4.4 DEVELOPMENT OF A 30-YEAR SOIL MOISTURE CLIMATOLOGY FOR SITUATIONAL AWARENESS AND PUBLIC HEALTH APPLICATIONS

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1. INTRODUCTION

The NASA Short-term Prediction Research and Transition (SPoRT) Center in Huntsville, AL (Jedlovec 2013; Ralph et al. 2013; Merceret et al. 2013) runs a real-time configuration of the Noah land surface model (LSM) within the NASA Land Information System (LIS) framework (hereafter referred to as the "SPoRT-LIS"). Output from the real-time SPoRT-LIS is used for (1) initializing land surface variables for local modeling applications, and (2) displaying in decision support systems for situational awareness and drought monitoring at select NOAA/National Weather Service (NWS) partner weather forecast offices (WFOs). The SPoRT-LIS is currently run over a domain covering the southeastern half of the Continental United States (CONUS), with an additional experimental real-time run over the entire CONUS and surrounding portions of southern Canada and northern Mexico (Case 2014), both of which incorporate SPoRT's real-time green vegetation fraction (GVF) derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) (Case et al. 2014). The experimental CONUS run incorporates hourly quantitative precipitation estimation (QPE) from the National Severe Storms Laboratory Multi-Radar Multi-Sensor (MRMS) product (Zhang et al. 2011, 2014), which was transitioned into operations at the National Centers for Environmental Prediction (NCEP) Environmental Modeling Center (EMC) in fall 2014.

An assessment of selected SPoRT-LIS soil moisture output variables was conducted from August to October 2014 at three partner NOAA/NWS WFOs to identify its potential utility for drought monitoring and assessing areal/river flooding potential (White and Case 2015). While the SPoRT-LIS output was found to exhibit a favorable utility for contributing to drought monitoring (and to a lesser extent areal flooding potential) on finer sub-county scales than current national drought products, a limitation is that the soil moisture data by themselves cannot provide the proper historical context of the soil state in terms of anomalies or departures from a "normal" condition. Therefore, efforts are underway to develop a 30-year soil moisture climatology over the entire CONUS at ~3-km grid spacing (the same horizontal resolution as the current SPoRT-LIS), with intentions of upgrading to a full CONUS domain with near real-time soil moisture anomalies similar to the current NCEP Climate Prediction Center (CPC) soil moisture anomaly products (e.g., http://www.cpc.ncep.noaa.gov/products/Soilmst_Monitoring/US/Soilmst/Soilmst.shtml) and NCEP/EMC's operational North American Land Data Assimilation System-Phase 2 (NLDAS-2; Xia et al. 2012), but at considerably higher spatial resolution.

The remainder of this paper is organized as follows: Section 2 provides background on the NASA LIS and its configuration for a 30-year soil moisture climatology over the CONUS. Section 3 presents the methodology for developing a daily, 30-year soil moisture climatology by county. Comparisons between output from the two SPoRT-LIS Preliminary results and comparisons to the U.S. Drought Monitor (USDM) drought classification products are shown in Section 4, followed by a discussion of future work for applications at the NOAA/NWS forecast offices and public health arena in Section 5.

2. LIS RUN FOR SOIL MOISTURE CLIMATOLOGY

2.1 NASA LIS software modeling framework

The NASA LIS is a high performance land surface modeling and data assimilation system that integrates satellite-derived datasets, ground-based observations and model reanalyses to force a variety of LSMs (Kumar et al. 2006; Peters-Lidard et al. 2007). By using scalable, high-performance computing and data management technologies, LIS can run LSMs offline globally with a grid spacing as fine as 1 km (or better) to characterize land surface states and fluxes. The framework features an Ensemble Kalman filter (EnKF) algorithm for conducting land surface data assimilation (Kumar et al. 2008; Kumar et al. 2009) for a variety of datasets and variables such as soil moisture, land surface temperature and snow (e.g., Liu et al. 2013). The system also supports an optimization and uncertainty analysis for calibrating land surface model parameters to observations (Santanello et al. 2013). LIS has also been coupled to the Advanced Research Weather Research and Forecasting (WRF) dynamical core (Kumar et al. 2007) for numerical weather prediction (NWP) applications using the NASA Unified-WRF modeling framework (Peters-Lidard et al. 2015; each of these features are summarized diagrammatically in Figure 1.). Finally, a land surface

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verification toolkit has been implemented to provide validation of land surface models against a variety of in situ, satellite, and reanalysis data (Kumar et al. 2012).

2.2 LIS setup for 30-year soil moisture climatology

Version 7 of LIS is used to develop a long-term high-resolution soil moisture climatology by running version 3.3 of the Noah LSM (Ek et al. 2003; Chen and Dudhia 2001). LIS-Noah is run in analysis mode (i.e., uncoupled from an NWP model) over a full CONUS domain at 0.03-degree grid spacing. The soil temperature and volumetric soil moisture fields were initialized at constant values of 290 K and 20 % in all four Noah soil layers (0-10, 10-40, 40-100, and 100-200 cm) on 1 January 1979. Details on the parameter specifications, integration and meteorological forcing are given in the following sub-sections.

2.2.1 **Prescribed input fields**

The LIS-Noah climatology run uses the International Geosphere-Biosphere Programme (IGBP) land-use classification (Loveland et al. 2000) applied to the MODIS instrument (Friedl et al. 2010). All static and dynamic land surface fields are masked based on the IGBP/MODIS land-use classes. The soil properties are represented by the State Soil Geographic (STATSGO; Miller and White 1998) database.

Additional parameters include a 0.05° resolution maximum snow surface albedo derived from MODIS (Barlage et al. 2005) and a deep soil temperature climatology (serving as a lower boundary condition for the soil layers) at 3 meters below ground, derived from 6 years of Global Data Assimilation System 3-hourly averaged 2-m air temperatures using the method described in Chen and Dudhia (2001). Monthly climatologies of green vegetation fraction (GVF) data derived from MODIS fraction of photosynthetically active radiation data are incorporated into the LIS runs in place of the default coarser-resolution monthly climatology GVF dataset (Gutman and Ignatov 1998), commonly used by the WRF NWP modeling community and within NCEP/EMC operational models. The MODIS GVF monthly climatology resides on a native 30 arcsecond grid (~0.925 km resolution) and was made available to the WRF modeling community with the release of WRF version 3.5 (NCAR 2014). This detailed GVF database was used to help develop realistic distributions of fluxes at high resolution for the duration of the LIS-Noah climatological simulation.

2.2.2 **Simulation and atmospheric forcing**

LIS-Noah was integrated using a 30-minute timestep from 1979 to 1 Jan 2011. To ensure a properly spun-up deep soil layer in equilibrium with forcing meteorology (with no memory of the prescribed initial conditions), the entire simulation was re-ran from 1979 to 2011 using a restart file from 1 Jan 2011. The atmospheric forcing variables required to drive the LIS-Noah integration consist of surface pressure, 2-m temperature and specific humidity, 10-m winds, downward-directed shortwave and longwave radiation, and precipitation rate. In the long-term simulation, all atmospheric forcing variables were provided by hourly analyses from NLDAS-2, largely based on the North American Regional Reanalyses and gauge/radar precipitation estimates adjusted by PRISM (i.e., Parameter elevation Regression on Independent Slopes Model) statistical-topographical relationships in complex terrain (Xia et al. 2012; Daly et al. 1994). The long-term land surface states of LIS-Noah ultimately converge to the input NLDAS-2 meteorology as it interacts with the prescribed input fields.

3. SOIL MOISTURE CLIMATOLOGY METHOD

For developing the 30-year soil moisture climatology by county, LIS-Noah fields were output once per day at 0000 UTC from the restarted run spanning 1 January 1981 to 31 December 2010. For initial development of soil moisture anomalies, the total column relative soil moisture variable ($RSM_{0\text{-}2m}$; Eq. [1]) was used to construct the soil moisture distribution by county,

$$RSM_{0-2m} = \frac{\theta - \theta_{wilt}}{\theta_{sat} - \theta_{wilt}} \quad (1),$$

where θ is the volumetric soil moisture, θ_{sat} is the field capacity, and θ_{wilt} is the wilting point of the STATSGO soil classification at a given grid point. A CONUS database of NOAA/NWS county shapefiles were then applied to group all grid points together that reside within a specific county. For each individual county, $RSM_{0\text{-}2m}$ were sorted into a ranked histogram to form a daily distribution or "climatology" of $RSM_{0\text{-}2m}$ values. A sample histogram on 21 August for Madison county, AL is shown in Figure 2, along with the daily mean $RSM_{0\text{-}2m}$ from 21 August 2007 during the peak of a severe drought. The specific percentile/anomaly within the histogram can then be determined at each grid point based on where the grid point's $RSM_{0\text{-}2m}$ value lies within the county's daily distribution. Daily maps of percentiles were then output to gridded binary files for generating plots.

For the purposes of comparing the soil moisture percentiles to the USDM drought classification product, a proxy soil moisture percentile threshold was applied to correspond to the individual USDM categories (i.e., D0 through D4), following the method used by Xia et al. (2014a,b). In their studies, the authors developed a calibrated drought proxy index off of multiple LSM variables. The proxy thresholds are as follows:

- D0 (abnormally dry; percentile ≤ 30%),
- D1 (moderate drought; percentile ≤ 20%),
- D2 (severe drought; percentile ≤ 10%),
- D3 (extreme drought; percentile ≤ 5%), and
- D4 (exceptional drought; percentile ≤ 2%).

For our study, we invoked a simple procedure by only using a single, uncalibrated variable ($RSM_{0\text{-}2m}$) for creating maps of proxy drought based on the above dry soil moisture percentile thresholds. The same RGB color scale as in the USDM weekly products was applied to the maps for a quick visual comparison.

4. SAMPLE RESULTS COMPARED TO USDM

A comparison between the proxy percentile map and USDM drought classification on 21 August 2007 depicts quite a good qualitative match, especially over the eastern half of the U.S. (Figure 3). The severe and exceptional drought classifications (D3 and D4) over the southeastern U.S. and western Great Lakes regions (right panel) are represented well by the proxy percentiles of $RSM_{0\text{-}2m}$. Dry soil moisture anomalies appear to be strongly correlated to drought occurrence in the eastern U.S. (at least for this date) and thus are represented well by the $RSM_{0\text{-}2m}$ proxy percentiles.

The pattern similarities tend to break down over the western U.S. and High Plains, possibly because of the predominantly arid climatic regimes. Small changes in soil moisture from a rain event could yield substantial changes to the percentile within a given county's probability density function. There is still a tendency for more arid soil moisture anomalies in the western U.S. where the USDM product indicates D2 and D3 drought categories. However, other factors such as reservoir levels, baseflow, and snowpack/snowmelt likely contribute to drought severity in the western U.S. in addition to soil moisture anomalies. A closer investigation of the distributions of $RSM_{0\text{-}2m}$ over the western U.S. are needed to understand the relationship between soil moisture anomaly and drought occurrence. Other LSM variables may need to be examined that may better correlate to drought in the western U.S. such as snow water equivalent/snowmelt, for example.

These soil moisture data and anomalies are being used to form the basis for a soil moisture index that can be used by the Public Health community. Certain variations in soil moisture over the semi-arid southwestern U.S. can promote the development of airborne illnesses such as Valley Fever. Figure 4 highlights the portions of the southwestern U.S. and Mexico that are vulnerable to Valley Fever (left panel). This airborne illness is an emerging potential crisis, as the rates of Valley Fever incidence has risen dramatically in Arizona and California in recent years (right panel). It is the goal of this project to provide a meaningful soil moisture index product that can be used within the Centers for Disease Control's (CDC) Public Health Tracking Tool to monitor and track conditions favoring the development and onset of Valley Fever.

5. SUMMARY AND FUTURE WORK

This paper provided a brief background on the work being done at NASA SPoRT and the CDC to create a soil moisture climatology over the CONUS at high spatial resolution, and to provide a valuable source of soil moisture information to the CDC for monitoring conditions that could favor the development of Valley Fever. The soil moisture climatology has multi-faceted applications for both the NOAA/NWS situational awareness in the areas of drought and flooding, and for the Public Health community. SPoRT plans to increase its interaction with the drought monitoring and Public Health communities by enhancing this testbed soil moisture anomaly product.

This soil moisture climatology run will also serve as a foundation for upgrading the real-time (currently southeastern CONUS) SPoRT-LIS to a full CONUS domain based on LIS version 7 and incorporating real-time GVF data from the Suomi-NPP Visible Infrared Imaging Radiometer Suite (Vargas et al. 2013) into LIS-Noah. The upgraded SPoRT-LIS run will serve as a testbed proof-of-concept of a higher-resolution NLDAS-2 modeling member. The climatology run will be extended to near real-time using the NLDAS-2 meteorological forcing from 2011 to present. The fixed 1981-2010 climatology shall provide the soil moisture "normals" for the production of real-time soil moisture anomalies. SPoRT also envisions a web-mapping type of service in which an end-user could put in a request for either an historical or real-time soil moisture anomaly graph for a specified county (as exemplified by Figure 2) and/or for local and regional maps of soil moisture proxy percentiles.

Finally, SPoRT seeks to assimilate satellite soil moisture data from the current Soil Moisture Ocean Salinity (SMOS; Blankenship et al. 2014) and the recently-launched NASA Soil Moisture Active Passive (SMAP; Entekhabi et al. 2010) missions, using the EnKF capability within LIS. The 9-km combined active radar and passive microwave retrieval product from SMAP (Das et al. 2011) has the potential to provide valuable information about the near-surface soil moisture state for improving land surface modeling output.

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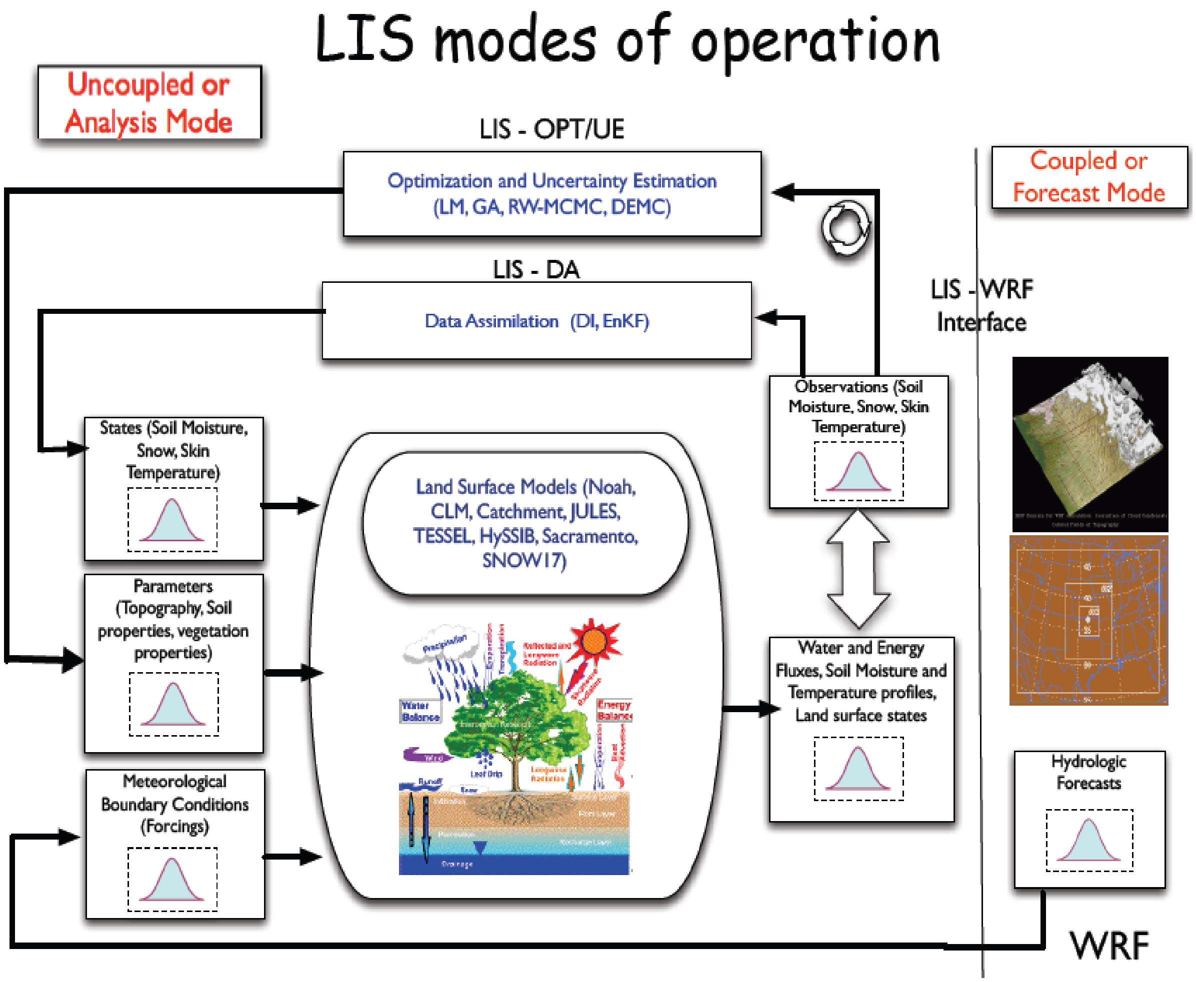

Figure 1. Mode of operations within the NASA LIS land surface modeling and data assimilation framework.

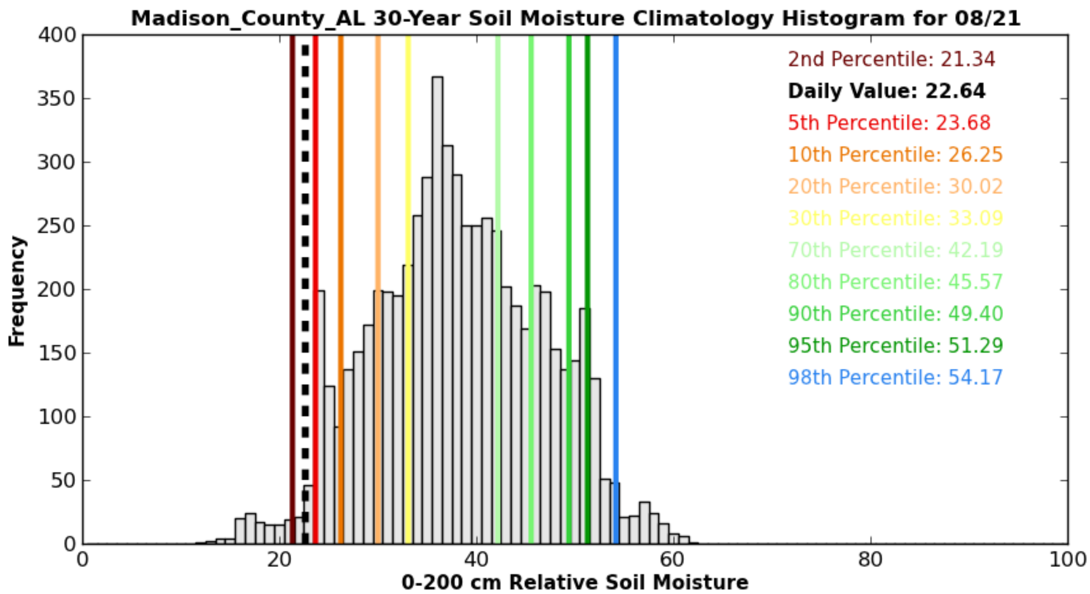

Figure 2. Sample daily histogram of 0-2 m relative soil moisture ($RSM_{0\text{-}2m}$; in %) on 21 August from the 30-year LIS soil moisture climatology run spanning 1981-2010, using all grid points residing within Madison county, AL. The colored vertical lines represent the values of $RSM_{0\text{-}2m}$ corresponding to the proxy percentile thresholds for D4 (2^{nd} percentile), D3 (5^{th} percentile), D2 (10^{th} percentile), D1 (20^{th} percentile), and D0 (30^{th} percentile), along with their mirror analogs on the moist side of the histogram. The bold dashed vertical line represents the county-averaged $RSM_{0\text{-}2m}$ for 21 August 2007 during the severe drought in the Southeastern U.S.

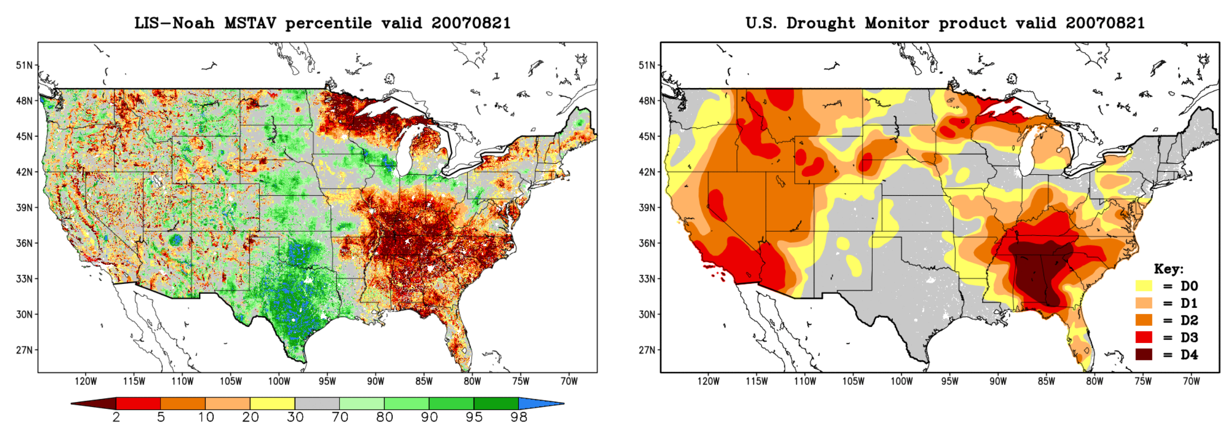

Figure 3. Plot of LIS-Noah $RSM_{0\text{-}2m}$ percentiles on 21 August 2007 colorized by proxy USDM drought classification and moist analogs (left), and the corresponding USDM drought classification map from 21 August 2007 (right).

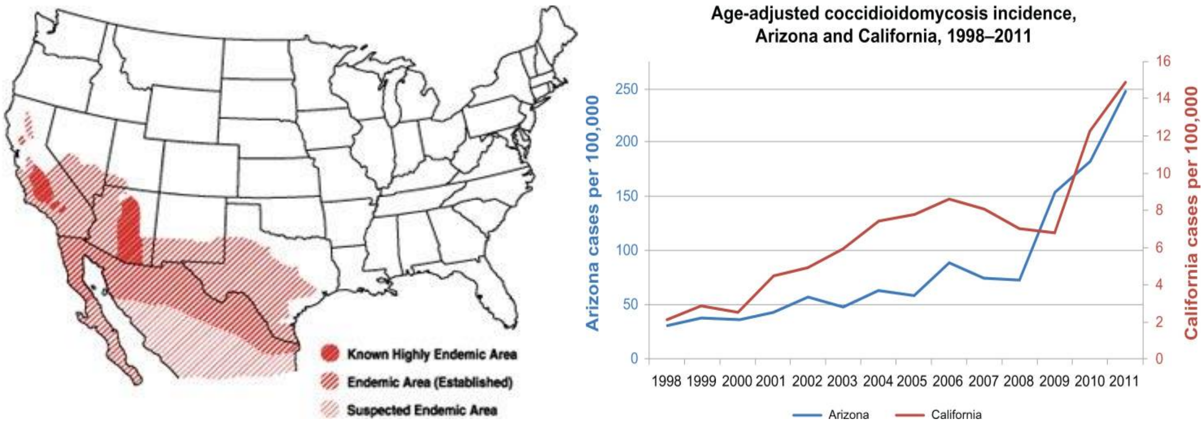

Figure 4. Display of regions most prone to Valley Fever in the Southwestern U.S. (left), and recent trends in the rate of Valley Fever incidence in Arizona and California (right).