Final Report

Project Title: Understanding the Role of Land-Atmospheric Coupling in Drought Forecast Skill for the 2011 and 2012 US Droughts

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Project Overview

US experienced intense droughts in 2011 and 2012, particularly during the summer months over Texas in 2011 and over the upper mid-west in 2012 (Karl et al. 2012). These severe drought events decimated the food production and interrupted the food market thus brought negative economic impact in the US (Karl et al. 2012). Though the societal impact of these extreme events can be mitigated through earlier planning and preparation, the predictive skill of seasonal forecasts from models such as NCEP’s CFSv2 is low, which limits their practical use. This is particularly true during the summer season in North American, when the need for predictions is the greatest.

The attribution of the loss of seasonal forecast drought skill remains a significant challenge for the community and the operational seasonal forecast centers. Results by (Roundy et al. 2014) demonstrate that land-atmospheric coupling breaks down in CFSv2 during drought conditions (dry coupling) leading to the weakening and termination of the drought conditions. The loss of seasonal forecast drought skill is attributed to the failure of CFSv2 in holding drought conditions, especially in the major droughts of 2011 and 2012.

This project is built on basis of the approaches that used in (Roundy et al. 2013, 2014) in understanding the land-atmospheric coupling processes in CFSv2, and further carries out recycling analysis and reforecast experiments to understand the roles of land-atmosphere coupling processes in the predictability of drought development, intensification and termination, and to perform attribution and modeling studies for the improvement of drought predictions.

The overarching goal of this project as stated above is achieved by analyzing CFSv2 forecast from the droughts of 2011 and 2012 via the five major tasks below:

Task 1: Obtain CFSv2 and CFSR data for 2011 and 2012 drought events.
Task 2: Assess the 2011 and 2012 CFSv2 forecasts to figure out which forecast period to be used in the project.
Task 3: Compute CDI index for forecasts and CFSR for the 2011 and 2012 events.
Task 4: Analyzing the moisture sources from the CFSv2 precipitation.
Task 5: Develop statistical drought forecasts using CDI and the 28-year CFSR.
Task 6: Modifying and assessing difference vegetation and Noah parameterizations in CFS.

Results and Accomplishments

During year 1 of the project, Princeton and NCEP/EMC have worked on Task 1; Princeton initiated activities under Tasks 2 and 3; and NCEP/EMC has worked on Task 4. Efforts have been made in three major aspects: (1) Delivery of CFSv2 and CFSR data for 2011 and 2012 summer drought events, which was completed in the beginning of year 2. This transfer required significant amounts of data and took
many months of effort. During the year 2 reporting period, Princeton carried out an assessment of the 2011 and 2012 CFSv2 forecasts for the selection of forecast period to be used in this project, and computed and analyzed the CDI indices for CFSv2 and CFSR for the 2011 and 2012 summer drought events. During the year 3 reporting period, an assessment of the ocean conditions for the 2011 and 2012 droughts were analyzed, which is reported under Task 2.1. One hypothesis put forward in the proposal is the lack of adaptive vegetation that will reduce transpiration in response to drought conditions. In Task 5 this report will only discuss the accomplishments made at Princeton on Tasks 2 and 3 during year 2. The current report (year 4) includes the key findings from the recycling study using the CFSv2 analysis and forecast data.

**Task 1 and task 2 Activities: CFSv2 and CFSR data delivery for 2011 and 2012 drought events and selected analysis period**

As indicated in the project proposal, the NCEP CFSv2 and CFSR data needed for this study (for both 2011 and 2012) are available from NCEP. The CFSv2 forecast data, which are 6-hrly outputs from 72 ensemble members (for a single year) initialized from 15 May to 1 June with 4 cycles daily and around one season long (June-July-August-September), will be used in this project (Figure 1). The surface files from CFSv2 and CFSR (4 times/day) are on T126 (~100km) and T382 (~35km) native Gaussian grids, respectively. The atmospheric fields from both CFSv2 and CFSR are on the same 1x1 lat/lon grid with 37 vertical levels at 6-hrly temporal resolution as well. In addition, high resolution atmospheric fields from 0.5x0.5 lat/lon grid CFSR are also available.

These data sets listed below have been delivered from NCEP to Princeton:

- All variables from surface files on T126 (~100km) throughout the full forecast periods at 6-hrly from CFSv2 initialized 4 times/day at 00z, 06z, 12z and 18z from 15 May to 1 June for both 2011 and 2012
- All variables from atmospheric fields on 1x1 lat/lon grid with 37 vertical levels throughout the full forecast periods at 6-hrly from CFSv2 initialized 4 times/day at 00z, 06z, 12z and 18z from 15 May to 1 June for both 2011 and 2012
- All variables from surface files on T382 (~35km) throughout 15 May to 30 Sep at 6-hrly from CFSR 4 times/day at 00z, 06z, 12z and 18z for both 2011 and 2012
- All variables from atmospheric fields on 1x1 lat/lon grid with 37 vertical levels throughout 15 May to 30 Sep at 6-hrly from CFSR 4 times/day at 00z, 06z, 12z and 18z for both 2011 and 2012
- All variables from atmospheric fields on 0.5x0.5 lat/lon grid with 37 vertical levels throughout 15 May to 30 Sep at 6-hrly from CFSR 4 times/day at 00z, 06z, 12z and 18z for both 2011 and 2012
Task 2.1: Ocean conditions/role on 2011-2012 U.S. droughts

Skillful short-term weather forecasts, which rely heavily on quality atmospheric initial conditions, have a fundamental limit of about two weeks owing to the chaotic nature of the atmosphere. Useful climate forecasts on seasonal time scales, on the other hand, require well-simulated large-scale atmospheric response to slowly varying lower-boundary forcings from both ocean and land surface.

The critical importance of ocean memory has been well recognized, whereby large-scale anomalies in the atmospheric general circulation on seasonally averaged time scales are forced first and foremost by large-scale anomalies in sea surface temperature (SST), especially over the El Niño–Southern Oscillation (ENSO) regions of the tropical Pacific Ocean during the cold season. In contrast to SST anomalies, it has proven notably more difficult to demonstrate that land surface (such as soil moisture, vegetation treatment and associated evapotranspiration) has meaningful positive impact on continental seasonal forecast skill in either coupled climate models or statistical seasonal forecast techniques.

Seeds for the drought of 2012 were shown during the back-to-back La Niña episodes of 2010–11 and 2011–12. La Niña often correlates with drought development and expansion across the southern United States. The drought began to develop across the southern tier of the U.S. during the winter of 2010–11, and quickly intensified during the 2011 growing season. The 2011 drought was particularly severe in the south-central U.S.

During the winter of 2011–12, a resurgent La Niña again contributed to drier-than-normal conditions in parts of the U.S. In addition, an unusual configuration of weather systems over the North Atlantic Ocean—including a very strong polar jet stream—kept the prevailing track of major winter storms far to the north over Canada. As a result, much of the U.S. experienced a much warmer winter.

In contrast to the dominant controls of ocean SST during cold season, in summer times when the SST signal is weak, land surface treatments can have notable impact on precipitation and modify other surface quantities through surface energy processes. In this project, we specifically
investigate the impact of vegetation treatment in NCEP Coupled Forecast System (CFS) on the precipitation predictions of the 2011-2012 drought.

To examine if the vegetation treatment can make a difference, warm-season prediction experiments were carried out using the NCEP CFS. We took two different pathways. The first is to replace the currently used climatology GVF in Noah LSM with real-time satellite observation. The second is to replace the Noah LSM in CFS with a new Noah Multiple Parameterization (Noah MP) land model, where the dynamic vegetation option is available.

**Task 3 Activities: Computation of CDI index for CFSv2 and CFSR for the 2011 and 2012 events**

(a) Coupling regime classification based on CTP-HI-SM from historical CFSR

We calculated the historical time series of Convective Triggering Potential (CTP), low level Humidity Index (HI), which were developed from (Findell and Eltahir 2003), from CFSR (0.5° lat/lon grids) over continental US during 1982-2009 at 06z, daily. Here, the CTP is a measure of the stability in the 1km-3km region above the ground by integrating the region between the atmospheric profile and the moist adiabatic temperature lapse rate. The HI is a measure of wetness of the atmosphere and is defined by the 50-150 hPa above ground level dew point depression, where a lower value of HI indicates a wetter atmospheric state. Meanwhile, we also calculated the daily averaged top layer soil moisture (0-0.1m). All of these variables are then up-scaled onto 1.25° lat/lon grids. The “CTP-HI-surface soil moisture” classification scheme that was developed from (Roundy et al. 2013) is applied to classify each 1.25° lat/lon grid into four coupling regimes (wet, dry, transitional and atmospherically controlled) for CFSR datasets. Figure 2 is an example of the classified CTP-HI space from CFSR for a specific grid as well as over the U.S. Areas of the CTP-HI space with predominantly wetter soils are considered wet coupling and areas that are predominantly drier are dry coupling. Areas that are neither dry nor wet (in a climatological sense) are transitional, and areas outside of the main cluster of points are considered atmospherically controlled.
Figure 2. The CTP-HI climatological (dominant) classification using CFSR (purple: wet coupling; green: transitional; grey: atmospheric controlled)

(b) CDI from historical CFSR for summer season (Jun-Sep) over continental US

Once the CTP-HI space is classified, it is then used to create a time series of coupling types (i.e. wet, dry, transitional and atmospherically controlled), given estimates of CTP-HI. The Coupling Drought Index (CDI), which is simply the number of dry coupling days minus the wet coupling days divided by the total number of days in the evaluation period, was calculated based on the time series of the coupling types. CDI is ranging from -1 (which indicates every day during the evaluation period is a wet coupling event) to 1 (which indicates every day during the evaluation period is a dry coupling event). Figure 3 shows in the upper panels the 35-year (1979-2013) average CDI from CFSR for the summer months (June - September) over the continental US and the 31-year (1982-2013) CFSv2 climatology. These results show the significant wet bias in CFSv2, especially in the upper mid-west and a dry bias in the SW inter-mountain region.

Figure 3. The CDI climatology computed over the summer months (June - September) for the continental US from CFSR and CFSv2.

The inter-annual variability in CDI for the two study regions is shown in Figure 4, which confirms the results in Figure 3. For the Texas region, CFSR CDI is drier than the CFSv2 ensemble mean but for most years falls within the ensemble spread (based on 24 forecasts issued during May.) For the 2011 event year, the CFSR-based CDI falls outside the forecasts. This isn’t the case for the upper mid-west where CFSR based CDI is almost always drier than any of the forecast ensembles.
Figure 4: Summertime (June – September) CDI time series for CFSv2 and CFSR for the Texas and upper mid-west regions. Vertical blue lines indicate the 2011 Texas and 2012 upper mid-west drought event.

(c) CDI Time Series for CFSv2 and CFSR during 2011 and 2012 summer (Jun-Sep)

In order to evaluate the whether CFSv2 forecast can predict the coupling regimes during the 2011 and 2012 droughts, using 24 forecast ensembles, initialized four times per day at 00, 06, 12 and 18z on May 01, 11, 16, 21, 26, 31, for forecasts from June 1 to September 30, are used to classify the CDI. CDI is also computed using CFSR. Figure 5 presents the results, including the frequency (number of days) that CFSv2 predicted each CTP-HI coupling regime, and similarly for CFSR. The results are striking that CFSv2 has a pronounced wet bias (similar to its climatology). The bias is particularly evident for the upper mid-west 2012 drought.

Figure 5: The summer period CDI computed for 2011 and 2012 from CFSR and CFSv2 along with the number of days in each coupling regime.
Task 4: Analyzing the moisture sources from the CFSv2 precipitation

A central task of the project is understanding the moisture sources related to the CFSv2 forecasts, because this is directly related to the holding of drought during these events. To analyze these, we worked at implementing a recycling model that identifies the sources of moisture leading to precipitation. Essentially, the problem being addressed is as follows: given that the CFSv2 forecasts have anomalous precipitation, what is the source of the moisture? It appears to be either advected into the region, or its source is local evapotranspiration.

The model is from Martinez and Dominguez 2014, which is an extended version of the original model from Dominguez et al., 2006. The model can separate moisture sources into recycled and advected components. The basis equations are given in Fig. 6.

- Splitting conservation equation into advected and local components:
  \[
  \frac{\partial}{\partial t}w_x + \frac{\partial}{\partial x}(w_v, v) + \frac{\partial}{\partial y}(w_v, v) = -P_n
  \]
  \[
  \frac{\partial}{\partial t}w_x + \frac{\partial}{\partial x}(w_v, v) + \frac{\partial}{\partial y}(w_v, v) = E - P_n
  \]

- Defining recycling ratio and substituting:
  \[
  \rho = \frac{w}{w_n}
  \]
  \[
  w_x \frac{\partial}{\partial x} \rho + w_v \frac{\partial}{\partial y} \rho + \frac{\partial}{\partial y} \rho = E(1 - \rho)
  \]

- Conservation of atmospheric water vapor
  \[
  \frac{\partial}{\partial t}w + \frac{\partial}{\partial x}(w) = E - P
  \]

- Precipitation has an advected and a recycled component
  \[
  P = P_a + P_n
  \]

- Assumes a well mixed atmosphere

\[
\begin{align*}
\frac{\partial}{\partial x} w_x & = \frac{1}{w} \left[ \int_{x_0}^{x} q_v \frac{\partial}{\partial x} \rho dx - \int_{x_0}^{x} q_v \frac{\partial}{\partial x} \rho dx \right] \\
\frac{\partial}{\partial y} w_y & = \frac{1}{w} \left[ \int_{y_0}^{y} q_v \frac{\partial}{\partial y} \rho dy - \int_{y_0}^{y} q_v \frac{\partial}{\partial y} \rho dy \right] \\
\end{align*}
\]

**Figure 6**: Recycling equations for the model of Dominguez et al., 2006

As a test, the recycling rate over CONUS was computed for one year, as shown in Figure 7. We now plan to focus on recycling of the anomalous precipitation in CFSv2 forecasts during the 2011 Texas drought and the 2012 upper mid-west droughts to understand the deficiencies in the forecasts compared to the conditions in CFSR.

**Figure 7**: Precipitation recycling from land during 1998.
Task 4.1: New results from moisture recycling

The moisture recycling study was carried out using the CFSv2 Analysis and Forecast data. NCEP replaced the CFS Reanalysis (CFSR) data with CFSv2 Analysis from April 2011 onwards. We extended our study for four consecutive years (2010-2013), and so both datasets (Reanalysis and Analysis) were used to cover the 4-year time period. Here we used the term “Analysis” to represent both Reanalysis and Analysis data interchangeably.

In order to evaluate the performance of CFSv2 Analysis, we compared the precipitation field against two state-of-the art products: North American Land Data Assimilation System Phase 2 (NLDAS2) forcings [Mitchell, 2004] and the Multi-Source Weighted-Ensemble Precipitation (MSWEP) [Beck et al., 2017]. The overall spatial fields match quite well, although CFSv2 Analysis shows high precipitation, especially during the month of July and August, in the southwest and Mexico. Similar pattern is also reflected to some extent in MSWEP. Note that NLDAS2 doesn’t have data for Mexico.

![Figure 8: CFSR, NLDAS2 and MSWEP precipitation fields during the 2011 summer (drought year for Texas). Note that there is no NLDAS2 precipitation available for Mexico.](image)

The cumulative plots of precipitation, precipitable water, evapotranspiration, and soil moisture from the CFSv2 Analysis are shown in Figure 9 for both Texas (2010-2012) and the Upper Midwest (2011-2013), which experienced drought in 2011 and 2012, respectively. Note that we plotted the cumulative values of all the variables to visualize the differences more clearly, even though precipitable water and soil moisture are storage variables. As can be seen, all four variables show drought signals by their lower values during the corresponding drought years. Precipitation and evapotranspiration show the strongest signal. Drought onset in Texas was in April 2011, while June and July were the driest months. However, the drought signal was evident in soil moisture as early as February during the same year. Drought emerged during June 2012 in the Upper Midwest, but the duration was shorter as compared to the Texas drought in 2011. July and August show the largest differences in evapotranspiration between the drought and non-drought years. In Texas, there was a slight decrease in the precipitable water, however, in the Upper Midwest, there was no or little changes, which indicates that the drought
in the Upper Midwest was driven by the lack of precipitation generating mechanisms. In both regions, drought terminated by the end of August.

Figure 9: Precipitation, precipitable water, evapotranspiration and soil moisture cumulative plots for Texas (2010-2012) and the Upper Midwest (2011-2013) from the CFSv2 analysis.

The recycling model DRM was run for 2010-2012 for Texas and 2011-2013 for the Upper Midwest to include the respective drought years along with the preceding and the following years. The distribution of moisture sources for Texas and the Upper Midwest is shown in Figure 10 for the three consecutive years. The overall spatial distribution patterns are similar for drought and non-drought years, however, the amount is low during the drought years. Tropical Atlantic (R28) was the main moisture source for Texas, followed by the Mid-latitude Atlantic Ocean (R26) and recycling (R14). Recycling was a significant contributor of moisture to the Upper Midwest along with the parts of the northern U.S. (R03) and the south-west (R10), the Tropical Atlantic Ocean (R28), etc. Thus, in the Upper Midwest, terrestrial evapotranspiration and recycling played a significant role, while in Texas, oceanic contributions were predominant. During the drought year in Texas (2011), contributions from the Mid-latitudes Atlantic Ocean (R26) and the Pacific Ocean were reduced. The spatial patterns of moisture distribution were similar during the post-drought year. Advection from different sources as well as recycling were also reduced during the drought year in the Upper Midwest (2012).
Figure 10: Moisture sources in Texas and the Upper Midwest during the summer of 2011 and 2012.

The temporal patterns of recycling and advection are shown in Figure 11 both for Texas and the Upper Midwest. As can be seen, recycling was significantly low in both cases during the corresponding drought years, but the amount of reduction was higher in the Upper Midwest. The Atlantic Ocean including the Caribbean Sea (R24, R26 and R28) was the most significant source of advected moisture for Texas, which was low during the drought year from the beginning until the late summer. There was also increased advection at the end of summer which most likely terminated the drought. Although some regions showed slight increase in the advection, the magnitude of those increments was low. Advection from the CONUS did not change much, which indicates that the terrestrial evapotranspiration helped pacify the drought intensity. In the Upper Midwest, the main contributors of moisture were local recycling, Atlantic Ocean (Tropical Atlantic; R28), Pacific Ocean, and CONUS. In this case, the contribution of CONUS also decreased. Although recycling started decreasing in March, the advection actually decreased in June, and so the onset of the drought was also delayed.
We checked how well the CFSv2 Forecasts capture different characteristics of the Analysis data (Figure 12) within the context of the two drought events. We ran 20 member ensemble separately for Texas (2011 summer) and the Upper Midwest (2012 summer). Ensemble members were selected based on 5 initialization days (May-11, May-16, May-21, May-26 and May-31) and 4 records per day (00z, 06z, 12z and 18z). The hydrometeorological variables as well as the recycled and advected precipitation from the Forecasts were compared against the Analysis (Figure 12 and 13). The ensemble mean precipitation from the Forecasts closely followed the Analysis in Texas, however, the Forecasts were seen to overestimate precipitation in the Upper Midwest. In general, the older ensemble members overestimated more. In both regions, evapotranspiration was overestimated, but it was more striking during July and August of 2012 in the Upper Midwest. The overestimation of evapotranspiration could be attributed to the absence of dynamic vegetation parameterization in the Noah land-surface model within the CFS modeling system, in which case, the model keeps producing evapotranspiration to meet the temperature bias, even in dry conditions. Precipitable water profiles of Forecasts and Analysis were similar in Texas, while the Forecasts showed slight overestimation in the Upper Midwest. Majority of the Forecasts underestimated soil moisture in Texas. In general, the younger ensemble members matched the ensemble mean more closely, which implies that the variability of the ensemble members reduces with the initialization time (newer members have lower variability and vice versa).

Figure 11: CFSv2 analysis recycled and advected precipitation over Texas and the Upper Midwest (Note the difference units for the two regions).
Figure 12: Comparison of hydrometeorological variables from CFSv2 Analysis and Forecasts. Newer ensemble members are represented by darker dots.

Figure 13 shows the comparison between CFSv2 Analysis and Forecasts in terms of advected and recycled precipitation components. In general, the younger Forecast ensemble members were closer to the Analysis. The Forecast ensemble well captured the advected and recycled components of precipitation in Texas, however, in the Upper Midwest, the forecasts overestimated these components. In the Analysis data, the advected precipitation was about 9.2 times higher than the recycled precipitation during the summer in Texas, while this ratio was reduced to 7.8 for the Forecasts (based on ensemble mean). The same ratios were 8.5 and 3.8, respectively, in the Upper Midwest during the 2012 summer. These results indicate that in Texas, the partitioning of recycled and advected precipitation, was better represented by the Forecasts as compared to the Analysis.
Figure 13: Cumulative series of advected and recycled precipitation from CFSv2 Forecasts and Analysis. Newer ensemble members are represented by darker dots. Note the differences in y-axis scale between panels.

Task 5: Develop statistical drought forecasts using CDI and the 28-year CFSR.

Better understanding the predictability of land atmosphere interactions is a central question by the weather and seasonal forecasting community since such coupling impacts the recycling of moisture at both local and at-distance scales. In particular recent work by the PI’s group (Roundy et al. 2014) has developed a new classification of land-atmosphere interactions that was the bases for a coupling drought index that assesses the impact of coupling on drought. This metric is used in this project to understand the predictability of land-atmosphere interactions in the NCEP Climate Forecasts System version 2 (CFSv2). Results indicate that there are strong biases in the coupling that lead to biases in CFSv2 seasonal precipitation and temperature predictions.

We’ve assessed the extent to which the predictability is hindered by these biases and analyzed the attribution of the predictability. This is done by comparing the CFSv2 forecasts with those made by statistical models of precipitation, temperature and coupling developed in the project. Three models have been used: (i) The Coupling Potential Model (CPM), which uses the observed coupling state from CFSR as the forecast of daily coupling. Although the CPM is not a forecast model, it provides a means to isolate the predictability of the weather model and as the name applies provides an estimate of the potential predictability; (ii) Coupling Statistical Model (CSM), which is based on a conditional Markov Chain process, i.e. the future coupling state is dependent on the previous coupling state and precipitation. The conditional transitional probabilities are estimated from observations for each month from May to September. The uncertainties associated with estimating these probabilities are the highest on the west coast for dry coupling and near the Rocky Mountains for wet coupling. The CSM model indicates the probabilities that are the highest for each coupling regime are the persistence probabilities. Furthermore, these persistent probabilities are lower (higher) for days with preceding precipitation for dry (wet) coupling respectively. However, the persistence of the atmospherically controlled state has little or no difference for days that were preceded by rain. This is consistent with the nature of coupling defined by Roundy et al. (2013b) in that dry persists in dry and wet in wet, while the atmospheric regime is unaffected by local conditions. The local nature and dependency on the previous state of coupling and precipitation in the CSM allows for the isolation of the predictability due to the
persistence of initial conditions through local coupling. This is achieved through two versions of the model, the CSM, which is initialized by randomly selecting a coupling regime from the May climatology and the CSMi, which uses the observed May coupling, weighted toward the latter half of the month, to define the initial coupling state. Both versions of the model use the observed initial condition of precipitation. (iii) Corrected Dynamic coupling Model (CDM), which is based on correcting the biases in the Convective Triggering Potential (CTP) and Humidity Index (HI) from the CFSRR model. The corrected CTP and HI model is then used to reclassify coupling and drive the weather model to make the seasonal forecasts. This provides a type of hybrid model that utilizes the benefits of a dynamical model for predictions of coupling and uses a statistical model for forecasts of precipitation and temperature.

The forecast bias during the 28-year hindcast period for the three-month forecasts from June, July and August (JJA) of the CDI, precipitation and daily maximum and minimum temperature is shown in Fig. 14 for the CFSRR, CDM and CSMi models. The CFSRR shows strong biases across all variables (Fig. 14a). In particular, the CDI shows a strong negative bias over most of the country. The precipitation shows a strong positive bias in the north and a negative bias in the south. While there is some connection between the CDI and the precipitation (North Central and Southwest), the precipitation bias is not completely described by the CDI. On the other hand, the daily maximum temperature shows a very strong negative bias that is reasonably correlated with the negative bias of the CDI. In contrast the daily minimum temperature has the lowest bias in the areas where the daily maximum temperature is the strongest. The CDM (Fig. 14b), which is the corrected version of the CFSRR, still has a small positive bias for the CDI in the southwest and southeast, but shows a dramatic improvement in the bias. This indicates that correction model was effective. Furthermore, the forecasts of precipitation and daily maximum and minimum temperature show little or no bias and offer a dramatic improvement over the CFSRR forecasts. The CSMi (Fig. 14c), which simulates the coupling using a statistical model, has no bias in the CDI or any of the variables derived from it. Results show (see Fig. 14) that the 3-month forecast can be best removed using the hybrid dynamical statistical CSMi model.

Figure 14. The 3 month (JJA) forecast bias for the Coupling Drought Index (CDI), Precipitation (P), daily maximum temperature (Tmax) and daily minimum temperature (Tmin) for a) CFSRR, b) CDM and c) CSMi.
The results indicate that the local impact of initial conditions has some skill over the hindcast period and for drought events, however the skill is greatly enhanced by the inclusion of spatial interactions. Furthermore, the statistical model that corrects the biases in CFSv2 provides an unbiased prediction and maintains a similar level of skill that provides better precipitation predictions during drought. For drought conditions, the predictions of precipitation from the local statistical model were often more skillful, which indicates that the CFSv2 predictions are limited by the representation of coupling. However, the predictions of daily maximum temperature from the CFSv2 were still more skillful.

**Task 6: Modifying and assessing difference vegetation and Noah parameterizations in CFS**

6.1 CFS Seasonal forecast experiments with different vegetation treatment and a different land model

The CFS used in our experiments is a modified version of the NCEP CFSv2. The atmospheric component of the CFS is taken from a recent operational version of the NCEP medium-range GFS. Key atmospheric physical parameterizations of this GFS include the simplified Arakawa-Schubert convection, a Rapid Radiative Transfer Model for longwave and the radiative transfer parameterization for shortwave radiation, explicit cloud microphysics, non-local vertical diffusion and gravity wave drag. The ocean component (GFDL MOM4) also includes recently developed treatment for the Near Sea Surface Temperature (NSST).

6.2 CFS with Noah 2.7 LSM and different vegetation treatment

The land component of the CFS is represented by the Noah Land Surface Model. The Noah LSM was originated from the Oregon State University (OSU) LSM, but includes a lot of physical improvements/enhancements by many researchers. The Noah LSM is equipped with more advanced land physics compared to its ancestor OSU LSM, including four soil layers, snow pack and frozen soil physics, and snow-cover weighted surface fluxes, improved seasonal cycle of vegetation, spatially varying root depth, improved soil and snow thermal conductivity, and higher canopy resistance, among others. The Noah LSM 2.7 was implemented in NCEP’s operational medium-range Global Forecast System (GFS) in late May 2005, and is still used in the currently operational CFS for seasonal predictions.

In the Noah 2.7 LSM, monthly climatological Greenness Vegetation Fraction (GVF) is used. The climatology is derived from five years of weekly AVHRR satellite observations. The actual GVF values used in the calculation are interpolated from two adjacent months (the values are assumed to be valid in the middle of each month) based on the “distance” (model time) to each of the months. This treatment assumes no inter-annual variation and potentially produces large biases over extreme years when the GVF interannual variability is pronounced. In this study, The CFS will be run with real-time weekly AVHRR observation and will be compared with control run where climatological values are used.

6.3 CFS with Noah LSM with Multiple Parameterization (Noah-MP) options

Since its first release in early 2000s, the Noah LSM has had a lot of enhancements, the latest version Noah 3.4.1 (released in August 2012) now has improved treatments for saturation slope, background emissivity, and snow albedo. To utilize the recent developments in Land Use and Land Classification (LULC), the new vegetation (MODIS/IGBP) classification and soil type (STATGO) datasets are introduced in this release.
Even with the improvements, the Noah LSM has several limitations in its overall structure, such as the combined surface layer of vegetation and ground, a bulk layer of snow and soil, shallow soil column, among others. In addition, only one option for the parameterizations is provided. To overcome these shortcomings, a new paradigm is proposed by the Noah community, where the Noah LSM is equipped with advanced model physics and allows for Multiple Parameterization (Noah-MP) options.

The community Noah-MP LSM uses multiple options for key land-atmosphere interaction processes. It was developed to overcome the limitations of the Noah LSM. An important feature of the Noah-MP LSM is the option for prognostic vegetation growth that combines Ball-Berry photosynthesis-based stomatal conductance with a dynamic vegetation model that allocates carbon to various parts of the vegetation (leaf, stem, wood and root) and soil carbon pools (fast and slow). This dynamic vegetation model allows for year-to-year variability, and thus provides advantages in investigating land-atmospheric coupling strength, especially during the ENSO neutral years when the ocean impact is relatively small.

6.4 CFS experiments

To examine impact of different vegetation treatment and the Noah-MP LSM with dynamic vegetation option on seasonal precipitation predictions, T126 CFS reforecast experiments are carried out for selected eleven years (1982, 1987, 1996, 1988, 2000, 2007, 1986, 1991, 1999, 2011, 2012) with four ensemble members (00z of May 1 to May 4). The eleven years are composed of three ENSO-cold, three ENSO-warm and five neutral years (MJJ - summer season). The results from ensemble means indicate that the Noah-MP LSM with dynamic vegetation has a large impact over areas with strong GVF seasonality and the "hot spots" where the effect of soil moisture memory and land-atmospheric coupling are pronounced as the Noah-MP LSM can access deep soil water (with an attached unconfined aquifer to the bottom of soil layer). The precipitation Anomaly Correlation (AC) scores are comparable among the three vegetation treatment options, with a slightly better performance over the Eastern U.S. when the realtime GVF is used (not shown). Figure 1 provides a comparison of actual precipitation predicted by the CFS with the observation for the month of July 2011 (Texas drought). Figure 1 shows, in agreement with its AC score, the CFS with realtime GVF is closer to the observation over the Eastern CONUS (vegetated) and the CFS with Noah-MP dynamic vegetation can predict the right location of the drought but exhibits a high bias. The results are consistent with the near-surface temperature prediction, where 2-meter temperature in the Noah-MP CFS is lower (not shown). It is suspected that the initial land states for Noah MP LSM might play a role.
**Figure 15:** Comparison of monthly mean precipitation rate predicted by the CFS with Noah LSM 2.7 climatology GVF (top left), Noah LSM with realtime GVF (top right), Noah MP LSM with dynamic vegetation (bottom left), and observations (bottom right), for July of 2011.

**Highlights of Accomplishments**

By analyzing the CTP-HI coupling regimes, and the resulting Coupling Drought Index (CDI), we have demonstrated that CFSv2 forecasts have a wet coupling bias, particularly in the upper mid-west region of the US. This helps explain why CFSv2 forecasts tend to produce anomalous precipitation during the 2011 and 2012 droughts and thereby fail to hold drought conditions.

A statistical model that corrects the biases in CFSv2 provides an unbiased prediction and maintains a similar level of skill that provides better precipitation predictions during drought. However, the predictions of daily maximum temperature from the CFSv2 were still more skillful than the statistical models.

In the CFS experiments with Noah MP with dynamic vegetation, the ensemble means indicate that the Noah-MP LSM with dynamic vegetation has a large impact over areas with strong GVF seasonality and the "hot spots" where the effect of soil moisture memory and land-atmospheric coupling are pronounced.

**Publications and presentations from the Project**


Zhang, Y, Joshua Roundy, Michael Ek and Eric Wood. 2015 Understanding the land-atmospheric interaction in drought forecast from CFSv2 for the 2011 Texas and 2012 Upper Midwest US droughts, presented at the 2015 American Geophysical Union Fall Meeting, 14-18 December 2015, San Francisco, CA.

Tirthankar Roy, J. Alejandro Martinez, Julio E. Herrera-Estrada, Yu Zhang, Francina Dominguez, Alexis Berg, Mike Ek, Eric F. Wood, Comparison of CFSv2 analysis and forecasts within the context of two recent droughts in Texas and Upper Midwest, *J Hydromet.*, In Review

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**References**


