Investigation of summer land-atmosphere feedback over the U.S. with observations, reanalysis data and models

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1. Abstract

The first part of this study examines the impact of sea surface temperature (SST) and soil moisture on summer precipitation over two regions of the U.S. (the Upper Mississippi River Basin and the Great Plains) using data from observational SST and precipitation, and VIC-simulated soil moisture. Based on conditioned soil moisture-precipitation correlation analysis, soil moisture-precipitation feedback is more likely to be positive and significant during the years when the skill of precipitation prediction based on SST alone is low, and in the years of large precipitation anomalies, which underlines the complementary roles both SST and soil moisture play in determining precipitation and the importance of considering soil moisture in predicting climate extremes. The second part compares land atmosphere coupling strength over the U.S. between observations (and reanalysis) and model output, with as a coupling strength indicator the probability density functions of conditioned correlation over the years of large precipitation anomalies. Among the eight different regions classified by land cover types, our results identify the Great Plains as a hot spot for strong land-atmosphere coupling strength; results of comparison between soil moistureprecipitation coupling and soil moisture-surface temperature coupling indicate that soil moisture is more promising for predicting surface temperature than precipitation. In addition, contrary to previous speculation of models overestimating soil moisture-precipitation coupling, our results suggest that the coupling strength is stronger in observational data than in the CAM-CLM models. Part of the reason is due to the strong decrease of coupling strength from CAM3-CLM3 to CAM4-CLM4, which is further supported by GLACE1 experiments and attributed to changes in CAM.

5. Method and Results

5.1 Conditioned soil moisture-precipitation correlation
Regions: Great Plains (GP: 37.5N-45N, 105W-95W); Upper Mississippi River Basin (UM: 36N-44N, 92W-85W)
Data: HadISST, CPC precipitation, VIC soil moisture (1950-1997)
5.1.1 SST-precipitation linear regression
Two approaches to derive the SST predictors:
> Use SST averaged over identified Oceanic Areas: correlate summer precipitation averaged for a specific region (e.g., Great Plains) with summer SST of the globe, produce a global correlation map, and identify oceanic areas that present significant correlation;

➤Use leading EOFs derived from Empirical Orthogonal Functions analysis: isolate the leading patterns (EOFs) of summer SST using EOF/REOF analysis under different domains (Pacific, Atlantic and global), and identify the EOFs with significant correlations to summer precipitation of the two regions.



5.2 Comparison of summer land-atmosphere coupling strength between observations, reanalysis data and models



Fig3: Biome distribution for the United States from EROS Data Center's

Regions	CPC-VIC		NARR		CFSR		
	1950-1997NGp0.32(0.04)SGp0.29(0.05)NSh0.31(0.05)SSh0.05(0.40)MW0.25(0.09)SE0.29(0.05)		1979-20080.27(0.04)0.47(0.00)0.23(0.10)0.26(0.07)0.25(0.11)0.26(0.04)		1979-2008 0.41(0.00) 0.33(0.04) 0.22(0.12) 0.23(0.06) 0.59(0.00) 0.66(0.00)		Average PC
NGp							0.33
SGp							0.36
NSh							0.25
SSh							0.18
MW							0.36
SE							0.40
NW	0.21(0.12)	0.21(0.12) <i>0.26(0.07)</i>		0.10(0.30) <i>0.36(0.02)</i>).15(0.24)	0.15
NE	0.26(0.07)).33(0.03)	0.32
Regions	cam3	cam4		cam3		cam4	
	1950-1997	1950-1997		1978-2007		1978-2007	Average PC
NGp	0.42(0.00)	0.27	7(0.05)	0.45(0.00)		0.39(0.00)	0.38
SGp	0.30(0.06)	0.05(0.40)		0.27(0.04)		0.34(0.03)	0.24
NSh	0.48(0.00)	0.12(0.26)		0.28(0.06)		0.11(0.28)	0.25
SSh	0.10(0.26)	0.09	9(0.31)	0.01(0.47)		0.17(0.18)	0.09
MW	0.27(0.06)	0.11	1(0.27) 0.24(0 6 (0.07) 0.29(0		0.09) 0.06)	0.33(0.04)	0.24
SE	0.27(0.08)	0.26				0.24(0.08)	0.27
NW	0.19(0.11)	0.0	2(0.4)	0.18(0	0.08)	0.14(0.20)	0.13
NE	0.08(0.34)	0.13	3(0.24)	0.28(0	0.06)	0.14(0.21)	0.16

Table1: Values of PC and SI (in parenthesis) for pdf of correlation between 1day soil moisture and 21-day precipitation for different datasets over the eight regions in outer quartiles: values with SI less than 0.1 are in bold and italic; dataset-averaged PC values presented in the last column are in red bold and

2. Background and Motivation

The potential positive feedback (i.e., dominant view) between soil moisture and precipitation, which tends to perpetuate and sustain anomalous hydrological conditions such as floods or droughts, promotes a long land memory and improves predictability of the land-atmosphere system (Koster and Suarez 2001; Dirmeyer et al. 2009), leading to the contribution of realistic soil moisture initialization to sub-seasonal precipitation prediction (Koster et al. 2011). Soil moisture therefore may serve as a potential predictor for precipitation over regions with a long land memory and therefore strong land-atmosphere coupling.

Numerical modeling studies have demonstrated the prevailing

Fig.1: Observed and SST-predicted time series of summer precipitation. SST1 (180W-165W, 30N-35N), and SST2 (162W-152W, 0-8N) are identified oceanic areas; Pacific EOF1 and 2, and Global EOF1 and 3 are identified EOF patterns derived from pacific and global domain, respectively. Note both SST1 and 2, and Pacific EOF1, Global EOF1 are highly related to signal of ENSO or Pacific decadal oscillation.

5.1.2 Conditioned soil moisture-precipitation correlation analysis Two methods to categorize 48 years data into two categories (24 in each) > Outer quartiles vs. Inner quartiles: based on total summer precipitation > Low-skill SST vs. High-skill SST: based on the predicted error for summer precipitation derived from SST averaged over identified oceanic areas from Fig.1

For each specific categorization method, two approaches are used to investigate soil moisture-precipitation feedback between different

global land cover classification dataset (from figure 3 in Notaro et al. 2006). The classified sub-regions considered in this part of study include: Northern Great Plains (NGp: 105W-96W, 34.4N-49N), Southern Great Plains (SGp: 105W-96W, 25N-34.4N), Northern Shrubland (NSh:119.4W-105W, 40N-49N), Southern Shrubland (SSh:119.4W-105W, 30.8N-40N), Midwest (MW: 96W-80W, 38N-45N), Southeast (SE: 92.5W-75W, 30N-34.5N), Northwest (NW: 124W-119.4W, 40N-49N) and Northeast (NE: 80W-67W, 38N-47.5N).

Regions: shown above in Fig3.

Data: 1) CPC-VIC(1950-1997); NARR and CFSR (1979-2008);

2)CAM3-CLM3, CAM4-CLM4 (1950-1997,1978-2007).
CAM-CLM (verison 3 and 4) are driven by HadISST during 1940-2007
Conditioned Correlation using Probability density function (pdf)
➢ Soil Moisture-Precipitation;

> Soil Moisture-Surface Temperature;

➢Soil Moisture-Evaporative fraction;

Two indicators for comparison of pdf:

Peak correlation (PC): correlation value with peak probability density
 Significance index (SI): fraction of correlation values smaller (larger) than zero as the indicator for the significance of positive (negative) correlation



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a	1C	when	consensus-	-view	shows	significance.

Regions	NAF	R	CF	Average			
	1979-2	2008	1979	PC			
NGp	-0.44(0.00)	-0.39	-0.42			
SGp	-0.56(0.00)	-0.49	-0.53			
NSh	-0.19(0	D.10)	-0.13	-0.16			
SSh	-0.23(0	0.10)	-0.32	-0.28			
MW	-0.37(0.04)	-0.57	-0.47			
SE	-0.50(0.00)	-0.62	-0.56			
NW	-0.30(0.03)	-0.25	-0.28			
NE	-0.30(0.04)	-0.36	-0.36(0.01)			
Regions	cam3	cam4	cam3	cam4	Average		
	1950-1997	1950-1997	1978-2007	1978-2007	PC		
NGp	-0.58(0.00)	-0.36(0.01)	-0.59(0.00)	-0.44(0.00)	-0.49		
SGp	-0.51(0.00)	-0.28(0.07)	-0.46(0.00)	-0.44(0.01)	-0.42		
NSh	-0.38(0.03)	-0.30(0.03)	-0.42(0.01)	-0.41(0.00)	-0.38		
SSh	-0.12(0.23)	-0.05(0.38)	-0.10(0.26)	-0.20(0.10)	-0.12		
MW	-0.36(0.02)	-0.26(0.08)	-0.42(0.00)	-0.20(0.10)	-0.31		
SE	-0.44(0.00)	-0.41(0.01)	-0.55(0.00)	-0.28(0.06)	-0.42		
NW	-0.21(0.10)	-0.05(0.40)	-0.27(0.05)	-0.14(0.22)	-0.17		
NE	-0.20(0.14)	0.12(0.75)	-0.31(0.05)	0.12(0.78)	-0.07		
Table2	: Same as table	1 but for surf	ace temperatur	e			
Regions	NAF	RR	CF	Average			
	1979-2	2008	1979	PC			
NGp	0.83(0.00)		0.80	0.82			
SGp	0.79(0.00)		0.70	0.75			
NSh	0.94(0.00)		0.75	0.85			
SSh	0.8(0.00)		0.57	0.69			
MW	0.87(0).00)	0.86	0.87			
SE	0.9(0	0.9(0.00)		0.80(0.00)			
NW	0.82(0.00)		0.55	0.69			
NE	0.5(0	.00)	0.55	0.00)	0.53		
Regions	cam3	cam4	cam3	cam4	Average		
	1950-1997	1950-1997	1978-2007	1978-2007	PC		
NGp	0.61(0.00)	0.55(0.00)	0.63(0.00)	0.65(0.00)	0.61		
SGp	0.50(0.00)	0.35(0.03)	0.47(0.00)	0.55(0.00)	0.47		
NSh	0.62(0.00)	0.52(0.00)	0.51(0.00)	0.36(0.02)	0.50		
SSh	0.50(0.00) 0.40(0.01)		0.57(0.00)	0.50			
MW	0.46(0.01)	0.47(0.00)	0.41(0.01)	0.56(0.00)	0.48		
SE	0.32(0.03)	0.51(0.00)	0.39(0.01)	0.49(0.00)	0.43		
NW	0.56(0.00)	0.55(0.00)	0.53(0.00)	0.63(0.00)	0.57		
NE	0.08(0.30)	0.25(0.08)	0.28(0.06)	0.22(0.10)	0.21		

view of the positive soil moisture precipitation feedback over various regions in the U.S. including the Midwest and the Great Plains (e.g., Pal and Eltahir 2001; Kim and Wang 2007). However, observational studies on this idea are still inconclusive (Findell and Eltahir 1997; Salvucci et al. 2002; D'Odorico and Porporato 2004; Ruiz-Barradas and Nigam 2005).

A fundamental issue related to the model-observation contrast is the comparability of results from numerical modeling studies and observational analysis. Specifically, most numerical studies examining the impact of soil moisture on subsequent precipitation were based on an ensemble approach. However, short observational record technically represents one member of a potential ensemble simulation.

On the other hand, numerous studies also suggest that sea surface temperature (SST) can play an important role affecting precipitation over the continental U.S. (e.g., Trenberth and Guillemot 1996; Schubert et al. 2009).

3. Objective

To understand and quantify the significance of land surface feedback in the context of large scale SST forcing, and facilitate the application of land surface conditions in operational prediction at sub-seasonal and seasonal time scales. The specific research questions are:

categories:

➤Temporal correlation between 1-day soil moisture and subsequent 21-day precipitation (amount or frequency), results not shown.

➢Probability density function (pdf) of correlation between 1-day soil moisture and subsequent 21-day precipitation (amount or frequency), results shown below.



The pool of each category has a size of 24x92 (24 years in each category, 92 days in summer); while the pool of the whole data has a size of 48x92. The sample size for correlation calculation is 24.

Random sampling with a constraint. i.e., the closest two data pairs should not

Fig.4: Probability distribution function of correlation between 1 day soil moisture and subsequent 21-day precipitation amount from CPC-VIC; PC ⁴⁰ and SI are indicated by the arrow and shadow for outer quartile of ³⁰ Northwest for example.

Fig.4 indicates that summer soil moisture-precipitation correlation for the whole dataset tends to be positive in most of the regions; such positive feedback signal is obviously amplified in outer quartiles. In inner quartiles, the correlations are mostly negative, indicating a negative soil moisture-precipitation feedback, although the signal is rather weak compared with the outer quartiles. Due to the insignificance of negative correlation in inner quartiles and the strong evidence for the widely held notion of positive soil moisture-precipitation feedback in outer quartiles, we will focus on comparison of soil moisture-precipitation correlation among different products in outer quartiles.

The soil moisture-temperature (or evaporative fraction) correlation in inner



Fig.5: Distribution of $\Delta\Omega_p$ (land atmosphere coupling strength for precipitation) and $\Delta\Omega_E * \sigma_E$ (product of land atmosphere coupling strength for evaporation and its standard deviation) for the CAM-CLM models, derived from GLACE1-type experiments, are presented in the left two columns; distribution of gridded PC value for pdf of correlation between 1-day soil moisture and 21-day precipitation for CAM-CLM models during 1950-1997 for outer quartiles are presented in the right column. (See Koster et a. 2006 for GLACE1 approach)

How does the impact of local soil moisture on subsequent precipitation depend on the impact of SST and on specific precipitation regimes based on observations?
 How does land-atmosphere coupling strength in models compare with observations and reanalysis data?

4. Data and Model

Climate Prediction Center (CPC) U.S. UNIFIED daily precipitation; Variable Infiltration Capacity (VIC) modeled daily soil moisture (1950-1997)
North American Regional Reanalysis (NARR) daily and Climate Forecast System Reanalysis (CFSR) 6-hourly data (1979-2008)
Hadley Centre, Meteorological Office HadISST 1.1 Global monthly sea surface temperature (1950-2008)

•National Center for Atmospheric Research (NCAR) CAM3-CLM3 (Community Atmosphere Model 3-Community Land Surface Model 3) and its improved version CAM4-CLM4 (driven by observed HadISST) daily output (1950-2007) overlap for precipitation. e.g., in the calculation of one correlation value, if the pair of data with soil moisture on June 6th and precipitation during June 7th-27th in some year is drawn, the closest neighboring data pair that can potentially be drawn is soil moisture on June 27th and precipitation during June 28th-July 18th in the same year. quartiles in all regions and products (results not shown) has the same sign negative (or positive) as, but is much weaker than, the correlation in outer quartiles. Therefore, comparison of soil moisture-temperature (or evaporative fraction) correlation analysis is also focused on in outer quartiles.

6. Summary and Conclusion

For the first part:

For both GP and UM, regardless of whether precipitation amount or frequency is considered, the conditioned soil moisture-precipitation correlation is stronger during the years with large summer precipitation anomalies, and is stronger during years when SST presents low skill in summer precipitation prediction than during years when SST exhibits high skill, which highlights the critical importance of including soil moisture in predicting climate extremes. *For the second part:*

Among the eight classified regions, the correlation analysis from both observations and models identify the Great Plains, i.e., NGp and SGp, as hot spots for strong land-atmosphere coupling, which is consistent with previous studies using different methodologies. In addition, Midwest and Southeast also stand out with rather strong correlations.

≻The soil moisture-precipitation coupling is weaker than soil moisture-surface temperature coupling, as supported by both correlation analysis and GLACE1-type of experiments. These may be a reflection of the rather straightforward effects of soil moisture-induced evaporative cooling and the more complicated soil moisture-precipitation relationship that involves competing mechanisms.

The CAM-CLM models underestimate the land-atmosphere coupling strength as compared with both observational data and reanalysis data. This may be related to the underestimation of soil moisture-evaporation correlation in the model (relative to reanalysis), which would indicate the need for improving the parameterization of evapotranspiration response to soil water stress in CLM. Further scrutiny is needed in follow-up studies.
 From CAM3-CLM3 to CAM4-CLM4, the coupling strength decreases according to both correlation analysis and GLACE1-type of experiments. This decrease most likely results from modifications to the convection scheme in CAM rather than changes in CLM.

D'Odorico, P., and A. Porporato, 2004: Preferential states in soil moisture and climate dynamics. Proc. Natl. Acad. Sci. USA, 101, 8848-8851.
Findell, K. L., and E. A. B. Eltahir, 1997: An analysis of the soil moisture-precipitation feedback, based on direct observations from Illinois. Water Resour. Res., 33, 725-735.
Koster, R. D., and M. J. Suarez, 2001: Soil moisture memory in climate models. J. Hydrometeor., 2, 558-570.
Koster, R. D., and Coauthors, 2006: GLACE: The Global land-atmosphere Coupling Experiment: Part 1: Overview. *J. Hydrometeor.*, 7, 590-610.
Koster, R. D., et al. 2011: The Second Phase of the Global Land-Atmosphere Coupling Experiment: Soil Moisture Contributions to Subseasonal Forecast Skill. J Hydrometeor 12, 805–822.
Kim, Y. J., and G. L. Wang, 2007: Impact of initial soil moisture anomalies on subsequent precipitation over North America in the coupled land-atmosphere model CAM3-CLM3. J. Hydrometeor., 8, 513-533
Notaro, M., Z. Liu, and J. W. Williams, 2006: Observed vegetation-climate feedbacks in the United States. *J. Climate*, 19, 763-786.
Pal, J. S., and E. A. B. Eltahir, 2001: Pathways relating soil moisture conditions to future summer precipitation within a model of the land-atmosphere system. J.

Dirmeyer, P. A., et al. 2009: Precipitation, recycling and Land memory: An integrated analysis. J. Hydrometeor., 10, 278-288.

Climate, 14, 1227-1242. Ruiz-Barradas, A., and S. Nigam, 2005: Warm season precipitation variability over the US great plains in observations, NCEP and ERA-40 reanalyses, and NCAR and NASA atmospheric model simulations. J. Climate, 18, 1808-1830.

Schubert, S. D., et al. 2009: A U.S. CLIVAR project to assess and compare the responses of global climate models to drought-related SST forcing patterns: Overview and results. J. Climate, 22, 5251-5272.

Salvucci, G. D., et al. 2002: Investigating soil moisture feedbacks on precipitation with tests of Granger causality. Adv. Water Resour., 25, 1305-1312. Trenberth, K. E., and C. J. Guillemot, 1996: Physical processes involved in the 1988 drought and 1993 floods in North America. J. Climate, 9, 1288-1298

Related papers

Reference

Mei R, Wang GL, 2011: Summer land-atmosphere coupling strength in the United States: Comparison among observations, re-analysis data, and numerical models. Submitted to *Journal of Hydrometeorology*

Mei R, Wang GL, 2011: Impact of sea surface temperature and soil moisture on summer precipitation in the United States based on observational data. *Journal of Hydrometeorology*, 12, 1086-1099

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