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

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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

The main research accomplishments during this project include: 1) development of an innovative hybrid-statistical empirical forecasting method that is used to generate probabilistic drought intensification forecasts over sub-seasonal time scales, 2) a detailed analysis that examined the evolution of several model-based and satellite-derived metrics sensitive to soil moisture and vegetation health conditions during the 2012 flash drought event over the central U.S., 3) a climatological study that examined relationships between the ESI and various meteorological and land surface variables during the growing season across the U.S., and 4) publication of a review article in the *Bulletin of the American Meteorological Society* that described recent research on flash droughts and presented a definition for these important climate features that focuses on their unusually rapid rate of intensification. Each of these accomplishments is described in greater detail below.

A) Probabilistic drought intensification forecasts using a hybrid statistical method

A key component of this project was the development of a hybrid statistical method to generate probabilistic drought intensification forecasts using anomalies in the ESI, SPI, and NLDAS combined with forecast model output from the Climate Forecasting System (CFS) contribution to the NMME. During the first two years of the project, development efforts focused on extracting useful information from current anomalies in the ESI, SPI, NLDAS, and other near-surface atmospheric datasets. As such, this version of the method 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. A brief summary of the basic framework is provided here, with a more detailed description given in Lorenz et al. (2017a,b).

The probabilistic drought intensification forecasting method has 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 categorical version of the USDM. The second component is used to predict the probability of future changes in the USDM state using recent anomalies in precipitation (SPI), soil moisture (NLDAS), and evapotranspiration (ESI). Results from Lorenz et al. (2017a,b) showed that the improved estimate of the current USDM state obtained through development of the continuous version of the USDM substantially increased the skill of the probabilistic forecasts. The state information was useful because the USDM is more likely to intensify when it is "close" to switching 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 provide reliable forecasts across the U.S., especially for rapid onset flash droughts where frequent updates and rapid response of predictors is critical for early warning of these high-impact events. Figure 1 shows several examples comparing the drought intensification probabilities computed using this method to changes in the USDM for several regions that experienced flash drought. For each case, the intensification probabilities became very large several weeks prior to when rapid drought intensification was depicted by the USDM and then diminished as the drought conditions became more severe. These examples demonstrate that statistical regression methods that combine drought early warning signals in rapid response variables such as the ESI, topsoil moisture, and short-term precipitation can produce useful probabilistic forecasts of drought development.

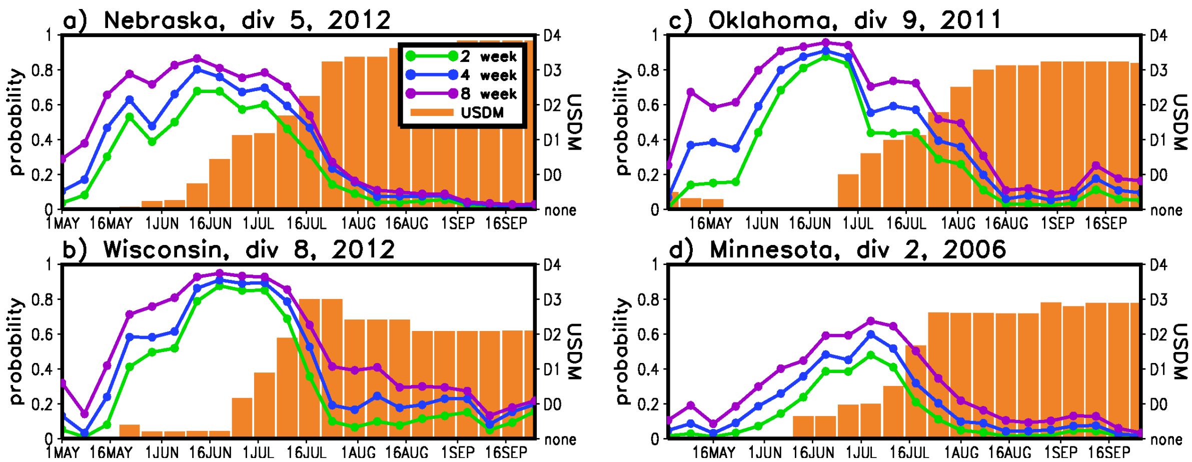

Figure 1. Time series of the USDM drought depiction (orange) and cross-validated drought intensification probabilities over 2, 4, and 8-week time periods (green, blue, and purple lines). The probability axis is shown on the left side of each panel, with the USDM axis shown on the right side.

As part of the development process, we explored potential reasons for variations in the forecast skill found across different parts of the U.S. and for different USDM drought intensities. We found that the forecast skill is largest for the most intense droughts and for droughts that intensify most rapidly. For the USDM state estimates, the skill was highest for the “no drought” and “exceptional drought” categories, which are the extremes of the USDM distribution, and conversely, was lower for the intermediate drought categories. This behavior is illustrated in Fig.2, which shows the Brier Skill Score (BSS) averaged over the contiguous U.S. for each of the six categories. Overall, forecast skill is highest for the “no drought” category, drops significantly for the “abnormally dry” category and then gradually increases for more extreme drought categories.

It turns out that the USDM state estimate model predicts the same dependence of skill on drought category. This can be demonstrated by assuming that our conditional probability distribution function (PDF) of the USDM is in fact the true PDF of the USDM given the chosen predictors. We then randomly sample the PDF to make a synthetic time series of the USDM that is perfectly consistent with our statistical model and then compute the BSS for the synthetic time series. The domain average BSS for each drought category for the observed and synthetic USDM is shown in Fig. 2. As expected, because the synthetic USDM estimates are perfectly consistent with our predicted PDF, its BSS is higher. The interesting result, however, is that the observed dependence of the BSS on drought category is very well captured by the synthetic data. This demonstrates that the low BSS observed for the intermediate drought categories is not a result of a poor fit to the data, but instead indicates that intermediate drought categories are inherently less predictable.

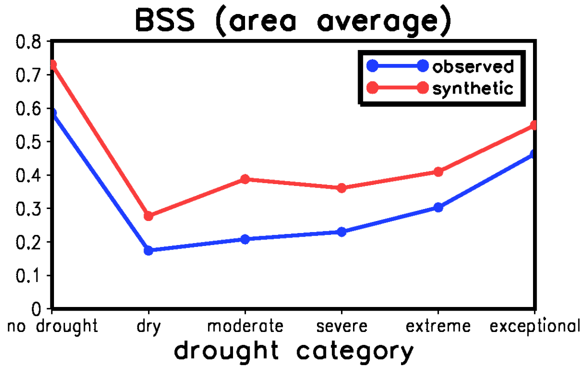

Fig. 2. Domain averaged Brier Skill Scores (BSS) plotted as a function of USDM drought category for the cross-validated empirically derived estimates (blue) and from synthetic estimates that are perfectly consistent with our USDM state estimation model (red).

The empirical method described in Lorenz et al. (2017a,b) 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 atmospheric conditions during the next 1-3 months. To explore this possibility, we expanded the empirical method during the second half of the project to also include output from the CFS model. To this end, we initially evaluated the relationship between USDM intensification and various predictor variables from 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 expanded version of the hybrid statistical method uses logistic regression with a sign constraint placed on the predictor coefficients, which is unchanged from the previous version described in Lorenz et al (2017a, b). The predictors used in the expanded method include anomalies in precipitation, potential evapotranspiration, dew point depression, and soil moisture from the forecast model, along with current anomalies as used in the original version of the method. The cross-validated BSS for 2-wk drought intensification forecasts generated with and without using climate model output as additional predictors are shown in Figs. 3a and 3b, respectively, with the change in skill shown in Fig. 3c. Comparisons between the baseline forecast skill obtained using recent anomalies only and the skill obtained by adding CFS forecast fields as predictors show that the inclusion of the CFS model output leads to a very modest increase in skill. An analysis of this result revealed that the small increase in skill was due to the limited skill of the CFS forecasts themselves rather than to a time delay in the USDM depiction of drought conditions. Perfect model experiments also showed that not all of the forecast lead times (e.g., 1, 2, 3, and 4 weeks) were equally important. For example, in the upper Midwest and western U.S., the first two weeks of the CFS forecasts account for at least two thirds of the total realizable skill in the four-week drought intensification forecasts.

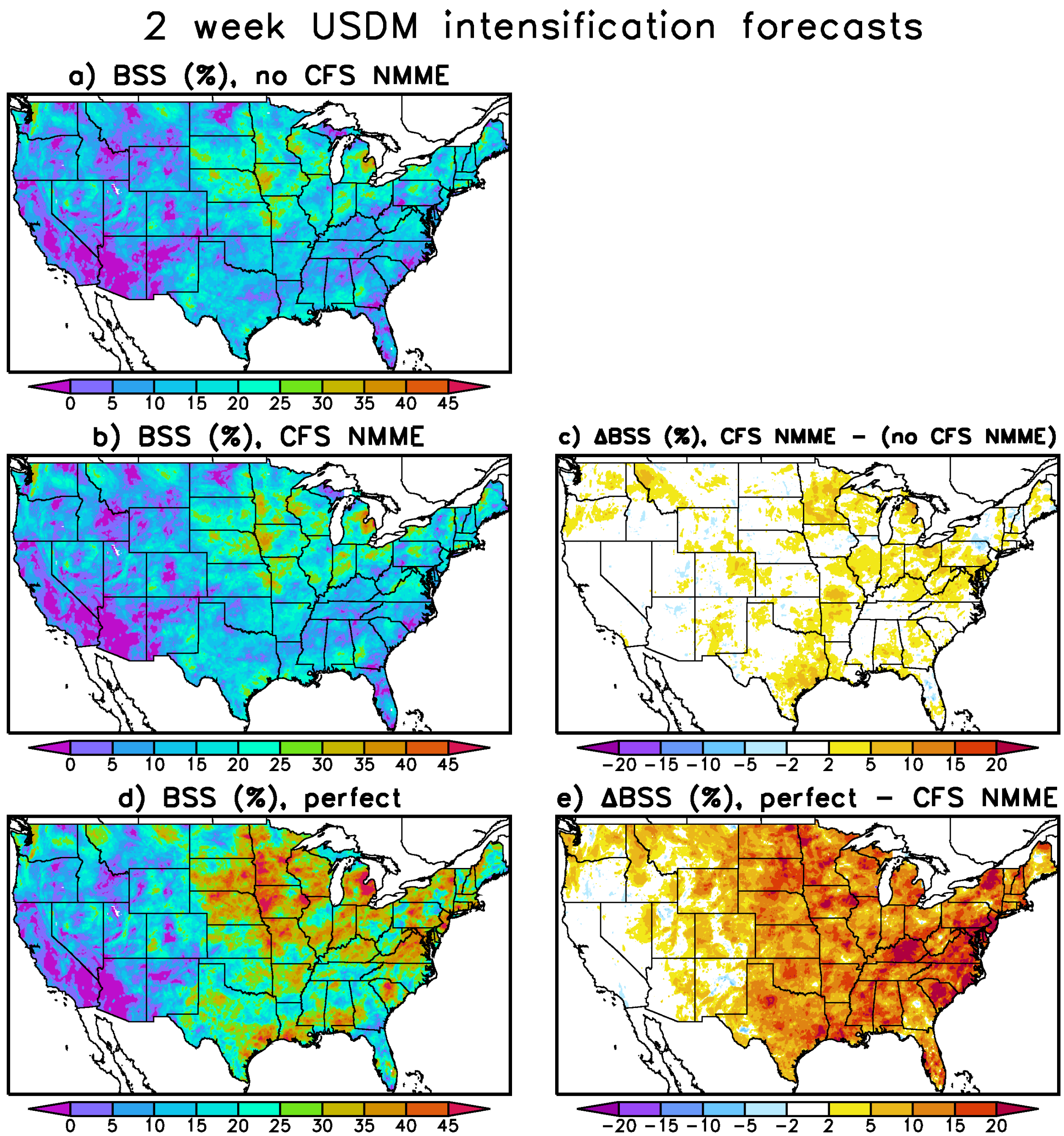

Figure 3a) Brier Skill Scores (BSS) for the 2 week USDM intensification forecasts using only current and past CFSR data as the predictors. b) Same as (a) except including future CFS NMME predictors. c) The difference in BSS between panels (a) and (b). d) Same as (a) except for using future observed CFSR 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. 3 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 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 forecasts of the future. The result of this "perfect" CFS forecast experiment is shown in Fig. 3d and the change compared to the original "imperfect" CFS forecast experiment is shown in Fig. 3e. Overall, the improvements in 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 model could lead to significant improvements in forecasts of USDM drought development.

B) 2012 Central U.S. flash drought analysis

To increase our understanding regarding the response of vegetation and soil moisture during flash drought onset and its subsequent evolution, we completed a study (Otkin et al. 2016) that examined the evolution of various drought datasets during the flash drought event that impacted major agricultural areas in the central U.S. during 2012. Standardized anomalies from the remote sensing based ESI and Vegetation Drought Response Index (VegDRI) and modeled soil moisture anomalies from NLDAS were compared to drought analyses from the USDM, surface meteorological conditions, and crop and soil moisture datasets compiled by the National Agricultural Statistics Service (NASS).

Overall, the results showed that rapid decreases in the ESI and NLDAS anomalies often preceded drought intensification in the USDM by up to 6 weeks depending on the region. Decreases in the ESI tended to occur up to several weeks before deteriorations were first observed in the NASS crop condition datasets. The NLDAS soil moisture anomalies were similar to those depicted in the NASS soil moisture datasets; however, some differences were noted in how each of the NLDAS land surface models responded to the changing drought conditions. The VegDRI anomalies tracked the evolution of the USDM drought depiction in regions with slow drought development, but lagged the USDM and other drought indicators when conditions were changing rapidly.

The impact of the severe flash drought conditions on end-of-season crop yields was also assessed. Figure 4 shows the trend-adjusted yield departures for corn, soybeans, winter wheat, and spring wheat, along with ESI, NLDAS, VegDRI, and SPI anomalies during critical stages for yield production in each crop. The yield departures are expressed as percentages above and below the 2000-2014 yield trend for each county to account for local differences in crop yield and trend. One of the most critical periods for wheat yield production occurs between the booting and soft dough stages during late spring for winter wheat and early summer for spring wheat. For winter wheat, there is a strong relationship between above average yield over Oklahoma and southeastern Kansas and positive ESI anomalies on 12 May, with negative ESI anomalies over the High Plains and the eastern Corn Belt where yields were below average. For spring wheat, the ESI also contains large negative anomalies in regions with below average yield, such as Montana and western South Dakota. A strong correspondence also exists between the VegDRI anomalies and wheat yield departures across most of the central U.S. The NLDAS anomalies, however, exhibit a much weaker relationship to the final yield for both crops. For example, the NLDAS anomalies are mostly negative across the southern Plains on 12 May where winter wheat yields were well above average but were mostly positive across Montana on 16 June where spring wheat yields were below normal.

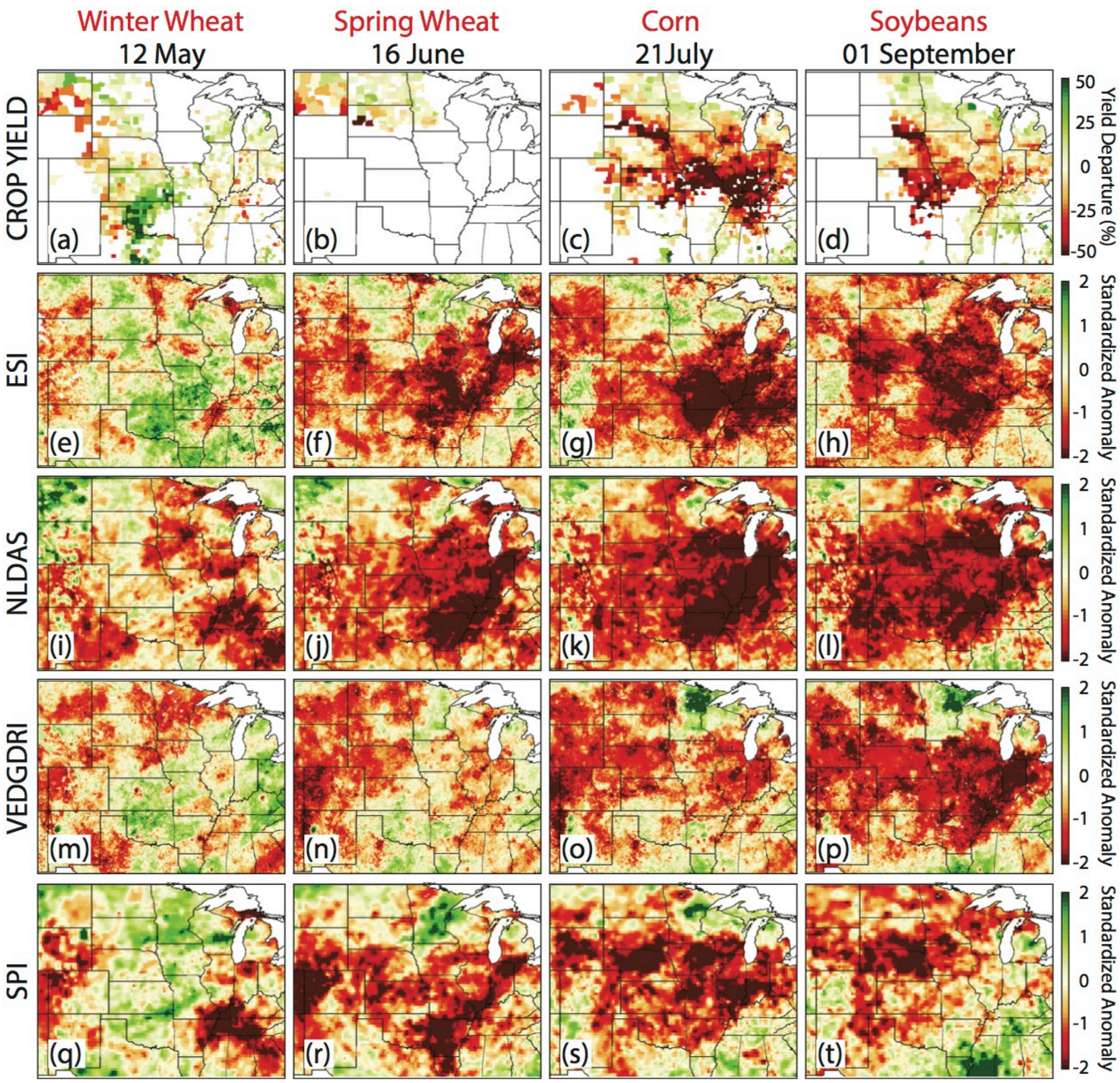

Fig. 4. Trend-adjusted yield departures (%) for 2012 for (a) winter wheat, (b) spring wheat, (c) corn, and (d) soybeans for each county computed with respect to the 2000-2014 base line period. ESI 4-week standardized anomalies for (e) 12 May, (f) 16 June, (g) 21 July, and (h) 01 September. (i-l) Same as (e-h) except for 4-week NLDAS soil moisture standardized anomalies. (m-p) Same as (e-h) except for VegDRI standardized anomalies. (q-t) Same as (e-h) except for 8-week SPI standardized anomalies.

The extreme drought conditions had a much larger impact on corn and soybean yields across the Midwest. July is the most important month for corn yield because excessive heat during that month can significantly decrease pollination efficiency during the critical silking and tasseling stages. For soybeans, however, the most important development stages occur during the second half of summer when soybean pods develop and the seeds still have time to increase in size if the plants receive adequate rainfall. Comparison of the drought indices on 21 July reveals that the spatial pattern in the ESI anomalies most accurately corresponds to the observed corn yield departures, including below average yield from Missouri to southern Indiana and the above average yield over Minnesota and North Dakota. The NLDAS anomalies were also strongly negative across the central and eastern Corn Belt; however, the large anomalies extended too far to the north into areas that had near to above average yields. Though VegDRI also exhibits negative anomalies in most locations, its correspondence to the final corn yield is much weaker than the other datasets because of its slow response to the rapidly changing conditions experienced during this drought. Its performance improved for soybeans, with negative anomalies and a spatial pattern that more closely matches those depicted by the other variables during the bean filling stage (e.g., 01 September).

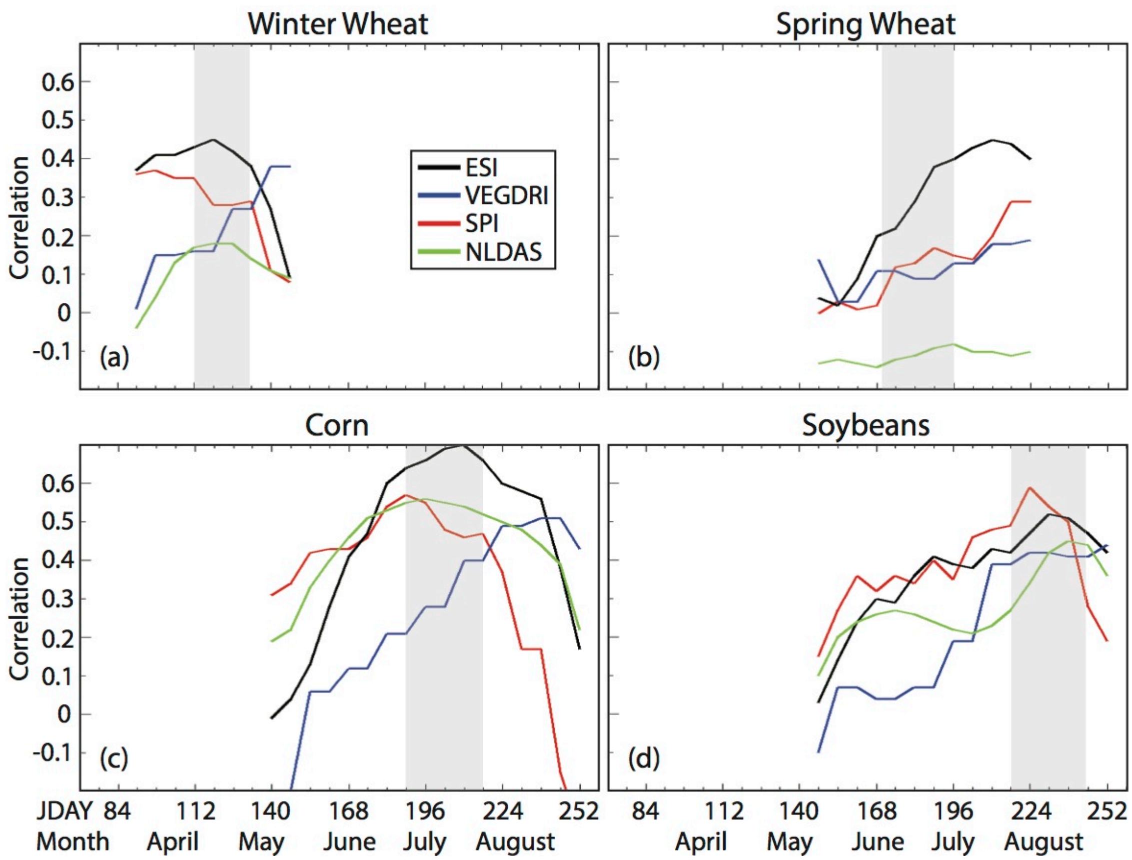

Fig. 5. Time series of correlations between county-level trend-adjusted crop yield departures (%) for (a) winter wheat, (b) spring wheat, (c) corn, and (d) soybeans and ESI (black), VEGDRI (blue), SPI (red), and NLDAS (green) anomalies at weekly intervals during 2012. The gray-shaded regions indicate critical development periods for each crop. The time series are only plotted during the growing season for a given crop.

To further assess relationships between the various drought indices and the 2012 crop yields, correlations were computed between the NASS county-level trend-adjusted crop yield departures and the ESI, SPI, VegDRI, and NLDAS anomalies at weekly intervals during the growing season (Fig. 5). The correlations typically increase for each crop as the growing season progresses and reach their peak values near critical stages of yield development. For most crops, the ESI data exhibited the strongest correlations to yield anomalies during these critical stages, most notably for corn and wheat. Given the importance of rainfall for yield production, the SPI correlations were also strong, but were weaker than those computed using the ESI data except for soybeans. The stronger correlations exhibited by the ESI demonstrate that although rainfall departures are important for yield production, it is also necessary to consider other drivers of drought such as hot temperatures when assessing agricultural drought severity and potential impact on yield. Finally, although the NLDAS correlations were relatively strong for corn, they were weaker for the other crops and were even negative for spring wheat. Taken together, these results show that datasets that are sensitive to ET and soil moisture anomalies can be used not only to depict current drought conditions but also to predict annual crop yield departures for major agricultural crops.

C) Climatological study of factors influencing stress signals in the ESI

To better understand the relationship between the ESI and various atmospheric and land surface variables during the warm season, we performed a correlation analysis across the U.S. (Otkin et al. 2018). In particular, correlations were computed between the ESI and anomalies in precipitation (SPI), topsoil and total column soil moisture (TS and TC) from NLDAS, and 2-m dew point depression, 2-m air temperature, 10-m wind speed and downward shortwave radiation (DPD, TEMP, WSPD, and DSW) from CFSR. Figures 6 and 7 show the Pearson correlation coefficients between the 4-week ESI and the 4-week SPI, TS, TC, DPD, TEMP, WSPD, and DSW anomalies at monthly intervals from April to September. Note that the sign is reversed for the DPD, TEMP, WSPD, and DSW correlations given the expectation that larger (smaller) values for each of these variables will typically be associated with higher (lower) moisture stress and negative (positive) ESI anomalies when assessed over long time periods. The correlations were computed separately for each grid point and month using all of the weekly analyses from 2001-2015 for which the end of the 4-week period used to compute the anomalies for each dataset fell within a given month.

Inspection of Figs. 6 and 7 reveals that in most locations the strongest correlations occur for the DPD, TS, TC, and SPI variables. This combination indicates that anomalies in the ESI are most closely related to anomalies in soil moisture and near surface humidity. The correlations for these variables show that periods characterized by larger (smaller) DPD and below (above) average TS, TC, and SPI often contain negative (positive) ESI values. In contrast, correlations for T, WSPD, and DSW are much weaker across most of the U.S., with the exception of the south central U.S. where correlations are large for each of these variables at some point during the growing season. This region is located within an east-west transition zone between arid climates to the west and humid climates to the east where longitudinal shifts in the rainfall gradient strongly impact the weather. It is also a well-known hot spot for land-atmosphere coupling, which occurs when soil moisture and vegetation anomalies influence the partitioning of surface energy between sensible and latent heat fluxes. The results also show that the strengths of these relationships vary during the growing season across this region. For example, the correlations for DSW are largest during the spring and early summer when surface radiation anomalies due to changes in cloud cover influence the timing and vigor of early plant growth and its release of ET, whereas TEMP anomalies are more important during the second half of the growing season when unusually hot (cool) temperatures may hasten (delay) vegetation senescence. For the remaining variables (DPD, TS, TC, and SPI), the correlations are large during most of the growing season. Together, this indicates that ET fraction anomalies within this region of enhanced land-atmosphere coupling are most closely related to variables capturing changes in the supply and demand of surface moisture.

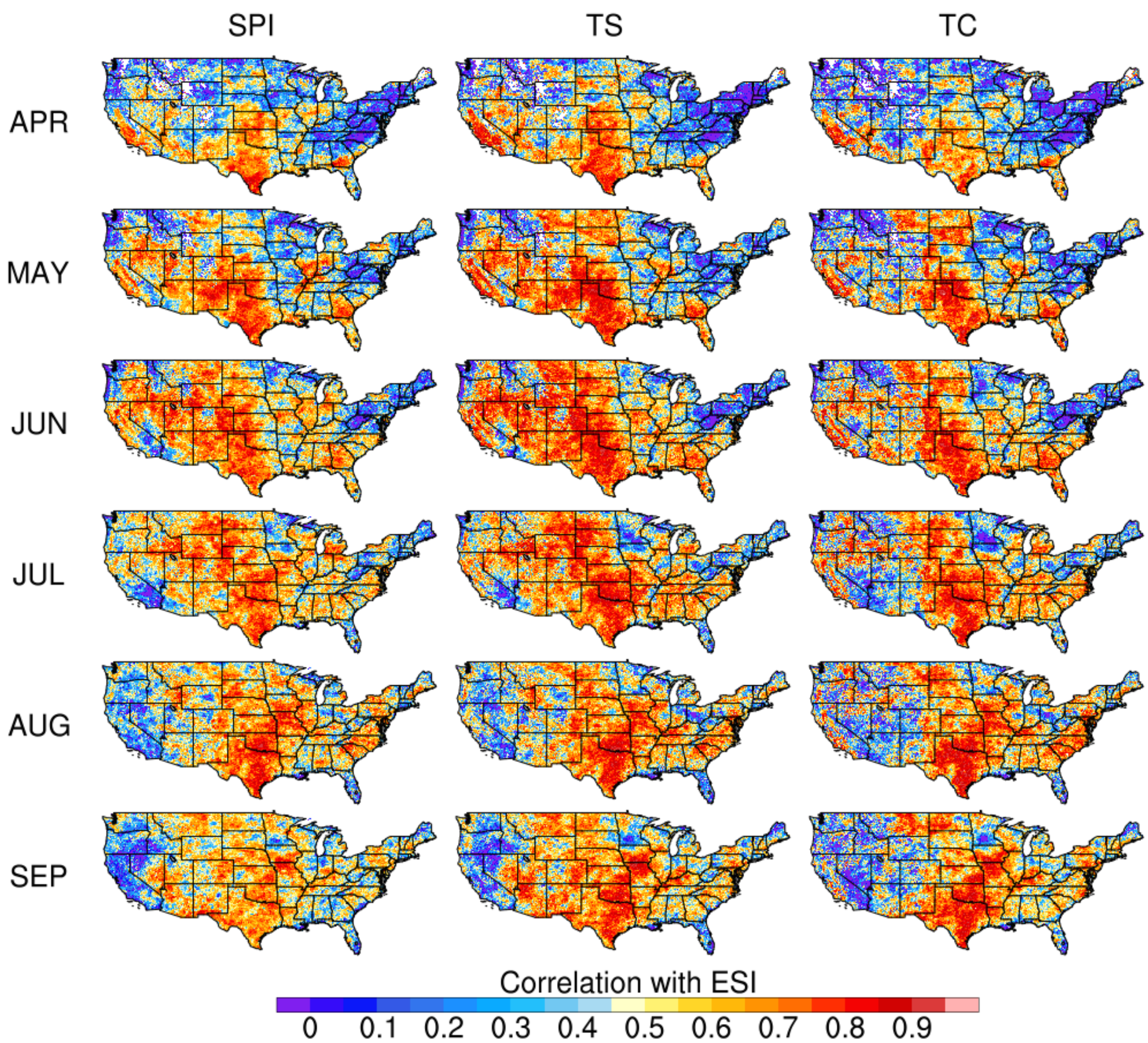

Figure 6. Pearson correlation coefficients computed between the 4-week ESI and 4-week SPI, TS, and TC anomalies. The correlations were computed separately for each grid point and month using all of the weekly analyses from 2001-2015 for which the end of the 4-wk period was within a given month.

Unlike the south central U.S. where strong correlations exist between the ESI and each of the variables, much weaker correlations occur across other parts of the U.S. For example, very low correlations (< 0.2) predominate across most of the northeastern U.S. during the spring and early summer. The strength of the correlations increases during the second half of the growing season, with the largest correlations found for DPD, SPI, TS, and TC; however, they remain weaker than those found across the south central U.S. A similar evolution occurs within an east-west band extending from the Pacific Northwest to the Great Lakes, with the smallest correlations generally occurring in regions containing extensive forests. The small correlations indicate that there are no dominant drivers of normalized ET during the first half of the growing season in these regions, presumably because of their relatively cool and moist climates and the much deeper root structures in forests that allow trees to tap into deeper soil moisture than other types of vegetation. ET becomes more strongly coupled to the atmospheric and land surface variables later in the growing season as these regions move from being primarily energy-limited regimes to potentially moisture-limited regimes.

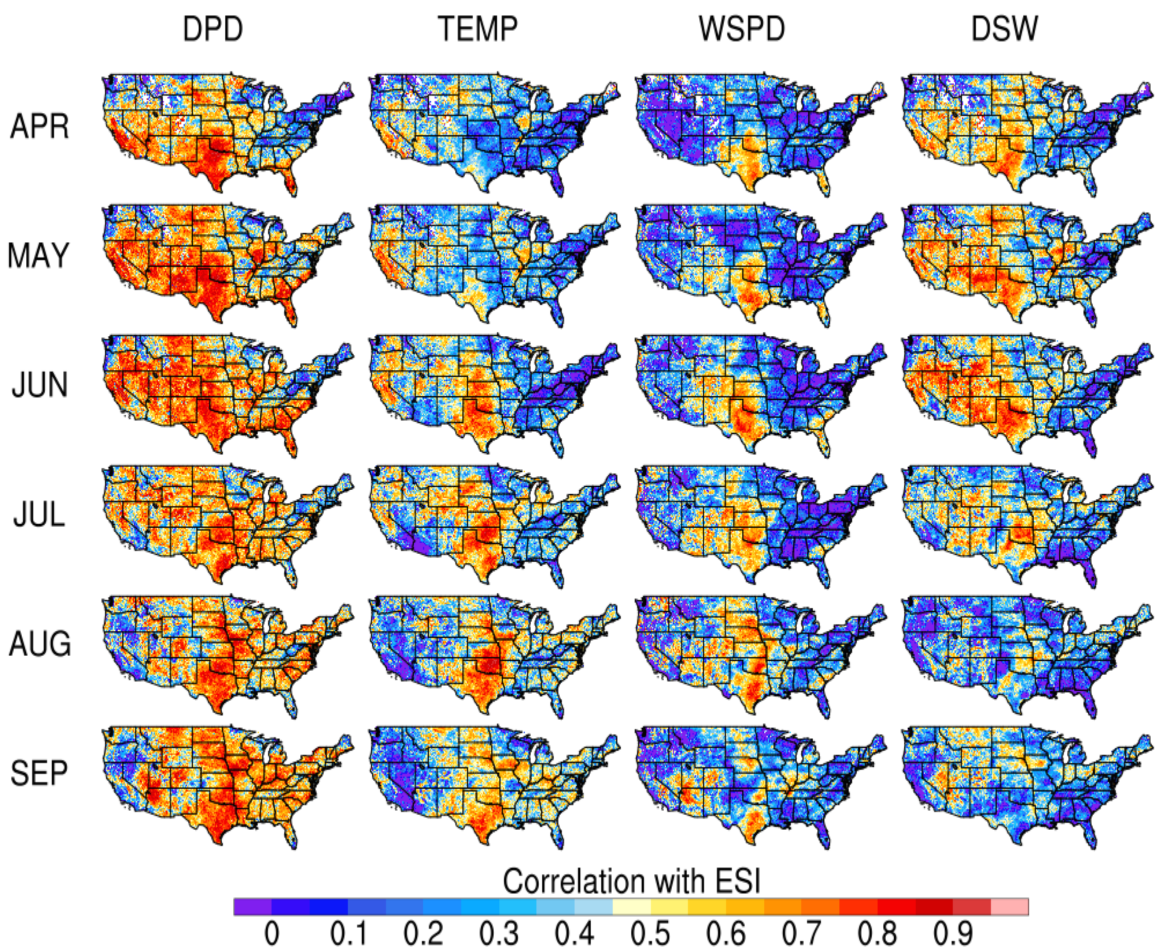

Figure 7. Same as Fig. 6, except for showing correlations computed between the 4-week ESI and 4-week DPD, TEMP, WSPD, and DSW anomalies. Note that the sign has been reversed for the correlations so that positive correlations indicative of enhanced drying are shown in yellow and red colors.

D) Flash drought review paper

In recent years, two distinct approaches have been used to identify features of the climate system referred to as “flash droughts.” The first approach identifies them based on their unusually rapid rate of intensification whereas the second approach implicitly focuses on their duration. These conflicting notions for what constitutes a flash drought (unusually rapid intensification versus short duration) introduce ambiguity that affects our ability to detect their onset, monitor their development, and understand the processes that control their evolution. Given the increasing use of the term “flash drought” by the media and scientific community, it is prudent to develop a consistent definition that can be used to identify these high impact climate events and to understand their salient characteristics. To address this need, the project team leveraged funds from this and other projects to write a flash drought review article that was published in the May 2018 issue of the *Bulletin of the American Meteorological Society*. In that article, we propose that the definition for flash drought should explicitly focus on its rate of intensification rather than its duration, with droughts that develop much more rapidly than normal identified as flash droughts. There are two primary reasons for favoring the intensification approach over the duration approach. First, longevity and impact are fundamental characteristics of drought. Thus, short-term events lasting only a few days and having minimal impacts are inconsistent with the general understanding of drought and therefore should not be considered flash droughts. Second, by focusing on their rapid rate of intensification, the proposed flash drought definition highlights the unique challenges faced by stakeholders who have less time to prepare for its adverse affects.

3. Transitions to operations

A) Transitioning the Evaporative Stress Index into NOAA operations

Prior studies aimed at enhancing our ability to monitor and forecast drought conditions used the ESI in a research setting; however, real-time access to the ESI is necessary to develop a reliable and robust drought early warning system. Thus, we provided assistance during a jointly funded effort by NOAA and NASA led by Co-PI Hain that transitioned the ALEXI/ESI modeling system to NOAA operations. This system, known as the “GOES Evapotranspiration and Drought Product System (GET-D)”, became operational in 2016 and produces ESI datasets covering most of North America with 8-km horizontal resolution and the contiguous U.S. with 4-km resolution. We assisted development efforts by evaluating prototype versions of the GET-D processing system and identifying errors in preliminary datasets.

B) Transitioning the probabilistic forecasts to collaborators at NASA SPoRT

To promote the potential use of the drought intensification forecasting method within an operational system, work was underway at the end of the project to include it within the quasi-operational ESI-Global Drought Product System (ESI-GDPS) being developed at the NASA Short-term Prediction Research Transition (SPoRT). All of the programs, scripts, and datasets required to generate the probabilistic forecasts were delivered to Co-PI Hain in 2018. A recently hired post-doc at NASA is currently implementing the source code at NASA SPoRT and internal testing will occur in Fall of 2018 and near-real-time production is targeted for early 2019. After testing is complete and the products are being generated in real-time, the NASA SPoRT webpage (https://weather.msfc.nasa.gov/sport/) will be expanded to include a drought-themed page for the ESI that will include the drought intensification probabilistic forecasts. Inclusion of the probabilistic forecasts on this quasi-operational webpage will promote their routine use by project stakeholders.

4. Highlights of accomplishments

- Developed an innovative hybrid-statistical method that is able to generate skillful probabilistic drought intensification forecasts over sub-seasonal time scales
- Performed a detailed case study analysis of the 2012 flash drought event over the central U.S. that assessed the evolution of several satellite-derived and model-based drought metrics sensitive to ET, soil moisture, and vegetation conditions
- Demonstrated that anomalies in drought metrics such as the ESI can be used not only to depict current drought conditions but also to predict end-of-season crop yields for major agricultural crops
- 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
- Published a review article in the *Bulletin of the American Meteorological Society* describing recent research on flash droughts and presented a definition for these climate features that focuses on their unusually rapid rate of intensification
- Published six journal articles describing results from research performed during this project
- Supported research-to-operations (R20) efforts led by Co-I Hain to transition the ALEXI/ESI system from a research tool to a NOAA operational data product
- Delivered model code to collaborators at NASA SPoRT that will promote the use of the probabilistic drought intensification forecasts through their inclusion in a quasi-operational system

5. Publications funded entirely or partially by the project

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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.,* **18**, 1943-1962.

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.,* **18**, 1963-1982.

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Otkin, J. A., Y. Zhong, D. Lorenz, M. C. Anderson, and C. Hain, 2018: Exploring seasonal and regional relationships between the Evaporative Stress Index and surface weather and soil moisture anomalies across the United States. *Hydrology Earth System Sciences*, in press.

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