**NASA DEVELOP National Program**



NASA Langley Research Center

*Spring 2016*

Texas Water Resources II

Using NASA Earth Observations to Assess Soil Moisture in Texas for Wildfire Mitigation

 **Technical Report**

Rough Draft – Feb 9, 2016

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# I. Abstract

[Placeholder - do not put anything here until the final draft submission. The abstract in the project summary is where the working draft of the abstract should “live”]

**Keywords**

**SMAP, SCAN, TAMU, Soil Moisture, Drought Severity Index (DSI), Texas**

# II. Introduction

In 2011, Texas experienced a record-breaking drought, resulting in $5.2 billion lost in agricultural resources, damaged roads and infrastructure (Combs 2012). As a result of the drought, wildfire severity and frequency also increased (Combs 2012). Lack of precipitation resulted in plentiful vegetative fuel sources for intense and rapid spread of wildfires. From November 15, 2010 through September 29, 2011, 23, 835 fires burned more than 3.8 million acres and destroyed 2,763 homes (Combs 2012). Eighty percent of fires occurred within two miles of a community, thus threatening life, property, and infrastructure (Texas A&M Wildfires 2015). Wildfires also result in soil degradation, soil erosion, loss of biodiversity, and agricultural losses(Texas A&M Wildfires 2015).

Because of the prevalence and intensity of recent droughts and fire seasons, the Texas Forest Service (TFS) now identifies areas in danger of ignition. They utilize weather patterns, drought severity indices, and assessment of available vegetative fuels to identify these threatened areas(Texas A&M Wildfires). Popular drought indices, like the Standard Precipitation Index and the Keetch-Byram Drought Index, estimate evapotranspiration, fuel potential, and soil moisture from precipitation and temperature data to quantify severity of drought across varied spatial and temporal scales (Ambrosia et al. 1998). The Forest Service then uses these data to justify budget requests, coordinate between agencies across jurisdictions, educate and communicate alerts to the public, and craft response and suppression plans.

This study focuses on the soil moisture component of wildfire prediction. Soil moisture is critical in predicting The Keetch-Byram Index assumes a 203 mm soil moisture storage capacity and that moisture is lost exponentially throughout a 24 hour period (Keetch & Byram 1968). The model thus estimates soil moisture depletion based on a daily water budget, previous drought conditions and daily precipitation and temperature (Ambrosia et al. 1998). The Index is widely used by Fire Control Managers because it estimates dead fuel available for combustion, as well as live fuel moisture, important indicators of fire susceptibility (P.E. Dennison et al. 2003) (Dimitrakopoulos and Bemmerzouk 2003).

The NASA DEVELOP Texas Water Resources team partnered with the Texas Forest Service to refine ways to accurately measure soil moisture content using satellite data from NASA’s recently launched Soil Moisture Active Passive (SMAP) mission. SMAP launched in January of 2015 and data became available late in 2015. Because of data availability, our study period includes 2015 and early 2016. An ability to incorporate more accurate soil moisture volume into existing drought indices will help the Texas Forest Service better monitor drought conditions and identify areas susceptible to wildfires. In doing so, this project addressed the Water Resources and Disasters National Application Areas. This project correlated NASA’s SMAP Satellite data with *in situ* data from the Soil Climate Analysis Network (SCAN) and Texas A&M University Soil Moisture Database to provide the Texas Forest Service with a normalized single correction soil moisture model for the state of Texas and assist their efforts to predict and prevent wildfires.

# III. Methodology

**Data Acquisition**

SMAP Data were downloaded from the NASA National Snow and Ice Data Center Distributed Active Archive Center (NSIDC DAAC) and were downloaded as GeoTIFFS from NASA’s REVERB Website. Data were downloaded both globally and specifically for the state of Texas, following the latitude and longitude used by Texas A&M Forest Service (N 36.50 S 25.837 E -93.508 W -106.645).

SCAN data from testing stations in Texas were downloaded from the National Resources Conservation Service as .csv files. The sensor is a dielectric constant measuring device, at a depth of 5.08cm (SCAN Brochure).

Oklahoma Mesonet and West Texas Mesonet are systems designed to measure various weather-related conditions across their respective states and compile the data for analysis. Datasets were downloaded from the Texas A&M Geoservices North American Soil Moisture Database in .txt format.

**Data Processing**:

Because of the availability of SMAP data, we chose to calculate the minimum soil moisture values over any given three day period. After mosaicking three dates of raster data together, we calculated the minimum value using the Raster Calculator tool. We then created a model using Model Builder to iterate this process for our entire dataset.

Mesonet data were copied from the .txt format into an excel worksheet. Latitude and longitude columns were added for the station locations. A pivot table was then used to average the soil moisture measurements per day of the year. Finally the worksheet was formatted as a table using site ID’s, site names, dates, average soil moisture for the 5 cm depth, latitude and longitude as the columns headers. This table was used to import point data into Arcmap.

Scan data was available by yearly segments, so the data was consolidated into a single excel worksheet. The soil moisture data was converted from a percentage to a decimal to match up with the Mesonet data. Latitude and longitude columns were added for the station locations. A pivot table was then used to average the soil moisture measurement per day of the year. Finally the worksheet was formatted as a table with the site ID’s site names, dates, average soil moisture for the 5 cm depth, latitude and longitude as the columns headers. This table was used to import point data into Arcmap.

A polygon grid was created using the pixel size of the SMAP raster data. The SCAN and Mesonet point data were then index to a specific square in the grid using the join function in ArcMap

**Data Analysis**:

The grid indexed SCAN and Mesonet data were used to validate the SMAP data by averaging the soil moisture data within a grid and comparing that average to the corresponding pixel soil moisture reading from SMAP.

An optimized set of SCAN and Mesonet stations were then chosen by similar periods of record use in a geostatistical interpolation to create a visually appealing relative measurement for any given day to compare SMAP data to.

# IV. Results & Discussion

# V. Conclusions

# VI. Acknowledgments

# VII. References

# VIII. Content Innovation

# IV. Appendices

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