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Key Points:
- We develop a statistical, probabilistic flash drought forecasting method using recent observations and subseasonal climate model forecasts
- Due to modest climate model forecast skill, recent observations dominate the overall skill of the forecasting method
- Perfect model experiments show that short forecast lead times are most important for the upper Midwest and western United States

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Forecasting Rapid Drought Intensification Using the Climate Forecast System (CFS)

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Abstract In this study, a statistical method is developed to generate probabilistic forecasts of U.S. Drought Monitor (USDM)-depicted drought intensification over two-, four-, and six-week time periods using recent observations and forecast model output from the Climate Forecasting System (CFS). The predictors used include weekly anomalies in precipitation, potential evapotranspiration, dew point depression, and soil moisture computed over different time lags. A comparison between the baseline skill obtained using recent observations only and the skill obtained by adding CFS forecast fields as predictors shows that the inclusion of CFS model output leads to only a very modest increase in skill (about 14% increase in variance explained over the central and eastern United States). An analysis of this result reveals that the small increase in skill is due to limited skill in the CFS forecasts themselves, rather than to a time delay in the USDM response to conditions on the ground. Perfect model experiments also show that not all forecast lead times are equally important. For example, in the upper Midwest and western United States, the first two weeks account for at least two thirds of the total realizable skill for a four-week forecast.

Plain Language Summary Among the most damaging droughts are those that develop very rapidly because they provide less time to prepare or make decisions. In this study, we develop a methodology to forecast these rapidly evolving *flash droughts* using information from a combination of recent weather observations and seasonal climate model forecasts.

1. Introduction

Drought is a natural form of climate variability that has destructive impacts on agriculture (Hatfield et al., 2011; Mallya et al., 2013; Zhang et al., 2014), water resources (Shukla et al., 2015; van Dijk et al., 2013), human health (Pappagianis, 1994; Park et al., 2005; Stanke et al., 2013), and natural ecosystems (Bond et al., 2008; Bréda et al., 2006; Humphries & Baldwin, 2003; van Dijk et al., 2013). Because of the wide range of different impacts, precisely defining drought has proven to be difficult (Hayes et al., 2011; Vicente-Serrano et al., 2012). In the United States, one of the most comprehensive drought indices is the U.S. Drought Monitor (USDM; Svoboda et al., 2002). The USDM is created each week through expert synthesis of numerous data sources, including surface streamflow, soil moisture, rainfall anomalies, temperature anomalies, and crop and range conditions. In the USDM, each location is classified into one of six categories ranging from wet to dry: *no drought*, *abnormally dry* (D0), and moderate (D1), severe (D2), extreme (D3), and exceptional (D4) droughts.

Droughts have a large range of intensities, durations, and rates of evolution. Among the most damaging droughts are those that develop very rapidly (e.g., Ford & Labosier, 2017; Hunt et al., 2014; Mozny et al., 2012; Otkin et al., 2013, 2018; Svoboda et al., 2002) because they provide less time for stakeholders to implement proactive measures in a timely manner. Such *flash droughts* have traditionally received less attention in drought forecasts, which tend to focus on seasonal time scales. Hence, there is a pressing need for drought warning systems on subseasonal time scales with frequent updates. A promising approach to subseasonal drought forecasting is the use of short-term temporal tendencies in drought indices to identify regions with increased likelihood of drought. For example, Otkin et al. (2013, 2015) produced skillful USDM forecasts using a newly proposed Rapid Change Index, which is based on the temporal tendency of the Evaporative Stress Index (ESI; Anderson et al., 1997; Anderson, Kustas, & Norman, 2007; Anderson et al., 2011). Similarly, Ford et al. (2015) show that anomalies in observed soil moisture often precede the development of drought in Oklahoma.

Recently, Lorenz et al. (2017a, 2017b) developed a probabilistic statistical forecasting methodology that uses recent anomalies in precipitation, ESI, and modeled soil moisture to predict the probability of USDM intensification occurring over subseasonal time scales. In this paper, we extend the results of Lorenz et al. (2017a, 2017b) by including forecasts of drought-related fields from the North American Multi-Model Ensemble (NMME; Kirtman et al., 2014). The NMME has been used to forecast future drought (Yuan and Wood, 2013; Mo and Lyon, 2015; Thober et al., 2015); however, this guidance has typically been applied to seasonal time scales. In this paper, the Climate Forecast System version 2 (CFSv2) component of the NMME will be used to predict drought intensification at two-, four-, and six-week time scales through an extension of the statistical methodology of Lorenz et al. (2017a, 2017b). One advantage of this methodology is that the current and past observations can be combined with CFS forecasts into a single USDM intensification probability that takes into account both sources of predictability. We begin by discussing the statistical methodology, and the data and model inputs. Second, baseline USDM predictions using recent observations only are compared with predictions that also include fields from the CFS. Next, we analyze the source of skill and the potential for further improvement. Finally, we summarize the results and discuss the highest priority directions for future work that will likely have the most positive impact on forecasting changes in the USDM or other drought metrics.

2. Methodology

A detailed description of the statistical methodology to predict USDM-depicted drought intensification is given in Lorenz et al. (2017a, 2017b). In this paper, forecast fields from the CFS are used as predictors to improve the accuracy of the USDM predictions in Lorenz et al. (2017b). A summary of the most relevant parts of the methodology are given here.

Because the USDM drought depiction is represented by discrete values, a straightforward methodology such as standard linear regression is not appropriate. Therefore, we use logistic regression to predict a binary variable that takes the value 1 if the USDM is more intense in n weeks and 0 otherwise. In this paper, n is two, four, or six weeks. The predictors for the logistic regression include weekly composites of precipitation, potential evapotranspiration (PET), dew point depression, and topsoil moisture (0–10 cm). All predictors are standardized prior to the logistic regression. Instead of using only one predictor for each variable, we implement a range of different weekly time lags as separate predictors. For example, in Lorenz et al. (2017b), precipitation accumulation over the most recent week as well as weekly composites for one, two, and three weeks prior is used as separate individual predictors. In this paper, this same set of current and past weekly composites is used (i.e., weeks 0, -1, -2 and -3, where negative corresponds to the past); however, we now add additional weekly composites of future conditions as forecasted by the CFS. For an n week USDM forecast, we use n additional predictors per variable: one for each week from 1 to n in the future. For example, for the two-week USDM forecasts, each variable has six total predictor time lags for -3, -2, -1, 0, 1, and 2 weeks relative to the present time. This scheme allows the data to choose the optimal weighting in time, or equivalently, the data chooses the optimal time scale for averaging each predictor.

In this study, as in Lorenz et al. (2017b), standard logistic regression is modified so that the regression coefficients multiplying the predictors are constrained to be nonnegative using Non-Negative Logistic Regression (NNLR). The advantage of NNLR is found in its regularization properties (Meinshausen, 2013; Slawski & Hein, 2013), which penalize excessive complexity (i.e., large positive and negative coefficients whose effects mostly cancel), and therefore, NNLR almost always shows better skill on independent data compared to standard linear regression. Moreover, NNLR is easy to apply for drought prediction because the sign of the true, physically based coefficients is known a priori. Note that if the physically based coefficient is negative, simply multiply the predictor by -1. With many predictors, NNLR regression will result in nonzero weights for a subset of the predictors and the rest of the weights will be exactly zero. Hence, NNLR is able to discard unimportant or redundant variables. See Lorenz et al. (2017a, 2017b) for more details.

A key finding of Lorenz et al. (2017b) is that including information on how far the current USDM state is from next higher or lower drought category helps improve skill significantly. This USDM state variable is used as an additional predictor for the logistic regression in this paper as well. The USDM state variable is calculated in exactly the same way as in Lorenz et al. (2017b) except it is extended through the year 2016. We do not discuss this aspect of the methodology further because it is independent of the use of CFS forecasts, which is the

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subject of this paper. Also, we use the (cross-validated) climatological intensification probability as a predictor as well (Lorenz et al., 2017b). This predictor is useful if the USDM is more likely to intensify during a particular time of year compared to other times. All skill scores shown below are cross validated: we incrementally leave one year out of the fit and then test predictions on that year.

3. Observed and CFS Forecast Data

The weekly USDM classifies conditions into six categories based on expert synthesis of numerous data sources (Svoboda et al., 2002). The six categories from wettest to driest are no drought, abnormally dry (D0), moderate drought (D1), severe drought (D2), extreme drought (D3), and exceptional drought (D4) and are based on a ranking percentile classification scheme.

The predictors in this study have been modified from Lorenz et al. (2017b): the predictor variables are restricted to those available as CFS NMME output. For example, the ESI (Anderson, Norman, et al., 2007) is a satellite-based drought indicator, based on a surface energy balance model (ALEXI; Anderson et al., 1997) driven by changes in land surface temperature that is statistically independent to the CFS, and therefore, it is not used (except for the USDM state predictor; see section 2). The predictors chosen for this study are weekly mean precipitation, PET, dew point depression, and soil moisture in the top 10 cm of the soil profile. The PET is calculated using the Penman-type algorithm in Mahrt and Ek (1984). The USDM and all predictors are gridded to the same $0.12 \times 0.12°$ resolution grid using the methods in Lorenz et al. (2017a).

3.1. Current and Past Data

As shown in Otkin et al. (2014, 2015) and Lorenz et al. (2017b) past anomalies in soil moisture, ET, and precipitation have skill in predicting future USDM intensification. Therefore, we continue to use current and past anomalies in these variables while also adding CFS-derived predictors of future conditions. Precipitation data are obtained from the Climate Prediction Center's gridded analysis of daily precipitation reports from National Weather Service reporting stations and cooperative observers (Higgins et al. 2000). Soil Moisture (total water mass per area from 0- to 10-cm depth) is taken from the North American Land Data Assimilation System (NLDAS; Mitchell et al., 2004; Xia et al., 2012). The soil moisture is the ensemble average value over three NLDAS models: (1) NOAH, (2) MOSAIC, and (3) VIC because this has been shown to more accurately depict drought conditions (Xia et al., 2014). The top-soil moisture is used instead of the total column soil moisture because we found it is more highly correlated with USDM intensification (not shown). PET and dew point depression are taken from the CFS Reanalysis (Saha et al., 2010).

3.2. CFS Forecasts

In this study, the CFS is used because more variables are available in the CFS than other NMME models. Using lagged correlation analysis between the USDM time tendency and various predictor fields, we found that soil moisture, PET, and dew point depression were much more highly correlated with USDM change than the more widely available air temperature fields. This is also consistent with recent studies by Otkin et al. (2018) and Ford and Labosier (2017), both of whom found stronger relationships between drought development and soil moisture, PET, and dew point depression. These variables are only available for the CFS and therefore only that model is used. The CFS NMME fields are the same as those that are used for current and past data: precipitation, PET, dew point depression, and 0–10 cm soil moisture.

From 1982 to 2011, four CFS forecasts were initialized at 0, 6, 12, and 18 UTC on every fifth day. After 1999, four CFS NMME forecasts were made every day; however, we only use forecasts from every fifth day so that a longer climatology can be used to help reduce model bias. The CFS forecasts are composited into weekly mean values from Tuesday morning to Tuesday morning (Tuesday morning is the data cutoff time for the USDM). The data from each of the four model runs produced each day are then averaged together to form a four-member ensemble-mean. To remove any bias in the mean forecast state, CFS data from 1982 to 2016 are used to form a climatological forecast for each initialization date and forecast lead time. This climatology is then subtracted from the forecasts. Next, values are normalized by the standard deviation to form standardized forecast anomalies. The longest USDM forecast presented here is for six weeks; therefore, the maximum CFS lead time is also six weeks plus up to four days to account for the five-day frequency of CFS forecasts used here.

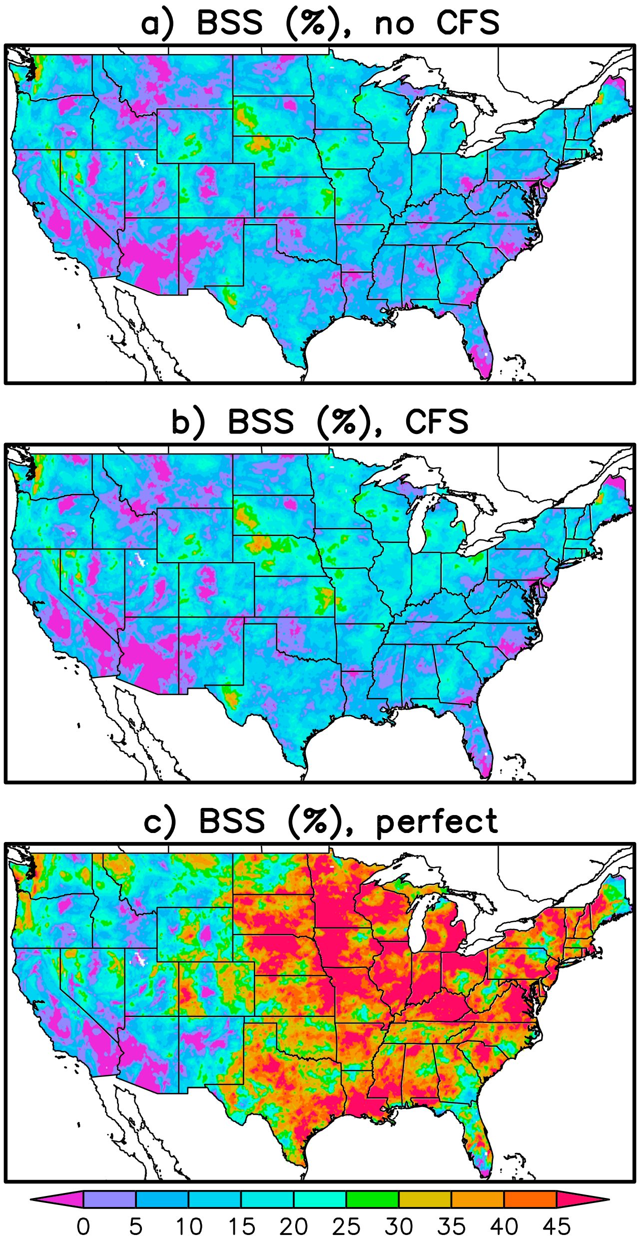

Figure 1. (a) Brier Skill Score (BSS) for the baseline four-week USDM intensification forecasts using current and past data only (no CFS forecasts). (b) As in (a) but with CFS forecasts fields added as predictors. (c) As in (b) but with future observations substituted for CFS forecasts. This panel shows potential predictability possible from a *perfect* CFS forecast.

4. Results

We begin by focusing on the four-week intensification forecasts and use the Brier Skill Score (BSS) as our forecast skill metric. The climatological intensification probability is used as the reference Brier score. The BSS using only current and past data (Figure 1a) shows highest skill in the north-central United States, which is consistent with Lorenz et al. (2017b). Adding four weeks of CFS NMME forecast data to this baseline forecast, however, leads to only very minor changes in USDM forecast skill (Figure 1b). As we will show shortly, the skill does tend to increase almost everywhere; however, the change is minor. There are two possible causes for the small effect of CFS forecast data: (1) a large portion of the USDM variability has a delayed response to conditions on the ground; therefore, very recent changes (i.e., last several weeks) do not yet impact the USDM, and (2) the CFS forecasts themselves have relatively little skill over these time scales (four weeks). The first possible cause is consistent with the fact that current and past information do have skill predicting future USDM intensification (Figure 1a and Lorenz et al., 2017b and Otkin et al., 2014, 2015), but to test this more rigorously a more quantitative approach is needed. To this end, we will test the second possible cause by substituting future *observations* for CFS forecasts in the prediction scheme. We call this experiment the *perfect* CFS forecast experiment. The BSS for the perfect CFS forecast (Figure 1c) is substantially larger than the actual CFS-based forecasts (Figure 1b); therefore, it appears that the USDM does respond in real time to conditions on the ground and that poor CFS forecast accuracy is the primary reason for the small improvements in BSS going from Figures 1a and 1b.

Because BSS is a squared measure analogous to the fraction variance explained, it is useful to average the BSS spatially to get a general, smoothed sense of the effect of the CFS forecasts. Averaged over the domain east of 105°W longitude, the BSS for the no CFS, CFS, and perfect CFS are 10.7%, 12.1%, and 37.7%, respectively. The CFS forecasts lead to a modest increase in variance explained compared to the baseline (from 10.7% to 12.1%). With a perfect CFS forecast, however, the fraction of variance explained more than triples. Therefore, the majority of the USDM variance is responding in real time as far as these four-week forecasts are concerned. Therefore, it is assumed that the limited CFS forecast accuracy over subseasonal time scales is the primary cause for the small improvements, although there is some portion of USDM variability that is determined by current and past conditions.

Expanding the analysis to include the two- and six-week predictions, Figure 2 shows the change in BSS going from no-CFS (i.e., baseline) forecasts to CFS-based forecasts (Figures 2a–2c) and the change in BSS going from the CFS-based forecasts to the perfect CFS forecasts (Figures 2d–2f). The top, middle, and bottom panels show the results for the two-, four-, and six-week forecasts, respectively. Hence, Figure 2b is the difference between Figures 1b and 1a, and Figure 2e is the difference between Figures 1c and 1b.

The effect of the CFS forecasts on the USDM skill is small but consistently positive (Figures 2a–2c). The improvement is largest and most robust for the four-week predictions and least consistently positive for the six-week predictions. The two-week improvements are almost as much as the four-week improvements but nevertheless tend to be slightly smaller. The fact that the six-week predictions tend to be less accurate than the 4-week forecasts on average indicates that the CFS forecast skill degrades at longer lead times. The two-week predictions, however, do not follow this rule. We believe that the two-week forecasts are

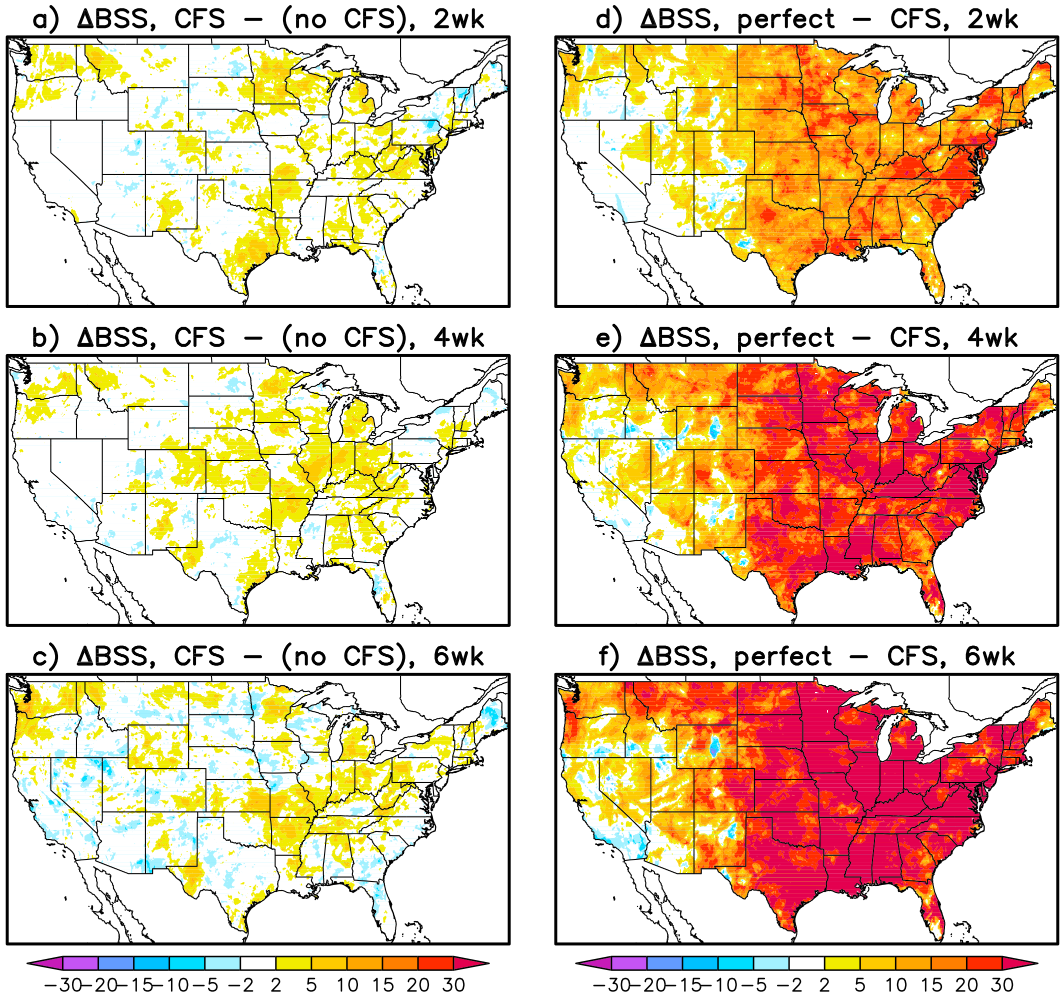

Figure 2. (a) The change in BSS going from the baseline (i.e. no CFS) two-week forecasts to the CFS-based forecasts. (b) As in (a) but for the four-week forecasts. (c) As in (a) but for the 6 week forecasts. (d) The change in BSS going from the CFS-based two-week forecasts to the *perfect* CFS-based (i.e., future observations) forecasts. (e) As in (d) but for the four-week forecasts. (f) As in (d) but for the six-week forecasts.

less accurate than the four-week forecasts because the precise timing of the intensification, in both the USDM and the CFS forecasts, matters more for the two-week predictions. For example, for the four-week forecast, the USDM can intensify during any of the following four weeks. The two-week forecasts, on the other hand, have a smaller time window where the intensification can occur and so the precise timing is more important.

The effect of perfect CFS forecasts (e.g., with actual observations used as the predictors) on USDM intensification forecasts in shown in Figures 2d–2f. As expected from Figure 1, the improvements in BSS are much larger here than for the actual CFS forecasts. In this case, the improvement increases as the forecast lead time increases from two to six weeks. In this case, the CFS skill degradation at longer forecast lead times is not an issue. Instead, the timing issue described in the previous paragraph implies that the USDM is easier to forecast at longer lead times because less precision in the timing of the USDM intensification is necessary.

The relative weight of the different predictor variables and predictor lags is shown in Figure 3. Because all variables are standardized before the logistic regression, the relative size of the regression coefficients (i.e., weights) quantifies the relative importance of the different predictors and time lags. To reduce noise, the regression coefficients are averaged over the domain east of 105°W (longitude of Denver, CO). Because of

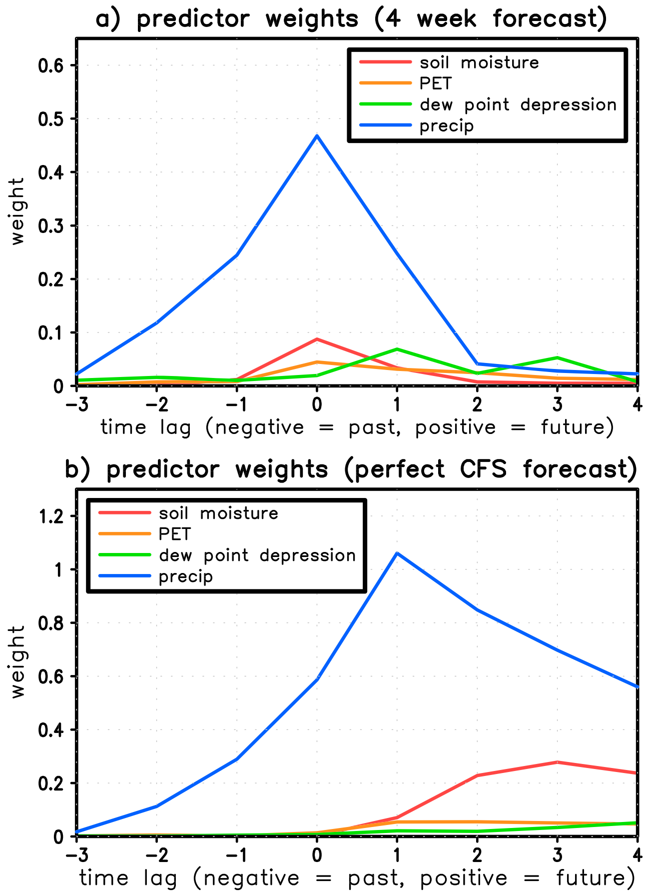

Figure 3. (a) Regression coefficients (i.e., predictor weights) averaged over the domain east of 105°W for the four-week CFS-based intensification forecasts. All predictors are standardized prior to the analysis, and therefore, the relative size of the weights tracks the relative importance of the predictor. Positive lags are the weights for future CFS forecasted fields and negative/zero lags are for past and current observations. (b) As in (a) but for the *perfect* CFS-based (i.e., future observations) forecasts.

the nonnegativity constraint in the logistic regression (see section 2), there is no possibility of large negative coefficients canceling large positive coefficients in the area average.

For the CFS-based forecasts, precipitation has the largest weight by far; however, some of this is due to the fact that the PET, dew point depression, and soil moisture are more strongly correlated with each other than they are to precipitation. In other words, the PET, dew point depression, and soil moisture variables are somewhat redundant, and therefore, the aggregate weight of these three variables is perhaps a more relevant measure of their importance. The precipitation weight is largest at zero lag, which means that the current precipitation is a better predictor of USDM intensification than the CFS forecast precipitation. The weight for the one-week forecast (+1) has about the same weight as one-week previous (−1). Beyond two weeks, there is almost no precipitation weight presumably because the skill of precipitation forecasts in the CFS degrades substantially at longer forecast times. The PET, dew point depression, and soil moisture weights are largest from lag 0 to lag +1, and all these predictors have almost no weight from past lags (−3 to −1). The fact that the peak weight is shifted toward positive lags compared to the precipitation suggests that CFS forecasts of these variables are more skillful, which is consistent with McEvoy et al. (2016).

For the perfect CFS forecasts, the weights increase because USDM forecast skill improves and the weights shift toward positive lags. For precipitation, the peak weight is at lag +1 and the current week precipitation (lag 0) is smaller than all future weights except possibly lag +4. Unlike precipitation, PET, dew point depression, and soil moisture have essentially zero weight for current and past time lags. The soil moisture weight peaks at two weeks, and the PET and dew point depression have uniformly small weights over all positive time lags. Also interesting is the fact that the small weights for PET and dew point depression suggest that they are unimportant once the future soil moisture is *known* with precision. The weights for the two and six-week forecasts are similar to the four-week forecasts (not shown).

The spatial structure of the regression weights is shown in Figure 4. To help summarize the results, the weights are summed over time lag for each predictor. Next, we add the weights of the nonprecipitation variables together (dew point depression, PET, and soil moisture) to better compare their aggregate importance to the more dominant precipitation. For the CFS forecasts, the precipitation dominates in the Midwest and is also very important through much of the central and eastern United States (Figure 4a). The other three variables are most important in the western United States where together they sometimes have more weight than precipitation (for example, the four corners region; Figure 4b). For the perfect model experiments, the precipitation is by far the most dominant predictor east of 100°W (Figure 4c). It is only in the western United States that the other predictors become comparable to or more important than precipitation.

The weights in Figure 3b suggest that the most important forecast times are lags +1 and +2 weeks, which is encouraging because two-week CFS skill is much more attainable than that at longer lead times. To quantify the effect of perfect one-week skill on the four-week USDM forecasts, we ran an additional experiment where we include only one week of future observations and no information at greater time lags (weeks 2, 3, and 4). We also repeated this experiment but for perfect two-week skill. The change in BSS relative to the CFS based forecasts is shown in Figures 5a and 5b. These maps should be compared with the change in BSS using the full four-week of future observations (Figure 2e). For the eastern United States the four-week perfect is substantially bigger than the one- or two-week perfect; however, as one moves west the difference becomes less big. To better compare these experiments, the ratio between the one- and four-week experiments is shown

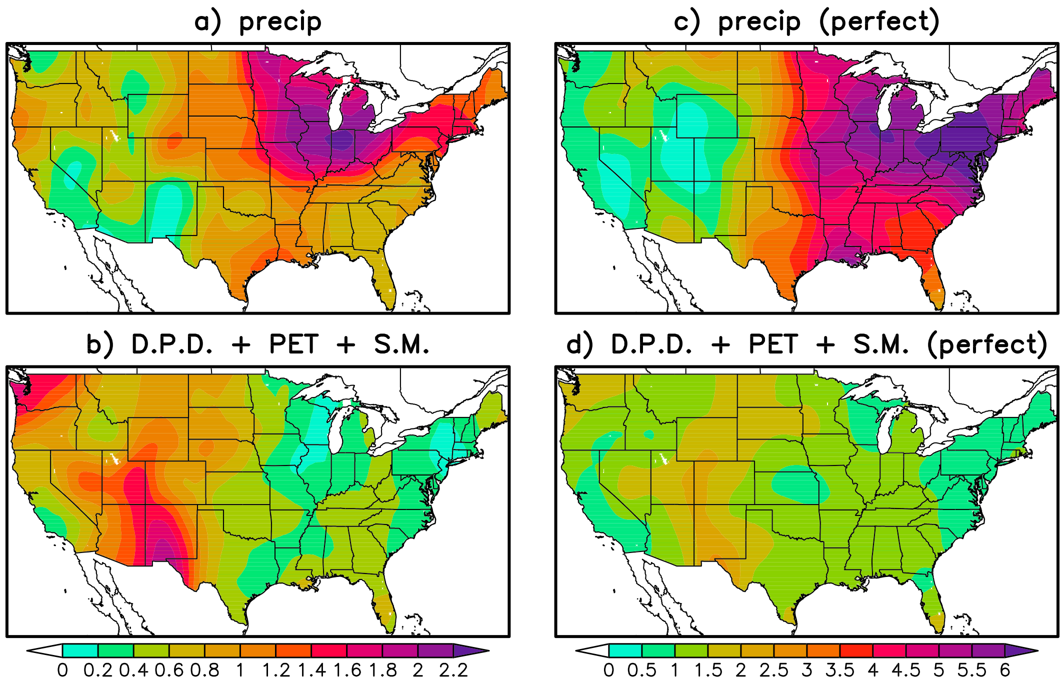

Figure 4. (a) Precipitation weights summed over all time lags for the four-week CFS forecasts. (b) As in (a) but for the sum of dew point depression, PET, and soil moisture. (c and d) Same as (a) and (b) but for the perfect model forecasts.

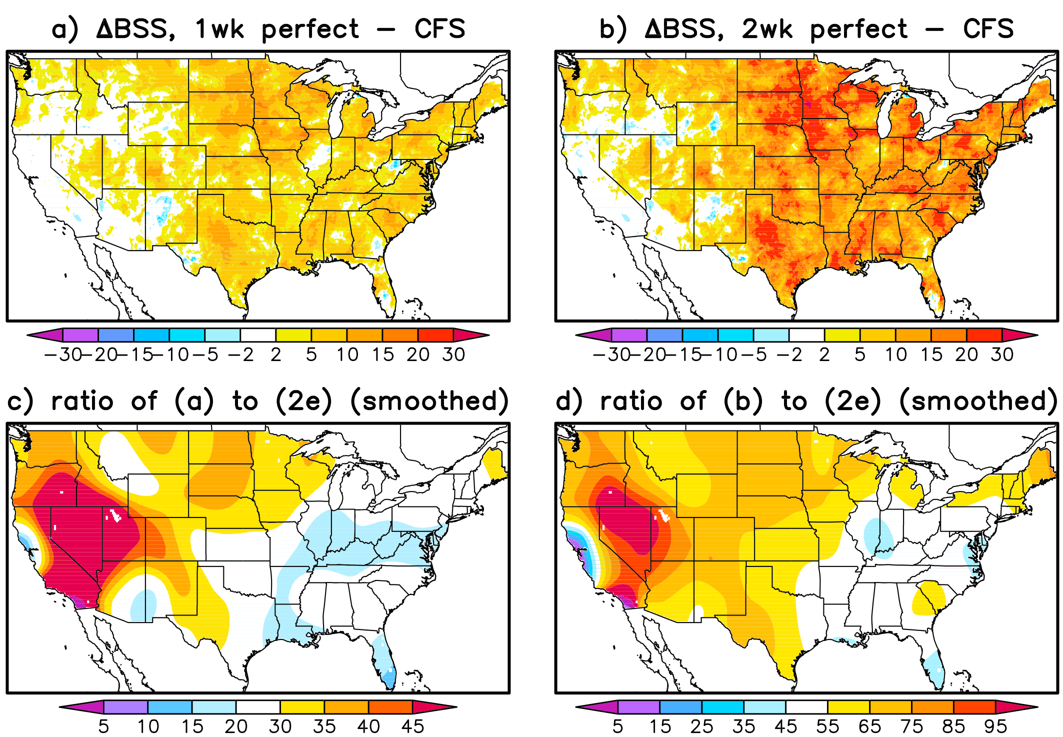

Figure 5. (a) As in Figure 2e but for only one week of future observations (i.e., no predictors for two, three, and four weeks into future) instead of four weeks of future observations. (b) As in (a) but for two weeks of future observations. (c) The ratio of impact of one week of future observations (a) to the impact of four weeks of future observations (Figure 2e) given in percent. The BSS has been smoothed in order help focus on the large-scale features. (d) Same as (c) but for the ratio of two to four weeks of future observations.

in Figure 5c. To help show the important large-scale features, the fields are smoothed in space prior to computing the ratio. If all future time lags are equally important, then one expects that the ratio of the one- to the four-week experiment will be 25%, which is denoted by the absence of shading in the figure. For the northern and western United States the ratio is larger than 25% suggesting that the first week carries more weight than later weeks for these regions. Similarly, Figure 5d shows the ratio of the two- to the four-week experiment. In this case a ratio of 50% implies equal importance, and therefore, ratios near this value have no shading in the figure. In this case, the first two weeks carry more weight than the later times over an even broader region of the United States. Focusing on the northern plains where skill is very good (Figure 1c), one sees that the first two-weeks account for over two thirds of the total *realizable* skill (Figure 5d). The larger than expected role of the one- and two-week forecasts suggests that substantial drought forecasting skill is attainable through improved precipitation forecasts in the CFS.

5. Conclusions

This paper explores the use of CFS NMME forecasts to improve statistical forecasts of USDM intensification at two, four, and six weeks in the future. First, the baseline USDM forecast skill using current and past anomalies in precipitation, PET, dew point depression, and soil moisture is computed. Next, future CFS forecasts of the above predictors are added to the statistical forecasting scheme. While adding CFS forecast data improves the drought forecasting skill for much the central and eastern United States, the improvements are very modest (about a 14% increase in variance explained on average). Next, we explored whether the modest increase in USDM skill is due to the modest skill of the CFS forecasts themselves or whether the USDM forecast skill is more-or-less already determined by current and past conditions because the USDM has a delayed response to conditions on the ground. In an experiment using future observations rather than CFS forecasts as predictors, it is found that USDM skill more than triples, which suggests that the CFS forecasts are responsible for the small improvement in skill. Further experiments show that the first two weeks of the CFS forecast have a larger than expected impact on the four-week USDM forecasts (for the northern and western United States), suggesting that significant improvement in drought forecasting is attainable.

The relative importance of short-term (i.e., one- and two-week) long-term information even in a perfect forecast scenario suggests that perhaps the most fruitful monthly USDM forecasts would be based on standard long-range weather forecasting models rather than using output from climate models. Weather forecasting models have the added benefit of higher resolution and more ensemble members. In addition, the above results suggest that the USDM forecast skill presented here is limited by the five-day interval between successive CFS forecasts used here. This means that the latest initialization time is typically not optimal given the weekly interval of the USDM. For example, sometimes the one-week composite forecast used here is actually based on a 5- to 12-day CFS forecast. Repeating the analysis including more recent daily CFS reforecasts or, alternatively, using the Global Ensemble Forecast System (GEFS) might yield substantial improvements.

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References

Anderson, M. C., Hain, C. R., Wardlow, B., Mecikalski, J. R., & Kustas, W. P. (2011). Evaluation of drought indices based on thermal remote sensing of evapotranspiration over the continental U.S. *Journal of Climate*, *24*, 2025–2044.

Anderson, M. C., Kustas, W. P., & Norman, J. M. (2007). Upscaling flux observations from local to continental scales using thermal remote sensing. *Agronomy Journal*, *99*(1), 240–254.

Anderson, M. C., Norman, J. M., Diak, G. R., Kustas, W. P., & Mecikalski, J. R. (1997). A two-source time-integrated model for estimating surface fluxes using thermal infrared remote sensing. *Remote Sensing of Environment*, *60*(2), 195–216. https://doi.org/10.1016/S0034-4257(96)00215-5

Anderson, M. C., Norman, J. M., Mecikalski, J. R., Otkin, J. A., & Kustas, W. P. (2007). A climatological study of evapotranspiration and moisture stress across the continental U.S. based on thermal remote sensing: 1. Model formulation. *Journal of Geophysical Research*, *112*, D10117. https://doi.org/10.1029/2006JD007506

Bond, N. R., Lake, P. S., & Arthington, A. H. (2008). The impacts of drought on freshwater ecosystems: An Australian perspective. *Hydrobiologia*, *600*(1), 3–16. https://doi.org/10.1007/s10750-008-9326-z

Bréda, N., Huc, R., Granier, A., & Dreyer, E. (2006). Temperate forest trees and stands under severe drought: A review of ecophysiological responses, adaptation processes and long-term consequences. *Annals of Forest Science*, *63*(6), 625–644. https://doi.org/10.1051/forest:2006042

Ford, T. W., & Labosier, C. F. (2017). Meteorological conditions associated with the onset of flash drought in the eastern United States. *Agricultural and Forest Meteorology*, *247*, 414–423. https://doi.org/10.1016/j.agrformet.2017.08.031

Ford, T. W., McRoberts, D. B., Quiring, S. M., & Hall, R. E. (2015). On the utility of in situ soil moisture observations for flash drought early warning in Oklahoma, USA. *Geophysical Research Letters*, *42*, 9790–9798. https://doi.org/10.1002/2015GL066600

Hatfield, J. L., Boote, K. J., Kimball, B. A., Ziska, L. H., Izaurralde, R. C., Ort, D., et al. (2011). Climate impacts of agriculture: Implications for crop production. *Agronomy Journal*, *103*(2), 351–370. https://doi.org/10.2134/agronj2010.0303

Hayes, M., Svoboda, M., Wall, N., & Wildhalm, M. (2011). The Lincoln declaration on drought indices: Universal meteorological drought index recommended. *Bulletin of the American Meteorological Society*, *92*(4), 485–488. https://doi.org/10.1175/2010BAMS3103.1

Higgins, R. W., Shi, W., Yarosh, E., & Joyce, R. (2000). Improved United States precipitation quality control system and analysis. NCEP/Climate Prediction Center Atlas 7, NOAA (40 pp.). Retrieved from http://www.cpc.ncep.noaa.gov/research_papers/ncep_cpc_atlas/7/toc.html

Humphries, P., & Baldwin, D. S. (2003). Drought and aquatic ecosystems: An introduction. *Freshwater Biology*, *48*(7), 1141–1146. https://doi.org/10.1046/j.1365-2427.2003.01092.x

Hunt, E., Svoboda, M., Wardlow, B., Hubbard, K., Hayes, M. J., & Arkebauer, T. (2014). Monitoring the effects of rapid onset of drought on non-irrigated maize with agronomic data and climate-based drought indices. *Journal of Agricultural and Forest Meteorology*, *191*, 1–11. https://doi.org/10.1016/j.agrformet.2014.02.001

Kirtman, B. P., Min, D., Infanti, J. M., Kinter, J. L. III, Paolino, D. A., Zhang, Q., et al. (2014). The North American multimodel ensemble: Phase-1 seasonalvto-interannual prediction; phase-2 toward developing intraseasonal prediction. *Bulletin of the American Meteorological Society*, *95*(4), 585–601.

Lorenz, D. J., Otkin, J. A., Svoboda, M., Hain, C. R., Anderson, M. C., & Zhong, Y. (2017a). Predicting US Drought Monitor (USDM) states using precipitation, soil moisture, and evapotranspiration anomalies. Part I: Development of a non-discrete USDM index. *Journal of Hydrometeorology*, *18*(7), 1943–1962. https://doi.org/10.1175/JHM-D-16-0066.1

Lorenz, D. J., Otkin, J. A., Svoboda, M., Hain, C. R., Anderson, M. C., & Zhong, Y. (2017b). Predicting US Drought Monitor (USDM) states using precipitation, soil moisture, and evapotranspiration anomalies. Part II: Intraseasonal drought intensification forecasts. *Journal of Hydrometeorology*, *18*(7), 1963–1982. https://doi.org/10.1175/JHM-D-16-0067.1

Mahrt, L., & Ek, M. (1984). The influence of atmospheric stability on potential evaporation. *Journal of Climate and Applied Meteorology*, *23*(2), 222–234. https://doi.org/10.1175/1520-0450(1984)023%3C0222:TIOASO%3E2.0.CO;2

Mallya, G., Tripathi, S., Kirshner, S., & Govindaraju, R. S. (2013). Probabilistic assessment of drought characteristics using hidden Markov model. *Journal of Hydrologic Engineering*, *18*(7), 834–845. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000699

McEvoy, D. J., Huntington, J. L., Mejia, J. F., & Hobbins, M. T. (2016). Improved seasonal drought forecasts using reference evapotranspiration anomalies. *Geophysical Research Letters*, *43*, 377–385. https://doi.org/10.1002/2015GL067009

Meinshausen, N. (2013). Sign-constrained least squares estimation for high-dimensional regression. *Electronic Journal of Statistics*, *7*(0), 1607–1631. https://doi.org/10.1214/13-EJS818

Mitchell, K. E., Lohmann, D., Houser, P. R., Wood, E. F., Schaake, J. C., Robock, A., et al. (2004). The multi-institution North American Land Data Assimilation System (NLDAS): Utilizing multiple GCIP products and partners in a continental distributed hydrological modeling system. *Journal of Geophysical Research*, *109*, D07S90. https://doi.org/10.1029/2003JD003823

Mo, K. C., & Lyon, B. (2015). Global meteorological drought prediction using the North American multi-model ensemble. *Journal of Hydrometeorology*, *16*, 1409–1424.

Mozny, M., Trnka, M., Zalud, Z., Hlavinka, P., Nekovar, J., Potop, V., & Virag, M. (2012). Use of a soil moisture network for drought monitoring in the Czech Republic. *Theoretical and Applied Climatology*, *107*(1–2), 99–111. https://doi.org/10.1007/s00704-011-0460-6

Otkin, J. A., Anderson, M. C., Hain, C., Mladenova, I., Basara, J., & Svoboda, M. (2013). Examining flash drought development using the thermal infrared based Evaporative Stress Index. *Journal of Hydrometeorology*, *14*(4), 1057–1074. https://doi.org/10.1175/JHM-D-12-0144.1

Otkin, J. A., Anderson, M. C., Hain, C., & Svoboda, M. (2014). Examining the relationship between drought development and rapid changes in the Evaporative Stress Index. *Journal of Hydrometeorology*, *15*(3), 938–956. https://doi.org/10.1175/JHM-D-13-0110.1

Otkin, J. A., Anderson, M. C., Hain, C., & Svoboda, M. (2015). Using temporal changes in drought indices to generate probabilistic drought intensification forecasts. *Journal of Hydrometeorology*, *16*(1), 88–105. https://doi.org/10.1175/JHM-D-14-0064.1

Otkin, J. A., Svoboda, M., Hunt, E. D., Ford, T. W., Anderson, M. C., Hain, C., & Basara, J. B. (2018). Flash droughts: A review and assessment of the challenges imposed by rapid onset droughts in the United States. *Bulletin of the American Meteorological Society*, *99*, 911–919. https://doi.org/10.1175/BAMS-D-17-0149.1

Pappagianis, D. (1994). Marked increase in cases of coccidioidomycosis in California: 1991, 1992, and 1993. *Clinical Infectious Diseases*, *19*(Supplement_1), S14–S18. https://doi.org/10.1093/clinids/19.Supplement_1.14

Park, B. J., Sigel, K., Vaz, V., Komatsu, K., McRill, C., Phelan, M., et al. (2005). An epidemic of coccidioidomycosis in Arizona associated with climatic changes, 1998–2001. *The Journal of Infectious Diseases*, *191*(11), 1981–1987. https://doi.org/10.1086/430092

Saha, S., Moorthi, S., Pan, H. L., Wu, X., Wang, J., Nadiga, S., et al. (2010). The NCEP Climate System Forecast Reanalysis. *Bulletin of the American Meteorological Society*, *91*(8), 1015–1058. https://doi.org/10.1175/2010BAMS3001.1

Shukla, S., Safeeq, M., AghaKouchak, A., Guan, K., & Funk, C. (2015). Temperature impacts on the water year 2014 drought in California. *Geophysical Research Letters*, *42*, 4384–4393. https://doi.org/10.1002/2015GL063666

Slawski, M., & Hein, M. (2013). Non-negative least squares for high-dimensional linear models: Consistency and sparse recovery without regularization. *Electronic Journal of Statistics*, *7*(0), 3004–3056. https://doi.org/10.1214/13-EJS868

Stanke, C., Kerac, M., Prudhomme, C., Medlock, J., & Murray, V. (2013). Health effects of drought: A systematic review of the evidence. *PLoS Currents*, *5*.

Svoboda, M., LeComte, D., Hayes, M., Heim, R., Gleason, K., Angel, J., et al. (2002). The drought monitor. *Bulletin of the American Meteorological Society*, *83*(8), 1181–1190. https://doi.org/10.1175/1520-0477-83.8.1181

Thober, S., Kumar, R., Sheffield, J., Mai, J., Schäfer, D., & Samaniego, L. (2015). Seasonal soil moisture drought prediction over Europe using the North American Multi-Model Ensemble (NMME). *Journal of Hydrometeorology*, *16*(6), 2329–2344.

van Dijk, A. I. J. M., Beck, H. E., Crosbie, R. S., de Jeu, R. A. M., Liu, Y. Y., Podger, G. M., et al. (2013). The millennium drought in southeast Australia (2001–2009): Natural and human causes and implications for water resources, ecosystems, economy, and society. *Water Resources Research*, *49*, 1040–1057. https://doi.org/10.1002/wrcr.20123

Vicente-Serrano, S. M., Beguería, S., Lorenzo-Lacruz, J., Camarero, J. J., López-Moreno, J. I., Azorin-Molina, C., et al. (2012). Performance of drought indices for ecological, agricultural, and hydrological applications. *Earth Interactions*, *16*(10), 1–27. https://doi.org/10.1175/2012EI000434.1

Xia, Y., Mitchell, K., Ek, M., Sheffield, J., Cosgrove, B., Wood, E., et al. (2012). Continental-scale water and energy flux analysis and validation for the North American Land Data Assimilation System project phase 2 (NLDAS-2): 1. Intercomparison and application of model products. *Journal of Geophysical Research*, *117*, D03109. https://doi.org/10.1029/2011JD016048

Xia, Y., Sheffield, J., Ek, M. B., Dong, J., Chaney, N., Wei, H., et al. (2014). Evaluation of multi-model simulated soil moisture in NLDAS-2. *Journal of Hydrology*, *512*, 107–125. https://doi.org/10.1016/j.jhydrol.2014.02.027

Yuan, X., & Wood, E. F. (2013). Multimodel seasonal forecasting of global drought onset. *Geophysical Research Letters*, *40*, 4900–4905.

Zhang, Q., Sun, P., Li, J., Singh, V. P., & Liu, J. (2014). Spatiotemporal properties of droughts and related impacts on agriculture in Xinjiang, China. *International Journal of Climatology*, *35*(7), 1254–1266. https://doi.org/10.1002/joc.4052