Multiscale Land–Atmosphere Coupling and Its Application in Assessing Subseasonal Forecasts over East Asia^①

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ABSTRACT

The land surface, with a memory longer than the atmosphere in nature, has been recognized as an important source for Subseasonal to Seasonal (S2S) predictability through land–atmosphere coupling at multiple time scales. Understanding of the land–atmosphere coupling is important for improving subseasonal forecasting that is expected to fill the gap between medium-range weather forecasts and seasonal forecasts. Based on reanalysis and S2S reforecast datasets, land–atmosphere coupling is investigated over East Asia from daily to monthly time scales during summertime. Reanalysis results show that soil moisture–evapotranspiration (ET) coupling is closely related to the monsoonal rain belt shift. The coupling can be significant over humid regions (e.g., south China) during postmonsoon periods, where soil is usually drier, but insignificant over semiarid regions (e.g., north China) after the arrival of a monsoon, where soil is wetter. The dependence of soil moisture–ET coupling on soil wetness conditions decreases as the time scale increases, indicating more significant coupling at longer time scales. Similar sensitivities to time scales are found between ET and lifting condensation level (LCL), and between ET and precipitation, especially over land–atmosphere coupling hotspots. Monthly coupling strength analysis shows that ET–LCL coupling is a key process that determines the soil moisture–precipitation coupling, and the response of convective instability to ET is stronger at longer time scales. Subseasonal forecasting models also show more significant land–atmosphere coupling at monthly than daily time scales, where the ECMWF and NCEP models that best reproduce the coupling and its changes with monsoonal rain belt shifts have the best precipitation forecast skill among S2S models.

1. Introduction

Weather and climate forecasts at different time scales rely on different predictable sources, such as the atmosphere, land, and ocean. The subseasonal forecast that fills the gap between weather forecasts and seasonal forecasts (Brown et al. 2012; Yuan et al. 2014) is significantly influenced by the predictability originating from the land surface, because the memory of the atmosphere is too short (although recurring atmospheric circulation variations can persist for a few weeks) and the variability of the ocean is too small to have a strong influence at subseasonal time scales (Koster et al.

2010; Guo et al. 2011; Yuan et al. 2015; Vitart et al. 2017). Therefore, understanding the feedback of land to atmosphere is crucial for improving subseasonal forecasting.

Anomalies in land surface conditions can affect the atmosphere through thermodynamic, dynamic, and hydrologic processes depending on the conditions of topography, vegetation, and soil. For instance, soil moisture (SM) is a key land surface variable that affects land–atmosphere coupling; it influences the surface fluxes, then exerts an impact on the atmospheric states (e.g., lifting condensation level, planetary boundary layer height, etc.), and ultimately affects the precipitation. Soil moisture anomalies can last for several weeks, and they change the surface energy and

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water cycle and affect the variability of precipitation at subseasonal time scales (Koster et al. 2010; Dirmeyer and Halder 2017). A realistic soil moisture initialization may enhance precipitation predictive skill significantly in the subsequent 2–3 months (Guo et al. 2011), including extreme events (Weisheimer et al. 2011).

Coupling between soil moisture and precipitation plays an important role in weather and climate predictions (Seneviratne et al. 2010). However, the feedback from soil moisture to precipitation is complicated because it is difficult to observe and quantify the coupling between soil moisture and evapotranspiration (ET), as well as the atmospheric boundary layer processes that link ET to precipitation (Betts 2009; Wei and Dirmeyer 2012). Specifically, surface soil moisture influences ET through soil evaporation, while deep-layer soil moisture can affect ET directly through vegetation transpiration and indirectly by influencing surface soil moisture as well as soil evaporation (Canadell et al. 1996). ET affects the boundary layer by changing surface humidity and couples soil moisture dynamics to the lifting condensation level (LCL) and finally to precipitation (Betts 2004). The coupling between soil moisture and precipitation has a regional preference and manifests differently under different soil conditions. The transitional zone between humid and arid regions has the strongest coupling, and the coupling tends to be stronger (weaker) when the soil is anomalously dry (wet) over climatologically wet regions and anomalously wet (dry) over dry regions, respectively (Seneviratne et al. 2006; Koster et al. 2009; Wei and Dirmeyer 2012). In addition, Roundy et al. (2013) used soil moisture to classify the convective triggering potential and low-level humidity index space into four coupling regimes—atmospheric controlled, transition, dry coupling, and wet coupling—and found that the wet coupling is associated with wetter soil, which leads to a positive feedback that induces convection through increasing latent heat and moist static energy and lowering the lifting condensation level. An overestimation of wet coupling may preclude the forecast model from predicting and maintaining drought (Roundy et al. 2014).

The land–atmosphere coupling has been investigated at multiple time scales. Synoptic-scale atmospheric circulations supply a background for land–atmosphere coupling (Tawfik and Dirmeyer 2014), and conversely, soil moisture anomalies may cause anomalies in the atmospheric heat budget and then change synoptic circulations (Fischer et al. 2007). The feedback from soil moisture to precipitation exists at synoptic (Koster et al. 2003), pentad (Wei and Dirmeyer 2012), and monthly time scales (Zhang et al. 2008). Dirmeyer et al. (2009) found that soil moisture–ET correlation is slightly more significant at monthly than at daily time scales, except for the dry seasons of monsoon

regions. Van den Hurk and Meijgaard (2010) calculated the correlation between monthly soil moisture and ET to analyze seasonal cycles of land–atmosphere coupling over West Africa and found similar scale-dependent results to Dirmeyer et al. (2009). Betts (2004) showed that the daily and pentad-mean SM–ET relationships are inherently tied to processes (such as surface energy transport and boundary layer growth) at subdaily time scales.

Over East Asia, there is a lack of systematic comparison for the land–atmosphere coupling characteristics at multiple time scales. Furthermore, how does the land–atmosphere coupling vary under different soil wetness conditions at different time scales? What is the role of boundary layer dynamics in the soil moisture–precipitation coupling? Are the above land–atmosphere coupling characteristics captured by subseasonal forecasting models? In this study, we are trying to answer these questions by using reanalysis and subseasonal reforecast datasets. The paper is arranged as follows. Section 2 briefly describes the reanalysis and reforecast data used in this study. Section 3 presents the land–atmosphere coupling characteristics from daily to monthly time scales based on reanalysis data. The land–atmosphere coupling characteristics in subseasonal forecast models are investigated in section 4, and the results of this study are concluded and discussed in section 5.

2. Data and methods

a. Reanalysis data and subseasonal reforecasts

In this study, the boreal warm season from May to August was selected because of strong land–atmosphere coupling (Koster et al. 2004). To explore characteristics of land–atmosphere coupling, daily data including 0–20- and 20–100-cm soil moisture ($\text{m}^3 \text{m}^{-3}$), ET (mm day^{-1}), surface air temperature T (K) and dewpoint temperature T_d (K) at 2 m, and precipitation (mm day^{-1}) at a horizontal resolution of $0.75^\circ \times 0.75^\circ$ were derived from the ERA-Interim reanalysis (Dee et al. 2011) from 1979 to 2016. Planetary boundary layer height (PBLH; m) and LCL (m) were also used to study the coupling between the boundary layer and surface. The LCL was defined as $(T - T_d)/(\Gamma_d - \Gamma_{\text{dew}}) = 125 \times (T - T_d)$ (in meters), where the lapse rate for dry adiabatic Γ_d lifting is about 9.8 K km^{-1} and the lapse rate of the dewpoint Γ_{dew} is about 1.8 K km^{-1} . The ERA-Interim reanalysis data were widely used for land–atmosphere coupling studies (Miralles et al. 2012; Betts and Beljaars 2017). To reduce the uncertainty in reanalysis data (Santanello et al. 2015), we also used the same variables from Climate Forecast System Reanalysis (CFSR) data (Saha et al. 2014), and averaged results from the two reanalysis datasets were used in this study.

TABLE 1. Information for five selected subseasonal forecast models from the S2S prediction project database (Vitart et al. 2017).

	Time range (day)	Reforecast frequency	Reforecast period	Resolution
ECMWF	Days 0–46	Twice weekly	1996–2015	$0.25^{\circ} \times 0.25^{\circ}$ days 0–10, $0.5^{\circ} \times 0.5^{\circ}$ after day 10; L91
NCEP	Days 0–44	Daily	1999–2010	$1.0^{\circ} \times 1.0^{\circ}$; L64
CMA	Days 0–60	Daily	1994–2014	$1.0^{\circ} \times 1.0^{\circ}$; L40
HMCR	Days 0–61	Weekly	1985–2010	$1.1^{\circ} \times 1.4^{\circ}$; L28
BoM	Days 0–60	Twice weekly	1981–2013	$2.0^{\circ} \times 2.0^{\circ}$; L17

The same hydrometeorological variables from the Subseasonal to Seasonal (S2S) prediction project database (Vitart et al. 2017) were analyzed for the land–atmosphere coupling assessment. The database provided results from 11 models, but only 5 models [ECMWF, NCEP, China Meteorological Administration (CMA), Hydrometeorological Centre of Russia (HMCR), and Australian Bureau of Meteorology (BoM)] that provide soil moisture data were used; the details for the models (e.g., forecast frequency, forecast length) are listed in Table 1 (Vitart et al. 2017). To ensure enough samples for the correlation calculation, two sets of reforecasts started (with a lag of 7 days) close to (but before) the first day of each month (i.e., May–August) were selected. For example, ECMWF reforecasts started every 7 days during 1996–2015, so the reforecasts initialized at 18 April and 25 April were selected for May, which resulted in 2 (initializations) $\times 20$ (years) $\times 31$ (days) = 1240 samples (days) for the analysis. To compare with reanalysis data, all model reforecasts were bilinearly interpolated to 0.75° . In this study, only the reforecast data from control experiments (i.e., without perturbations in initial conditions) were used.

To evaluate the forecast skill of precipitation for the S2S models, CPC daily gridded precipitation data at 0.5° (Chen et al. 2008) were used as observations. The reason for using observed precipitation instead of reanalysis precipitation as a verification reference is to obtain a more objective validation of the forecast skill of S2S models, given that reanalysis precipitation usually has model-related errors. While for the analysis of land–atmosphere coupling, S2S model-predicted precipitation was used.

b. Land–atmosphere coupling metrics

Pearson correlation between daily time series of SM and ET was calculated for each grid cell as a measure of sensitivity of ET to SM. The sensitivity may vary with soil wetness conditions (Dirmeyer and Halder 2017; Koster et al. 2009). Therefore, SM–ET correlations conditional on dry (lower tercile), moderate (middle tercile), and wet (upper tercile) soil conditions were calculated after ranking all daily SM for the target month during 1979–2016. The variance of soil moisture is small over arid regions for all months and over India during May (Fig. S1 in the online supplemental material). Except for these cases, soil moisture has a reasonable

variance that allows for the tercile analysis. For each grid point, three pairs of SM and ET time series corresponding to dry, moderate, and wet soil conditions were obtained before calculating the correlations. If the SM–ET correlation was significant under all three soil conditions, the grid point was marked as “All.” If the correlation was significant both for “Dry” and “Mod” conditions, it was marked as “Dry + Mod,” etc. The unconditional and conditional correlations between ET and precipitation and ET and LCL were also calculated. The same procedure was also applied for pentad, 10-day, and monthly mean time series. Given that each model has different climatology, the terciles were calculated for each S2S model or reanalysis data separately.

To quantify land–atmosphere coupling strength, several indices were defined. For the SM ranges between wilting point and field capacity, ET is usually assumed to follow a linear relationship with SM. Several land–atmosphere coupling metrics were developed based on this assumption, such as a correlation index and a coupling index (Wei and Dirmeyer 2012). In this study, ET was also assumed to follow a linear relationship with SM expressed as $\partial(\text{ET})/\partial(\text{SM}) = \text{COV}(\text{ET}, \text{SM})/\sigma^2(\text{SM})$, where $\text{COV}(\text{ET}, \text{SM})$ is the covariance between SM and ET and $\sigma(\text{SM})$ is the standard deviation of soil moisture. Then, the impact of soil moisture on ET could be expressed as a coupling strength index $\text{CSI}_{\text{SM-ET}} = [\partial(\text{ET})/\partial(\text{SM})]\sigma(\text{SM}) = \text{COV}(\text{ET}, \text{SM})/\sigma(\text{SM})$ (Wei and Dirmeyer 2012), where soil moisture was considered as a forcing variable and ET as a response variable (Santanello et al. 2011). Similarly, coupling strength indices $\text{CSI}_{\text{SM-P}}$, $\text{CSI}_{\text{ET-LCL}}$, and $\text{CSI}_{\text{LCL-P}}$ were defined as $[\partial P/\partial(\text{SM})] \times \sigma(\text{SM})$, $[\partial(\text{LCL})/\partial(\text{ET})] \times \sigma(\text{ET})$, and $[\partial P/\partial(\text{LCL})] \times \sigma(\text{LCL})$ to measure the forcing from soil moisture to precipitation, from ET to LCL, and from LCL to precipitation, respectively.

3. Land–atmosphere coupling analysis based on reanalysis data

a. Correlation analysis between soil moisture and evapotranspiration at the daily time scale

Here, correlation between surface soil moisture (0–20 cm) and ET from reanalysis data was calculated as a representation of land–atmosphere coupling sensitivity.

FIG. 1. Correlation between daily SM and ET in (a) May, (b) June, (c) July, and (d) August from reanalysis during 1979–2016. Correlations were calculated by using ERA-Interim and CFSR reanalyses separately, and the averaged correlations were shown here.

Figure 1 shows that there are significant positive correlations between soil moisture and ET across the warm season months over midlatitude arid and semiarid regions including south Mongolia and northwest and northeast China, where the soil is usually unsaturated. In fact, land–atmosphere coupling starts from SM–ET coupling (Guo et al. 2006; Seneviratne et al. 2010), so a significant positive correlation between soil moisture and ET indicates that there is a positive surface feedback to the atmosphere over arid and semiarid regions, where soil moisture is a controlling factor for ET. Significant negative correlations exist over South China with a humid climate (Figs. 1a–d). This is because soil moisture is usually plentiful for ET over South China, and the ET is controlled by available energy. The increase in available energy may increase ET and dries down the soil, and the presence of precipitation increases soil moisture but may decrease ET due to less solar radiation reaching the land surface. These mechanisms result in the negative SM–ET correlation over humid regions, including south China.

Over east India, the correlation switches from positive to negative in June and July, which is related to the Indian monsoon onset in mid-June (Shin and Huang 2016). Before the Indian monsoon onset, there is little precipitation during May and early June, and soil

moisture is a controlling factor for ET, so the correlation is positive. After the monsoon onset during July and August, soil becomes wetter because of increased precipitation, so energy is the controlling factor for ET, which results in a negative correlation.

Figure 2 shows the dry/wet soil conditions when the correlation between soil moisture and ET is statistically significant. Over the midlatitude arid belt (region I in Fig. 2a) including west Mongolia and northwest China, the correlation is large (Fig. 1) and significant across all soil wetness conditions (All denoted as light blue) from May to August (Fig. 2). But the variance of soil moisture is actually very small (Fig. S1). Over the south and north edges of the arid belt (region I), the correlation is significant under dry and moderate soil wetness conditions (red area), indicating a transition from a dry to wet region (Fig. 2). To study the temporal evolution, the number of grid points with significant correlations for the main categories in each region for each month was counted. Figure 3a shows that fractions of different category grid points have small variations from May to August for the arid region.

Over northeast and north China (region II in Fig. 2a), the pattern shows transitional characteristics from May to August (Fig. 2). The number of grid points with

FIG. 2. Soil moisture bins over East Asia where conditional correlations between daily SM and ET are statistically significant at the 95% confidence level for certain soil wetness conditions. Dry, Mod, and Wet refer to the lower, middle, and upper terciles of soil wetness conditions, respectively, so Dry + Mod represents that the grid point has significant correlations both for dry and moderate conditions, etc. All correlations are the average results based on ERA-Interim and CFSR reanalyses.

significant correlations under all soil wetness conditions (light blue areas in Fig. 2) decreases quickly from May to July (Fig. 3b, All column). The dominant category is Dry from June to August (Figs. 2b–d, 3b). The above characteristics are well matched with the rain belt shift, where the East Asian summer monsoon arrives in north China (region II) in late June and reaches the peak in July (Shin and Huang 2016). For India (region III in Fig. 2a), the dominant category is All in May (Figs. 2a, 3c), just before the arrival of the Indian summer monsoons, but it gradually changes to None (i.e., no significant correlation under any soil wetness conditions) in August after the monsoon onset because of wet soil (Fig. 2d). This sensitivity of SM–ET correlation to soil wetness conditions over north China (region II) and India (region III) is also consistent with the land–atmosphere coupling hot spots in the Global Land–Atmosphere Coupling Experiment (GLACE-1) result (Koster et al. 2004).

South China (region IV in Fig. 2a) is usually considered as an energy-controlled region where ET is

primarily affected by atmospheric radiation instead of soil moisture. But in July and August, the SM–ET correlation can be significant under dry conditions (Figs. 2c,d), which are also associated with the rain belt shift. The East Asian monsoon starts in May and stays over south China (region IV) in June, so the soil is usually wet, resulting in no significant surface feedback to the atmosphere (Figs. 2a,b). But when the rain belt moves toward the north, the decrease of precipitation over south China leads to drier soil and a significant positive feedback under dry conditions (Fig. 3d). This feature is also reflected in Figs. 1c and 1d, where a weaker negative correlation occurs over south China (region IV) during July and August.

Figures 1–3 show that the effect of the South Asian summer monsoon on land–atmosphere coupling over India is much stronger than the influence of the East Asian summer monsoon over south China, which is also consistent with a previous study that India is a land–atmosphere hot spot (Koster et al. 2004). While south China is a humid region, there is little land surface

FIG. 3. Fraction of grid points with significant correlations between daily SM and ET for four categories of soil wetness conditions (Dry, Dry + Mod, Wet, and All) over four regions shown in Fig. 2. (a) Arid belt in midlatitude (region I; 35°–55°N, 75°–100°E), (b) north and northeast China (region II; 35°–55°N, 105°–135°E), (c) India (region III; 15°–30°N, 70°–90°E), and (d) south China (region IV; 20°–30°N, 105°–120°E). All correlations are the average results based on ERA-Interim and CFSR reanalyses.

feedback to the atmosphere, except a weak coupling for dry soil condition after the plum rain period in August (Fig. 2d).

b. Correlation analysis at multiple time scales

To study the characteristics of land–atmosphere coupling at multiple time scales, correlations were also calculated based on pentad, 10-day, and monthly mean variables. It is found that there are more obvious surface feedbacks to the atmosphere in terms of soil moisture–ET correlations (Figs. 4a–d,m) at longer time scales over northeast and north China (region II) and India (region III). Similar variations with time scales were also found for the correlation between ET and precipitation, where the correlations over India (region III) become more significant as time scale increases (Figs. 4e–h,n). In addition, the ET–precipitation correlations over north and

northeast China are insignificant at daily time scales (Figs. 4e,n), but they become significant at pentad scales (Figs. 4g,n) and are enhanced at monthly scales (Figs. 4h,n). If there is only feedback from land to atmosphere, the correlations should be always positive. But when precipitation occurs, the positive relationship might switch to negative if the soil moisture is too wet to have a control on ET. At shorter time scales, the instantaneous perturbation of precipitation would have a larger impact on the land–atmosphere relationship, while for longer time scales, the relation becomes more stable due to less impact from instantaneous perturbation.

Correlations under different soil wetness conditions at multiple time scales were also calculated. Consistent with unconditional correlations calculated by using all samples (Figs. 4a–h), both SM–ET and ET–precipitation correlations conditional on different soil wetness show

FIG. 4. Correlations between (left) SM and ET, (center) ET and P , and (right) ET and LCL at (a),(e),(i) daily, (b),(f),(j) pentad, (c),(g),(k) 10-day, and (d),(h),(l) monthly time scales. (m)–(o) Regional mean correlations over northeast and north China (blue) and India (red) across time scales. The correlations were calculated by using samples in all boreal summer months (from May to August) during 1979–2016. All correlations are the average results based on ERA-Interim and CFSR reanalyses.

FIG. 5. (a)–(l) As in Figs. 4a–l, but for categories with significant correlations under different soil wetness conditions defined in Fig. 2. (m)–(o) The proportions of All category grid points over northeast and north China (blue) and India (red). All correlations are the average results based on ERA-Interim and CFSR reanalyses.

FIG. 6. Land-atmosphere CSIs for (a) SM-ET (mm day^{-1}), (b) ET-LCL (m), (c) LCL- P (mm day^{-1}), and (d) SM- P (mm day^{-1}) at monthly time scales. CSI_{A-B} represents how much change of B is expected when one standard deviation change of A occurs. The values in the upper-right corner of each panel are the mean values of coupling indices averaged over East Asia. $\text{CSI}_{\text{SM-ET}}$ and $\text{CSI}_{\text{ET-LCL}}$ are shown only when positive and negative correlations are statistically significant, respectively. $\text{CSI}_{\text{SM-P}}$ and $\text{CSI}_{\text{LCL-P}}$ are shown only when four coupling indices ($\text{CSI}_{\text{SM-ET}}$, $\text{CSI}_{\text{ET-LCL}}$, $\text{CSI}_{\text{LCL-P}}$, $\text{CSI}_{\text{SM-P}}$) are all statistically significant. All indices are the average results based on ERA-Interim and CFSR reanalyses.

significant increases along time scales (Figs. 5a–h,m,n). For instance, many areas over northeast and north China (region II) and India (region III) are categorized as Dry + Mod at daily time scales (Fig. 5a) according to the soil moisture–ET correlation, but they change to the All category at monthly scales (Fig. 5d), suggesting more significant land–atmosphere coupling at longer time scales (Fig. 5m). The same analysis was also carried out for the deep soil moisture (20–100 cm) at multiple time scales, and the results are similar except for region I (Fig. S2). Region I is an arid region; a dry or moderate deep soil moisture condition might suggest that the soil column is too dry to have an association with ET. The dependence of coupling on time scales might be partly because our study only focused on time scales of less than a month. In fact, surface and deep soil moisture may have opposite long-term changes, where global warming–induced increases in evaporative demand reduce surface soil moisture, but the

increase in precipitation has increased the deep-layer soil moisture (Berg et al. 2017).

To further study the intermediate processes in the cause–effect chain from ET to precipitation, both unconditional and conditional correlations between ET and LCL were calculated at multiple time scales (Figs. 4i–l, 5i–l). LCL is strongly coupled to precipitation and ET (Betts 2009), which is low over humid regions and high over dry regions. South China is usually regarded as an energy-controlling humid region; a possible mechanism for the positive ET–LCL correlation (Figs. 4i–l) might suggest that higher (lower) LCL is associated with less (more) precipitation and clouds, which results in more (less) solar radiation for ET. A negative correlation between ET and LCL indicates a positive feedback: an increase in ET results in a decrease in LCL, and a lower LCL suggests more chance for precipitation, providing more water for ET. Negative ET–LCL correlations occur over arid, semiarid, and

FIG. 7. Regional mean land-atmosphere CSIs ($-1 \times \text{CSI ET-LCL deficit; m}$) for ET (considered as a forcing variable) and LCL deficit (considered as a response variable and defined as the difference between LCL and PBLH) over north and northeast China and India at multiple time scales. All indices are the average results based on ERA-Interim and CFSR reanalyses.

semihumid regions, with areas expanding from daily to monthly scales (Figs. 4i–l). The expanding negative ET–LCL correlations (Figs. 4i–l) well explain the transition of ET feedback to precipitation over northeast and north China (region II; Figs. 4e–h). The conditional ET–LCL correlations with different soil wetness conditions (Figs. 5i–l) also show that ET–LCL coupling is a key process that determines the soil moisture–precipitation coupling at different time scales.

c. Land–atmosphere coupling strength analysis

Feedback from the land to the atmosphere is more significant at monthly time scales, as mentioned above. Therefore, we try to separate the monthly cause–effect chain (Wei and Dirmeyer 2012) from soil moisture to precipitation into three steps: soil moisture to ET, ET to boundary layer, and boundary layer to precipitation by the coupling strength indices defined as $\text{CSI}_{\text{SM-P}}$, $\text{CSI}_{\text{SM-ET}}$, $\text{CSI}_{\text{ET-LCL}}$, and $\text{CSI}_{\text{LCL-P}}$ in section 2b. It is found that the dry regions over midlatitudes (region I) with a high soil moisture–ET correlation (Fig. 4d) show a very weak coupling strength (Fig. 6a) because of a small variability of forcing variables (soil moisture), while the climate transition zones show strong couplings, such as northeast and north China (region II) and India (region III). Similar regional differences are also revealed in the coupling of ET–LCL, LCL–P, and SM–P (Figs. 6b–d). Spatial correlation between coupling strength indices $\text{CSI}_{\text{SM-P}}$ and $\text{CSI}_{\text{ET-LCL}}$ is -0.80 and is 0.86 and -0.71 for $(\text{CSI}_{\text{SM-P}}, \text{CSI}_{\text{SM-ET}})$ and $(\text{CSI}_{\text{SM-P}}, \text{CSI}_{\text{LCL-P}})$, respectively. The transitions of the coupling strength indices during summer season months are

shown in Fig. S3, and they are consistent with the correlation analysis (Fig. 2) where obvious monthly variations exist over the hotspots (regions II and III).

Given that the LCL cannot fully represent the boundary layer dynamics, the information from PBLH was also used. Here, the LCL deficit, which is defined as LCL minus PBLH, can reflect the impact of boundary layer dynamics on the potential formation of clouds and precipitation. If the PBLH is higher than the LCL, then the potential for condensation and cloud development exists. We consider ET as a forcing variable and the LCL deficit as a response variable to calculate the coupling index defined in section 2b. If the index is negative, it means a more humid surface condition leading to a low PBLH but a lower LCL, indicating a more unstable boundary layer and a higher chance for precipitation. Figure 7 shows the regional mean ET–LCL deficit coupling strength (multiplied by -1) across time scales over northeast and north China (region II) and India (region III). There are obvious enhancements in ET–LCL deficit coupling strength as time scale increases, no matter under dry, moderate, or wet soil conditions. This is also consistent with the correlation analysis in section 3a.

4. Land–atmosphere coupling in subseasonal forecast models

As demonstrated by the second phase of GLACE (GLACE-2; Koster et al. 2010), soil moisture anomalies have an influence on the variability and forecasts of surface air temperature and precipitation at subseasonal time scales with regional and seasonal dependence. This

FIG. 8. As in Fig. 2, but for five S2S models (ECMWF, NCEP, CMA, HMCN, BoM). Here, all S2S model statistics are based on daily values during the first month reforecasts.

effect is achieved through soil moisture–ET–precipitation interaction, so it is necessary to evaluate subseasonal forecasts in terms of land–atmosphere coupling.

Figure 8 shows soil moisture–ET correlations under different soil wetness conditions for five S2S models. Over India (region III), the results for the ECMWF model (Figs. 8a–d) are in good agreement with reanalysis from May to August, as shown in Fig. 2. As mentioned in section 3a, the coupling is closely related to the shift of the rain belt in summer. In June, the ECMWF model reproduced the northwest–southeast gradient of preferable soil wetness conditions over India (region III) quite well (Fig. 8b), while the NCEP model showed more significant soil moisture–ET correlations under wet conditions (Fig. 8f) as compared with the

reference data (i.e., correlations averaged from ERA-Interim and CFSR reanalyses). This might be caused by the delayed onset of the Indian monsoon in the NCEP model (Shin and Huang 2016), where less precipitation leads to drier soil moisture and thus an overestimated land–atmosphere coupling in June. The other three models could not capture the onset of the Indian monsoon correctly either (Figs. 8j,n,r). Over South China (region IV), only the NCEP (Figs. 8e–h) and ECMWF (Figs. 8a–d) models reproduced the features with no significant feedback in May and June but a positive feedback under dry conditions in July and August, which is related to reasonable forecasts of the onset of South China Sea summer monsoon in May and the rain belt shift to north China (region II) in July. The other

FIG. 9. (a)–(t) Correlations between observed (CPC) and S2S model-predicted weekly mean precipitation for May–August. For each month, predicted precipitation averaged over the first 7 days from four sets of initialized reforecasts was used to compare with observations. (u)–(x) Regional mean correlations over the four boxed regions marked in Fig. 2a for May–August reforecasts.

three models did not reproduce this phenomenon (Figs. 8i–t). Over north and northeast China (region II), the ECMWF, NCEP, and CMA models captured the dry–wet transition of soil moisture from June to July.

Comparing spatiotemporal variations of the soil moisture–ET correlation (Fig. 8) with the predictive skill of precipitation (Fig. 9), it is found that models with

better predictive skill also have a better simulation of land–atmosphere coupling. For instance, the ECMWF model has precipitation predictive skill (in terms of correlation with CPC observations) up to 0.7 over northeast and north China (region II) and India (region III) for each month (Figs. 9a–d, u–x), and this model also performed the best in simulating the soil moisture and

FIG. 10. Categories for significant conditional correlations (defined in Fig. 2) between ET and precipitation, but for five S2S model reforecasts at (left) daily and (right) monthly time scales.

FIG. 11. As in Fig. 6, but for five S2S model reforecasts at monthly time scales. The first values in the upper-right corner of each panel are the model-predicted mean coupling indices averaged over East Asia, and the second values are spatial correlations between reforecasts and reanalysis indices (averaged between ERA-Interim and CFSR) shown in Fig. 6.

ET coupling characteristics over most regions of East Asia (Figs. 8a–d). For the NCEP model, the coupling features (Figs. 8e–h) over India are inconsistent with the reanalysis from May to August (Figs. 2a–d), and the forecast skill is lower in most areas over India (Figs. 9e–h,u–x). For south China (region IV), the NCEP model successfully reproduced the features of no land surface feedback from May to June and positive feedback from July to August only under dry conditions; this is consistent with a higher precipitation forecast skill over south China (Figs. 9u–x). For the CMA model, there is no precipitation forecast skill from May to June (Figs. 9i,j) over south China (region IV), which is associated with an overestimated land–atmosphere coupling under dry and moderate soil wetness conditions (Figs. 8i,j). With an improved representation of land–atmosphere coupling in July and August (Figs. 8k,l), the precipitation forecast skill from the CMA model also increased (Figs. 9w,x). The other two models have lower

precipitation forecast skill (Figs. 9m–x), as well as poorer representation of land–atmosphere coupling (Figs. 8m–t).

The land–atmosphere coupling differences between daily and monthly time scales for the S2S models were also investigated. Taking the ET–precipitation correlation as an example, Fig. 10 shows that there are more significant correlations at monthly time scales than daily scales, which is consistent throughout the five selected S2S models. In terms of capability in reproducing the ET–precipitation coupling patterns, the ECMWF model performed the best (Figs. 10a,b), followed by the NCEP and the CMA models (Figs. 10c,f). Similar results were found for conditional correlations for soil moisture and ET (not shown).

As mentioned in section 3c, there are strong coupling strengths between the surface and the boundary layer over northeast and north China (region II) and India (region III), which are consistent with the coupling hot spots demonstrated in GLACE-1 (Koster et al. 2004).

To investigate whether these characteristics can be reproduced by S2S models, four coupling indices defined in section 2b were calculated. Figure 11 shows that the ECMWF and the NCEP models well reproduced the strong coupling regions over northeast and north China (region II) and India (region III). The spatial correlation between reanalysis CSI_{SM-P} (averaged between the ERA-Interim and CFSR reanalyses) and the ECMWF reforecast CSI_{SM-P} reached 0.74 (Fig. 11d) and reached 0.69 (Fig. 11h) for the NCEP model. These are higher than the others, so these two models performed the best. The regional mean soil moisture–precipitation coupling strengths for the ECMWF and NCEP models reached 0.64 and 0.71 mm day^{-1} , respectively (Figs. 11d,h), which are close to the strength (0.83 mm day^{-1}) in reanalysis data (Fig. 7d). Similar forecasting performances were found for other coupling strength indices.

5. Conclusions

In this study, multiscale land–atmosphere coupling has been investigated over East Asia during the warm season based on 38-yr (1979–2016) ERA-Interim and CFSR reanalysis data and decades of subseasonal reforecast data from the S2S project. It is found that the correlation between soil moisture and evapotranspiration (ET) is closely related to the rain belt shift, with significant correlation over the edges of monsoonal regions before the arrival of summer monsoons, but insignificant correlation even under dry soil wetness conditions during monsoon periods. The land surface to the atmosphere feedback is more significant as time scales increase from daily to monthly. Similar gradual changes in correlation along with time scales are found between ET and precipitation, as well as between ET and lifting condensation level (LCL). At shorter time scales, the instantaneous perturbation of precipitation would have a larger impact on the land–atmosphere relationship. While for longer time scales, the relation becomes more stable due to less impact from instantaneous perturbation.

Subseasonal forecast models with a better representation of land–atmosphere coupling also have a better precipitation forecasting skill, where the ECMWF and NCEP models perform the best both for capturing the coupling sensitivity to the rain belt shift and for predicting precipitation over monsoonal regions. The consistency between the performance in land–atmosphere coupling and precipitation prediction does not necessarily suggest that there is a cause–effect relation between them. It is possible that the S2S models that are capable of reproducing the monsoonal rain belt shift also have higher precipitation forecast skill and better representations of

the temporal changes in land–atmosphere coupling. However, some studies showed that the atmospheric low-level vorticity variations induced by the soil moisture anomaly are a critical factor in producing intraseasonal fluctuations in rainfall during the West African monsoon (Taylor 2008). Whether this mechanism also applies for the Asian monsoon needs more sophisticated analysis or even numerical experiments. This study identified the weaknesses and limitations in subseasonal forecasts in terms of land–atmosphere coupling at multiple time scales, which is also important for the forecasting of extreme events such as droughts (Roundy et al. 2013, 2014), because droughts usually have higher predictability with anomalous oceanic or land surface conditions (Yuan et al. 2015).

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REFERENCES

- Berg, A., J. Sheffield, and P. C. D. Milly, 2017: Divergent surface and total soil moisture projections under global warming. *Geophys. Res. Lett.*, **44**, 236–244, <https://doi.org/10.1002/2016GL071921>.
- Betts, A. K., 2004: Understanding hydrometeorology using global models. *Bull. Amer. Meteor. Soc.*, **85**, 1673–1688, <https://doi.org/10.1175/BAMS-85-11-1673>.
- , 2009: Land-surface-atmosphere coupling in observations and models. *J. Adv. Model. Earth Syst.*, **1**, <https://doi.org/10.3894/JAMES.2009.1.4>.
- , and A. C. M. Beljaars, 2017: Analysis of near-surface biases in ERA-Interim over the Canadian Prairies. *J. Adv. Model. Earth Syst.*, **9**, <https://doi.org/10.1002/2017MS001025>.
- Brown, A., S. Milton, M. Cullen, B. Golding, J. Mitchell, and A. Shelly, 2012: Unified modeling and prediction of weather and climate: A 25-year journey. *Bull. Amer. Meteor. Soc.*, **93**, 1865–1877, <https://doi.org/10.1175/BAMS-D-12-00018.1>.
- Canadell, J., R. B. Jackson, J. B. Ehleringer, H. A. Mooney, O. E. Sala, and E. D. Schulze, 1996: Maximum rooting depth of vegetation types at the global scale. *Oecologia*, **108**, 583–595, <https://doi.org/10.1007/BF00329030>.
- Chen, M., W. Shi, P. Xie, V. B. S. Silva, V. E. Kousky, R. W. Higgins, and J. E. Janowiak, 2008: Assessing objective techniques for gauge-based analyses of global daily precipitation. *J. Geophys. Res.*, **113**, D04110, <https://doi.org/10.1029/2007JD009132>.
- Dee, D. P., and Coauthors, 2011: The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. *Quart. J. Roy. Meteor. Soc.*, **137**, 553–597, <https://doi.org/10.1002/qj.828>.

- Dirmeyer, P. A., and S. Halder, 2017: Application of the land–atmosphere coupling paradigm to the operational Coupled Forecast System, version 2 (CFSv2). *J. Hydrometeorol.*, **18**, 85–108, <https://doi.org/10.1175/JHM-D-16-0064.1>.
- , C. A. Schlosser, and K. L. Brubaker, 2009: Precipitation, recycling, and land memory: An integrated analysis. *J. Hydrometeorol.*, **10**, 278–288, <https://doi.org/10.1175/2008JHM1016.1>.
- Fischer, E. M., S. I. Seneviratne, P. L. Vidale, D. Lüthi, and C. Schär, 2007: Soil moisture–atmosphere interactions during the 2003 European summer heat wave. *J. Climate*, **20**, 5081–5099, <https://doi.org/10.1175/JCLI4288.1>.
- Guo, Z., and Coauthors, 2006: GLACE: The Global Land–Atmosphere Coupling Experiment. Part II: Analysis. *J. Hydrometeorol.*, **7**, 611–625, <https://doi.org/10.1175/JHM511.1>.
- , P. A. Dirmeyer, and T. DelSole, 2011: Land surface impacts on subseasonal and seasonal predictability. *Geophys. Res. Lett.*, **33**, L24812, <https://doi.org/10.1029/2011GL049945>.
- Koster, R. D., M. J. Suarez, R. W. Higgins, and H. M. van den Dool, 2003: Observational evidence that soil moisture variations affect precipitation. *Geophys. Res. Lett.*, **30**, 1241, <https://doi.org/10.1029/2002GL016571>.
- , and Coauthors, 2004: Regions of strong coupling between soil moisture and precipitation. *Science*, **305**, 1138–1140, <https://doi.org/10.1126/science.1100217>.
- , S. D. Schubert, and M. J. Suarez, 2009: Analyzing the concurrence of meteorological droughts and warm periods, with implications for the determination of evaporative regime. *J. Climate*, **22**, 3331–3341, <https://doi.org/10.1175/2008JCLI2718.1>.
- , and Coauthors, 2010: Contribution of land surface initialization to subseasonal forecast skill: First results from a multi-model experiment. *Geophys. Res. Lett.*, **37**, L02402, <https://doi.org/10.1029/2009GL041677>.
- Miralles, D. G., M. J. van den Berg, A. J. Teuling, and R. A. M. de Jeu, 2012: Soil moisture–temperature coupling: A multiscale observational analysis. *Geophys. Res. Lett.*, **39**, L21707, <https://doi.org/10.1029/2012GL053703>.
- Roundy, J. K., C. R. Ferguson, and E. F. Wood, 2013: Temporal variability of land–atmosphere coupling and its implications for drought over the southeast United States. *J. Hydrometeorol.*, **14**, 622–635, <https://doi.org/10.1175/JHM-D-12-090.1>.
- , —, and —, 2014: Impact of land–atmospheric coupling in CFSv2 on drought prediction. *Climate Dyn.*, **43**, 421–434, <https://doi.org/10.1007/s00382-013-1982-7>.
- Saha, S., and Coauthors, 2014: The NCEP Climate Forecast System version 2. *J. Climate*, **27**, 2185–2208, <https://doi.org/10.1175/JCLI-D-12-00823.1>.
- Santanello, J. A., C. D. Peters-Lidard, and S. V. Kumar, 2011: Diagnosing the sensitivity of local land–atmosphere coupling via the soil moisture–boundary layer interaction. *J. Hydrometeorol.*, **12**, 766–786, <https://doi.org/10.1175/JHM-D-10-05014.1>.
- , J. K. Roundy, and P. A. Dirmeyer, 2015: Quantifying the land–atmosphere coupling behavior in modern reanalysis products over the U.S. southern Great Plains. *J. Climate*, **28**, 5813–5829, <https://doi.org/10.1175/JCLI-D-14-00680.1>.
- Seneviratne, S. I., D. Lüthi, M. Litschi, and C. Schär, 2006: Land–atmosphere coupling and climate change in Europe. *Nature*, **443**, 205–209, <https://doi.org/10.1038/nature05095>.
- , T. Corti, E. L. Davin, M. Hirschi, E. B. Jaeger, I. Lehner, B. Orlowsky, and A. J. Teuling, 2010: Investigating soil moisture–climate interactions in a changing climate: A review. *Earth-Sci. Rev.*, **99**, 125–161, <https://doi.org/10.1016/j.earscirev.2010.02.004>.
- Shin, C., and B. Huang, 2016: Slow and fast annual cycles of the Asian summer monsoon in the NCEP CFSv2. *Climate Dyn.*, **47**, 529–553, <https://doi.org/10.1007/s00382-015-2854-0>.
- Tawfik, A. B., and P. A. Dirmeyer, 2014: A process-based framework for quantifying the atmospheric preconditioning of surface-triggered convection. *Geophys. Res. Lett.*, **41**, 173–178, <https://doi.org/10.1002/2013GL057984>.
- Taylor, C. M., 2008: Intraseasonal land–atmosphere coupling in the West African Monsoon. *J. Climate*, **21**, 6636–6648, <https://doi.org/10.1175/2008JCLI2475.1>.
- van den Hurk, B. J. J. M., and E. V. Meijgaard, 2010: Diagnosing land–atmosphere interaction from a regional climate model simulation over West Africa. *J. Hydrometeorol.*, **11**, 467–481, <https://doi.org/10.1175/2009JHM1173.1>.
- Vitart, F., and Coauthors, 2017: The Subseasonal to Seasonal (S2S) prediction project database. *Bull. Amer. Meteor. Soc.*, **98**, 163–173, <https://doi.org/10.1175/BAMS-D-16-0017.1>.
- Wei, J., and P. A. Dirmeyer, 2012: Dissecting soil moisture–precipitation coupling. *Geophys. Res. Lett.*, **39**, L19711, <https://doi.org/10.1029/2012GL052351>.
- Weisheimer, A., F. J. Doblas-Reyes, T. Jung, and T. N. Palmer, 2011: On the predictability of the extreme summer 2003 over Europe. *Geophys. Res. Lett.*, **38**, L05704, <https://doi.org/10.1029/2010GL046455>.
- Yuan, X., E. F. Wood, and M. Liang, 2014: Integrating weather and climate prediction: Toward seamless hydrologic forecasting. *Geophys. Res. Lett.*, **41**, 5891–5896, <https://doi.org/10.1002/2014GL061076>.
- , J. K. Roundy, E. F. Wood, and J. Sheffield, 2015: Seasonal forecasting of global hydrologic extremes: System development and evaluation over GEWEX basins. *Bull. Amer. Meteor. Soc.*, **96**, 1895–1912, <https://doi.org/10.1175/BAMS-D-14-00003.1>.
- Zhang, J. Y., W. C. Wang, and J. F. Wei, 2008: Assessing land–atmosphere coupling using soil moisture from the Global Land Data Assimilation System and observational precipitation. *J. Geophys. Res.*, **113**, D17119, <https://doi.org/10.1029/2008JD009807>.