

Oceanic Water Cycle, Sea Surface Salinity, and the Implications for Extreme Precipitation in the US Midwest

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1. Introduction

Moisture originating from the ocean surface is an ultimate source for precipitation on land. Over the global oceans, the largest moisture source regions are located over the subtropics where the excessive evaporation over precipitation has to be balanced by a net export of moisture (Schmitt 1995; Trenberth *et al.* 2011; Durack 2015). About a third of the subtropical moisture is transported and converged over the land area to sustain the terrestrial precipitation.

This ocean-to-land moisture transport leaves an imprint on sea surface salinity (SSS). Without an internal source of salt, surface freshwater flux associated with the oceanic water cycle is the only forcing mechanisms on SSS variation. Thus, the changes in SSS, interpreted as “Nature’s rain gauge”, reflect the variation of the oceanic water cycle (Curry *et al.* 2003; Durack and Wijffels 2010; Durack *et al.* 2012; Schmitt 2015).

The close relationship between the SSS and oceanic water cycle and the reliance of terrestrial precipitation on water input from the oceans indicate that SSS variation over moisture source regions can be potentially utilized as a predictor of precipitation on land. This study presents evidence that the springtime SSS over the subtropical North Atlantic can be indicative of summer precipitation over the US Midwest. We further show that the linkage between the pre-season SSS and Midwest summer precipitation is through the memory of the soil moisture and a combination of thermodynamic and dynamic effects of soil moisture on the regional moisture balance.

The prediction of US Midwest summer precipitation based on Random Forest algorithm suggests that pre-season SSS outperforms SST-based predictors, in which a model incorporating SSS increases the explained variance by two folds. The SSS-based prediction is especially skillful in capturing the extremely wet summers in the US Midwest, such as the 1993 and 2008 cases. Thus, the newly identified salinity-based predictor can significantly improve the seasonal forecast of precipitation in the US Midwest, especially the extremes.

2. Data and methodology

The precipitation data are from the NOAA CPC US precipitation at 0.25° spatial resolution and daily temporal resolution (Higgins *et al.* 2000). Summer season is defined as the June-July-August (JJA).

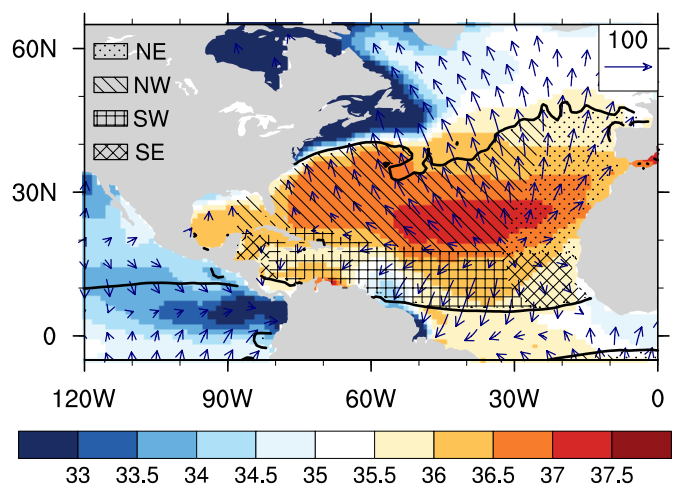


Fig. 1. MAM climatology (1950–2009) of SSS (shaded; PSU), moisture flux divergence (thick contours; mm day^{-1}) and the divergent component of moisture flux (vectors; $\text{kg m}^{-1}\text{s}^{-1}$) over the North Atlantic. The solid thick contour is the moisture flux divergence = 0 mm day^{-1} isoline, which defines the subtropical North Atlantic in this study. The domains used to calculate SSS indices in the four quadrants are stippled or hatched.

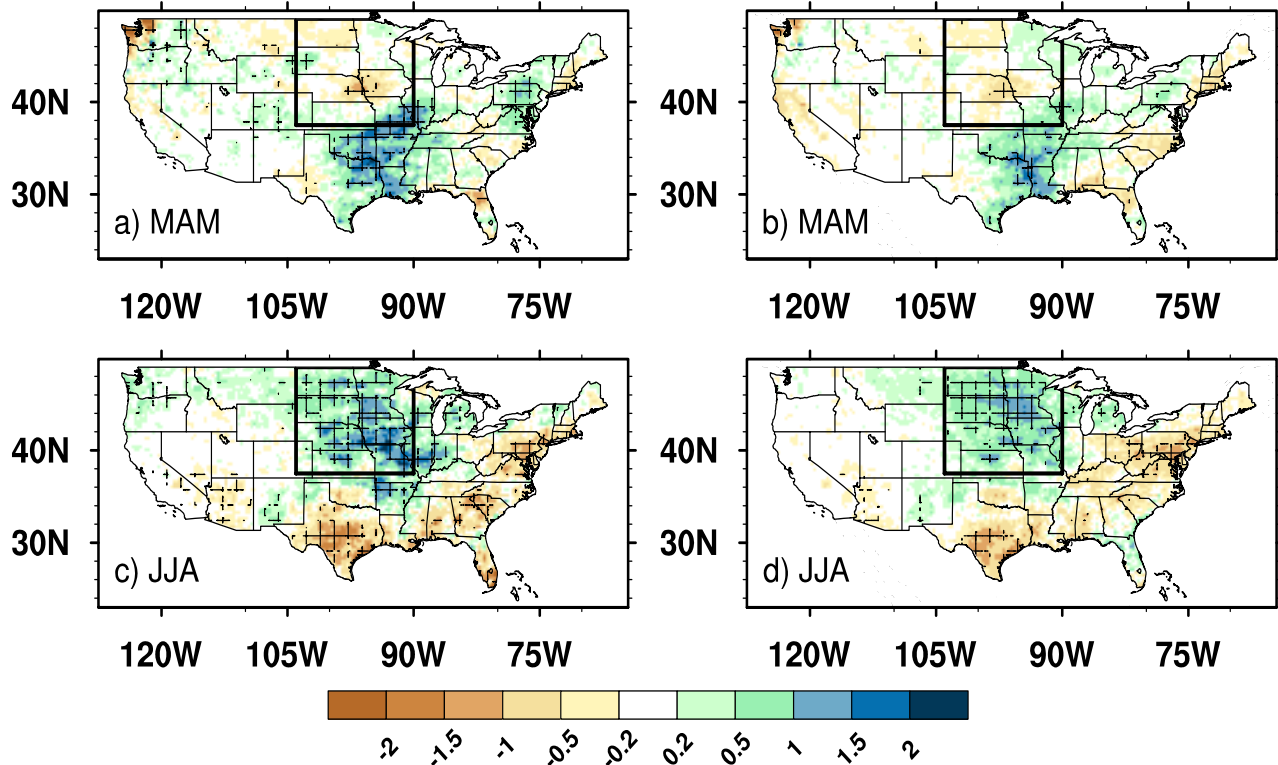


Fig. 2 US precipitation anomalies (shaded; mm day⁻¹) as (a), (c) composite and (b), (d) regressed upon MAM NW SSS index: (top) MAM and (bottom) JJA precipitation. The composite maps show precipitation difference between the top and bottom 10% SSS cases. The regions with composite/regression precipitation anomalies significant at the 0.05 level are hatched.

We construct a set of subtropical sea surface salinity (SSS) indices using the data archived by the EN4.2.1 (Good *et al.* 2013). We first define the subtropical ocean as an area of net divergence of atmospheric moisture (Fig. 1). Next, the subtropical ocean is further divided into four areas according to the direction of the divergent component of moisture flux. For example, the northwest (NW) is where the divergent component of moisture flux is directed northwest toward the North America (Fig. 1). The SSS within the northwest subdomain is averaged and the domain average defines the NW SSS index. The same definition applies to the NE, SW, and SE SSS indices (Fig. 1, and Li *et al.* 2016).

We applied Random Forest (RF), a machine-learning algorithm (Breiman 2001), to predict precipitation on land based on pre-season salinity over the subtropical North Atlantic. In this study, we train the RF algorithm with 11 predictors, including SSS, the persistence of regional precipitation, and nine climate indices representing the oceanic and atmospheric modes of variability. All climate variables are averaged over MAM to match the SSS predictor. The performance of the RF prediction is evaluated based on the coefficients of determination: $R^2 = 1 - SS_{res}/SS_{tot}$ (*i.e.*, the portion of variance explained by the prediction model); $SS_{tot} = \sum_{i=1}^N (Pr_i - \overline{Pr})^2$ is the total variance of observed precipitation; and $SS_{res} = \sum_{i=1}^N [f(X)_i - Pr_i]^2$ quantifies the sum of precipitation variance unexplained by the RF prediction $[f(X)]$.

3. Results

3.1 Relationships between pre-season salinity and US Midwest precipitation

Since the divergent component of moisture flux indicates where subtropical moisture will converge, the above defined SSS indices reflect not only the changes in surface freshwater flux but also potential geographical areas that will be influenced by the subtropical moisture flux. We focus on rainfall evolution over the US following the springtime NW SSS in that the moisture flux from this portion of the subtropical oceans tends to converge over the US (Fig. 1).

Both composite and linear regression analysis are applied to US precipitation. For the spring, the most significant precipitation anomalies associated with high NW SSS are located over the southern US (eastward of 100°W), where the positive precipitation anomalies exceed 1 mm day^{-1} (Fig. 2a-b). The positive precipitation anomalies appear to propagate northward to the Midwest in the summer (see mechanistic discussion below), leading to $1.5 - 2 \text{ mm day}^{-1}$ above normal precipitation there (Fig. 2c-d). The composite and linear regression results are qualitatively similar, suggesting that the relationship between SSS and precipitation is generally linear and symmetric (Fig. 2)

The processes linking the springtime SSS and precipitation in the southern United States and how they finally affect summer precipitation in the Midwest is evaluated and summarized in Fig. 3 (see details in Li *et al.* 2016, 2018). Initially, the increased moisture transport from ocean to land elevated soil moisture content in the Southern and Central US during the spring season. In the subsequent seasons, the high soil moisture content is preserved due to the 3-6-month land surface memory. The high soil moisture content serves as a moisture source to the local atmospheric column by increasing boundary layer humidity in the Southern and Central US. With the prevailing southerly wind in the summer, more moisture will be converged into the US Midwest, which is thermodynamically favorable for heavier precipitation (Meehl and Washington 1988; Delworth and Manabe 1989; Ek and Holtslag 2004). In addition, the spatial distribution of soil moisture influences precipitation through atmospheric dynamics, i.e. the intensity of the Great Plains Low-level jet (GPLLJ). Specifically, the increased soil moisture in the Central US enhances the west-to-east soil moisture gradient along the slope of the Rocky Mountains. The soil moisture content gradient increases the zonal pressure gradient and forces the GPLLJ to intensify to balance the enhanced pressure gradient (Fast and McCorcle 1990, 1991). The intensified GPLLJ brings more Gulf of Mexico moisture northward, favors moisture flux convergence in the Midwest, and thus contributes to high precipitation dynamically.

3.2 Improved rainfall prediction for the US Midwest

The physical linkage between springtime NW SSS and summer precipitation in the US Midwest suggests that pre-season SSS can be a physically meaningful predictor for Midwest precipitation (Fig. 3). We thus implemented the springtime NW SSS into the RF algorithm to predict summer precipitation over the US Midwest. According to the RF algorithm, the NW SSS is ranked as the most important rainfall predictor compared to the other 10 predictors: the importance factor of NW SSS is 0.98, but it drops to 0.53 for Niño 3.4, the second most important predictor (Fig. 4a). Using the top four predictors shown in Fig. 4a, we constructed an RF prediction model for Midwest summer precipitation. Fig. 4b shows that the four predictors together explain 41% of the observed precipitation variance, and the observed precipitation is within the 95% confidence interval (CI) of the predictions. The prediction without the NW SSS, however, largely underestimates the variability of Midwest precipitation, especially the extremely wet summer in 1993 and 2008 (Weaver *et al.* 2009). At the same time, the R^2 between the observation and prediction decreases to 0.16 (Fig. 4c).

3.3 Implications for extreme precipitation

The RF algorithm suggests that salty subtropical North Atlantic in the spring can be an indicator of extreme summer precipitation in the Midwest (Fig. 4). Assuming a linear relationship between SSS and precipitation, the positive SSS anomaly in 1993 will be followed by a 0.7 mm day^{-1} increase in Midwest summer precipitation, which alone explains 37% of the observed precipitation anomalies. In contrast, the previously identified ENSO predictor (Mei and Wang 2011) can only explain 8%, insufficient to account for the observed 1993 extreme

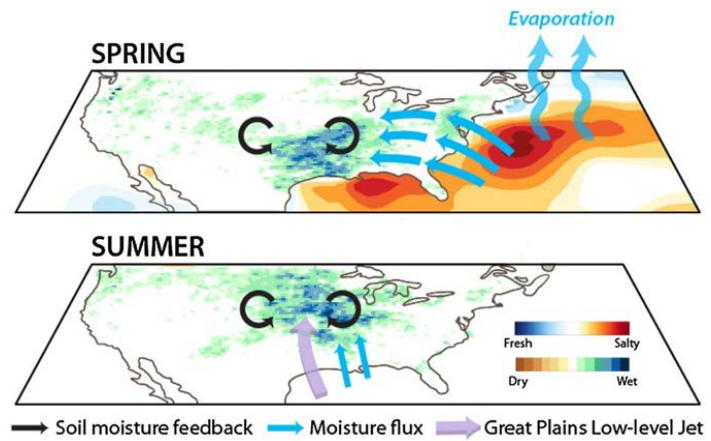


Fig. 3 Schematic figure showing the way soil moisture bridges the 3-mon time lag between spring SSS and Midwest summer precipitation (see Li *et al.* 2018 for detail).

precipitation (Patricola *et al.* 2015). Further, the SSS-based prediction forecasts 0.47 mm day^{-1} precipitation anomalies in the summer of 2008. The predicted precipitation equates to 78% of the observed precipitation anomaly. Over the 1950–2015 period analyzed in this study, a higher-than-normal springtime subtropical North Atlantic SSS occurs in five out of six historical extreme precipitation events in the Midwest. Meanwhile, in all of the 6 years with the saltiest subtropical ocean, a wet summer ensued in the Midwest.

In conclusion, the results demonstrate improvements in predicting Midwest summer precipitation with the knowledge of springtime NW SSS, especially the extreme precipitation events. In addition to the previously identified ENSO link (Trenberth and Guillemot 1996; Barlow *et al.* 2001; Hoerling and Kumar 2003), incorporating pre-season SSS into prediction models can thus benefit seasonal forecasting of Midwest summer precipitation.

4. Conclusions

From the perspective of moisture exchange between ocean and land, this study explores the feasibility of terrestrial rainfall prediction using SSS over the subtropical North Atlantic. According to the direction of the divergent component of moisture flux, we defined a set of SSS indices (Fig. 1). We found that springtime SSS over the NW part of the subtropical North Atlantic is significantly correlated with summer precipitation over the US Midwest (Fig. 2). The linkage between springtime SSS and Midwest summer precipitation is established through the ocean–land moisture transport, land surface–atmospheric coupling, and its impact on atmospheric dynamics and thermodynamics (Fig. 3).

The close relationship between springtime SSS and US Midwest summer precipitation indicates that salinity variations can provide predictive values for the US Midwest. By applying the RF algorithm to Midwest summer rainfall predictions, we show that NWSSS in the subtropical North Atlantic can generate higher prediction skill than previously identified for ENSO variability (Fig. 4). Thus, a knowledge of springtime SSS in the subtropical North Atlantic will be valuable for predicting summer precipitation over the US Midwest, an agricultural region vulnerable to floods and droughts.

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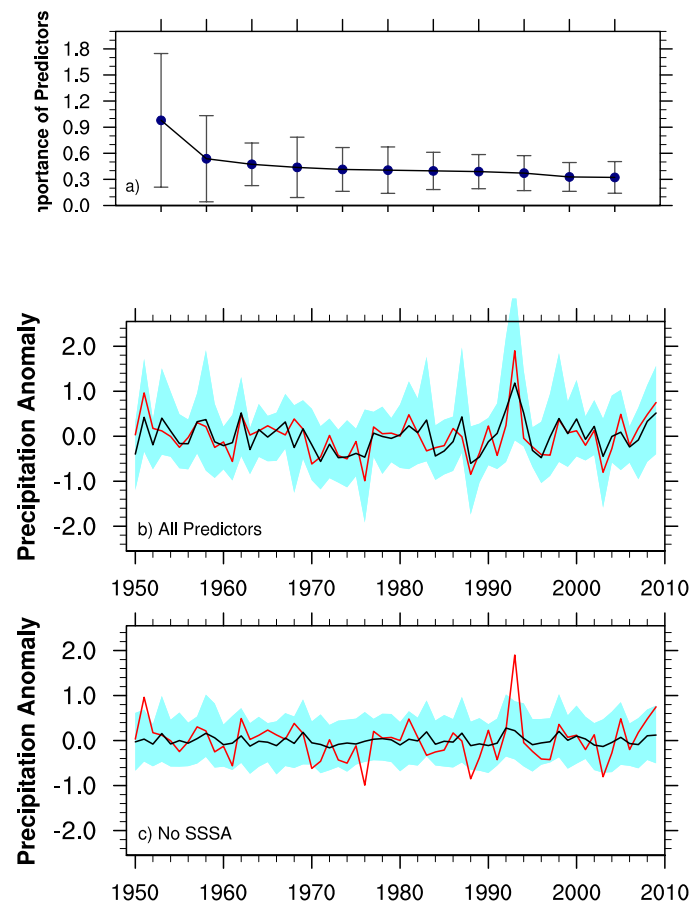


Fig. 4. (a) Importance of 11 predictors used in the RF model; (b) Prediction using top four predictors and (c) that without the NW SSS. In (b) and (c), the red (black) curves are the observations (predictions). The blue-shaded are the 95% CI of the predictions.

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