PROJECT TITLE: Development of probabilistic drought intensification forecasts using the GOES-based Evaporative Stress Index

INVESTIGATORS:

PI: Jason Otkin; University of Wisconsin-Madison; jasono@ssec.wisc.edu
Co-PI: Martha Anderson; USDA/ARS; Martha.Anderson@ars.usda.gov
Co-PI: Mark Svoboda; University of Nebraska; msvoboda2@unl.edu
Co-PI: Chris Hain; University of Maryland; chris.hain@noaa.gov

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1. Project objectives and methodology

This project will develop a drought early warning toolkit based on satellite-derived maps of evapotranspiration (ET) and forecast output from the National Multi Model Ensemble (NMME) that will provide probabilistic drought intensification forecasts over weekly to monthly time scales. Recent examples of rapid drought development have demonstrated the need for a reliable drought early warning system capable of providing vulnerable stakeholders additional time to prepare for worsening drought conditions. The project will use the Evaporative Stress Index (ESI) dataset generated with the Atmosphere-Land Exchange Inverse (ALEXI) surface energy balance model and GOES satellite thermal infrared observations. The ESI represents standardized anomalies in the ratio of actual-to-reference ET and can be used to depict moisture stress in vegetation with high spatial resolution. Because the ALEXI model computes ET using remotely sensed land surface temperatures that respond quickly to changes in soil moisture content, the ESI is often able to detect increasing moisture stress sooner than other drought metrics, thereby making it a useful drought early warning tool. Temporal changes in the ESI have been shown to provide valuable information about the rate of drought intensification, thus other variables have been developed to encapsulate the cumulative magnitude of the ESI changes occurring over longer time periods. Prior work has shown a strong relationship between the magnitude of the ESI changes and subsequent drought intensification as depicted by the U.S. Drought Monitor (USDM).

Probabilistic drought intensification forecasts will be generated each week across the contiguous U.S. using the ESI and other relevant drought monitoring variables. New insight into the causes of rapid drought development will be gained through detailed analyses of soil moisture, rainfall, and atmospheric anomalies both preceding and accompanying recent flash drought events. Refinements will be made to the ESI-based drought intensification forecasts based on these insights and through development of synergistic methods that combine drought early warning signals from multiple data sources, such as the Standardized Precipitation Index (SPI) and soil moisture anomalies from the North American Land Data Assimilation System (NLDAS). After evaluating the efficacy of these drought intensification probabilistic forecasts, new methods will be devised to incorporate ensemble forecasts of temperature and rainfall from the NMME as a means of further enhancing their forecast skill. The drought forecast products will be relevant to multiple end users, including authors of the NOAA Climate Prediction Center Seasonal and Monthly Drought Outlook products.

2. Research and accomplishments

During the past 12 months, we enhanced the empirical drought intensification forecasting method developed during the first two years of the project through inclusion of forecast model output from the NMME and performed a climatological study to identify the main forcing mechanisms contributing to changes in the ESI during the growing season.

A) Drought intensification forecast enhancements through inclusion of NMME output

Two papers describing an empirical method used to predict changes in the USDM over sub-seasonal time scales (2-8 weeks) using anomalies in the ESI, SPI, and NLDAS data sets computed over various time scales were accepted for publication in the *Journal of Hydrometeorology* in May 2017 (Lorenz et al. 2017a, b). Revisions were performed to both of these papers during this reporting period. Though this method has been described in detail in a previous report, a quick summary of the basic framework used to compute the drought intensification forecasts is provided here. The predictions are probabilistic and involve two main components. The first component is used to better characterize the current state of the USDM by quantifying how far the current USDM state is from the next higher or lower drought category. In effect, this component defines a "continuous" version of the USDM that is most consistent with the discrete, categorical version of the USDM. The second component is then used to predict the probability of future changes in the USDM using recent anomalies in precipitation (SPI), soil moisture (NLDAS) and evapotranspiration (ESI). Results from these studies showed that the improved USDM current state estimates obtained through development of the continuous version of the USDM added significant skill to the probabilistic forecasts. The state information was useful because the USDM is more likely to intensify when it is "close" to the next higher drought category. Overall, this version of the forecasting method that uses only recent anomalies to predict changes in the USDM was shown to produce skillful forecasts over sub-seasonal time scale.

The empirical method described above essentially relies on the long-term memory in soil moisture and land surface conditions combined with climatological information to predict changes in the USDM over sub-seasonal time scales. Additional forecasting skill should be achievable through inclusion of climate model forecast output depicting land surface and atmospheric conditions during the next 1-3 months. To explore this possibility, we expanded the empirical method to include model output from the Climate Forecasting System's contribution to the NMME (hereafter referred to as CFS NMME). To this end, we initially evaluated the relationship between the USDM intensification and various predictor variables in the CFS Reanalysis (CFSR) dataset using correlation analysis. Through this analysis, we determined that the predictor variables most closely related to

USDM intensification are the 2-m dew point depression, potential evapotranspiration (PET) and topsoil moisture content (1-10 cm).

The USDM forecasts generated with our empirical method are issued at weekly intervals to mimic the weekly release schedule of the USDM, however, the CFS NMME forecasts were available at five-day intervals during most of the 2000-2016 time period used during this study. Therefore, to more closely replicate an operational forecasting environment, only the CFS NMME forecasts available before the Tuesday morning data cut-off for the USDM are used to develop the enhanced version of our empirical method and to assess its accuracy. Because of the mismatch between the 5- and 7-day release schedules, some of the CFS NMME forecast lead times are shorter than others. The CFS NMME forecasts used here include four ensemble members that are distinguished by slight differences in their initialization time (00, 06, 12 and 18 UTC every fifth day). The CFS NMME predictors are then averaged over all ensemble members (4 total). Though the CFS NMME forecasts are issued on the same day, the multiple forecast times allow for some incorporation of forecast model uncertainty in the empirical method.

Most of the predictors are used over multiple time lags. These type predictors include the topsoil moisture (0-10 cm), PET, 2-m dew point depression, and precipitation. For the 2-week forecasts, the time lags are the future 1- and 2-week forecasts from the CFS NMME and the observed precipitation from the CPC gridded daily precipitation product (Higgins et al. 2000) and the CFSR for all variables other than precipitation during the past 3 weeks. Hence for the 2-week forecasts there are 6 temporal time lags (weeks -3, -2, -1, 0, 1 and 2 weeks from present) for each of the type predictors. From the perspective of the statistical model, each time lag is a separate predictor. The empirical model was designed this way so that the degree of temporal averaging/weighting (i.e. the relative size of the regression coefficients) is flexible and can be empirically determined by the data itself. For longer predictions, additional future time lags up until the end of the verification time are used. For example, the 4-week predictions also incorporate the 3- and 4-week CFS NMME forecasts. The remaining two predictors, including the USDM state predictor (Lorenz et al 2017a) and the climatological USDM intensification predictor (Lorenz et al 2017b), are used at a single "lag" valid at the present time. The statistical model uses logistic regression with a sign constraint placed on the predictor coefficients, which is unchanged from the previous work described in Lorenz et al (2017b).

To assess the effect of the CFS NMME forecasts on the drought intensification forecast skill, we compare the skill with the same statistical model but using only current and past time lags (i.e. no future CFS NMME forecasts are used). This is essentially the same as the USDM predictions shown in Lorenz et al (2017b) but with slightly different predictors. The cross-validated Brier Skill Scores (BSS) for the "no CFS NMME" forecasts and for the new forecasts incorporating CFS NMME model output are shown in Figs. 1a and 1b, respectively, with the change in skill shown in Fig. 1c. Overall, it is evident that inclusion of the CFS NMME forecast model output in the empirical method improves the drought intensification forecast skill in many locations; however, the change in skill is very modest.

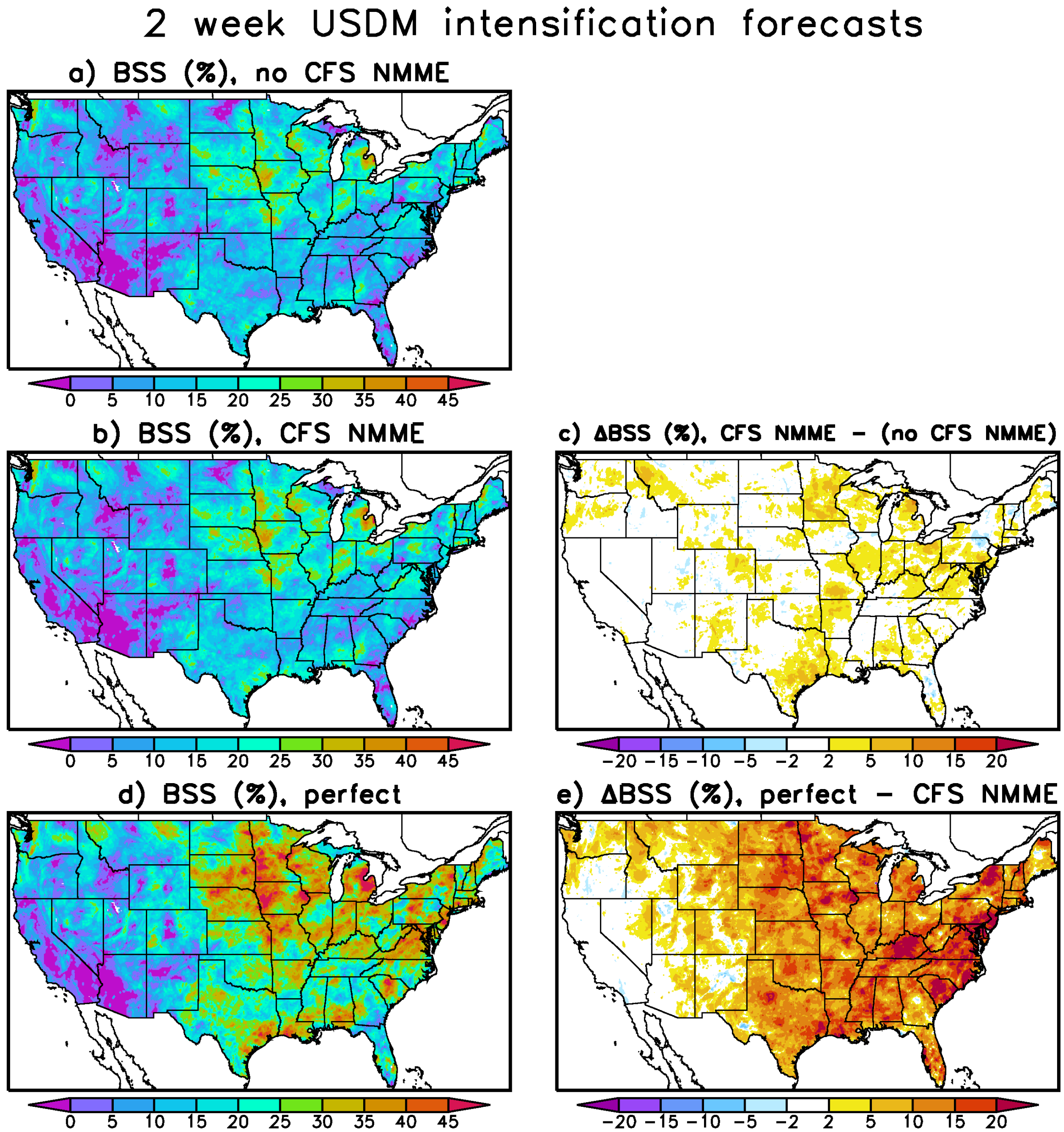

Figure 1a) Brier Skill Scores (BSS) for the 2 week USDM intensification forecasts using only current and past CFSR data as the predictors. b) Same as (a) except including future CFS NMME predictors. c) The difference in BSS between panels (a) and (b). d) Same as (a) except for using future observed CFSR analyses instead of CFS NMME forecasts (i.e. the realizable skill if the CFS NMME data had "perfect" forecast skill) e) The difference in BSS between the "perfect" and "imperfect" CFS NMME experiments.

Because the local impacts of recent events affecting the USDM analyzed drought severity are sometimes not known until after the USDM is issued each week, there is sometimes a lag between drought related anomalies on the ground and the USDM. Because of this potential time lag one might argue that there is not much more skill that is attainable from future CFS NMME predictors and perhaps that is why the forecast skill shown in Fig. 1 is only marginally better than that obtained using only current and past predictors. To test this hypothesis, we performed an additional experiment where we substituted future observations (CPC precipitation and CFSR) for the CFS NMME forecasts in the future time lags. In other words, for the 2-week drought intensification forecasts, the predictors for the 2 future weeks are taken from real future observations rather than the CFS NMME forecasts of the future. The result of this "perfect" CFS NMME forecast experiment is shown in Fig. 1d and the change compared to the original "imperfect" CFS NMME forecast experiment is shown in Fig. 1e. Overall, the improvements in the forecast skill are obvious and dramatic. This analysis demonstrates that a very significant portion of the USDM variability is reacting in real-time to changes in conditions on the ground. Moreover, these results show that future improvements in the CFS NMME forecast skill could lead to significant improvements in forecasts of USDM drought development.

B) Climatological study of factors controlling ESI anomalies

Correlation analyses were used to better understand which meteorological and land surface variables are most closely related to changes in the ESI during different parts of the growing season. Because previous work by Otkin et al. (2013) has shown that ESI anomalies computed over 2-, 4-, and 8-week time periods can convey unique information about the evolution of moisture stress, relationships were examined between each of the 3 ESI variables and anomalies in soil moisture, precipitation, and meteorological variables computed over different time periods. This includes 2, 4, and 8-week anomalies in 2-m temperature, 2-m dew point depression, 10-m wind speed, and downward shortwave radiation obtained from the CFSR; 0-10 cm and 0-2 m soil moisture anomalies computed using data from the North American Land Data Assimilation System (NLDAS); and 4, 8, and 12-week SPI anomalies computed using data from the CPC precipitation analyses.

Figure 2 shows the resultant correlations over the central U.S. computed using data from 2000-2015. As expected, soil moisture is positively correlated to the ESI during most of the growing season, with the correlations generally increasing during the second half of the summer. The shorter 2- and 4-week meteorological and topsoil moisture anomalies are more important for the 2-week ESI, whereas the longer-term meteorological and total column soil moisture anomalies are more important for the longer 8-week ESI. Together, this shows that anomalies in shorter (longer) ESI composite anomalies are most closely related to recent (longer-term) anomalies in the forcing variables. It is interesting to note that precipitation (SPI) and air temperature exhibit a much weaker correlation with the ESI, except for air temperature during late April – June, even though these two variables are often thought of as being the primary drivers of drought. On the other hand, the dew-point depression, an indicator of near surface humidity, is more strongly correlated with the ESI throughout the growing season and the correlations are even stronger than those associated with soil moisture during March – May. These results are consistent with a recent study by Ford and Labosier (2017) showing that surface moisture balance and atmospheric evaporative demand, rather than temperature and precipitation, are more closely linked to flash drought development (identified using soil moisture anomalies). The overarching conclusion is that ESI variability across the central U.S. is dominated by moisture availability (both soil and air) rather than to precipitation and temperature.

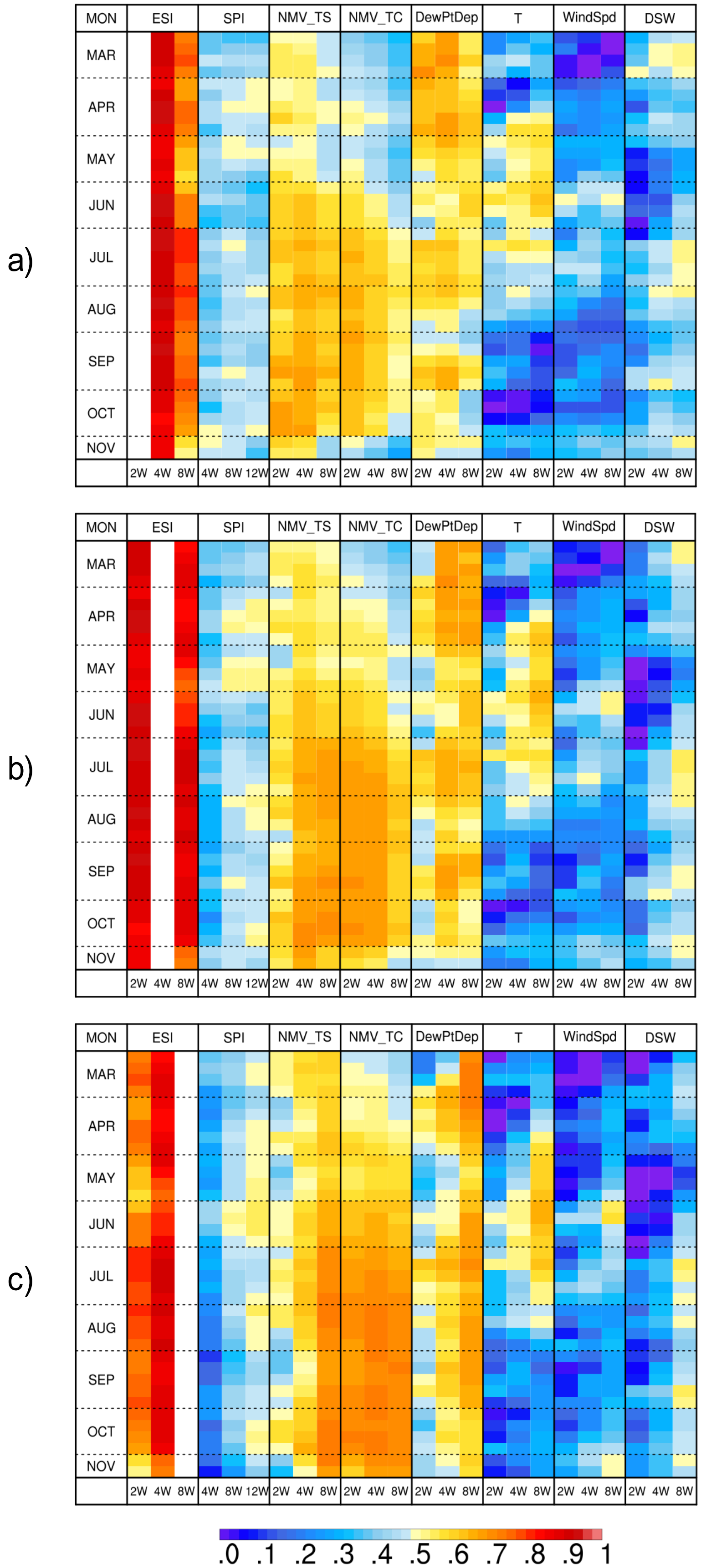

Figure 2. Correlations between the a) 2-, b) 4-, and c) 8-week ESI anomalies and the SPI computed over 4, 8, and 12 week periods; topsoil (NMV_TS) and root-zone (NMV_TC) soil moisture from NLDAS computed over 2, 4, and 8 week periods; 2-m dew point depression (DEWPTDEP), 2-m air temperature (T), 10-m wind speed (WSPD), and downward shortwave radiation (DSW) computed over 2, 4, and 8 week periods shown at weekly intervals from March to November. Please note that all of the DEWPTDEP, T, WSPD, and DSW correlations are sign-reversed.

3. Highlights of accomplishments

- Enhanced the logistic regression model developed during the first two years of the project to produce probabilistic drought intensification forecasts through inclusion of forecast model output from the CFS NMME
- Performed a climatological study that assessed relationships between the ESI and various soil moisture and atmospheric variables during the growing season; it was found that the ESI anomalies are most closely tied to anomalies in soil moisture and near surface humidity
- Revised two journal articles describing the empirical drought forecasting method developed during the first two years of the project and demonstrated their value as a drought early warning tool

4. Transitions to operations

We supported efforts led by Co-I Hain as part of the GET-D project to transition the ESI from a research tool into a NOAA operational product. The ESI became operational in August 2016. Images can be found at http://www.ospo.noaa.gov/Products/land/getd/.

5. Publications from the project

Otkin, J. A., M. C. Anderson, C. Hain, M. Svoboda, D. Johnson, R. Mueller, T. Tadesse, B. Wardlow, and J. Brown, 2016: Assessing the evolution of soil moisture and vegetation conditions during the 2012 United States flash drought. *Agr. Forest Meteorol.*, **218–219**, 230–242.

Lorenz, D. J., J. A. Otkin, M. Svoboda, C. Hain, M. C. Anderson, and Y. Zhong, 2017a: Predicting U.S. Drought Monitor (USDM) states using precipitation, soil moisture, and evapotranspiration anomalies. Part I: Development of a non-discrete USDM index. *J. Hydrometeor., in press.*

Lorenz, D. J., J. A. Otkin, M. Svoboda, C. Hain, M. C. Anderson, and Y. Zhong, 2017b: Predicting U.S. Drought Monitor (USDM) states using precipitation, soil moisture, and evapotranspiration anomalies. Part 2: Intraseasonal drought intensification forecasts. *J. Hydrometeor.*, in press.

6. PI contact information

Jason Otkin
CIMSS/SSEC
University of Wisconsin-Madison
1225 West Dayton Street
Madison, WI 53706
Phone: 608-265-2476
Email: jasono@ssec.wisc.edu

7. Budget for upcoming year

We have requested a 1-year no-cost extension to spend the remaining funds; therefore, no budget is provided here because it was not part of the original proposal.

8. Future work

During the no-cost extension period, we will complete the remaining project tasks. These include continuing to explore ways to increase the accuracy of the sub-seasonal drought intensification forecasts through inclusion of climate model forecast output, writing a journal article that describes the accuracy of the new forecasting method, and comparing the accuracy of the forecasting method to the NOAA CPC Seasonal Drought Outlook and Monthly Drought Outlook products.