**NASA DEVELOP National Program**



NASA Langley Research Center

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Texas Water Resources

Utilizing NASA Earth Observations to Monitor Drought Severity in Texas for Wildfire Mitigation Support

 **Technical Report**

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I. ABSTRACT

[Placeholder – working draft in project summary]

**Keywords:**

Texas, Drought, Wildfires, Drought Severity Index, Remote Sensing, MODIS

# II. INTRODUCTION

## ***Background Information***

The most recent multi-year drought in Texas began in October 2010, with dry conditions throughout the fall and winter seasons (Source). However, March 2011 delivered the greatest blow to the state with widespread extreme drought conditions ailing the majority of its counties (Nielson-Gammon, 2012). Receiving less than 16 inches in average annual precipitation, aquifers and lakes plunged to their lowest levels since the historic drought of the 1950s. The U.S. Drought Monitor, utilizing a six-month Standard Precipitation Index (SPI), placed 92.4% of the state’s counties in severe drought conditions or worse.

By early November of 2011, 1,000 of Texas’ 4,700 public water systems had imposed voluntary or mandatory water restrictions, twenty-three of which believed they were within 180 days of running out of water completely (source). Texas AgriLife Extension Service estimated the agricultural losses for the year at 5.2 billion dollars (Combs, 2012). Moreover, the Texas Forest Service (TFS) reported 23,835 wildfires from November 2010 through September 2011, scorching 3.8 million acres (source). An extremely wet 2010 growing season contributed to these extreme wildfires by allowing vegetation to prosper. According to the Texas Water Journal, these multi-year droughts are infrequent in nature but are a natural occurrence in the southwest region. The study of tree rings, for example, make it possible to measure drought conditions as far back as 1750. Using the Palmer Drought Severity Index (PDSI), the Texas Water Resources Institute (TWRI) created a chart that displays these occurrences by tracking the overall trend. However, the Texas Water Development Board (TWDB) emphasized that if nothing is done to address and prepare for these “mega-droughts”, the state groundwater supplies will fall 30% costing Texas businesses and workers nearly 116 billion dollars and 1.1 million in job losses from 2010 to 2060 (source).

## ***Project Objective***

The objective of the project at DEVELOP Langley is to assist the TFS in preparing for future wildfires by expanding upon a drought severity index (DSI) created during the summer 2013 Great Plains Agriculture project. This will allow the TFS to identify what geographical locations within the state of Texas are the most prone to wildfire disasters and where water resources may be concentrated in order to fight them efficiently. The DSI will also be compared to other drought severity indices, such as the PDSI currently used by the TWRI.

## ***Study Area***

The area being studied for this project is the state of Texas, which encompasses 268,820 square miles in total sum. The ecological regions within this territory are vast, and their unique environments should be given equal consideration when planning for disasters at the scale assigned to this project (Fig. 1). From the Chihuahuan Deserts in the west, to the Gulf Coastal Plains and Cross Timbers in the east, the factors contributing to drought will affect each of these regions differently.

Figure 1

Source: Environmental Protection Agency – Western Ecology Division

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## ***Study Period***

Moderate Resolution Imaging Spectroradiometer (MODIS) data were collected for the years 2010-2011 and 2014-2015, while the Multi-Sensor Precipitation Estimate (MPE) provided the daily precipitation data for the same time period. This period was selected because of the extreme drought conditions that began in the state in 2010, and brought about widespread wildfires to various regions the following year as the vegetation became stressed and the fuel load increased dramatically. The latter years were included in this study as they offer the most current timeline available for research.

## ***National Application(s) Addressed***

This project addressed the NASA Applied Sciences national application area of water resources, due to the scarcity of water available to the state during multi-year drought conditions and the necessity of the resource when suppressing wildfires. This project supports the goal of the Water Resources Program, which entails the application of NASA satellite data to improve the decision making tools of partners who manage water resources. With more information regarding the spatial coverage of drought conditions, the TFS can better allocate this resource to mitigate the spread of wildfires when they occur. This project expands the range of end users to those who may not be familiar with or have access to remote sensing technology but will have the ability to disseminate information to city and state government officials, non-profit organizations, and other organizations with a vested interest in water resource.

## ***Project Partners***

The project partners are Curt Stripling and Tom Spencer of the Texas A&M Forest Service. Curt is the Geospatial Systems Coordinator, while Tom is the Department Head of Predictive Services. A 17-year veteran of the TFS, Curt received the Vice Chancellor’s Award in Excellence for Public Service in Forestry for constructing a wildfire risk assessment in an easy format designed to increase public awareness into the nature of wildfires and the dangers posed by them across the state of Texas (**Texas Forest Service, 2015**). Lines of communication were reopened to Curt since DEVELOP’s last partnership with the TFS in 2011. Currently, the service uses products such as the Landscape Fire and Resource Management Planning Tools (LANDFIRE) and the National Predictive Services Unit which applies the Palmer Drought Severity Index as well as the Keetch-Byram Drought Index to classify drought severity. The TFS employs the LANDFIRE program to support fire planning, analysis, budgeting and evaluate fire planning alternatives. This project supplies Mr. Stripling with a DSI that incorporates soil moisture and vegetation data, two factors lacking in many drought severity indices [**Wang, 2000**], thus allowing the TFS to continue to monitor drought conditions across the state at greater and more reliable accuracy.

# III. METHODOLOGY

## ***Data Acquisition***

Multisensor Precipitation Estimator (MPE) data were collected from the National Oceanic and Atmospheric Administration (NOAA) National Weather Service (NWS) Advanced Hydrologic Prediction Service (AHPS). The MPE is an interactive software tool within the Advanced Weather Interactive Processing System that integrates rain gauge and satellite rainfall estimates with radar-only estimates and creates high-resolution gridded rainfall products at 4 km2 (Fulton, 2005). Each day during the study period were extracted in a batch using *wget*, *a* free utility tool for non-interactive downloading from the Web, through a script written in Python 2.7. These shapefiles were renamed and clipped within the boundaries of Texas in ArcGIS using a code constructed in Model Builder.

Data from NASA’s recently launched Soil Moisture Active Passive (SMAP) satellite were unavailable to use during this term. To conduct soil moisture calculations, data from the Advanced Microwave Scanning Radiometer – Earth Observing System Sensor on the NASA Aqua Satellite (AMSR-E) and North American Land Data Assimilation System (NLDAS) were obtained for the 2010-2011 study period. Soil Moisture and Ocean Salinity (SMOS) data were acquired from the European Space Agency (ESA) for the 2014-2015 study period.

## ***Data Processing***

The Scaled Drought Condition Index (SDCI) model C12 provides the foundation for the DSI. This particular model was chosen due its optimal performance as a remote sensing-based drought index for both arid and humid regions in the study undertaken by Rhee, Im & Carbone (2010). The applicability of C12 to our project encompasses both the semi-arid regions of Western Texas as well as the humid climate in the East. The C12 SDCI is calculated using the following formula suggested by Rhee et al. (2010):

(1/4) scaled *LST* + (1/2) scaled *TRMM* + (1/4) scaled *VI*

However, this equation was modified to reflect the alternate satellites used to acquire similar data, but at much greater efficiency. For instance, the Vegetation Index (*VI*) listed in the equation above was replaced with the Normalized Difference Vegetation Index (NDVI) because of its higher correlation coefficients within arid regions (Rhee et al., 2010). Due to its higher spatial resolution, MPE data were given preference over the Tropical Rainforest Monthly Mission (*TRMM*). MODIS MOD09A1 surface reflectance data in the Raster Calculator tool was used to calculate NDVI through the following equation:

(*NIR – Red*)/(*NIR* + *Red*)

Bands 2 and 1 of the Terra MODIS surface reflectance data are represented in the above equation as the Near Infrared band (*NIR*) and the visible light Red band (*Red*). A python script written by the Summer 2013 DEVELOP term, for the purpose of assessing drought in the Great Plains region, was implemented in order to scale land surface temperature, precipitation, and vegetation.

Before scaling the data, Model Builder and Raster Calculator were used to calculate a 30 day and 60 day rolling sum for both the precipitation and LST datasets. The rolling sum outputs were then applied to the Land Surface Temperature/NDVI calculated raster images.

The ArcGIS raster calculator tool was applied to measure the DSI by employing the following modified equation (Watkins, Lessel, Perillo, Ross; 2013):

(1/4) scaled *LST* + (1/2) scaled *MPE* + (1/4) scaled *NDVI*

In the equation above, *LST* represents the land surface temperature, *MPE* is the precipitation value, while the *NDVI* equates to the Normalized Difference Vegetation Index. The three inputs were scaled through the execution of the formulas:

*LST*: (LSTmax – LST)/(LSTmax – LSTmin)

*MPE*: (MPE – MPEmin)/(MPEmax - MPEmin)

*NDVI*: (NDVI - NDVImin)/(NDVImax – NDVImin)

In addition to the calculations performed by the Great Plains Study, soil moisture data was included in this equation as well. However, the Texas Disasters team at the John C. Stennis Space Center had completed the NDVI and LST portions of the equation earlier in the summer term. Therefore, the DSI equation was once again modified to incorporate a combined NDVI/LST data batch with MPE and Soil Moisture data, each with a rough estimate in given percentage weight in accordance with the level of significance in drought contribution and the accuracy of the data.

(1/4) scaled *NDVI/LST* + (1/2) scaled *MPE* + (1/4) scaled *SMOS*

## ***Data Analysis***

# IV. RESULTS & DISCUSSION

## **Analysis of Results**



## ***Errors & Uncertainty***

The Aqua/Terra MODIS functions at a 1 km2 spatial resolution, a much less coarse visual display than the 4 km2 resolution of the MPE. This discrepancy may cause local scale accuracy errors in the final product. Past studies have criticized the MPE for underestimating precipitation values (Westcott, Knapp, Hilberg, 2007). Moreover, MPE sensors, which rely on NEXRAD data, are susceptible to the typical errors common to weather radar. These errors include large radar scans that result in average precipitation levels in a 16 km2 area, bright banding, low topped convection, and the accuracy of the reflectivity-rainfall algorithm (NOAA NWS, 2013).

Easily the greatest concern is the applicability of the C12 values in the DSI equation to the ecological regions existing within Texas. In the article published by Rhee et al. (2010), the C12 values were developed for use within four separate states – two states for arid environments and two states for humid environments. Despite their close proximity to the area of study, Arizona, New Mexico, and the Carolinas, these environments may not accurately resonate with the coefficients that are needed for the unique regions in Texas.

## ***Future Work***

# V. CONCLUSIONS

# VI. ACKNOWLEDGMENTS

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# **VIII. Content Innovation**