Statistical evaluation of future soil moisture changes in East Asia projected in a CMIP5 multi-model ensemble

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Abstract:

Simple explanations for changes in surface soil moisture in the late 21st century under global warming were explored, based on statistical significance and without consideration of complicated mechanisms. The results of a multi-model ensemble (MME) analysis showed significant increases in surface soil moisture in one northwestern inland area, and significant decreases were projected in two inland areas in southern and northern China. Among three water flux variables, precipitation (P), evaporation (E), and total runoff (R), significant changes in E explained only 10% of the total area showing significant changes in surface soil moisture. Among three combinations of two water flux variables, (P – E), (E + R), and (P – R), significant changes in (P – E) were dominant in coastal northeastern China, but this area did not overlap with areas with significant changes in surface soil moisture. Individual analyses revealed that significant increases in E, (P – R), and (E + R) explained 26%, 13%, and 9%, respectively, of the total area showing a significant decrease in the MME mean surface soil moisture. This result indicates that reliance on the MME mean may hinder understanding of the geophysical mechanism linking water flux variables with surface soil moisture.

KEYWORDS soil moisture; CMIP5; future climate; statistical significance; East Asia; multi-model ensemble

INTRODUCTION

Soil moisture across the Earth’s surface determines how much sensible and latent heat is transferred to the boundary layer atmosphere by partitioning of net radiation. Land-surface interactions between soil moisture and climate are substantially responsible for projected changes in future climates (e.g., Seneviratne et al., 2010; Nakaegawa et al., 2014b).

The water balance equation over land is written as,

\[
\frac{dS}{dt} = P - E - R
\]

(1)

where \( S \) is soil moisture, \( P \) is precipitation, \( E \) is evaporation, and \( R \) is total runoff. Owing to an accelerated water cycle, distinct changes in the water flux variables \( P, E, \) and \( R \) are projected for future climates (e.g., Nakaegawa et al., 2013; Ishizaki et al., 2014), and Equation (1) indicates that these changes should contribute to changes in soil moisture. However, regional to global-scale changes in soil moisture are relatively uncertain compared with those in water flux variables (Kirtman et al., 2013). From Equation (1), changes in soil moisture are assumed to be the water balance residual. However, small changes in soil moisture projected under a future climate become buried in the uncertainties of future climate projections (e.g., Nakaegawa et al., 2014b) due to internal variability of atmosphere, the coupled general circulation model (CGCM), and emission scenario used (Mastrandrea et al., 2010). Therefore, multi-model ensemble (MME) analysis is essential for projecting changes in soil moisture in future climates along with the uncertainties associated with the changes. Thus, the Coupled Model Intercomparison Project Phase 5 (CMIP5; Taylor et al., 2012) provides more information than a single CGCM.

How water fluxes will change in the near future is uncertain. Changes in soil moisture and surface runoff are generally projected with low confidence (Collins et al., 2013). However, a decrease in soil moisture is projected with high confidence by the end of this century in the Mediterranean, the southwestern United States, and southern Africa, where enhancement of the descending flow of Hadley circulation is projected (Orlowsky and Seneviratne, 2012). Signals of soil moisture change in East Asia projected by different CGCMs have been inconsistent (Intergovernmental Panel on Climate Change, IPCC, 2014). Although Zahid et al. (2014) carried out a detailed analysis of projected changes in soil moisture in South Asia, no regional study of East Asia has yet been conducted. The mechanisms for future changes in precipitation in East Asia were even not described in the IPCC 5th assessment report (IPCC, 2014) due to insufficient understanding.

It is of scientific interest to determine how changes in the three water flux variables contribute to projected changes in soil moisture and which contribution is dominant. Moreover, in the more complicated case that \( P \) and \( E \), for example, both show statistically significant changes, do changes in \( P - E \) also contribute significantly to changes in soil moisture? In this study, soil moisture, precipitation, evaporation, and total runoff were analyzed using CMIP5 simulations for present and future climates in East Asia.

MME analysis of the CMIP5 simulations provide robustness in future change estimates (e.g. Nakaegawa et al., 2013).
2014a) but only two simulations for the present-day and future climates for each CMIP5 model are available. This prevents analysis of land-surface interactions between the three water flux variables and soil moisture or discrimination of the dominant water flux variable when there is multiple significant changes in water flux variables. This is a strong limitation of analyzing the CMIP5 simulations compared to previous studies (e.g., Nakaegawa and Sugi, 2001; see Seneviratne et al. (2010) for review) and previous projects such as GLACE (Koster et al., 2006). These simulations were designed for exploring land-surface interactions and the discrimination of variables, but the CMIP5 simulations were not. As a result, in this study the water flux variable contributing most to changes in soil moisture between the present and future climate was identified in a framework of statistical significance.

**METHOD**

One water flux variable is defined as the dominant variable among the three water flux variables for changes in surface soil moisture when changes in the variable between the present-day and future climates is significant but changes in the other two variables are insignificant. First, statistically significant changes in surface soil moisture between the present-day and future climates were identified with Welch’s t-test (p < 0.05). Second, significant changes in a single variable among the three water flux variables (accompanied by insignificant changes in the other two variables) were identified. In other words, no dominant variable is defined to exist when changes in two or more variables are significant. This definition can be justified since a single variable cannot be determined as dominant variable among the two variables or three with significant changes under the data availability in the CMIP5 simulations. Dominant combinations of two water flux variables (variable pairs) were identified in the same manner; combinations of two water flux variables with significant changes at the same level (accompanied by insignificant changes in the third variable) were identified. Thus, changes in three single water flux variables and in the three variable pairs were examined. Note that this method can identify the “dominant” variable among the three water flux variables or pairs but cannot identify the cause of changes in surface soil moisture. A dominant variable can explain the changes in surface soil moisture in a phenomenological manner but cannot do so in a physical manner.

Each model has its own grid system as seen in Table SI. In this study, all models’ outputs were first interpolated onto the grid system of MRI-CGCM since it has the finest horizontal resolution of the 29 CGCMs used in this study. A land-sea mask of MRI-CGCM was also applied to the interpolated outputs. Land in this study was defined as grids where all 29 CGCMs have land on the grid after the interpolation.

All of the CGCMs were weighted equally in the statistical analyses of the multi-model ensemble results, although different weightings have been proposed (e.g., Ishizaki et al., 2010).

**VALIDATION OF HISTORICAL SIMULATIONS**

Spatial correlations of climatological annual mean surface soil moisture and the three water flux variables between JRA-55 and each CMIP5 CGCM were examined (Figure S1). Nine CGCMs captured well the spatial distribution of climatological annual mean surface soil moisture (correlation coefficients greater than 0.70), and another nine CGCMs could not capture it (correlation coefficients less than 0.50). Low performance in capturing the spatial distribution of surface soil moisture might be due to differences in soil column depths and soil geographical distributions (Entin et al., 1999), as mentioned above, as well as to different land-cover types (e.g., Nakaegawa, 2011) used by the different CGCMs. Soil moisture is determined as the residual of the land-surface water balance after complicated land-atmosphere coupling.
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Ensemble mean analysis of MME

Table I shows the MME mean areas with significant increases or decreases in soil moisture. Here, the mean was obtained by first determining the values in each CGCM and then averaging the areas among the CGCMs. The large range between maximum and minimum area and the large standard deviations for both significant positive and significant negative changes indicate large variability in the MME results. The area showing a negative change in surface soil moisture is twice that showing a positive change. This result suggests that overall, surface soil moisture in East Asia will decrease under the future climate.

Table I. Multi-model ensemble mean areas (as a percentage of the total area of the domain) showing changes in soil moisture significant at the 5% level in the late 21st century. The values were first computed for each model, and then the MME means were calculated. SD, standard deviation; Max., maximum area; Min., minimum area. Surface refers to surface soil moisture (in the top 10 cm of the soil column), and Total refers to total soil column moisture. The number of CGCMs used is 29 for all cases. Note that the depth of the soil column varies among the models.

| Surface | Mean | SD  | Max. | Min. | | Total | Mean | SD  | Max. | Min. |
|---------|------|-----|------|------| |       |      |     |     |     |
| Increase| 16   | 16  | 59   | 0    | |       | 3    | 3   | 12   | 0    |
| Decrease| 34   | 25  | 89   | 0    | |       | 7    | 5   | 19   | 0    |
| Total   | 50   | 18  | 89   | 19   | |       | 11   | 4   | 19   | 4    |

Figure 1. Projected changes in soil moisture in the late 21st century in the MME mean analysis. (a) Changes in surface soil moisture (future climate minus present-day climate). Contours show the present-day climatology, and the color scale shows changes significant at the 5% level. Units are mm yr⁻¹. (b) Consistency of the sign change among models. The color scale shows the number of models projecting increases minus number projecting decreases. Contours and the dots denote changes in surface soil moisture and their significance at the 5% level, corresponding to color scales in (a).
The three single water flux variables and the three variable pairs were projected to increase in the future climate over most of East Asia, except southern China (Figure 3). In southern China, the positive projected changes in $P$ and the negative projected changes in $R$ were without statistical significance (Figures 3a and 3c), but only $E$ showed a significant increase there (Figure 3b). Previous studies have indicated that a significant increase in $E$ is likely in many regions of East Asia (e.g., Lu and Cai, 2009) and in other regions such as Kenya (Nakaegawa et al., 2012) and Panama (e.g., Fábrega et al., 2013). From the water balance (i.e., Equation (1)), the decreases in $(P - E)$ and $(E + R)$ in southern China (Figures 3d and 3e) are reasonable. In drier surface soil moisture conditions, $(P - E)$ as net water flux into the land surface generally tends to decrease, although the cause and effect between drier surfaces soil moisture and less $(P - E)$ cannot be determined. Drier surface soil moisture generally reduces evaporation and runoff and hence $E + R$ also decreases. Only $(P - R)$ among the water flux variable pairs is projected to increase significantly in southern China (Figure 3f), because in terms of absolute values, the decrease in runoff was larger than the increase in precipitation. Along the coast of northeastern China, increases in $R$, $(E + R)$, and $(P - R)$ were not significant (Figures 3c, 3e, and 3f). The water balance among these variables as Equation (1) reduces the area with a unique dominant variable. As a result, it is difficult to identify a dominant water flux variable explaining changes in surface soil moisture by examining only the CMIP5 ensemble results. In addition, use of the MME mean values may hinder understanding of the geophysical mechanism linking surface soil moisture with the water flux variables. In the next section, we investigate how changes in surface soil moisture are related to water flux variables in the individual CMIP5 CGCMs.

**Individual CMIP5 model analysis**

Table II shows the variables dominating surface soil moisture changes, based on statistically significant changes among the three single water flux variables and among the three variable pairs. A significant increase in $(E + R)$ was primarily responsible for significant positive changes in surface soil moisture, but only in 3% of the total area showing a significant positive change in the MME mean surface soil moisture. The remaining area showing a significant positive change cannot be explained by a single water flux variable or a single water flux variable pair. Among the models,
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Table II. Percentages of the MME mean area showing a significant increase or decrease in surface soil moisture in the future climate explained dominantly by a single water flux variable or variable pair, based on statistically significant changes in the individual MME models.

| variable or variable pair* | Increase | | | Decrease | | | |
|---------------------------|---------|---|---|---------|---|---|---|
|                           | Mean    | SD | Max. | Min.    | Mean | SD | Max. | Min. |
| $P^+$                     | 0       | 0  | 0    | 0       | 0    | 1  | 4    | 0    |
| $E^+$                     | 0       | 1  | 4    | 0       | 26   | 23 | 100  | 0    |
| $R^+$                     | 0       | 0  | 0    | 0       | 2    | 5  | 21   | 0    |
| $P^-$                     | 0       | 0  | 0    | 0       | 0    | 0  | 1    | 0    |
| $E^-$                     | 0       | 0  | 0    | 0       | 1    | 3  | 13   | 0    |
| $R^-$                     | 0       | 0  | 18   | 0       | 1    | 3  | 11   | 0    |
| $(P – E)^+$               | 0       | 0  | 2    | 0       | 0    | 0  | 0    | 0    |
| $(E + R)^+$               | 3       | 5  | 18   | 0       | 9    | 13 | 43   | 0    |
| $(P – R)^+$               | 0       | 0  | 1    | 0       | 13   | 15 | 51   | 0    |
| $(P – E)^-$               | 0       | 0  | 0    | 0       | 1    | 4  | 20   | 0    |
| $(E + R)^-$               | 0       | 0  | 0    | 0       | 2    | 6  | 21   | 0    |
| $(P – R)^-$               | 0       | 0  | 0    | 0       | 0    | 0  | 3    | 0    |

* + indicates an increase, and – indicates a decrease in the value of the variable or variable pair.

Increases in $(E + R)$ in GISS-E2-R-CC explained the maximum area (18%) with a significant positive change in the MME mean surface soil moisture, and in this model the increase in $(E + R)$ was significant in southern China at around 27°N (Figure S2). Three CGCMs showed an increase of $E$ in areas with a significant positive change in surface soil moisture. This finding seems counterintuitive, but this association was seen in only a maximum of 4% of the total area with a significant positive change in surface soil moisture.

A significant increase in $E$ explained 26% of the area with significant negative changes in surface soil moisture. The largest area with significant decreases in surface soil moisture explained by a significant increase in $E$ was in IPSL-CM5B-LR (Figure S3). A significant increase in $R$ was responsible for significant negative changes, but in only 2% of the MME mean area and in only seven CGCMs. Among the water flux variable pairs, significant increases in $(P – R)$ and $(E + R)$ explained 13% and 9%, respectively, of the area with significant negative changes in the MME mean surface soil moisture. The mechanism by which increases in $(P – R)$ lead to a negative change in surface soil moisture is hard to understand intuitively, but the mechanism by which an increase in $(E + R)$ results in decreases in surface soil moisture is easy to understand intuitively. Areas with significant increases in $(P – R)$ correspond well to or are included within areas showing significant increases in $E$. The water balance equation (Equation (1)) shows that $E$ cannot increase at the Earth’s surface unless $(P – R)$ also increases. The fact that significant increases in $(P – R)$ caused a negative change in surface soil moisture implies that $E$ increases more than $(P – R)$ in those areas. The MIROC5 results are a typical example of this relationship (Figure S4). In ACCESS1-0, a significant increase in $(E + R)$ in southern China explained 43% of the area with a significant negative change in surface soil moisture. Significant decreases in $(P – E)$ and $(E + R)$, however, explained decreases in surface soil moisture in only 1% and 2%, respectively, of the total area with significant decreases in surface soil moisture.

Changes in surface soil moisture and in dominant variables in MRI-CGCM3 are depicted in Figure 4, because the geographical distributions of the MRI-CGCM3 changes are similar to those of the MME means. In coastal and inland areas of southern China centered at 27°N, the unique dominant single variable was $E$ (Figure 4b), consistent with the ensemble mean analysis result, although the areas are not exactly the same. In the same areas, the unique dominant variable pair was $(P – R)$ (Figure 4c). This correspondence between $E$ and $(P – R)$ seems easy to understand from Equation (1) at first sight, but an underlying mechanism is not apparent since other results do not show such a straightforward correspondence. In the ensemble mean analysis result shown in Figure 2, $(P – R)$ was not the dominant variable anywhere in East Asia. This result suggests that it is important to perform an individual analysis to understand changes in surface soil moisture in the ensemble mean result, because the water balance determined by the land-surface interactions between surface soil moisture and water flux variables differ for each CGCM. The significant changes and the consistency in sign changes in the MME mean results (Figure 1) provide information about the likelihood of change in surface soil moisture and the confidence level of the MME results, but the mechanisms underlying the change in surface soil moisture varies among the different models.

CONCLUDING SUMMARY

This study focused on obtaining a simple understanding of projected changes in surface soil moisture in the late 21st century under global warming, based on the correspondence of statistically significant changes in water flux variables with statistically significant changes in surface soil moisture. Among three water flux variables, or three water flux variable pairs, a single variable or variable pair showing significant changes, when changes in the other two variables or variable pairs were insignificant, was identified as the domi-
nent cause of significant changes in surface soil moisture.

Significant increases in surface soil moisture in the multi-model analysis were confined to the edge of the target domain, along 110°N centered at 42°N. In contrast, significant decreases in surface soil moisture were seen in inland southern China centered at 30°N and along 50°N at the edge of the target domain in northern China. In coastal and inland areas centered at 27°N in southern China, evaporation was identified as the dominant variable, but it explained only 10% of the total area with significant changes in surface soil moisture. In the coastal areas along the Yellow Sea and the Japan Sea in northeastern China, \((P - E)\) was identified as the dominant variable, but there was no overlap between the area where \((P - E)\) was dominant and the area with significant changes in surface soil moisture.

Individual model analysis revealed that significant increases in evaporation, \((P - R)\), and \((E + R)\) explained 26%, 13%, and 9%, respectively, of the area with significant decreases in the MME mean surface soil moisture. Significant increases in \((E + R)\) explained 3% of the area with a significant increase in surface soil moisture. This result indicates that use of the MME mean may hinder understanding of geo-physical mechanisms linking surface soil moisture changes with water flux variables, whereas an individual analysis can provide insight into ensemble mean changes in surface soil moisture because the land-surface interactions between surface soil moisture and the water flux variables differ among the CGCMs owing to differences in how the land-surface interactions are modeled.

Ongoing intercomparison of Land Surface, Snow and Soil Moisture and Land Use models coordinated with the Global Soil Wetness Project phase 3 and other models that are included in CMIP phase 6 (Eyring et al., 2016) will provide opportunities for further analyses of the land-surface interactions between the three water flux variables and surface soil moisture and the discrimination of dominant water flux variables among multiple significant changes in water flux variables. This will potentially lead to a more comprehensive understanding of soil moisture changes through enhancement of the likelihood and confidence level of analysis results.

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SUPPLEMENTS

Figure S1. Distributions of spatial correlation coefficients between historical model simulations and observations
Figure S2. Dominant variable among the three single water flux variables and the three water flux variable pairs in the GISS-E2-R analysis results
Figure S3. Same as in Figure S2, but in the IPSL-CM5B-LR results
Figure S4. Same as in Figure S2, but in the MIROC5 results
Table S1. CMIP5 models used in the present study
Table SII. Correlation of spatial correlation coefficients between pairs of variables in the 29 CGCMs

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