Sensitivity of land precipitation to surface evapotranspiration: a nonlocal perspective based on water vapor transport

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Sensitivity of land precipitation to surface evapotranspiration (ET) is among the most uncertain issues in land-atmosphere interactions. Past studies have mostly investigated this issue locally, and it remains a challenge to assess the nonlocal impacts. Here, we use a moisture tracking method and statistical analyses to quantify the sensitivity of precipitation to both local and nonlocal ET. It is found that, in a point-to-point sense, boreal summer precipitation is more sensitive to local ET than nonlocal ET for about 2/3 of land areas, while for about 1/5 land areas, precipitation is sensitive to ET of more than 1,000 km away. Remote sensitivities are generally an order of magnitude smaller than local sensitivities, but their combined effect could be large and useful, especially for regions without significant local sensitivities. Future studies of land-atmosphere interactions should be careful when making local assumptions.

Plain Language Summary The water vapor for rainfall comes from the local and nonlocal surface evaporation, and evaporation is an important factor that may affect rainfall, in addition to wind and other factors. There have been many studies on the local impact of evaporation on rainfall, but it remains a challenge to assess the nonlocal impacts. Here, we use a moisture tracking method and statistical analyses to quantify the sensitivity of rainfall over land to both local and nonlocal evaporation. It is found that although rainfall is more sensitive to local evaporation than nonlocal evaporation over most land areas, there are still about 20% land areas where precipitation is overall sensitive to evaporation variations of more than 1,000 km away. Remote sensitivities are generally an order of magnitude smaller than local sensitivities, but their combined effect could be strong. For regions without significant local sensitivities, the remote sensitivities may provide useful information for precipitation prediction. Future studies of land-atmosphere interactions should be careful when making local assumptions.

1. Introduction

It has been widely recognized that the slowly evolving states of the land surface can enhance climate predictability through land-atmosphere interactions (Dickinson, 2000; Dirmeyer et al., 2003; Koster et al., 2000). Recognizing the importance of land surface states for climate prediction, efforts have been made to produce accurate land initial conditions for forecasts (Dirmeyer et al., 2006), and model performances have also been examined for their ability to produce accurate land surface states, fluxes, and land-atmosphere coupling (Dirmeyer et al., 2006, 2018). The impact of the land surface on the atmosphere, also known as the land-atmosphere coupling strength, has been in the spotlight for one and half decades (Koster et al., 2004; Seneviratne et al., 2006). Numerous efforts have tried to quantify the effect of land or, more accurately, soil moisture and surface evapotranspiration (ET), on precipitation and surface temperature (e.g., Guo et al., 2006; Mei & Wang, 2012; Seneviratne et al., 2010; Wei & Dirmeyer, 2012; Zhang et al., 2008). These studies face several challenges such as the availability of data, weak signal-to-noise ratio, and model deficiencies. Nevertheless, the spatial patterns of the land-atmosphere coupling strength they obtained are largely similar. The strongest couplings are in semiarid regions, where the atmosphere is sensitive to land surface variations and the land surface itself has the largest variability.

One assumption in most past studies on land-atmosphere interactions is that the land effect is dominantly local. However, more and more evidence show that the land surface can affect the downstream or remote
weather and climate through winds or atmospheric waves (Koster et al., 2016; Schumacher et al., 2019; Teng et al., 2019; Xue et al., 2018) or direct moisture transport (e.g., Alter et al., 2015; Herrera-Estrada et al., 2019; Lo & Famiglietti, 2013; Wei et al., 2013). Almost all these works are case studies, and a complete global picture is still elusive. Especially, it is still not clear what patterns and distances of the nonlocal effects are and how strong they are compared with the local effects.

Intuitively, if the precipitation in a region is strongly contributed by remote moisture transport, precipitation in this region could be greatly affected by moisture evapotranspired from these nonlocal sources. Therefore, in this study, we quantify the sensitivity of land precipitation to local and nonlocal ET based on a Lagrangian moisture tracking method, which determines surface evapotranspirative sources for precipitation. The sensitivity of precipitation to ET is then calculated based on statistical relationships between total ET at source regions, evaporative moisture contribution to precipitation, and precipitation amount. The mean remoteness of the nonlocal sensitivities is quantified based on two defined metrics. Section 2 introduces the data and methods, followed by results in Section 3 and conclusions and discussion in Section 4.

2. Data and Methods

2.1. Moisture Tracking Method and Data

The quasi isentropic back-trajectory (QIBT) method (Dirmeyer & Brubaker, 1999, 2007) is used to track the evaporative water vapor sources for each precipitation event during 1985–2014. It tracks water vapor backward in time along the isentropic surfaces, assuming precipitated water is drawn from the atmospheric column in a distribution that follows the vertical profile of specific humidity. Traces start from the grid cell and time step with precipitation, backward in time and space until all of its original precipitation is attributed to ET but no longer than 15 days. The time step for the calculation is 45 min. The output of this calculation is a spatial distribution of the evaporative source field around each grid cell with precipitation. The method has been used to study various water cycle problems (Dirmeyer & Kinter, 2010; Hoyos et al., 2018; Wei et al., 2012, 2013, 2016).

Observationally based data sets are used to drive the QIBT scheme. They include atmospheric temperature, humidity, and winds at different levels, surface pressure, surface ET, and precipitation, all at six hourly timescale. Atmosphere variables over different levels are from Modern Era Retrospective-analysis for Research and Applications (MERRA; Rienecker et al., 2011). ET over land is from MERRA-Land (Reichle et al., 2011), evaporation over the ocean is from MERRA but corrected by OAFlux evaporation (Yu & Weller, 2007) at the daily timescale, and evaporation over the ice is from MERRA. Precipitation is from MERRA but corrected by CPC Unified product (Xie et al., 2007) at the daily timescale. All data are at or regridded to the grid cells of MERRA at 2/3 × 0.5° resolution. The results from the QIBT calculations are used to estimate the sensitivity of precipitation to ET (next section).

2.2. Estimation of the Sensitivity of Precipitation to ET

The method to estimate the sensitivity of precipitation to ET is the same as used in Wei and Dirmeyer (2012). Here, we reiterate it based on updated understandings. The effect of ET on precipitation involves not only the process of directly supplying moisture, but the increased atmospheric humidity can also promote convection and precipitation by enhancing the convective available potential energy (CAPE). Locally, the role of land is mainly to trigger precipitation, and the direct moisture contribution is small (Wei et al., 2016); therefore, studies have primarily focused on the impact on precipitation occurrence (e.g., Findell et al., 2011, Taylor et al., 2012, Tuttle & Salvucci, 2016). In humid regions, remote ET from moisture sources directly supplies a large amount of moisture for precipitation. We define two metrics to consider these effects of ET:

i. The mean percentage contribution of the evaporative moisture supply at each grid cell to the precipitation at a grid cell (denoted \( \sqrt{\frac{s}{p}} \)), where \( s \) is evaporative moisture supply at source region points and \( p \) is precipitation at the destination point. For local point, \( s \) is the recycling ratio, the percentage of local moisture contribution to precipitation. The square root is used to make the scale consistent with other metrics.

ii. The correlation between precipitation at a grid cell and corresponding moisture supply from its source region points, denoted \( r(s,p) \).
These two factors together identify the dominant moisture sources that have consistent variability with precipitation, and it can be shown that the pattern of their product is similar to the first principal component mode of the moisture supply from source regions (Wei et al., 2012). However, being a dominant moisture source does not guarantee that the ET there has a strong impact on precipitation. The evaporative moisture supply could respond passively to large-scale circulations in the same way as precipitation does (Wei et al., 2012; Wei, Jin, et al., 2016). Therefore, we define the third metric to measure the connection between the total ET at each grid cell and its portion that contributes to precipitation, which is crucial to identify the driving effect of ET on precipitation:

iii The correlation between the total ET over each grid cell and the evaporative moisture supply of precipitation at the same grid cell, denoted \( r(ET, s) \).

The three metrics can be calculated over each grid cell of the moisture sources, and each metric is statistically significant over some grid cells. For ET to have a significant impact on precipitation, all three metrics need to be significant. To equally consider the importance of the three factors, we calculate their products for grid cells only where all three metrics are significant at \( p < 0.01 \) level (based on \( t \) tests) as

\[
\Psi_i = \sqrt{ \left( \frac{S_i}{P} \right) r(p, s_i) r(ET_i, s_i) }, \quad i = 1, \ldots, N, \tag{1}
\]

where \( N \) is the number of grid cells that all three metrics are significant. \( \Psi \) is thus a nondimensional metric of the sensitivity of precipitation at each grid cell to ET over its source regions or an approximation of the partial derivative \( \partial p/\partial ET_i \). For the special case of the same grid cell as precipitation, it is the sensitivity of precipitation to local ET (denoted \( \Psi_{\text{local}} \) vs. \( \Psi_{\text{nonlocal}} \) for nonlocal sensitivity). Significant negative sensitivity is possible, but our method is based on moisture contribution (no negative value), so we ignore negative sensitivity in this study and assume it to be insignificant. The Metrics ii and iii must be significantly positive for \( \Psi \) to be significant.

The June-July-August (JJA) 1985–2014 monthly output from the QIBT moisture tracking calculations is used for the calculation of \( \Psi \). We focus on JJA because this is the boreal warm season when most land areas have strongest land-atmosphere interaction. The seasonal cycles are removed from the variables before the calculations (this was not done in Wei & Dirmeyer, 2012, but the impact is small).

### 2.3. Methods to Quantify the Remoteness of the Sensitivity of Precipitation to ET

Two methods are used to quantify the remoteness of the sensitivity of precipitation to ET: weighted average radius \( (D_a) \) and distance to center of mass \( (D_m) \). \( D_a \) is the weighted average distance of \( N \) significant source region grid cells (same as in equation (1)) to the grid cell of precipitation and is calculated as

\[
D_a = \frac{\sum_{i=1}^{N} w_i d_i}{\sum_{i=1}^{N} w_i}, \tag{2}
\]

where \( w_i \) is the weight and \( d_i \) is the distance to each grid cell. \( w_i \) is given as \( \Psi_i \) or \( s_i \) according to different purposes.

\( D_m \) is the distance from the grid cell of precipitation to the center of mass of the \( N \) significant source region grid cells. The location of the center of mass is calculated as

\[
\bar{R} = \frac{\sum_{i=1}^{N} w_i \bar{r}_i}{\sum_{i=1}^{N} w_i}, \tag{3}
\]

where \( w_i \) is the same as above and \( \bar{r}_i (i = 1, \ldots, N) \) are coordinate vectors of the \( N \) points. For details on how to calculate the distance between two grid cells on the Earth’s surface, \( d_i \) and \( \bar{r}_i \) using their latitudes and longitudes, please see the supporting information.
According to the definition of the two metrics, $D_m$ is more sensitive to the spatial distribution or shape of the significant moisture source than $D_a$. If the moisture source is symmetrically distributed around the point of precipitation, the center of mass would be very close the point of precipitation, which can lead to a small $D_m$. 

**Figure 1.** (a) Sensitivity of precipitation to local ET ($\Psi_{\text{local}}$) and (b) number of grids significantly affecting precipitation at each grid cell ($N$) during JJA. (c) Probability distribution of the local and nonlocal sensitivities ($\Psi_{\text{local}}$ and $\Psi_{\text{nonlocal}}$). Land areas where the JJA climatological precipitation is less than 0.1 mm day$^{-1}$ are masked.
while $D_2$ could still be very large. Therefore, the two metrics describe slightly different aspects of the remoteness and together can give a better picture of it. Also, as the two metrics are based on largely different algorithms, their results can be cross verified.

3. Results

Figure 1a shows the pattern of the sensitivity of land precipitation to local ET ($\Psi_{\text{local}}$) in JJA. This pattern is largely similar to that in many previous studies—strongest impacts are over the semiarid regions. Precipitation at each grid cell is significantly affected by the ET of $N$ surrounding grid cells, and the pattern of $N$ in Figure 1b has some similarity to that of $\Psi_{\text{local}}$ in large scale and also has differences in detail (cf. Figure 2a). In a point-to-point sense, $\Psi_{\text{local}}$ is significant for about 68% of land grid cells (excluding Greenland and very dry regions where JJA mean precipitation is less than 0.1 mm day$^{-1}$; same for the analyses below). Comparing local and nonlocal $\Psi$ for each grid cell, we found that for 94% of grids that have significant local impact (that is about 65% of total land grid cells), precipitation is more sensitive to local ET than nonlocal ET variations. This indicates that there are about a third of land areas where precipitation is more sensitive to nonlocal ET or not sensitive to surface ET anywhere. By comparing the probability distributions of the local and nonlocal sensitivities (Figure 1c), we can see that $\Psi_{\text{local}}$ is generally much larger than $\Psi_{\text{nonlocal}}$ and the mean (median) value of $\Psi_{\text{local}}$ is about 18 (25) times the mean (median) value of $\Psi_{\text{nonlocal}}$.

Locally, $\Psi_{\text{local}}$ and recycling ratio show a very strong relationship (Figure 2b), partly because recycling ratio is one of the three terms of $\Psi_{\text{local}}$ (equation (1)). Recycling ratio has been used to measure the local effect of land on precipitation in previous studies (Dirmeyer et al., 2009). $\Psi_{\text{local}}$ and recycling ratio vary with the climatological ET with highest values in the semiarid regions (Figures 2c and 2d), consistent with Figure 1a.

Figure 2. The scatterplot between different variables and metrics. Each point is for a 2.5° × 2.5° land grid regressed from the original 2/3° × 0.5° grids of MERRA. The blue points are for grids over the Tibetan Plateau (>4,500 m above sea level). The red lines are fitted using the red points only; (a) and (b) are linear fit (both significant at $p < 0.01$ level), and (c) and (d) are second-degree polynomial fit.
The Tibetan Plateau and Mexico/southwestern United States are two regions where $\Psi_{\text{local}}$ is large but $N$ is relatively small (Figures 1a and 1b), which means that precipitation in these regions is mainly sensitive to local ET and the sensitivities are high, favorable for strong local land-atmosphere interactions. The Mexico/southwestern United States region has been shown in many studies to be a region of strong land-atmosphere interactions (refer to references above), while much less is known about the Tibetan Plateau. The Tibetan Plateau has been found to be a region with deep convection in summer driven by land surface heat fluxes (Sugimoto & Ueno, 2010; Yanai & Li, 1994; Zhu & Chen, 2003). But due to its lower water vapor amount and CAPE, the deep convections are typically weaker and less organized and have smaller horizontal scales, leading to smaller amounts of precipitation (Houze et al., 2007; Luo et al., 2011). It can be seen that grid cells over the Tibetan Plateau are mostly outliers in Figure 2, mainly because they have very high recycling ratio and $\Psi_{\text{local}}$, and their $N$ values are relatively small. This indicates that precipitation over the Tibetan Plateau is very sensitive to local ET but insensitive to nonlocal ET, consistent with its features in convection. However, due to the possible limitations and biases of the moisture tracking method for the high mountain regions, these results need to be further verified by observational and modeling studies (Xu & Gao, 2019).

Unlike the sensitivity of precipitation to local ET, its sensitivity to remote ET is distributed in space and difficult to quantify with a single number. We have shown the probability distribution of the strength of remote sensitivities, and here, we calculate the remoteness of the nonlocal sensitivities. Figures 3a and 3b show the remoteness of the sensitivity of precipitation to ET ($\Psi$) quantified by (a) weighted average radius ($D_a$) and (b) distance to center of mass ($D_m$). (c) and (d) are the same as (a) and (b) but for the remoteness of the moisture sources (95% moisture). The inserts are the probability distributions of the values in each panel. Land areas where the JJA climatological precipitation is less than 0.1 mm day$^{-1}$ are masked. The blue boxes enclose four regions with very remote ET impact for further analysis in Figure 4.
South America, West Africa, and the middle to lower reaches of the Yangtze River valley (YRV). The probability distribution of all $D_a$ or $D_m$ values over the globe follow gamma-like distributions with long tails at high values, indicating that there are fewer high values than low values. The percentages of land grid cells with $D_m < 300$ km or $D_m > 1,000$ km are both about 18%.

The moisture sources for precipitation (Figures 3c and 3d) are more remote than the regions of significant ET sensitivity, and the probability distributions of their remoteness are less skewed than those of $\Psi$. The patterns of the remoteness for $\Psi$ and moisture sources show some similarity, but regional differences are evident, for example, in West Africa and Indonesia/Malaysia. After all, moisture contribution is only one of the terms of $\Psi$.

Note that the South Asia monsoon region shows low values of $D_m$ (Figure 3b), although its moisture sources are still remote (Figures 3c and 3d). This is because the South Asia monsoon rainfall is mainly driven by the large-scale monsoon flow and the ET in remote source regions do not have a significant driving effect (not shown), while land precipitation in this region is sensitive to local ET (Figure 1a).

Figure 4a gives a snapshot of $\Psi$ in four regions with very remote ET sensitivities. It is interesting that the JJA precipitation in the northeastern United States is most sensitive to ET variations in the central United States, while in YRV, it is most sensitive to ET variations in the South China Sea, Indochina, and part of south China. Precipitation in these two regions are both not sensitive to local ET, which is related to their wet
climate (Wei et al., 2012). On the other hand, the JJA precipitation in the Amazon basin and West Africa are sensitive to both local and remote ET variations. Note that the original values in Figure 4a are multiplied by 10 to fit the same color scale as in Figure 1a. This indicates that these nonlocal sensitivities are generally an order of magnitude smaller than the local sensitivities shown in Figure 1a, confirming the results in Figure 1c. However, as there are many nonlocal grid cells, their combined effect could be large. This is similar to the effect of deforestation, which usually increases with the spatial scale of deforestation (Lorenz et al., 2016). For regions where local sensitivities are not significant, like the northeastern United States and YRV, the remote sensitivities may be useful for weather and climate predictions. The moisture sources show patterns different from those of the ET impact (Figure 4b), for example, the northeastern United States and YRV show a large amount of moisture contributions from local, and the moisture sources for West Africa are mostly local.

4. Discussion and Conclusions

The water vapor transport from the surface to the atmosphere and then later be precipitated is one of the most uncertain segments of the water cycle. Inherent in these hydrological processes is the impact of surface ET on precipitation, a key process in land-atmosphere interactions. Most past studies have focused on the local effects of ET on precipitation, and little is known about the nonlocal effects. The main reason for this is that the nonlocal effects cannot be directly observed and are also difficult to quantify. The moisture contributions from ET can be estimated with moisture tracking methods. However, the impact of ET on precipitation is not simply a problem of moisture transport. Some moisture supplies for precipitation from ET are driven by the atmosphere, not ET itself, that is, it is a passive response of ET. In addition to directly contributing moisture for precipitation, ET variations can change the thermodynamics and dynamics of the atmosphere and affect precipitation efficiency (how much available moisture turns into precipitation). Therefore, regions that contribute most moisture through ET to precipitation are not necessarily the regions where ET has the strongest impact on precipitation.

In this study, we have tracked the moisture sources for precipitation at each land grid cell and estimated the sensitivity of precipitation to local and nonlocal ET based on statistical relationships among total ET, evaporative moisture contribution to precipitation, and precipitation at the destination grid. In a point-to-point sense, JJA precipitation is sensitive to local ET for about 68% land grid cells, and for almost all of them, local sensitivities are higher than nonlocal sensitivities and are closely related to the recycling ratio. However, if we consider the local and nonlocal sensitivities as a whole and calculate the remoteness of the weighted total sensitivities, we found that over about a fifth of the land, the mean distances of the sensitivity of JJA precipitation to ET are more than 1,000 km. Generally, remote sensitivities are about an order of magnitude smaller than local sensitivities, but their combined effect could be large and useful. For regions without significant local sensitivity such as the northeastern United States and YRV, the remote sensitivities may provide useful information for precipitation prediction. There have been some case studies on the nonlocal effect of ET on precipitation in northeastern United States and YRV, which partly supports results in this study (Dirmeyer & Kinter, 2010; Gao et al., 2019; Wei et al., 2012). The spatial distributions of the remote sensitivities bear some relationship to those of the remote moisture contributions, but they are different in detail. This confirms that the regions supply most moisture and the regions where ET has the strongest impact on precipitation are not necessarily the same. This study has implications for large-scale land management and droughts/floods, which directly affects ET, as their nonlocal effects could cause remote droughts and floods (Herrera-Estrada et al., 2019; Lorenz et al., 2016). Future studies of land-atmosphere interactions should also be careful when making local assumptions.

Note that we have discussed the sensitivity of precipitation to ET in this study, and the exact impact of ET on precipitation is related to the variability of ET, which also has spatial variations. We also did not provide the percentage contribution of ET to precipitation, which should be generally larger than the percentage contribution of soil moisture (Wei, Su, & Yang, 2016) because of the more direct effect of ET. Due to uncertainties in the data sets and the methods we used, the nonlocal sensitivities of precipitation to ET obtained from this study should be verified by model simulations and further statistical data analysis, through which useful information may be obtained for improving the weather and climate predictions (Chen et al., 2019; Li et al., 2016).
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