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Uruguay Agriculture III

Deconstructing a Drought Severity Index Based on NASA Earth Observations into Principle Components for Better End-User Assessment of the Driving Factors Behind Local Scale Drought

 **Technical Report**

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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**

Drought, Remote Sensing, CMORPH, LST, NDWI, Monitoring, Drought Index

# II. Introduction

The importance of monitoring drought is indispensable for countries whose economic viability is strongly tied to agriculture. Uruguay is such a country. In 2009 the country lost an estimated $400 to $450 million USD due to a several months long drought (MercoPress, 2009). Moreover, a good proportion of Uruguay’s energy power is produced form hydroelectric sources, which are highly sensitive to drought conditions (MercoPress, 2009). During the late 1980’s drought reduced the output of hydroelectric power by so much that the country had to resort to the more expensive option of importing petroleum and adopting strict energy conservation efforts to keep up with the country’s energy demands (National Drought Mitigation Center, 2013). Therefore, decision support tools that specifically address response strategies to drought will become increasingly useful to farmers, insurance providers, and policy makers as they deal with an even more volatile climate in the coming future.

The preceding terms for this project created a Drought Severity Index (DSI) tool based on the methodology of Rhee et al. (2010). The DSI that was created uses the climatological anomalies of NASA’s Moderate-Resolution Imaging Spectrometer (MODIS) daytime land surface temperature (LST) data, precipitation data from the Climate Prediction Center’s Morphing Technique (CMORPH), and MODIS Normalized Difference Water Index (NDWI) data. In order to validate the DSI data, it was compared to percent available water (PAW) data from a soil water balance (SWB) model provided by the Instituto Nacional de Investigación Agropecuaria (INIA). The end result of the project produced the following index for drought monitoring to be used within Uruguay:

(1/4) *scaled LST-a* + (1/2) *scaled CMORPH-a* + (1/4) *scaled NDWI-a*. (1)

The SWB model data are generated from three parameters: 1) effective rainfall, which is calculated by deducting rainfall recorded at 84 meteorological stations, from a value of surface runoff estimate based on antecedent rain from 5 days earlier, 2) potential evapotranspiration, which is a physical model based on the daily values of temperature, air humidity, wind speed, and solar radiation using the Penman-Monteith method, and 3) water holding capacity defined by the Charter Soil Survey of Uruguay at 1:1,000,000 scale (INIA, 2015).

While the DSI has proved useful to the end-users in the country they have also expressed concerns with DSI. One concern is that it seems that the DSI maps seem to show more intense drought than had occurred in the country. Another concern from the end-users was that they were not able to assess the level to which the parameters of the DSI (precipitation, LST, and NDWI) were impacting the drought in their local area. For this concern, we decided to research the feasibility of implementing a ternary diagram of the DSI components so that it would be easy to distinguish the drivers of the drought in their local area. This work falls under the NASA national application area of agriculture as the new modified DSI has the potential to aid INIA and the Ministry of Agriculture of Uruguay to better inform land managers, farmers, insurance providers, and policy makers in drought preparation decisions and mitigation practices.

# III. Methodology

The DSI is computed within the International Research Institute for Climate and Society’s (IRI) data library and is based on the methodology presented in Rhee et al. (2010) for their CI2 model, which gives a general coefficient scheme of as follows:

(1/4) scaled *LST* + (1/2) scaled *Precipitation* + (1/4) scaled *Vegetation Index*.           (2)

This coefficient scheme was shown by Rhee et al. (2010) to be the best in both arid and humid environments and was shown in the previous term (Fall 2013) as the most optimal scheme for Uruguay. We therefore did not adjust the coefficient scheme for the DSI but in the most recent term (Spring 2015), we substituted a different precipitation source (NOAA’s CMORPH) in place of NASA’s Tropical Rainfall Measuring Mission (TRMM) and calculated the climatological anomalies for each component within the DSI (LST, precipitation, and vegetation indices). The scaling of each component within the DSI is done in order to create an index which operates between 0 and 1 and is calculated by the formulas shown in table 1.

**Table 1.**

Formulas used for scaling the various parameters found within the DSI (modified from Rhee et al., 2010). The variables within the formulas (LST, CMORPH, and NDWI) are the climatological anomaly for the respective variable, with the max and min subscript denoting the maximum and minimum monthly climatological anomaly over the study period.

|  |  |
| --- | --- |
| **DSI parameter** | **Formula** |
| **scaled LST-a** | (LSTmax – LST)/(LSTmax – LSTmin) |
| **scaled CMORPH-a** | (CMORPH – CMORPHmin)/(CMORPHmax – CMORPHmin) |
| **scaled NDWI-a** | (NDWI – NDWImin)/(NDWImax – NDWImin) |

 The first issue we sought to address in this term was that the end-users had the concern that the DSI appeared to be over estimating the severity of drought in its map interface, leading to the perception that the drought had affected larger regions of the country and to a greater degree. In order to address this concern, we first looked at the way in which the precipitation parameter was being scaled. Scaling the precipitation parameter using the maximum climatological anomaly (CMORPHmax) appears to give a skewed distribution of the CMORPH data towards < 0 with outliers towards the max and a total range between approximately -7 mm/day for the minimum and 25 mm/day for the maximum. This is different from the LST and NDWI parameters which have a normal distribution centered approximately at 0 with approximate ranges of -8 °C to 8 °C for LST and -0.75 and 0.63 for NDWI. It’s possible that due to the CMORPH data being skewed towards lower numbers because of the outliers in the maximum range, the total DSI itself could be forced to produce lower numbers, which in the case of the DSI would show as a more severe drought environment.

 To address this concern we attempted to counteract the maximum outlier effects by changing the scaling formula for the CMORPH data from that shown in table 1 to the following equation:

(CMORPH – CMORPHmin)/(( – CMORPHmin)– CMORPHmin) (3)

In equation (3) we replaced the maximum CMORPH anomaly value by the *negative* minimum CMORPH anomaly value. This in turn normalizes the CMORPH anomaly values so as to not have the index itself be driven into lower numbers because of outlier maximum values in the CMORPH anomaly data. After applying this change to the DSI we again chose to statistically analysis how well the new DSI correlated with the PAW data.

 The second issue we focused on in this term was giving the DSI the ability to show how the individual components of the DSI are affecting the overall output of the DSI on a per pixel basis. For example, if the DSI over a specific region of interest output a value of 0.25 (severe drought), how much of that is being driven by the precipitation component and how much of a role does the vegetation index play role? This could be useful for end-users as it may indicate areas where even if precipitation has been lacking, the resilience of specific vegetation types may be such that they are not prone to drought conditions as much as other vegetation types and thus emergency resources can be allocated in a more informed manner. To tackle this problem, we created a series of ternary diagrams such as that presented in figure 1.

**Figure 1.** General ternary diagram showing the different components of the DSI. Using this diagram, the end user would be able to select a region of interest on the DSI map and a ternary diagram would show the main driver of the drought severity for the given area as well as show the other components role in the drought.



Creating the ternary diagrams is accomplished by individually extracting each component in the DSI and placing its value on the diagram. Since the DSI is normalized between 1 and 0 it gives an accurate representation of how the components are driving the overall value of the DSI. Following this creation of the diagrams we investigated the outcomes of the diagrams and how they can be interpreted by the end-users. Specifically, with respect to how the roles of NDWI and precipitation play into the overall outcome of the DSI during times of drought.

# IV. Results & Discussion

Results forthcoming in final draft.

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Things to discuss:

* Analysis of Results: What can you tell from your graphs, images, etc? What does this mean for your project?
* Errors & Uncertainty: What factors could you not account for, what things didn’t work out like you expected they would, etc.
* Future Work: If this project was to be selected for another term, what would be the focus? What other areas would be of interest?

# V. Conclusions

Conclusions forthcoming in final draft.

Final conclusions. Word count: 200-600 (~a page).

# VI. Acknowledgments

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# VII. References

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# IV. Appendices

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