Exploring the Role of Antecedent Land Surface Conditions Associated with Wildfire Events in the Western United States

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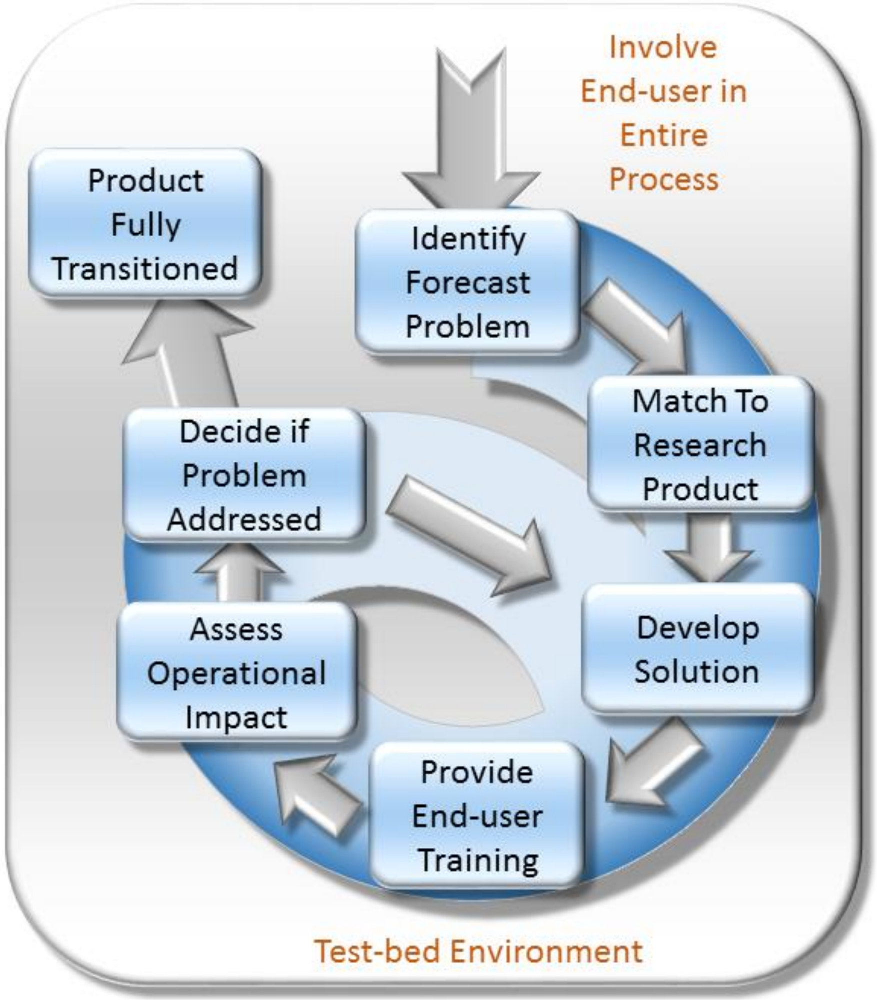
What is SPoRT?

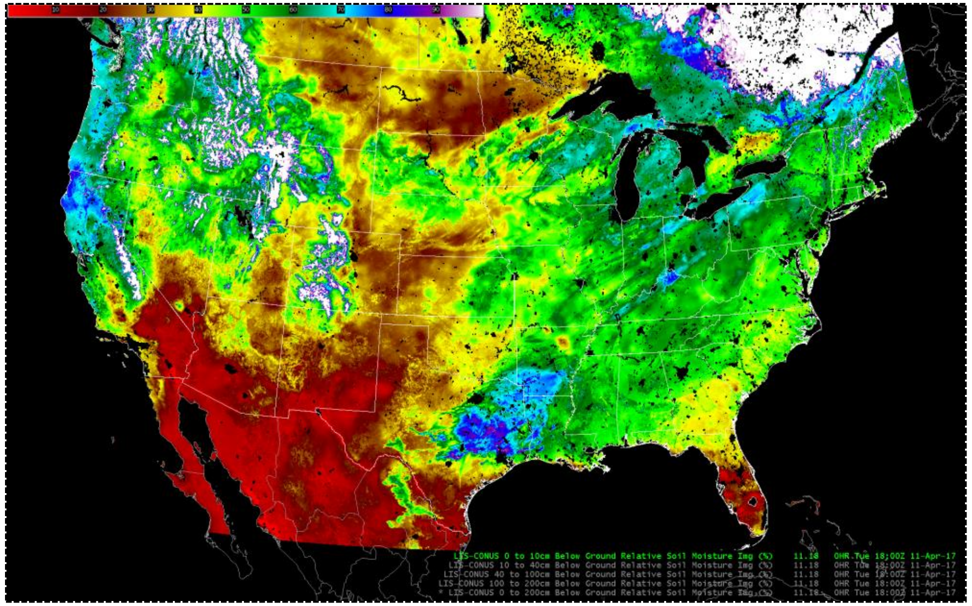
- Short-Term Prediction Research and Transition (SPoRT) Center
- Our main purpose is to transition experimental NASA datasets and products to operational end users
  - ✓ *Identify operational challenge*
  - ✓ *Determine how NASA data and products can aid in the decision making process.*

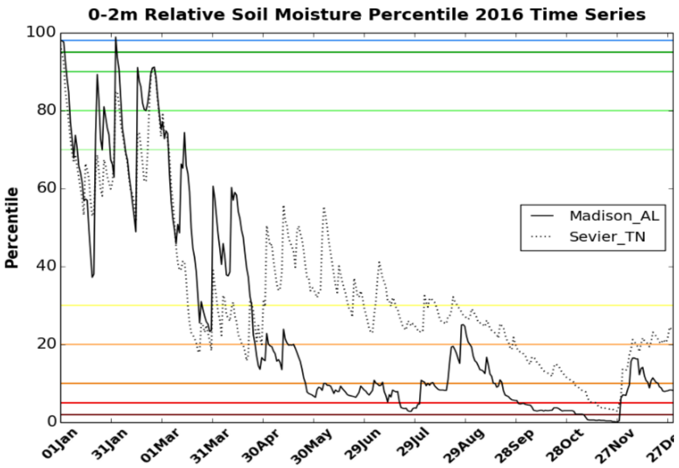
SPORT
Short-term Prediction Research and Transition Center



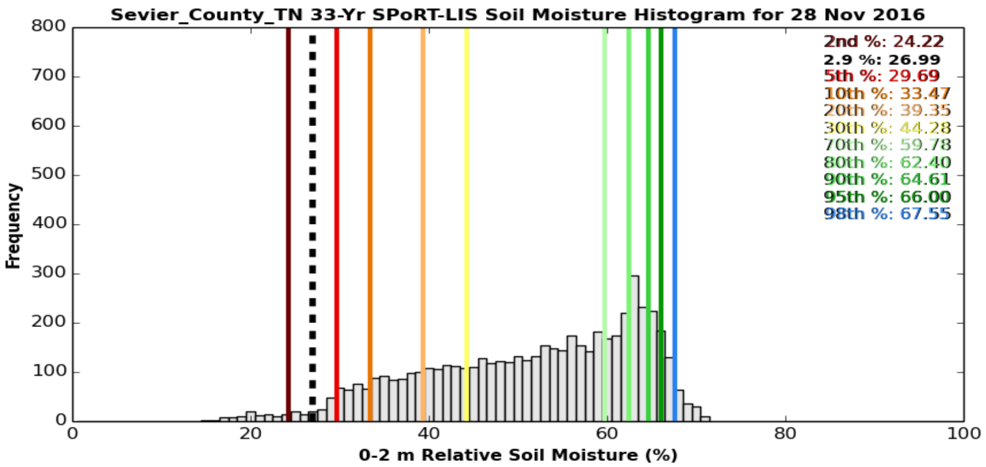
SPoRT-Land Information System (SPoRT-LIS)

- **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)



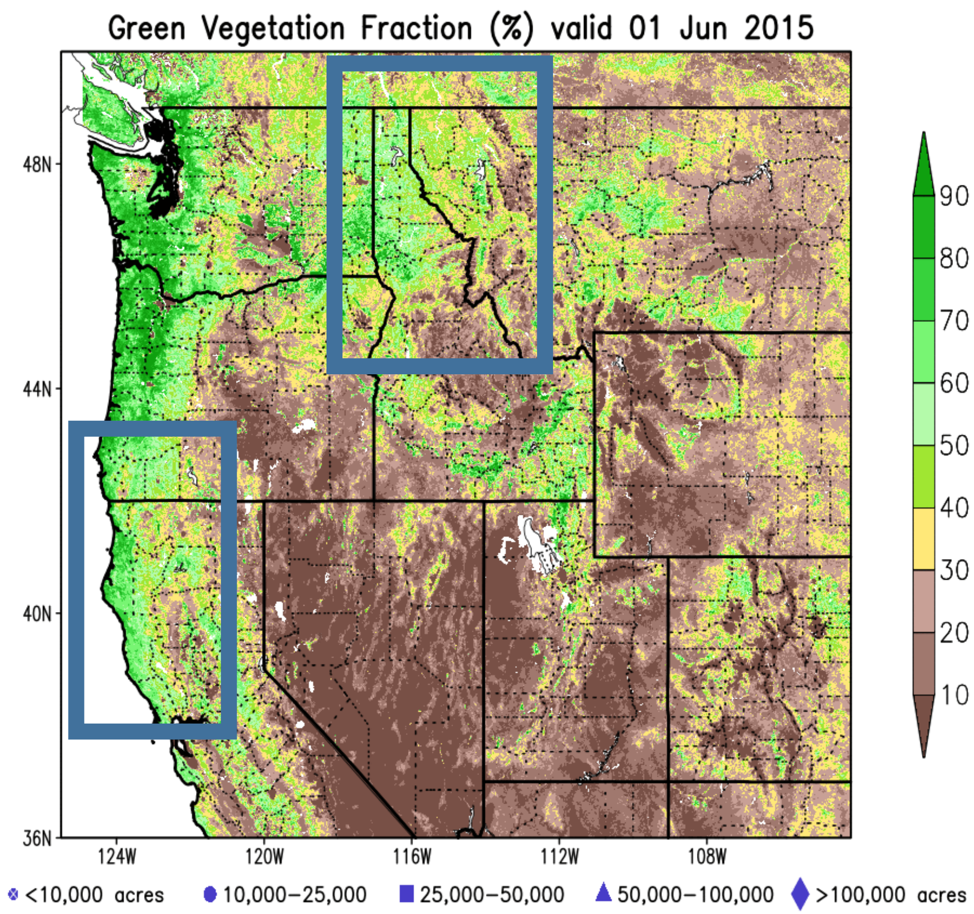
Recent Collaboration with the National Wildfire Coordinating Group (NWCG)

- 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.

Preliminary results: 1-km version of SPoRT-LIS from 2015 NW U.S. Wildfire Season

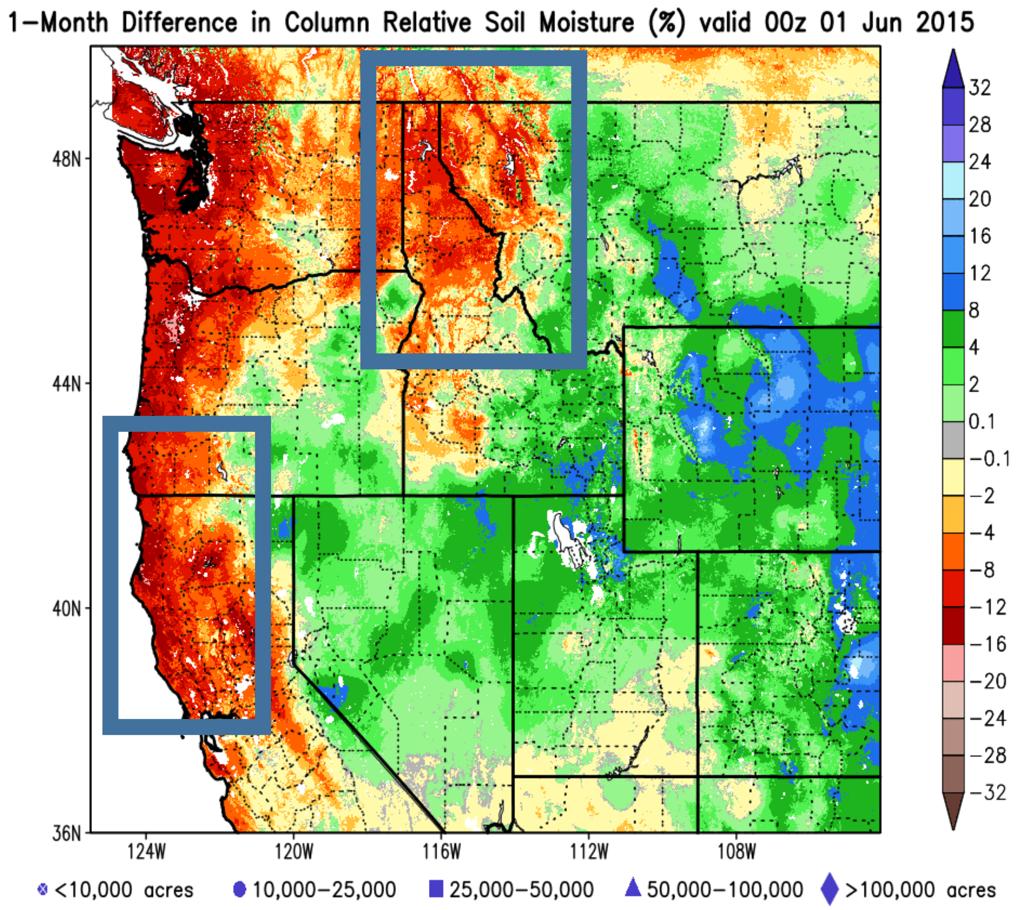
NWCG project: 2015 Pacific NW U.S. wildfire season

Green-up, Brown-down, and Fire Locations



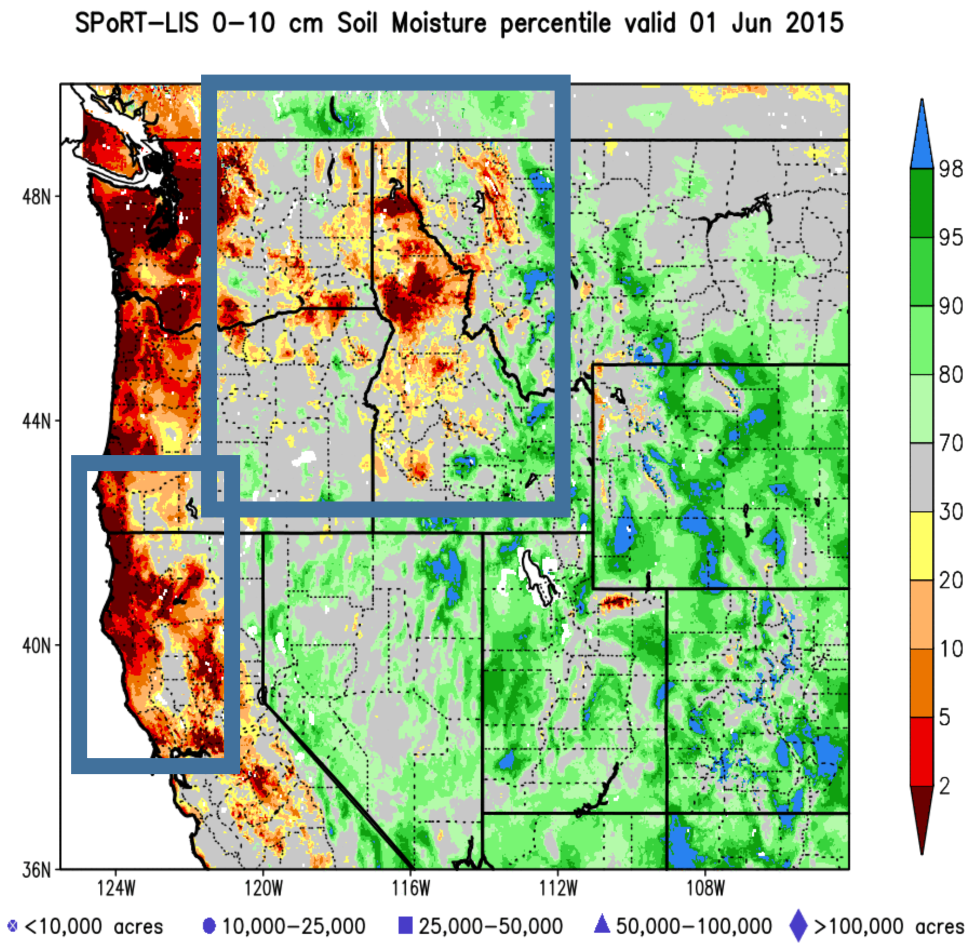
- 1 km Daily regional VIIRS GVF (non-operational)
- Initial green-up in highlighted areas (Jun)
- Decrease in Green Vegetation Fraction (GVF) during Jul, prior to cluster of fire initiation points in August (esp. northern Idaho and NW California)

Total-Column (2-m deep) Soil Moisture



- 1 km experimental LIS run
- Steady monthly decline in deep-column soil moisture leading up to fire events
- Maximum drying corresponds well with greatest concentration in fire locations
- Also prevalent in 1-year change in deep-column soil moisture (not shown)

0-10 cm Soil Moisture Percentiles



- 3-km real-time SPoRT-LIS
- Grid-point based assessment of how moist/dry the shallow soils are relative to 1981-2013 LIS climatology
- Minimum percentiles (< 5%) correspond well with greatest concentration in fire locations in ID, WA, OR, and N. CA
- Future product could include years as analogs for past fires based on current soil conditions.

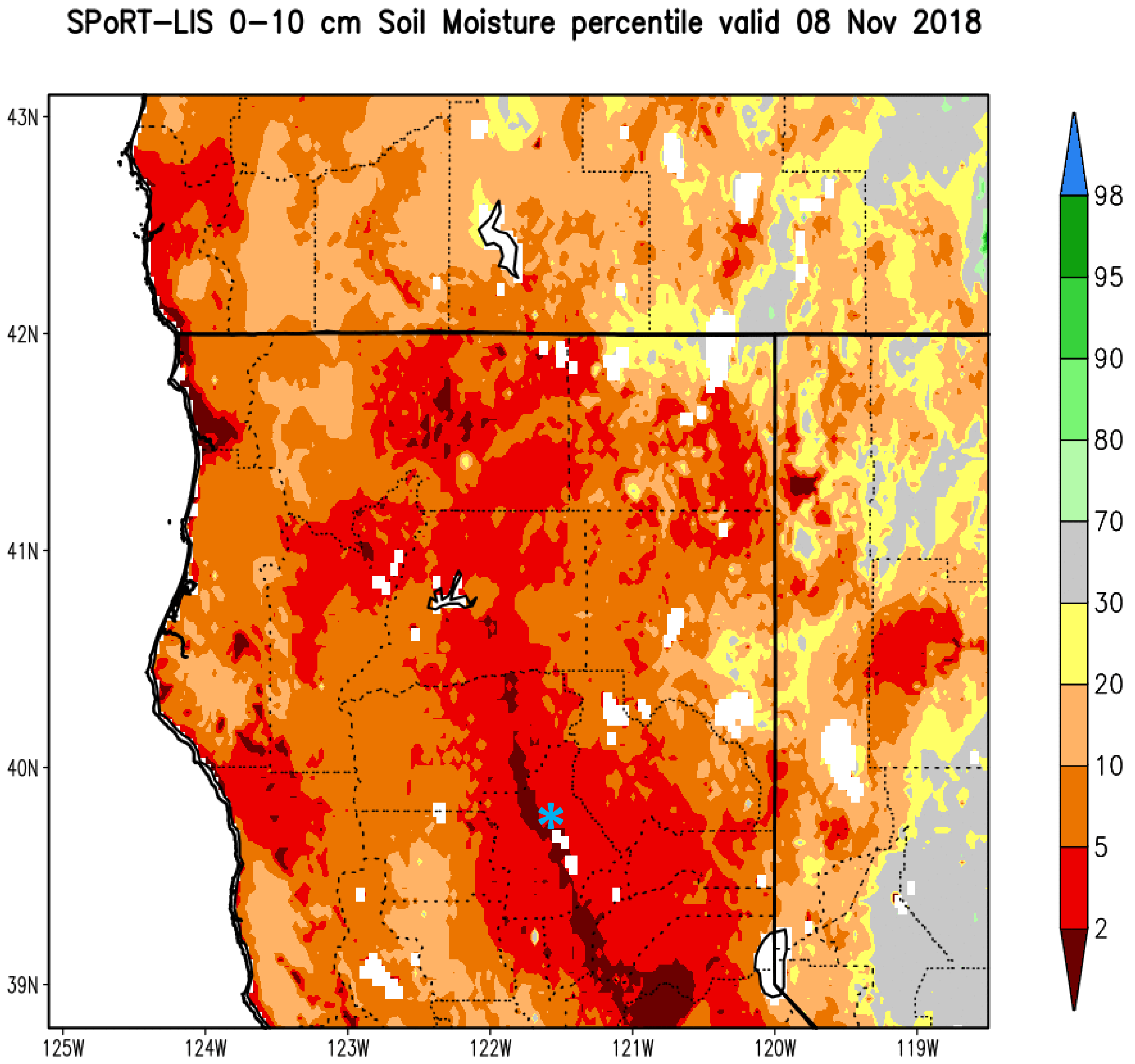
SPoRT-LIS soil moisture analysis associated with deadly Camp, CA wildfire

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

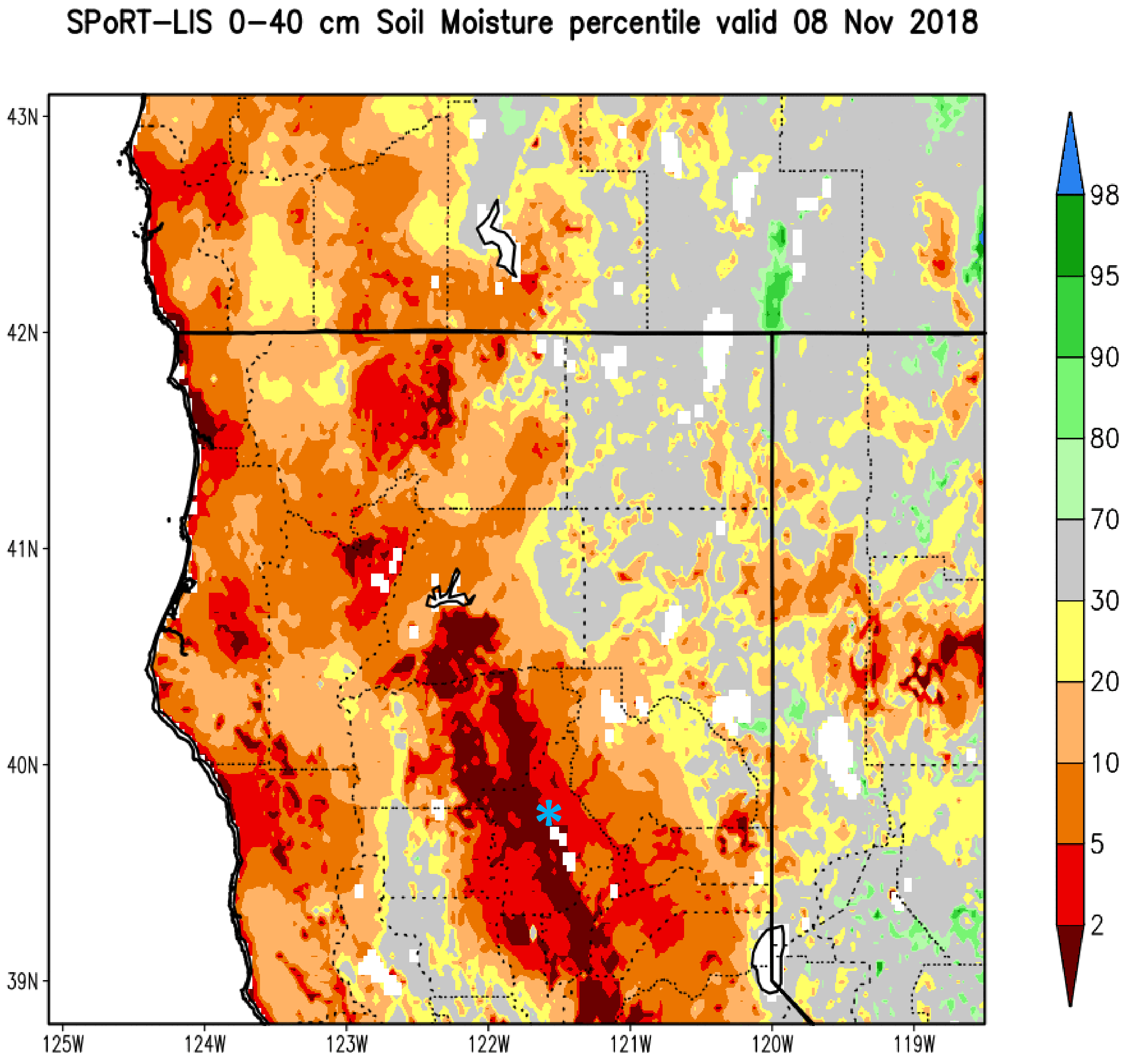
Top 10 cm soil moisture percentile valid on 8 Nov 2018

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

(Location of Paradise, CA given by blue asterisk)



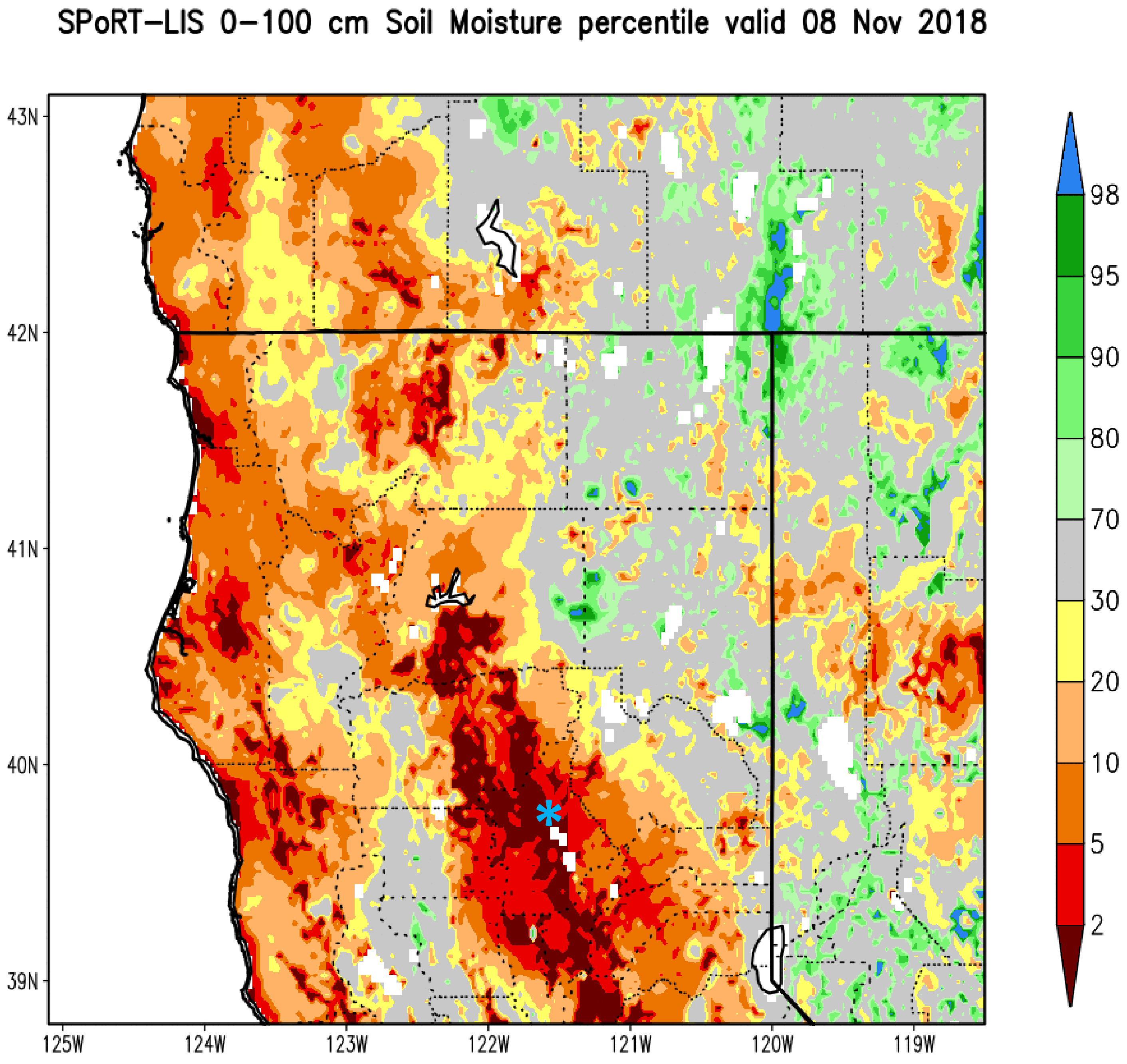
Top 40 cm soil moisture percentile valid on 8 Nov 2018



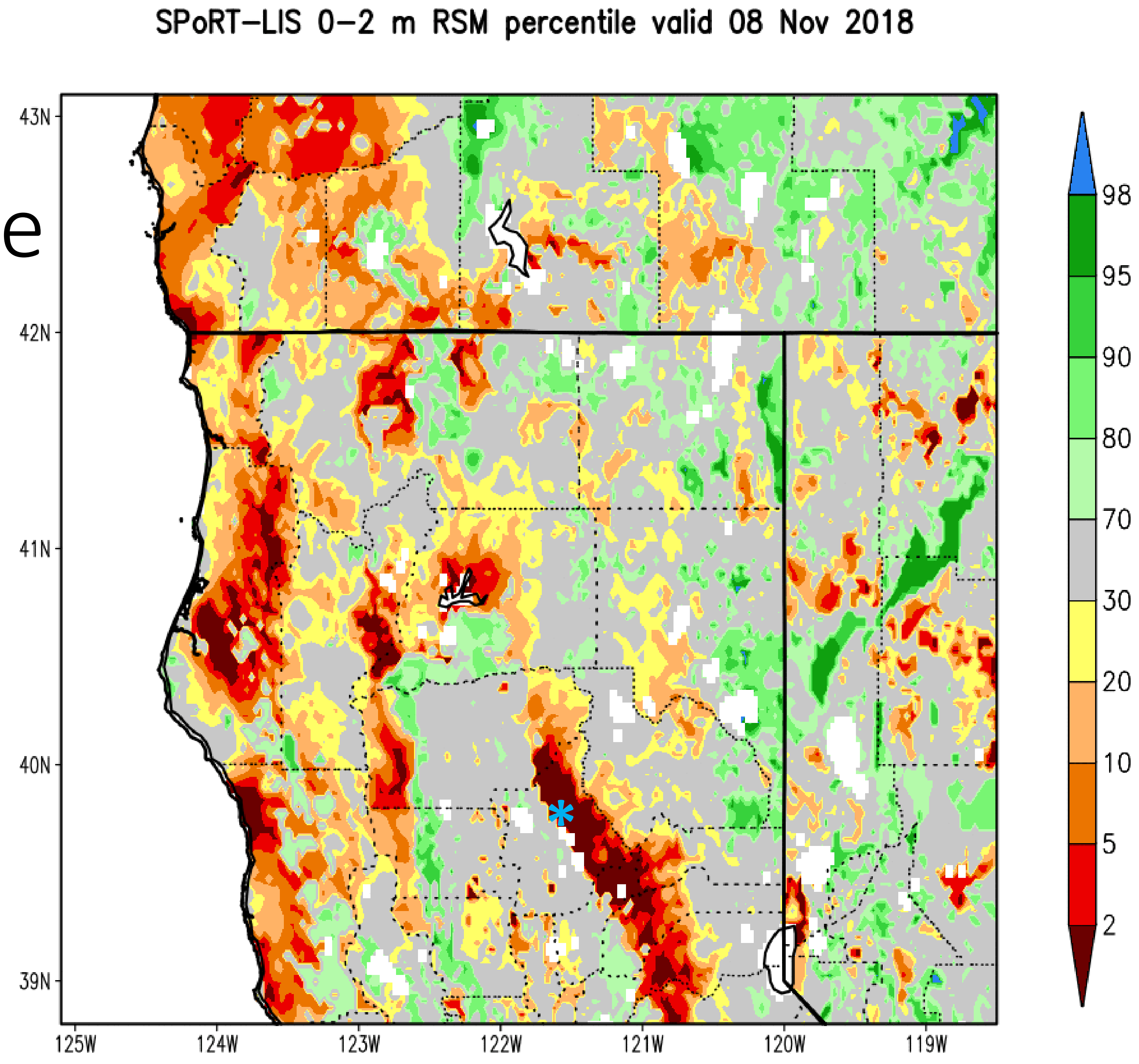
**Lowest percentiles a bit more concentrated on the eastern side of the valley to the Sierra foothills

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



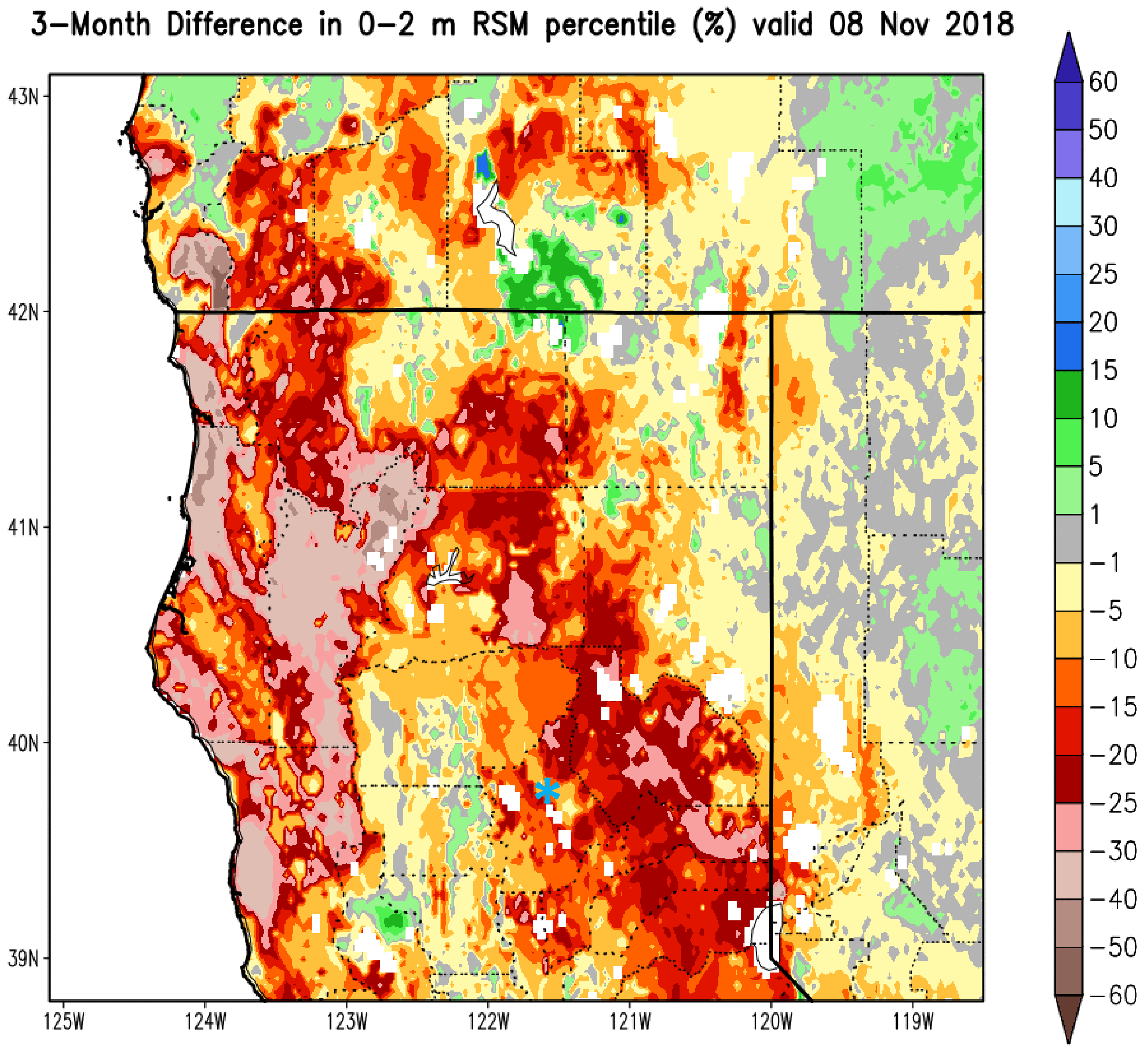
**Lowest percentiles concentrated along the Sierra foothills, and along NW CA/OR coastal range

NOTE: *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

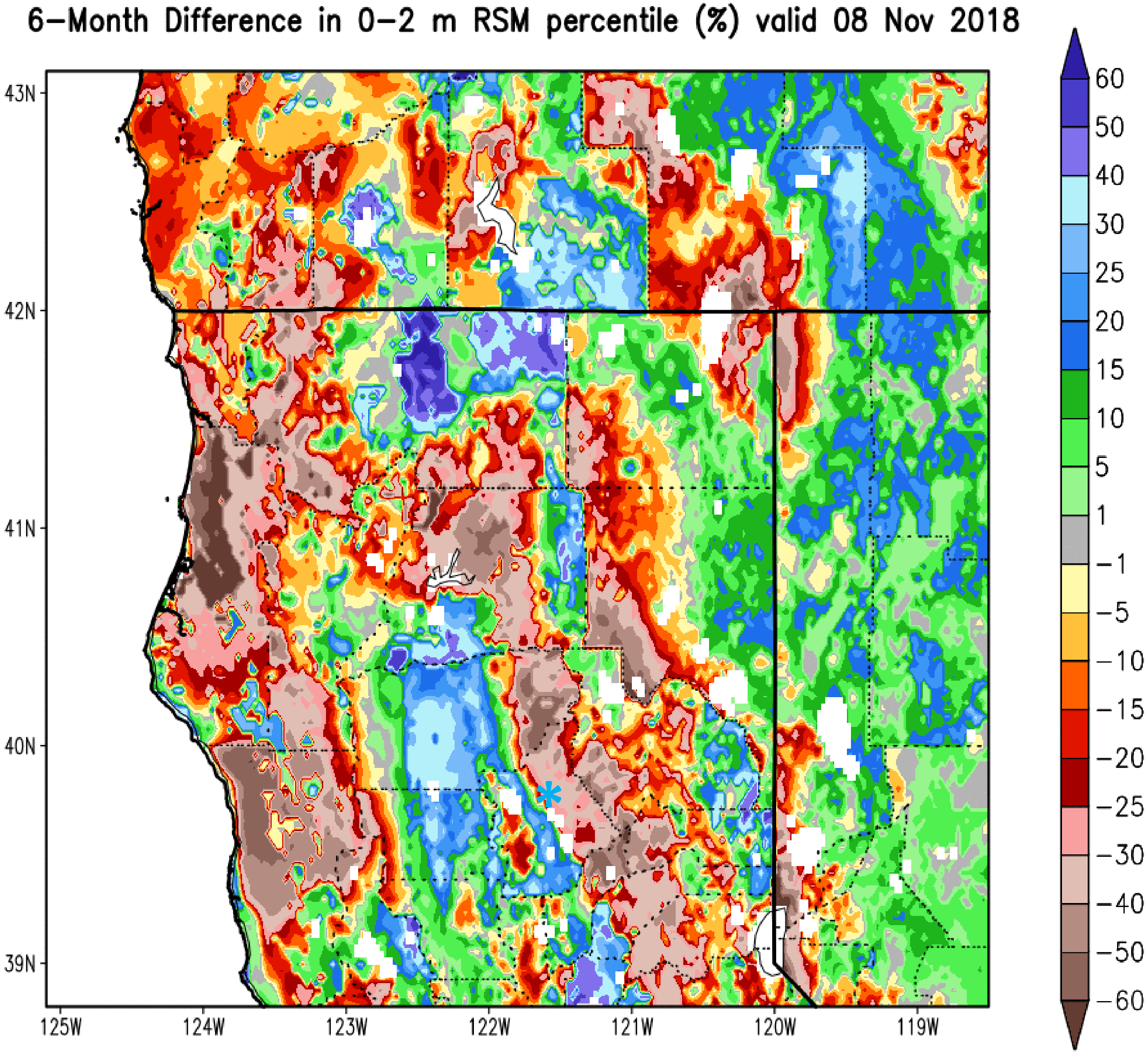
Percentile differences ranging from 7 days to 1 year

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



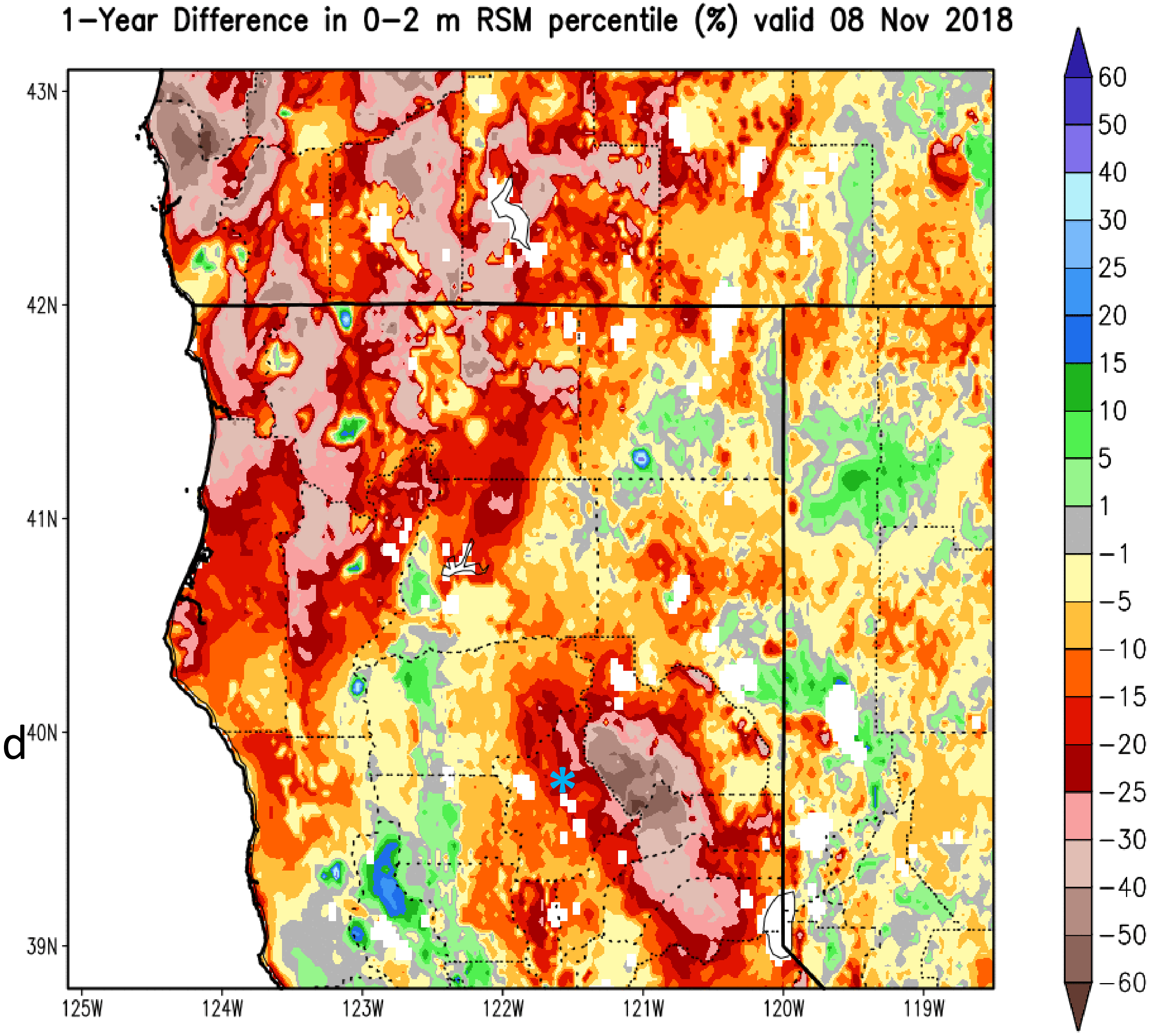
**Soil moisture percentile degradation most concentrated across NW coast/mountains and Sierras

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

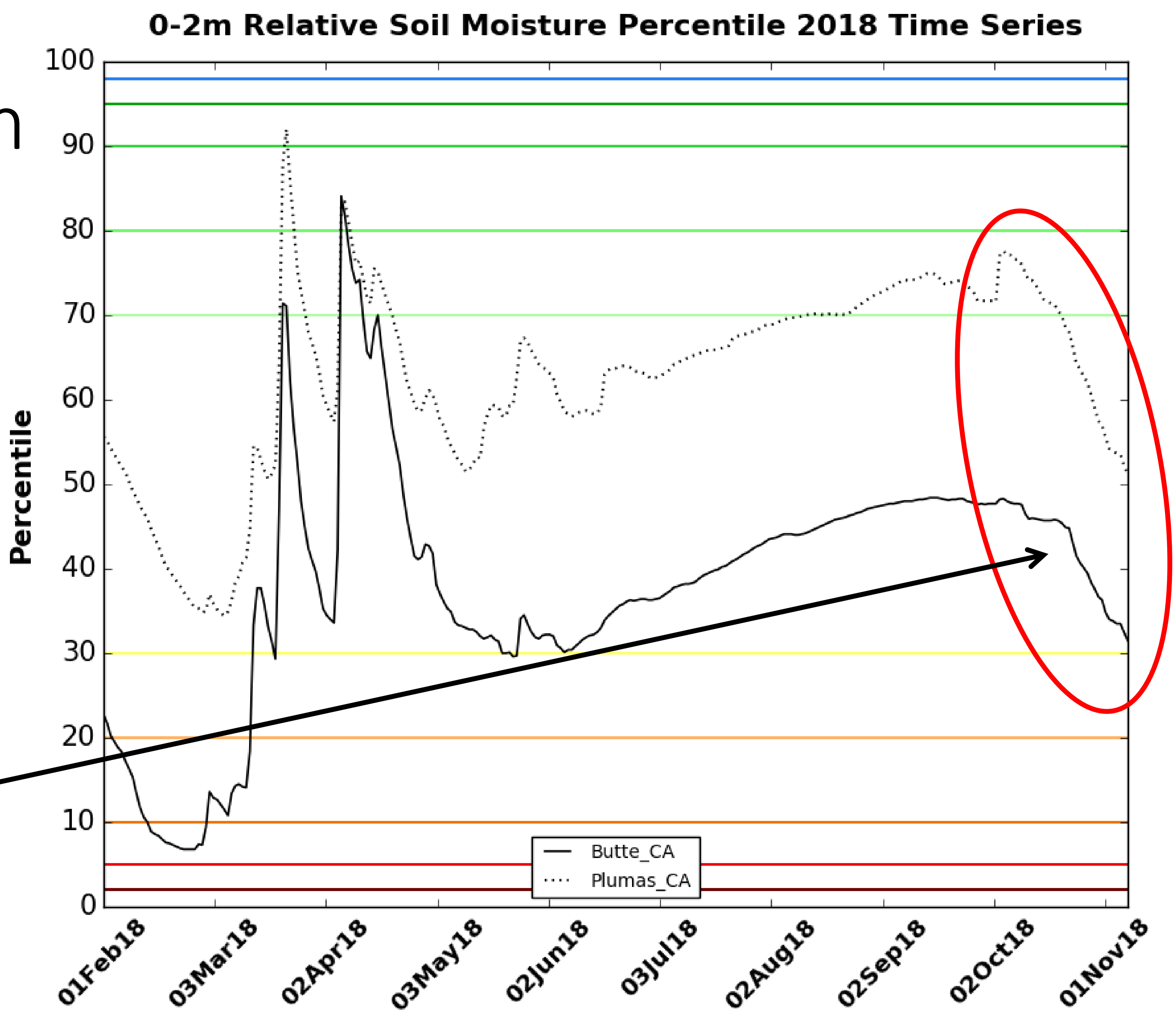
1-year change in 0-2 meter soil moisture percentile ending 8 Nov 2018



**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

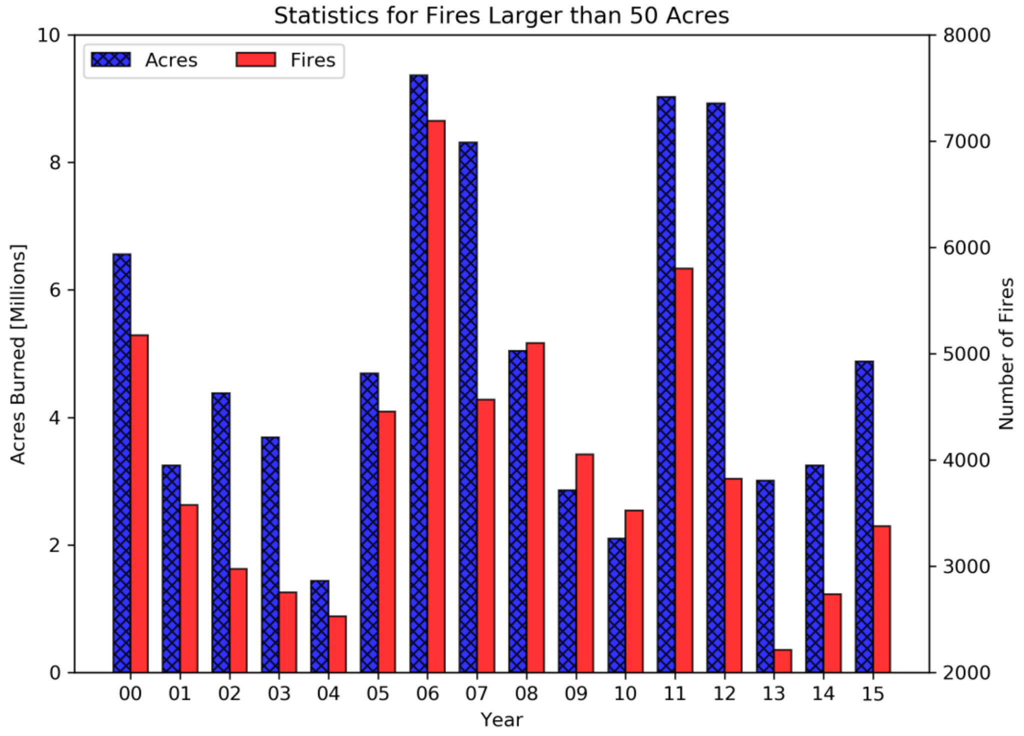
Notice rapid decline leading up to fire event



Next Steps: Machine Learning Applications

(*P186 White et al.; 18th Conf. Artificial / Comp. Intellig.; 4-6pm Mon*)

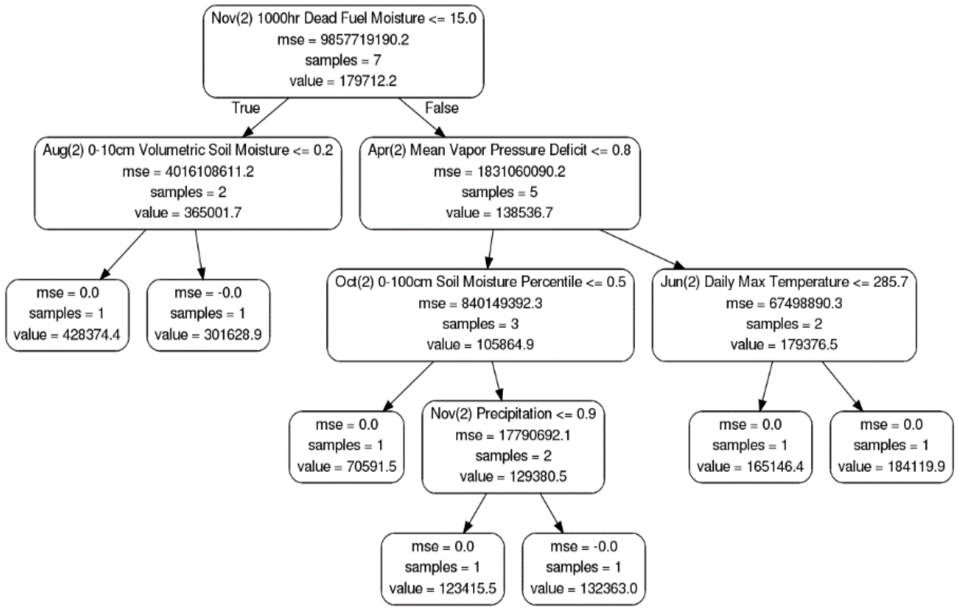
- With increasing fire-suppression costs, predictive estimates of future fire-season severity could benefit management officials.
- Fire severity is dependent on both the current and antecedent atmospheric and land surface conditions.
  - <u>Current</u>: temperature, dead fuel moisture, soil moisture, wind speed, etc.
  - <u>Antecedent</u>: seasonal precipitation, wet season fuel growth, soil moisture, etc.
- Due to the numerous amounts of available data related to fire potential, the use of a <u>random forest machine learning</u> algorithm to develop a fire season severity predictive model is being explored.



Yearly number of fires and acres burned across the CONUS domain; Chart indicates high year-to-year variability.

Methodology: Random Forest Regression

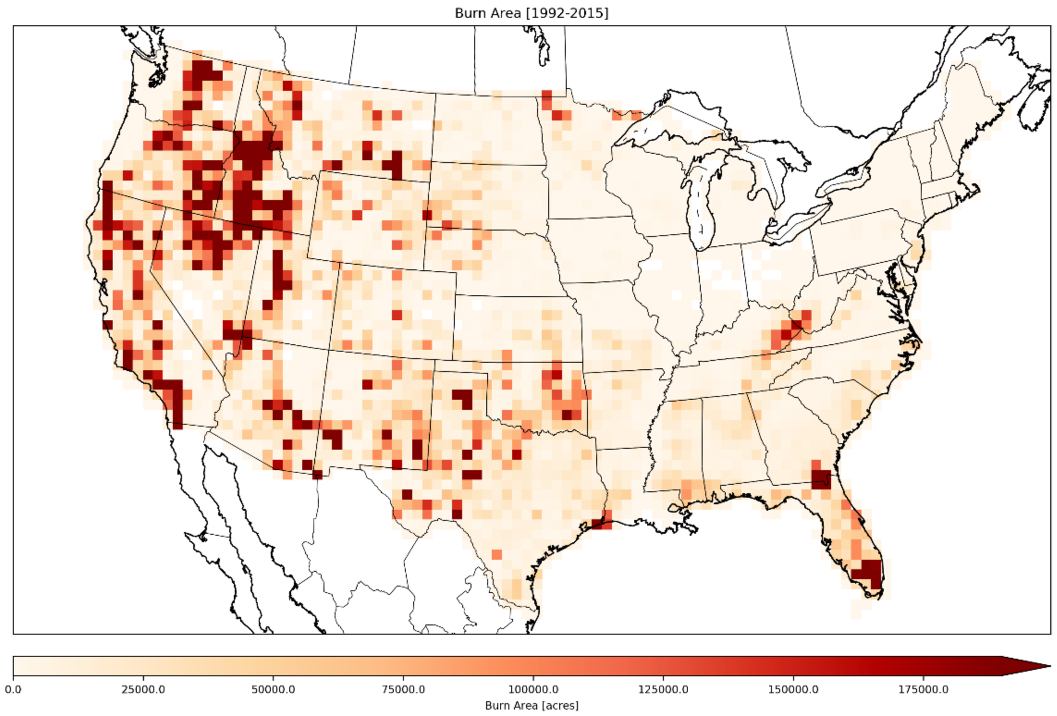
- <u>Random forest (RF)</u>: supervised ensemble machine learning algorithm that is composed of N number of decision trees.
  - ✓ Randomness between trees is introduced by taking bootstrap samples and using a random feature selection for node splitting within each tree (Breiman 2001).
  - ✓ In regression, 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

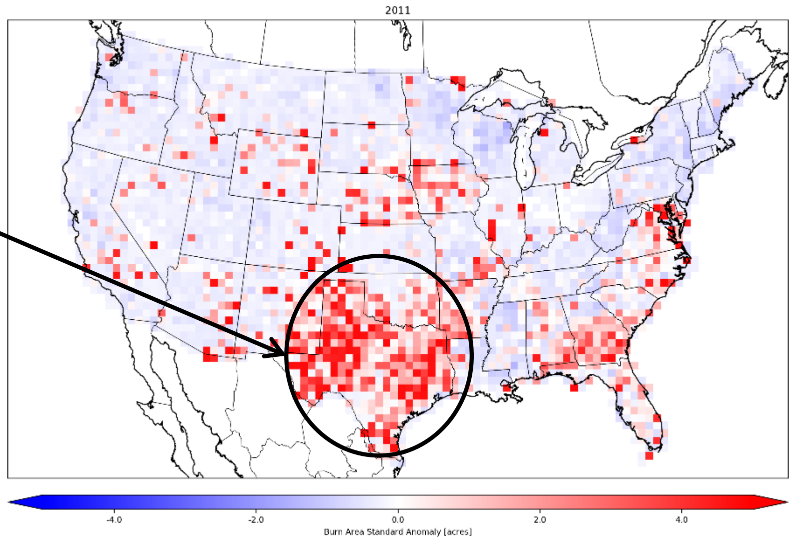
- Wildfire burn area database (1992 – 2015; right) was gridded to 50 km based on fire start location.
  - ✓ High spatial variability in the total number of acres burned.
  - ✓ On yearly time scales, the variability is even greater.
  - ✓ Due to the high variability, predicting anomalous fire seasons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

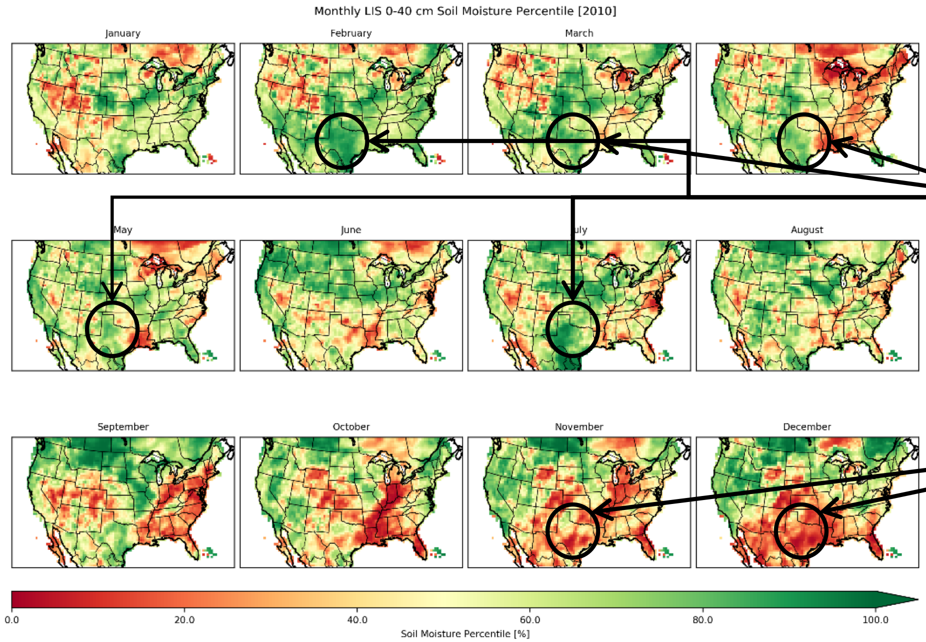


Antecedent Relationships

- 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.

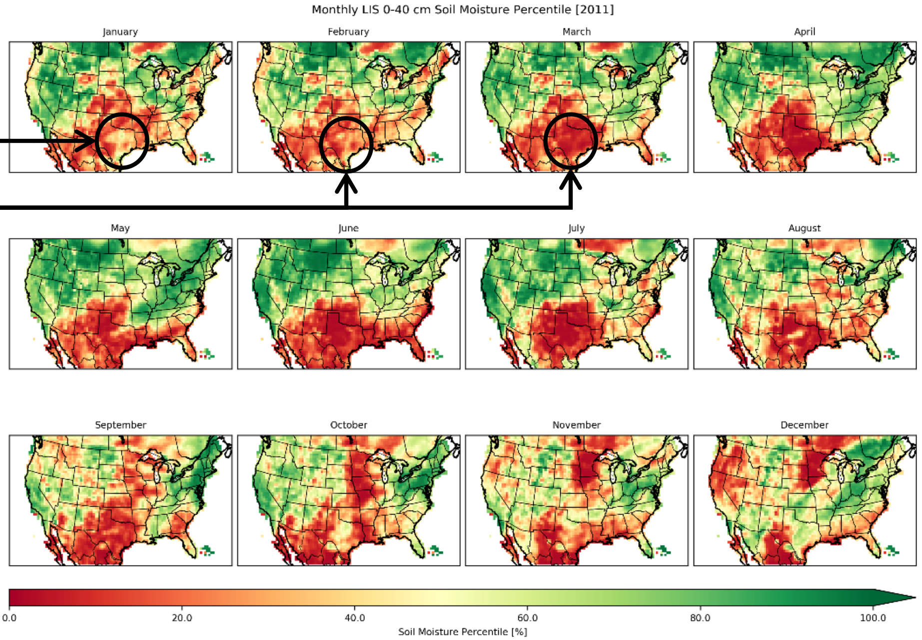


- Drying occurred from late fall 2010 and continued through 2011
- High antecedent soil moisture during growing season can lead to a build-up of available fuels.
- Low soil moisture leading up to fire season continually dries the available fuel.



High antecedent (2010) soil moisture during growing season

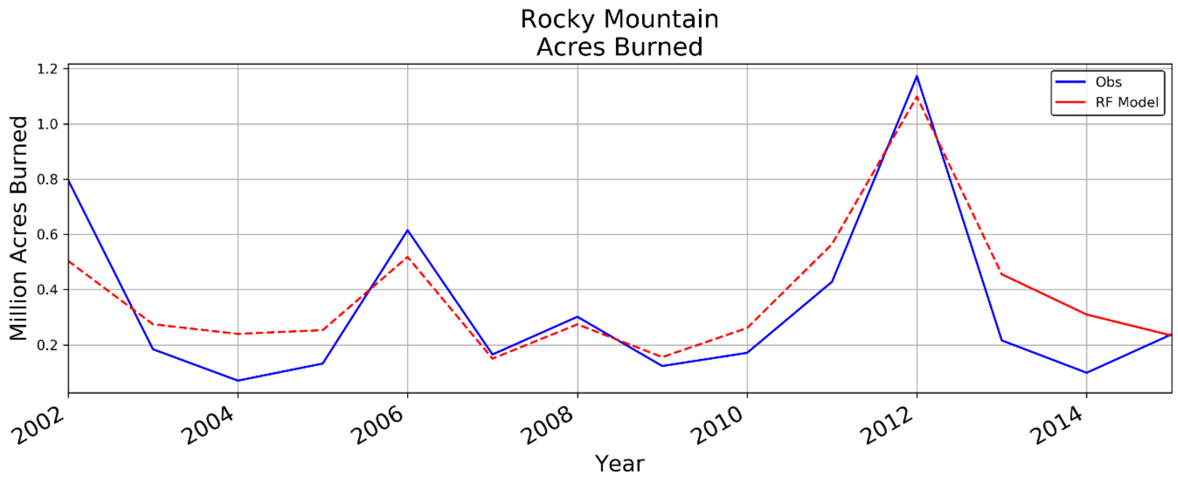
Low antecedent soil moisture during late Fall 2010 into early Spring 2011.



Random Forest (RF) Model Results

- RF forest model
  - ✓Trained on years 2002 – 2012
  - ✓Tested on years 2013 – 2015

- Model is able to capture the general trends in the data, based on antecedent atmospheric and land surface data
  - ✓Unable to account for the human ignition element which adds a level of uncertainty



Yearly observed (blue) and RF-predicted (red) acres burned for the Rocky Mountain GACC region. Red dashed line is the prediction on the training data. The solid red line is the prediction on the unseen test data.

Summary and Future Efforts

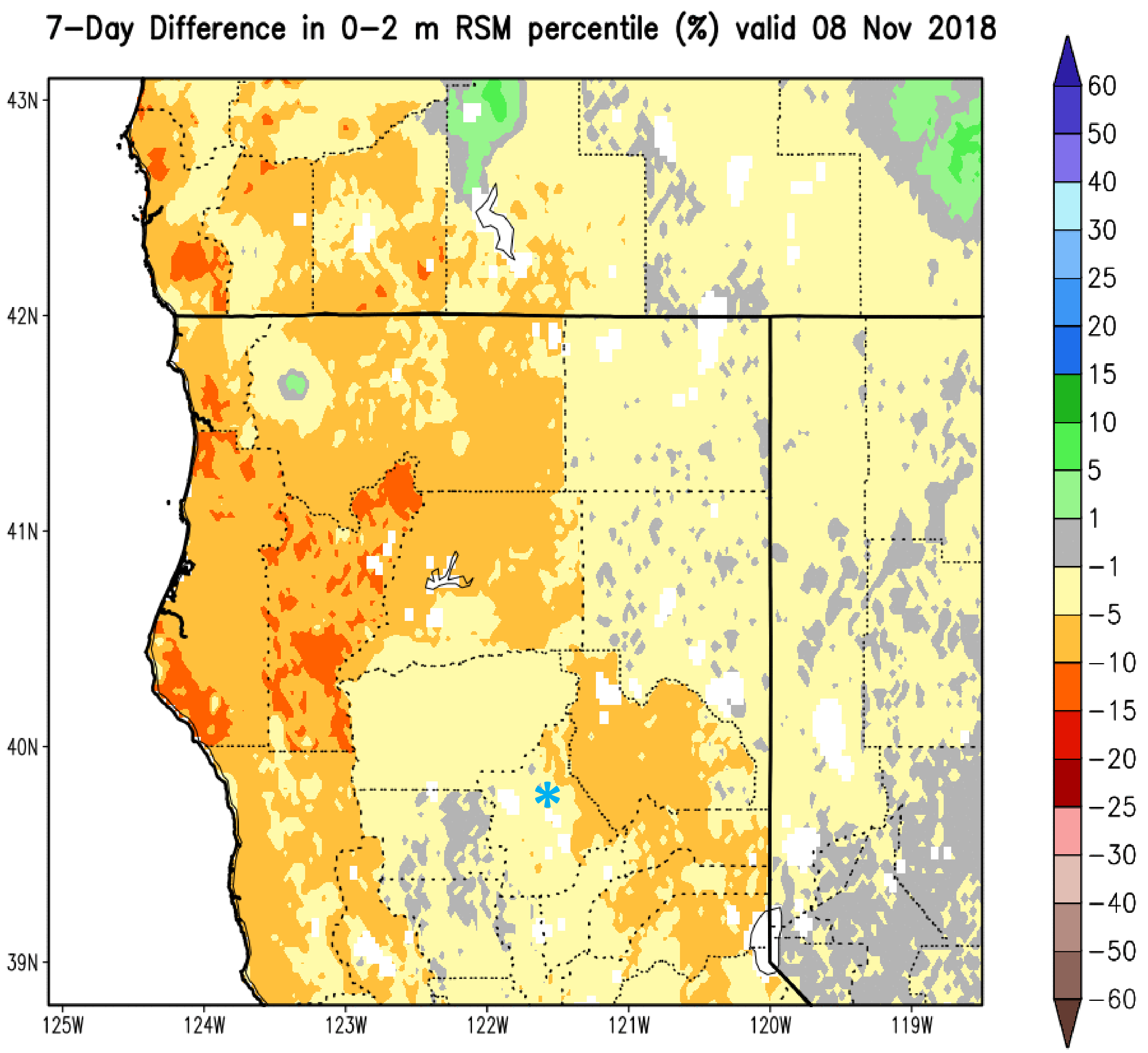
- Land surface evolution has connection to wildfire events
- Continue developing relationships between land-surface variables and wildfire seasonal events
- Refine machine-learning models and techniques to best predict wildfire seasonal behavior
- Characterization of wet/dry fuels in western U.S. (follow-on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

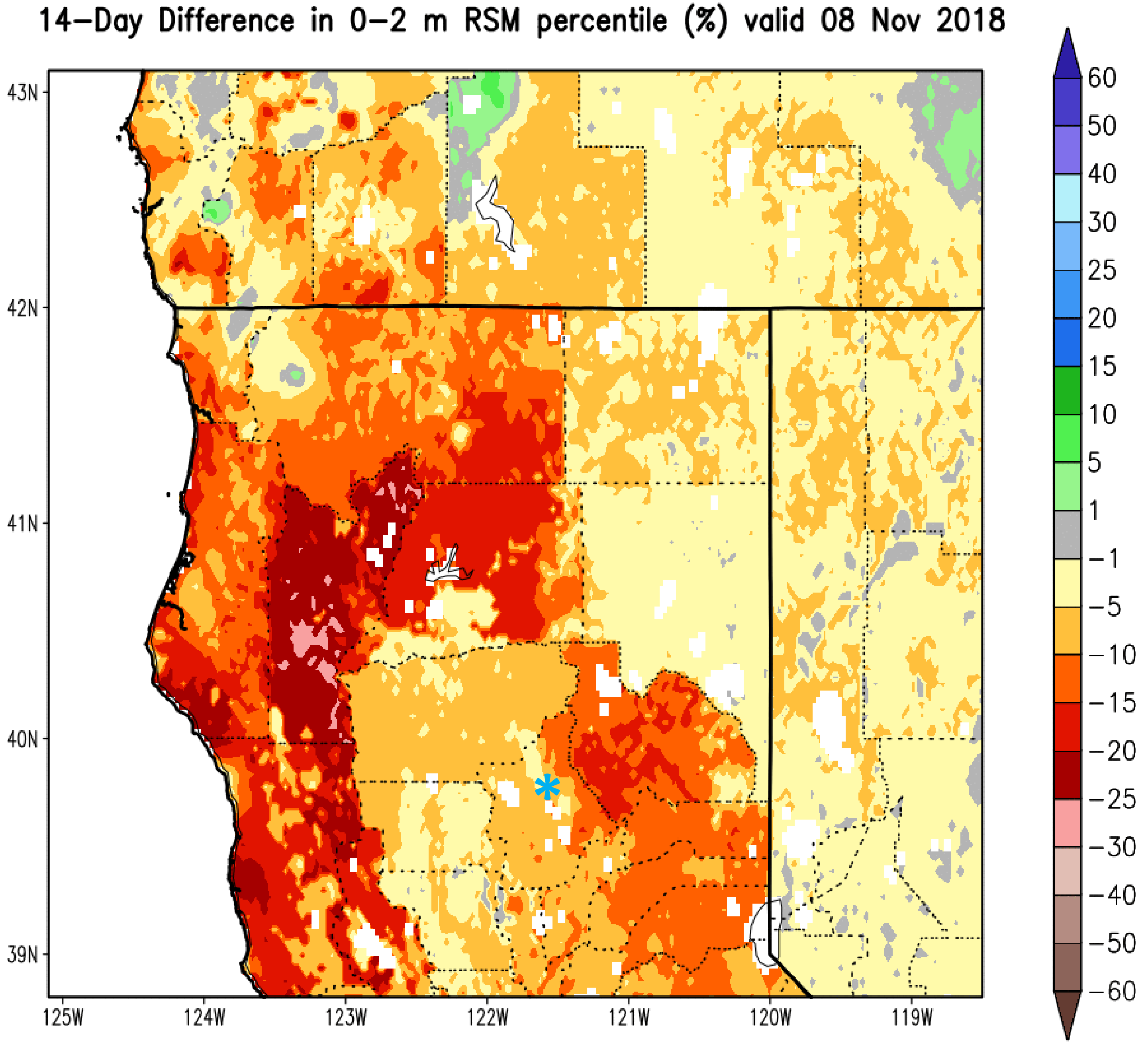
Backup Slides

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



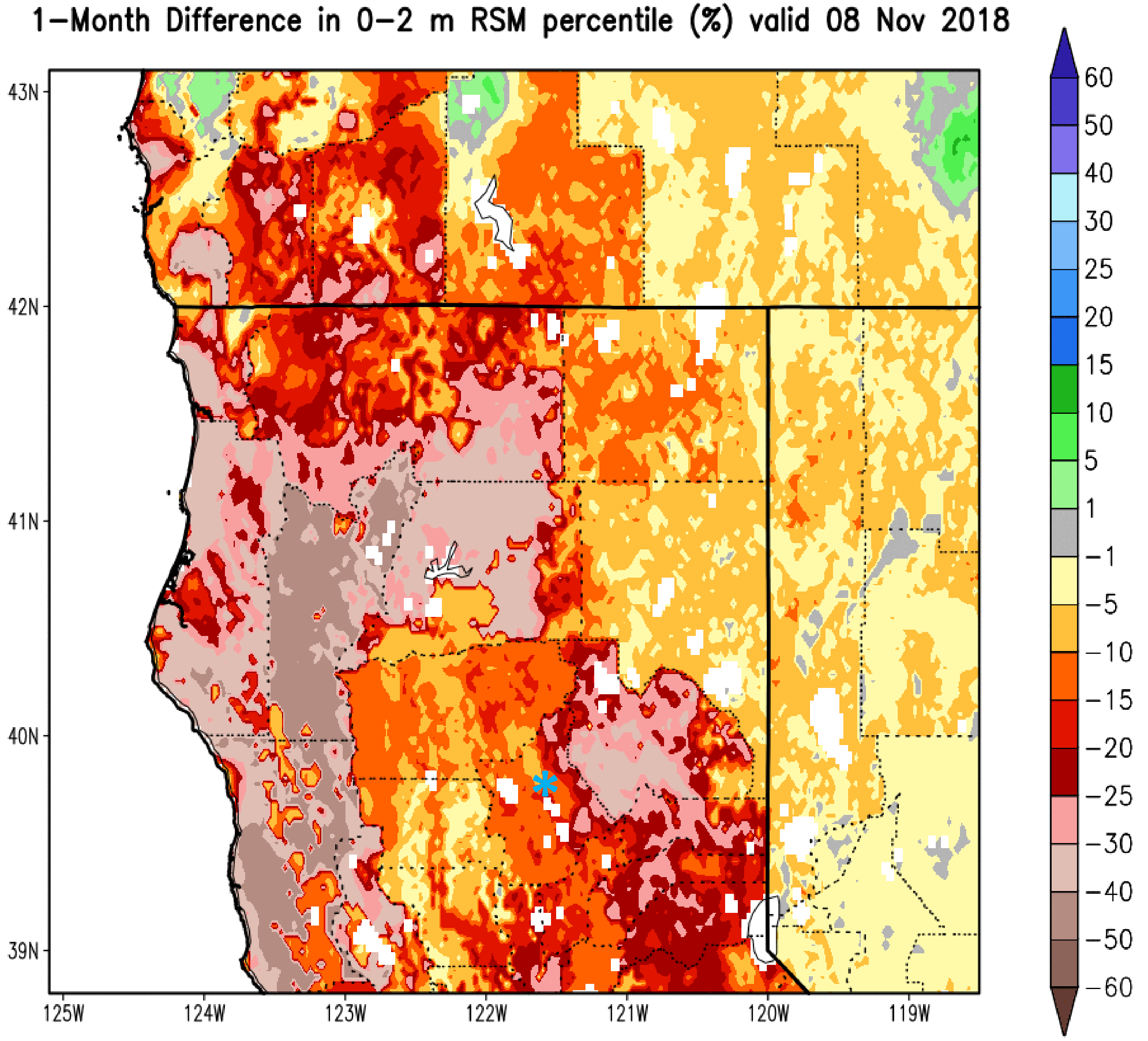
**Fairly uniform degradation in soil moisture percentile across NW California

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

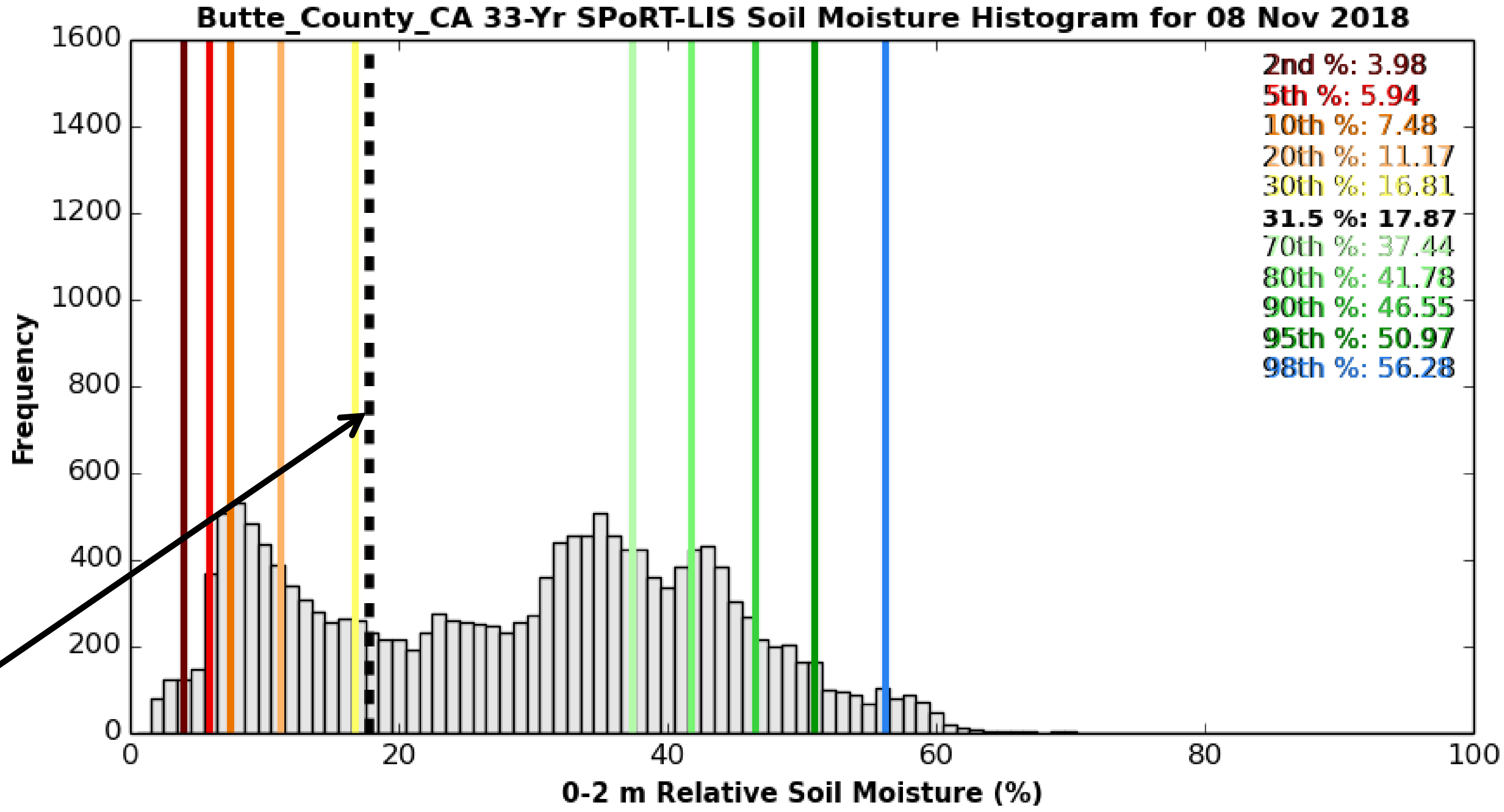
1-mon change in 0-2 meter soil moisture percentile ending 8 Nov 2018



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

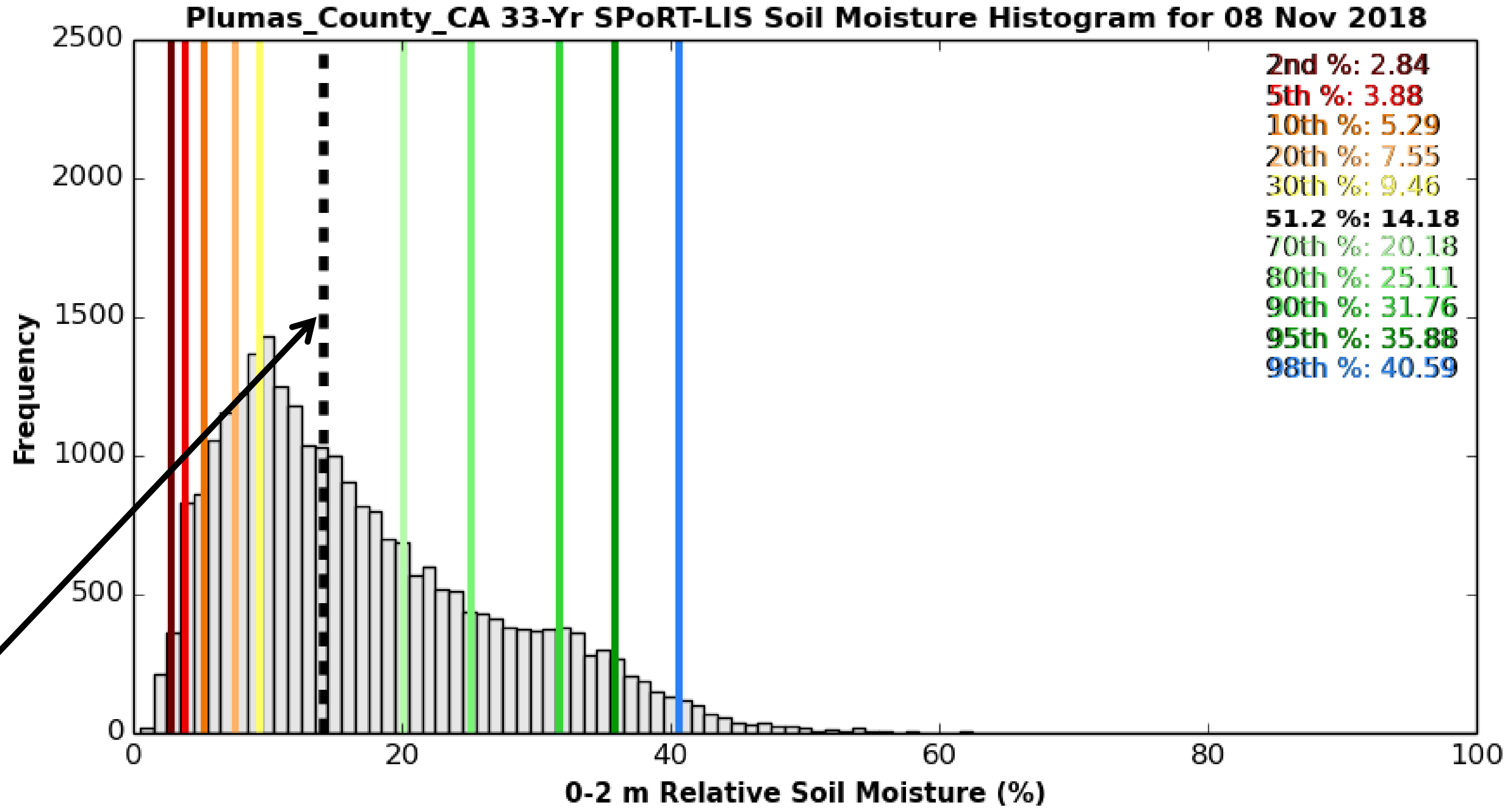
1981-2013 Histogram of 0-2 meter total column soil moisture: Butte County on 8 Nov 2018

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)

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