

SEASONAL PREDICTABILITY OF DROUGHT  
AND THE IMPORTANCE OF  
LAND-ATMOSPHERE INTERACTIONS

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PREVIEW

## Abstract

Hydrologic extremes in the form of flood and drought have large impacts on society. The ability to predict such extreme events at seasonal timescale allows for preparations that can reduce the risk of these events. However, seasonal prediction skill of global climate models varies seasonally and spatially, which severely limits their practical use. In this thesis a framework for assessing and attributing the seasonal predictability through a probabilistic predictability metric based on model skill across temporal and spatial scales; i.e. for the canonical events was developed and demonstrated. The attribution of predictability specific to land-atmosphere interactions and drought is also developed through a new classification of land-atmosphere interactions that includes the Coupling Drought Index (CDI). The CDI was used to understand the current predictability in NCEPs Climate Forecast System version 2 (CFSv2) and the new classification of coupling is used to develop statistical models to isolate attributes of predictability relevant to land-atmosphere interactions and drought. The results show clear seasonal and spatial patterns of predictability that vary with each forecast variable and provide a better understanding of when and where to have confidence in model predictions. The new classification of coupling indicates strong persistence and the CDI shows good agreement with the temporal and spatial variability of drought and highlights the role of coupling in drought recovery. The CDI in the CFSv2 forecasts indicates climatological bias toward the wet coupling regime that precludes the forecast model from consistently predicting and maintaining drought over the continental US. The attribution of the CFSv2 forecasts skill in the summer indicates that the local persistence of initial conditions provides some predictability over the hindcast period and for specific drought events, however the skill is greatly enhanced by the inclusion of spatial interactions. Furthermore, the

statistical model based on correcting coupling bias in CFSv2 provides an unbiased prediction and maintained a similar level of skill and provided better precipitation predictions during the 1988 drought. This argues that the wet bias in the coupling limits the precipitation predictability during drought events. The synthesis and extension of the results is also discussed.

PREVIEW

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PREVIEW

To my wife and daughters.

# Contents

Abstract . . . . .	iii
Acknowledgements . . . . .	v
List of Tables . . . . .	xi
List of Figures . . . . .	xii
<b>1 Introduction</b>	<b>1</b>
1.1 Motivation and Background . . . . .	1
1.2 Dissertation Goals . . . . .	4
1.3 Thesis Overview . . . . .	5
1.4 Publications and Presentations . . . . .	5
<b>2 A framework for analyzing seasonal prediction through canonical event analysis</b>	<b>8</b>
2.1 Introduction . . . . .	8
2.2 Methodology . . . . .	11
2.3 Results: Seasonal and spatial variation of predictability . . . . .	16
2.4 Results: Attribution of forecast skill . . . . .	20
2.5 Summary and Conclusions . . . . .	24
<b>3 Classification of land-atmosphere coupling and its implications for</b>	

<b>drought</b>	<b>35</b>
3.1 Introduction . . . . .	35
3.2 Datasets . . . . .	38
3.3 Classification methodology . . . . .	41
3.4 Classification results . . . . .	46
3.5 Temporal evolution of coupling . . . . .	48
3.6 Coupling events and drought . . . . .	51
3.7 Discussion and Conclusions . . . . .	53
<b>4 Impact of land-atmospheric coupling on drought prediction</b>	<b>62</b>
4.1 Introduction . . . . .	62
4.2 Methodology . . . . .	64
4.3 Results . . . . .	69
4.3.1 CFSR-CFSR-LR classification inter-comparison . . . . .	69
4.3.2 Reanalysis and forecast coupling comparison . . . . .	71
4.3.3 Reanalysis and forecast water and energy balance comparison . . . . .	74
4.4 Implications for drought prediction . . . . .	81
4.5 Summary and Conclusions . . . . .	83
<b>5 The attribution of land-atmosphere interactions on the seasonal predictability of drought</b>	<b>94</b>
5.1 Introduction . . . . .	94
5.2 Datasets and Methods . . . . .	97
5.2.1 Datasets . . . . .	97
5.2.2 Methods . . . . .	98
5.3 Models . . . . .	100
5.3.1 Weather Model . . . . .	100

5.3.2	Coupling Models . . . . .	104
5.4	Results . . . . .	107
5.4.1	Model Comparison and Predictability . . . . .	107
5.4.2	Predictability of Drought . . . . .	113
5.5	Summary and Conclusions . . . . .	115
<b>6</b>	<b>Conclusions</b>	<b>130</b>
6.1	Summary . . . . .	130
6.2	Synthesis . . . . .	135

PREVIEW

# List of Tables

2.1	The number of ensembles and validation time for each forecast initialization in the CFSRR hindcast dataset. . . . .	13
3.1	Description of datasets used in this study. Asterisks indicate variables used for classification of coupling; all others are used for evaluation only. SSO indicates sun synchronous orbit. . . . .	39
4.1	Average warm-season (June-September) value (in mm) of the following water budget variables: precipitation (P), evaporation (E), runoff (Q), change in layer 1-3 soil moisture ( $\Delta S_{1-3}$ ), change in layer 4 soil moisture ( $\Delta S_4$ ), and residual (R) from CFSR and CFSRR. Statistics are provided for both the Great Plains (GP) and the Southeast (SE) US. . . . .	78

# List of Figures

2.1	Diagrams illustrating a) the temporal scales (shown for forecasts initiated in January) and b) the spatial scales (shown for a single grid in Texas, 32.6°N, 96.7°W) used in this study. . . . .	27
2.2	Changes in the Spearman correlation across temporal and spatial scales at various lead-times for the CFSv2 precipitation forecasts with validation beginning in January, April, July and October for a grid cell in Texas (32.6°N, 96.7°W). The Probabilistic Predictability Metric (PPM see text for details) is given in parenthesis below each month. . . . .	28
2.3	The seasonal change in the average PPM over the CONUS across temporal scales (Time), spatial scales (Space) and lead-time (Lead) of the forecast for a) precipitation, b) daily maximum temperature and c) daily minimum temperature. . . . .	29
2.4	The a) Spearman correlation of the 1-month forecasts at the grid scale and 0-month lead-time and b) the PPM for forecast validation beginning at each month over the CONUS. . . . .	30
2.5	The PPM for forecast validation beginning at each month over the CONUS for a) daily maximum temperature and b) daily minimum temperature. . . . .	31

2.6	The a) annual average monthly temperature anomaly from the Nino-3.4 region with circles indicating the 4 strongest (red) and 4 weakest (blue) years and the CONUS average PPM using all years (black), excluding the strongest (red) and weakest (blue) ENSO years for b) precipitation, c) daily maximum temperature and d) daily minimum temperature. . . . .	32
2.7	The ENSO Influence on Predictability (EIP) for precipitation forecasts with validation beginning at each month over the CONUS. . . . .	33
2.8	The ENSO Influence on Predictability (EIP) for forecasts with validation beginning at each month over the CONUS for a) daily maximum temperature and b) daily minimum temperature. . . . .	34
3.1	Flowchart of the methodology. (a) The initial joint CTP-HI-SM space over the U.S. Southeast for the warm season (June-September) from 2003 to 2009. (b) Consider the 2D CTP-HI space with $n \times n$ bins. (c) Classify each bin based on the marginal distributions of SM using a KS test applied with a significance level. (d) Resampling to consistent resolution in the CTP-HI space. (e) Combination of all runs of different $n$ and $\alpha$ values to form probability estimates of classification from which (f) the final classification of the CTP-HI space is derived. Using (f) and (g) the time series of CTP-HI, (h) the time series of coupling is derived. (i) The final coupling time series after a temporal filter and filling in missing values. All subplots use the MERRA CTP-HI and VIC SM. Subplots (a)-(f) consider all 48 grid cells, while subplots (g)-(i) are for a single grid point ( $34.375^\circ\text{N}$ , $83.125^\circ\text{W}$ ). . . . .	56

3.2	(a) Normalized frequency (days) and (b) persistence probability of each coupling regime for the warm season in the Southeast before (wide bars) and after (narrow bars) temporal smoothing and filling in missing values (AIRS-AMSR-E only). The data source of CTP and HI is followed by the data source of SM, as in MERRA (CTP, HI) - MERRA (SM). (c) Wet coupling, dry coupling, transition, and atmospherically controlled coupling regime subspaces within the total CTP-HI space with the classification scheme of Findell and Eltahir (2003a) overlaid. (d) Mean daily precipitation (source given in top left corner) in the CTP-HI space overlaid by the classification scheme of this study. . . .	57
3.3	Examples of (a) dry and (b) wet coupling events for an arbitrary grid cell (34.375°N, 81.875°W) in the Southeast, classified using MERRA-VIC and using the NLDAS-2 daily precipitation. Vertical dotted lines indicate the start and end of each event. Values of CTP < -500 J kg <sup>-1</sup> are removed for clarity. . . . .	58
3.4	The average evolution of SM, HI, and CTP (top three rows from top to bottom) during the coupling event separated by initial values and average event duration (bottom row) based on initial SM for (a) MERRA-MERRA, (b) MERRA-MLAND, (c) MERRA-VIC, and (d) AIRS-AMSR-E for the Southeast warm season. . . . .	59
3.5	Average evolution of SM during the coupling event separated by initial values (as in the top row of 3.4) based on MERRA-VIC for (a) soil layer 1 (0-0.1 m), (b) 2 (0.1-0.4 m), and (c) 3 (0.4-1.0 m) for the Southeast warm season. . . . .	60

3.6	Seasonality of (a) the coupling drought index (CDI) for all classifications and (b) the average percent area of drought severity from the U.S. Drought Monitor for the Southeast for the period of 2000-10. Owing to data availability, AIRS-AMSR-E is for 2003-09 only. . . . .	60
3.7	The spatial and temporal variability of the 2003-09 June-July (a) drought severity for the start, duration, and end of the time period and (b) derived CDI over the entire period using various input datasets. . . . .	61
4.1	Coupling classification consistency between the full resolution reanalysis (CFSR) and the lower vertical resolution reanalysis (CFSR- LR), a) spatially over the continental US, b), c) for regional, regime-specific consistency (%), d), e) the CTP-HI classification using the CFSR and f), g) using the CFSR-LR for the Great Plains and Southeast regions, respectively. . . . .	87
4.2	The 28-year (1982-2009) average CDI for the summer months (June-September) over the continental US for a) the CFSR, b) CFSR-LR, c) forecast initiated at 00Z May 31 and d) forecast initiated at 00Z January 31. Missing values (no color) are areas that are predominately atmospherically controlled. . . . .	88
4.3	The 28-year average of a) the 30-day CDI and b) the 30-day cumulative precipitation bias from the reanalysis calculated from NLDAS-2, the CFSR, CFSR-LR and the forecasts at five different initialization times over the Great Plains Region of the US. The equivalent plots for the Southeast US are given in c) and d). . . . .	89

4.4	The 28 year summer time (June-September) average daily a) precipitation, b) runoff, c) latent heat flux, d) total soil moisture in layers 1-3, e) soil moisture in layer 4, f) sensible heat flux, g) humidity index, h) wind speed and i) net radiation from the CFSR data and 4 ensemble forecast initiated on May 31 at 00z, 06z, 12z and 18z for the Great Plains region of the US. . . . .	90
4.5	The same as Figure 4.4 except for the Southeast US. . . . .	91
4.6	The forecast (May 31 at 00z) minus the reanalysis for the average summer a) coupling drought index, b) precipitation, c) downward short-wave radiation, d) downward longwave radiation, e) net radiation, f) evaporation, g) change in soil moisture and h) humidity index for the 28 year hindcast period and i) the vegetation classification in the CFS model. All reanalysis variables are from the CFSR, except the CDI, which is from the CFSR-LR and the precipitation, which is from the NLDAS-2. . . . .	92
4.7	The June-July season of the 1998 drought in terms of CDI from a) CFSR-LR, b) ensemble-mean (n = 120) from CFSRR along with the c) the top three layers soil moisture percentile from Noah NLDAS-2. Precipitation and 2-m temperature versus CDI for all 120-ensemble members for the Great Plains (d, e) and the Southeast (f, g). . . . .	93
4.8	The same as Figure 4.7 except for the 2006 drought. . . . .	93
5.1	The distribution frequency, the Kolmogorov-Smirnov (KS) test p-value for each fitted distribution (histogram) and the average p-value at each grid for a) precipitation, b) daily maximum temperature and c) daily minimum temperature. . . . .	120

5.2	The uncertainty (standard deviation) in the weather model parameters for a)-c) the mean of the distribution, d)-f) the variance of the distribution for precipitation and daily maximum and minimum temperature respectively and g) the probability of precipitation. . . . .	121
5.3	The a) probability of precipitation and b)-d) select percentiles from the distributions of precipitation intensity and daily maximum and minimum temperature dependent on coupling and season in the weather model for an example grid in western Oklahoma. . . . .	122
5.4	The a) parameter uncertainty in the Coupling Statistical Model (CSM) and b) the transitional probabilities condition on the previous day coupling state ( $C_{i-1}$ ) and precipitation ( $P_{i-1}$ ) for the example grid in western Oklahoma. . . . .	123
5.5	The uncertainty in estimating the mean and standard deviation for both the forecast and observations for a) CTP and b) HI used in the correction model and the correction in the distribution of c) CTP and d) HI for the example grid in western Oklahoma. . . . .	124
5.6	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. . . . .	124
5.7	The 3 month (JJA) forecast skill (Spearman Correlation) for the Coupling Drought Index (CDI), Precipitation (P), daily maximum temperature (Tmax) and daily minimum temperature (Tmin) for a) CPM, b) CSM, c) CSMi d) CDM and e) CFSRR. . . . .	125

5.8	The variation of model a) - d) bias and e) - h) correlation with temporal resolutions of the forecast for CDI, precipitation and daily maximum and minimum temperature, respectively. . . . .	126
5.9	The predictability metric for the example grid in western Oklahoma for daily maximum temperature and its spatial variability for precipitation (P) and daily maximum (Tmax) and minimum (Tmin) temperature for a) the timescale of prediction, b) local coupling predictability, c) dynamic model coupling predictability, d) non-coupling dynamic model predictability and e) the potential increase in predictability. . . . .	127
5.10	The 1988 drought given by anomalies of a) the observations and the forecasts from the b) CSMi, c) CDM and d) CFSRR with the spatial correlation with observations given in lower right corner for CDI, precipitation (P) and daily maximum temperature (Tmax). . . . .	128
5.11	The fraction of drought area based on anomaly thresholds and the spatial correlation of the CSMi, CDM and CFSRR with the observations for 11 drought years for a) the CDI, b) precipitation and c) daily maximum temperature. . . . .	129

# Chapter 1

## Introduction

### 1.1 Motivation and Background

In many parts of the world, extreme hydrologic events in the form of floods and droughts are a significant source of social and economic damage. In recent years there have been several of these events such as the heavy rainfall that caused record flooding throughout large segments of Iowa in 2008 (Smith et al. 2013) and more recently the drought of 2011 and 2012, which have affected a historically large fraction of the country including the primary growing regions (Karl et al. 2012). Although, the average US precipitation during these events was not as low as previous years, the record high temperatures caused an intensification and expansion of drought that greatly impacted some regions, particularly during the summer months (Karl et al. 2012). In the United States, the average annual damage due to drought alone is estimated at \$6.8 billion (Wilhite 2000). The acute impacts of drought are also further amplified due to increasing populations and crop production that adds stress to a limited water supply (Seager et al. 2009). The ability to have a warning of such extremes would allow for the resulting impact on society to be reduced through

preparation. One such preparation is the ability of water managers to make decisions to ensure sufficient water supply during droughts and ample reservoir storage during flood events. In order to achieve the intended benefit, these preparations require sufficient warning on a seasonal time scale.

The prospect of seasonal predictability of hydrologic drivers, such as precipitation and temperature, to aid in reservoir management has motivated water managers and forecasters to develop prediction models. Historically these models were statistically based and incorporated a large array of predictors based on observations (Goddard et al. 2001). As computational resources and our understanding of the climate has improved, the use of physically based Global Climate Models (GCMs) to make seasonal predictions has become available. However, using the forecasts from GCMs is not always straightforward due to the coarse resolution and inherent model biases associated with their predictions. Even with these limitations, there have been many examples of using GCM for seasonal hydrologic prediction (Wood et al. 2002; Luo et al. 2007) which have shown predictability for some areas and events (Luo and Wood 2007). There have also been many studies that have compared the use of statistical methods against GCM for hydrologic forecasts, however the hydrologic forecast is greatly dependent on the skill of the precipitation forecasts (Yuan et al. 2011, 2013).

Individual storms that cause hydrologic extremes cannot be predicted due to the chaotic nature of the atmosphere, however some extremes are the result of a seasonal persistence into a wet or dry state. The 2008 flooding and the 2012 drought are examples of such extremes caused by a seasonal persistence (Karl et al. 2012; Smith et al. 2013) and not a single event. The source of predictability of the atmosphere on a seasonal time scales lies in the slowly varying boundary conditions (i.e. sea-surface temperatures and land surface characteristics) and can provide skillful seasonal forecasts to the extent that the boundary conditions are predictable

(Palmer and Anderson 1994; Goddard et al. 2001). There have been several studies that have shown the potential of seasonal predictability through a connection of large-scale climate patterns and land-atmosphere interactions (Palmer and Anderson 1994; Trenberth and Guillemot 1996; Goddard et al. 2001; Koster et al. 2010; Villarini et al. 2013). In particular, the cold season predictability of the atmosphere in the extratropics comes from the slowly varying ocean boundaries that play a role in circulation patterns (i.e., teleconnections) (Palmer and Anderson 1994). However, during the summer the teleconnections between tropical Pacific SST and precipitation across the US are weakened, which limits the predictability (Lavers et al. 2009; Seager et al. 2009; Quan et al. 2012). Even though the warm season teleconnections are weak and provide no means of predictability, there is still a potential of predictability via soil moisture-precipitation feedbacks (Koster et al. 2000b). The land-atmosphere interaction (hereafter coupling) impacts the diurnal precipitation cycle through the surface heat and moisture fluxes, which impact the growth and attributes of the atmospheric boundary layer. Modeling studies have shown that soil moisture conditions contributed to drought intensification in the case of the 1988 Great Plains drought (Atlas et al. 1993; Sud et al. 2003). Likewise, Trenberth and Guillemot (1996) argue that soil moisture played a role in perpetuating the drought of 1988 but also played a role in perpetuating the wet conditions in 1993 over the Mississippi River basin. In particular, the parameterization of the land surface plays a crucial role in the heat flux partitioning that contribute to the growth and attributes of the boundary layer that produces convection and can provide a feedback mechanism (Ek and Mahrt 1994; Findell and Eltahir 2003a).

There has been a great deal of work over the last decade to quantify land-atmosphere interactions and feedbacks over a variety of scales and for observations and prediction models. Working groups as part of the Global Energy and Water

Cycle Experiment (GEWEX) initiative have done much of this work. One such effort focuses on the local land-atmosphere coupling through diagnosing the interactions between the lands surface and the planetary boundary layer for models and observations using high-resolution test beds (Santanello et al. 2009, 2011). Other analyses have looked at the land-atmosphere interactions of models at the scale of GCMs (Dirmeyer et al. 2006) including the Global Land Atmosphere Coupling Experiment (GLACE) phase one (Koster et al. 2006; Guo et al. 2006) and phase two (Koster et al. 2011). A promising addition to these studies is the use of satellite remote sensing to classify and understand land-atmosphere interactions at the GCM scale (Ferguson and Wood 2011; Taylor et al. 2012).

## 1.2 Dissertation Goals

Although there are two distinct sources of seasonal predictability of the atmosphere through the boundary conditions (i.e. sea-surface and land surface), the seasonal and spatial variations of the predictability is not well understood, particularly in respect to the attribution of land-atmosphere interactions on seasonal predictions of drought. As a result of not knowing the attribution and the seasonal and spatial variation of skill of the forecasts from GCMs, the forecasts are often under utilized and do not provide the maximum benefit to society. The aim of this thesis is to provide a framework for understanding the spatial and seasonal variability of predictability and its attribution, with a particular focus on land-atmosphere interactions and the prediction of drought. The driving science questions in this thesis are, *What is the seasonal and spatial variation of predictability over the U.S.* and *What portion of this predictability is associated with land-atmosphere interactions?* Answering these key questions will provide the needed information to allow for a more effective use of

seasonal forecasts and provide a framework for model assessment that can lead to improvements in modeling techniques and ultimately better forecasts.

### 1.3 Thesis Overview

The remaining chapters of this thesis are organized as follows. In Chapter 2 the formation of a probabilistic predictability metric based on multiple temporal and spatial scales is used to understand the seasonal and spatial variability of predictability and its attribution to sea-surface temperature. In Chapter 3 the foundations for understanding the seasonal predictability of land-atmosphere interactions is established by developing a new classification of land-atmosphere interactions and its importance to drought through the Coupling Drought Index (CDI). In Chapter 4 the CDI is used as the primary measure of coupling to assess the seasonal predictability of a GCM and its implications to drought prediction. In Chapter 5 the attribution of land-atmosphere interactions on the summer time predictability, with an emphasis on drought prediction, is established through the use of statistical, hybrid and GCM models. Chapter 6 gives a summary of the findings and a synthesis and extension of the results.

### 1.4 Publications and Presentations

The core chapters of this dissertation (Chapters 2 through 5) have been published or submitted for publication. Below are the full references:

- Chapter 2: Roundy, J. K., X. Yuan, J. Schaake and E. F. Wood, 2014: A framework for analyzing seasonal prediction through canonical event analysis. Submitted to *Monthly Weather Review*.