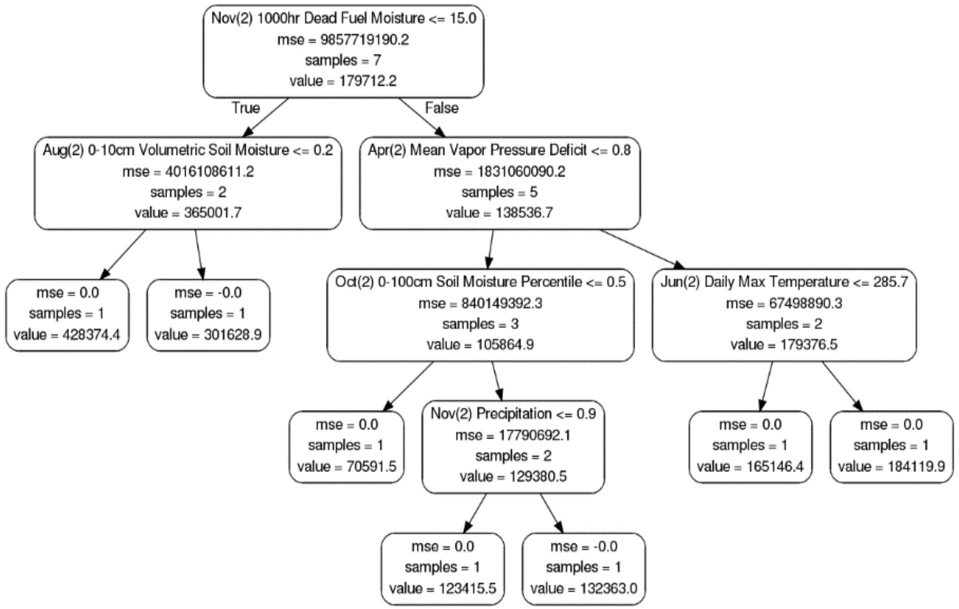


Present-day percentile, averaged over all SPoRT-LIS grid points within County (black dashed line)

**Values are not all that compelling because county is quite large and significant heterogeneity exists in soil moisture distribution (forthcoming slides)

Methodology: Random Forest Regression

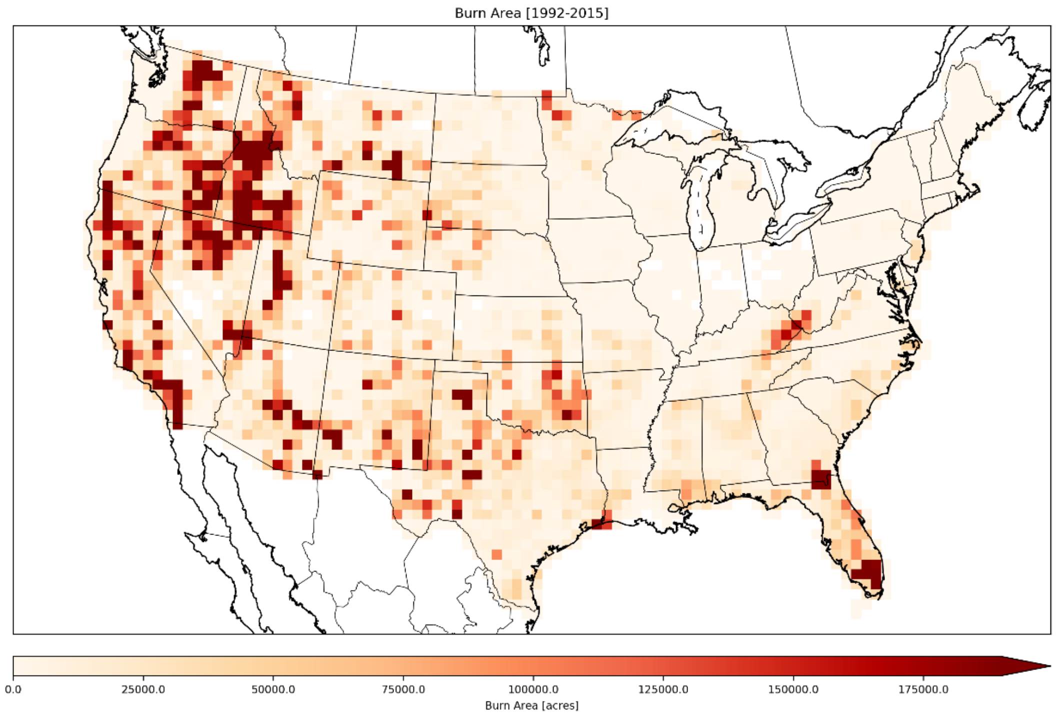
- Random forest (RF): supervised ensemble machine learning algorithm that is composed of N number of decision trees.
    - ✓ Randomness between trees is introduced by taking bootstrap samples and using a random feature selection for node splitting within each tree (Breiman 2001).
    - ✓ In regression, the result is the mean value of the individual trees in the forest.
- RF algorithm is used here to predict yearly fire severity (i.e., number of fires and burn area) using a variety of remotely sensed, model and in situ datasets.
    - US Forest Service Fire database (Short 2015) is used to characterize the spatial distribution of the wildfires across the CONUS region.
- Monthly averages of numerous predictors from the previous year up to climatological start of fire season used as RF predictors.
    - ✓ LIS Volumetric Soil Moisture (0 – 10 cm, 10 – 40 cm, 40 – 100 cm)
    - ✓ LIS Soil Moisture Percentiles (0 – 10 cm, 0 – 40 cm, 0 – 100 cm)
    - ✓ MODIS Leaf Area Index (LAI), Green Vegetation Fraction (GVF)
    - ✓ Evaporative Stress Index (ESI)
    - ✓ Dead fuel moisture (100-hr and 1000-hr)
    - ✓ Precipitation
    - ✓ Daily minimum and maximum temperature
    - ✓ Daily mean vapor pressure deficit



Wildfire Burn Area Spatial Distribution

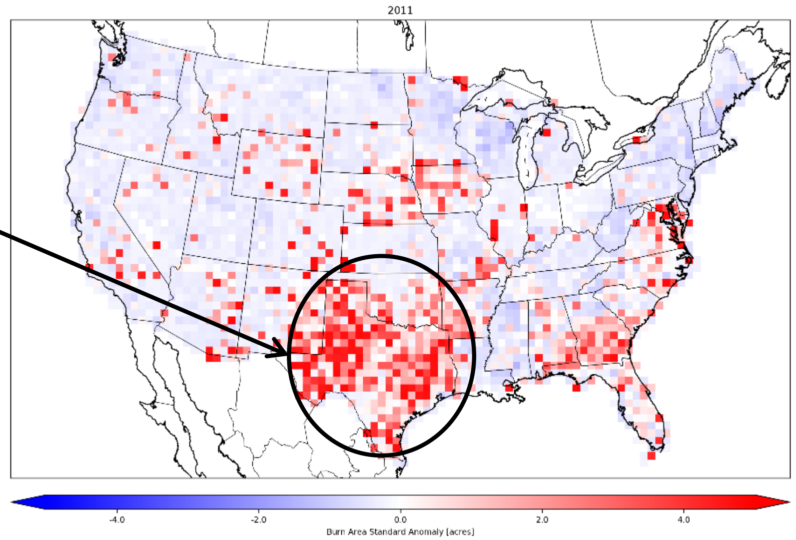
- Wildfire burn area database (1992 – 2015; right) was gridded to 50 km based on fire start location.
  - ✓ High spatial variability in the total number of acres burned.
  - ✓ On yearly time scales, the variability is even greater.
  - ✓ Due to the high variability, predicting anomalous fire seasons becomes advantageous.

- All of the data were transformed into standardized anomalies and re-gridded to a 50 km CONUS grid.
  - ✓ This process effectively increases the amount of data available to train the model.



Antecedent Relationships

- **Standardized burn area anomaly for 2011 shows anomalous amounts over much of Texas.**
- **LIS 0 – 40 cm Soil Moisture percentile is high for much of the precious year (2010), especially over the growing season.**



- **Drying occurred from late fall 2010 and continued through 2011**
- **High antecedent soil moisture during growing season can lead to a build-up of available fuels.**
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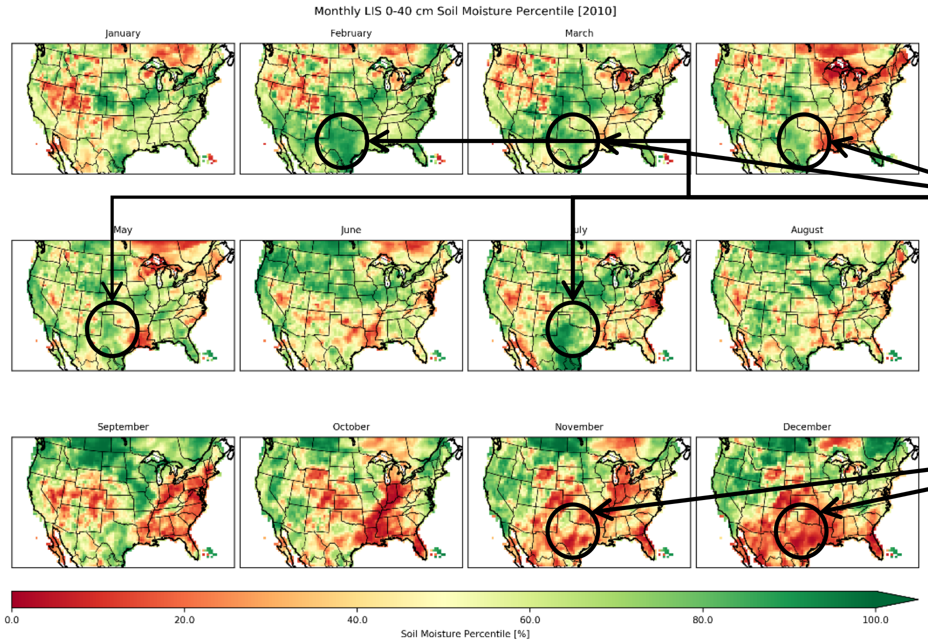

High antecedent (2010) soil moisture during growing season

Low antecedent soil moisture during late Fall 2010 into early Spring 2011.