The Magnitude and Causes of Global Drought Changes in the Twenty-First Century under a Low–Moderate Emissions Scenario

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ABSTRACT

Atmospheric demand for moisture and dry days are expected to increase, leading to drying over land in the twenty-first century. Here, the magnitude and key drivers of this drying are investigated using model simulations under a low–moderate scenario, RCP4.5. The self-calibrated Palmer drought severity index with the Penman–Monteith potential evapotranspiration (PET) (sc_PDSI_pm), top 10-cm soil moisture (SM), and runoff (R) from 14 models are analyzed. The change patterns are found to be comparable while the magnitude differs among these measures of drought. The frequency of the SM-based moderate (severe) agricultural drought could increase by 50%–100% (100%–200%) in a relative sense by the 2090s over most of the Americas, Europe, and southern Africa and parts of East and West Asia and Australia. Runoff-based hydrological drought frequency could also increase by 10%–50% over most land areas despite increases in mean runoff. The probability density functions (PDFs) flatten, enhancing the drought increases induced primarily by decreases in the mean. Precipitation (P) and evapotranspiration (E) changes contribute to the SM change; whereas decreases in sc_PDSI_pm result from ubiquitous PET increases of 10%–20% with contributions from decreased P over subtropical areas. Rising temperatures and vapor deficits explain most of the PET increase, which in turn explains most of the E increases over Asia and northern North America while decreased SM leads to lower E over the rest of the world. Radiation and wind speed changes have only small effects on future PET and drought. Globally, runoff ratio changes little while P, E, and R all increase by about 4%–5% in the twenty-first century.

1. Introduction

Drought is among the most damaging natural disasters in the world. It often causes extensive damages to crops and natural ecosystems, creates water shortages, and increases risks of heat waves and wildfires. Drought results from below-normal precipitation often combined with warm temperatures over a period of months to years (Dai 2011a). Because of its large impacts, changes and variations in drought frequency and severity are of great concern. Many studies have shown that drought may become more severe and widespread as the greenhouse gas (GHG)-induced global warming continues in the twenty-first century (Rind et al. 1990; Wang 2005; Burke et al. 2006; Sheffield and Wood 2008; Dai 2011a, 2013; Wehner et al. 2011; Taylor et al. 2013; Cook et al. 2014; Prudhomme et al. 2014). Although precipitation deficits are often the primary cause for historical droughts, large increases in atmospheric evaporative demand or potential evapotranspiration (PET) under a warming climate (Feng and Fu 2013; Scheff and Frierson 2014) are considered as a major cause for the widespread drying under global warming (Burke et al. 2006; Dai 2011a, 2013; Trenberth et al. 2007; Cook et al. 2014). Furthermore, decreases in precipitation frequency (Trenberth et al. 2003; Sun et al. 2007) and increases in the number of dry days (Meehl et al. 2007) could further enhance surface drying even if the precipitation amount increases.
All analyses of model-simulated changes in soil moisture (Wang 2005; Sheffield and Wood 2008) and drought indices (Burke et al. 2006; Burke and Brown 2008; Dai 2011a, 2013; Taylor et al. 2013; Cook et al. 2014; Prudhomme et al. 2014) show increased drying and increased frequency of drought over many land areas in the twenty-first century as GHGs increase. The commonly defined dryland areas (with annual precipitation $P$/PET ratio $<0.65$) are also expected to increase by $\sim10\%$ in the twenty-first century under a high emissions representative concentration pathway 8.5 (RCP8.5) scenario (Feng and Fu 2013). However, the magnitude of the drying and changes in drought severity vary substantially among these studies, and they depend on the indices as well as the future emissions scenarios analyzed (Burke and Brown 2008; Taylor et al. 2013). In particular, the original version of the Palmer drought severity index (PDSI; Palmer 1965), a widely used index for droughts in the United States and for quantifying past aridity changes around the world (Dai et al. 1998, 2004; Dai 2011b; van der Schrier et al. 2007, 2011; Cook et al. 2010), overestimates the drying trend associated with future global warming because of its use of the simple Thornthwaite equation for PET ($\text{PET}_{\text{th}}$), as stated clearly by Burke et al. (2006) and further investigated by Dai (2011b) and van der Schrier et al. (2011) for the recent drying trends and Hoerling et al. (2012) for future North American drought. The basic conclusion from these analyses is that, while the use of the Thornthwaite PET only slightly enhances the drying trend for the last 50–60 years, it grossly overestimates the drying trend during the twenty-first century when temperature increases are large, making it unsuitable for quantifying future drought changes. Besides the early work by Rind et al. (1990) and a recent North American analysis by Wehner et al. (2011), most analyses of future PDSI changes (e.g., Burke et al. 2006, Burke and Brown 2008; Dai 2011a, 2013; Taylor et al. 2013; Cook et al. 2014) are based on an improved version of the PDSI using the more realistic Penman–Monteith PET ($\text{PET}_{\text{pm}}$). Even with the $\text{PET}_{\text{pm}}$, the PDSI still shows substantially larger increases in drought frequency and severity than several other indices that are based on precipitation, soil moisture, or runoff (Taylor et al. 2013). We will explore the reasons for this discrepancy in this study.

Since precipitation does not account for the impacts of increasing evaporative demand for moisture in a warming climate, drought indices based on precipitation alone [e.g., the standardized precipitation index (SPI)] is not really adequate for addressing future drought changes, when large PET increases (Feng and Fu 2013; Scheff and Frierson 2014; Cook et al. 2014) are a major driver for future changes in the surface water balance and aridity. Normalized soil moisture content and runoff (or streamflow) are the best measures for quantifying agricultural and hydrological drought, respectively (Dai 2011a). However, soil moisture (SM) and runoff ($R$) have been poorly simulated in global climate models partly because of coarse model resolution (which lead to poor representation of land hydrological processes), as reflected by the very large range of change for these two fields among the global models used by IPCC (Meehl et al. 2007; Collins et al. 2014). Recently, Prudhomme et al. (2014) applied offline global impact models forced by future climate projections to estimate changes in hydrological drought. They found large increases of $10\%–40\%$ in the frequency of hydrological drought (defined as days with total runoff below a given threshold) over most land areas under the RCP8.5 scenario, even over areas with increasing streamflow (Koirala et al. 2014) and mean total runoff (Collins et al. 2014) in Eurasia and many other regions. This apparent discrepancy has yet to be resolved.

The PDSI has been traditionally considered as a measure of meteorological drought, which is an atmospheric condition that suppresses precipitation for weeks to months, by Palmer (1965) and many others (e.g., Heim 2002; Dai 2011a); however, it is actually a smoothed index of near-surface soil moisture content. Thus, the PDSI should be considered as a measure of agricultural drought, which is a period with dry soils that results from below-normal precipitation, intense but less frequent rain events, or above-normal evaporation, all of which lead to reduced crop production and plant growth (Dai 2011a). The PDSI with $\text{PET}_{\text{pm}}$ (PDSI$_{\text{pm}}$), especially its locally self-calibrated version (sc PDSI$_{\text{pm}}$; Wells et al. 2004; Dai 2011b), is arguably one of the best indices available for quantifying long-term changes in agricultural drought, since it incorporates antecedent and current moisture supply (precipitation $P$) and demand (PET) into a fairly complicated hydrological accounting system, despite of its many caveats as discussed previously (e.g., Dai 2011b). Compared with the top 10-cm SM, the PDSI measures agricultural drought on a longer time scale (e.g., 12–18 months) because of its smoothing. Because of the definition differences in the drought indices based on sc PDSI$_{\text{pm}}$, SM and $R$, some quantitative differences should be expected for their future changes. Since meteorological drought is usually measured by precipitation anomalies (e.g., the SPI) and precipitation changes have been examined extensively elsewhere (e.g., Collins et al. 2014), here we will focus only on agricultural and hydrological drought.

Relatively few studies have examined the processes or causes for the widespread increases in future drought. Sheffield and Wood (2008) analyzed soil moisture from
the phase 3 of the Coupled Model Intercomparison Project (CMIP3) simulations and found that increases in future agricultural droughts are driven primarily by reductions in precipitation over subtropical regions and increased evaporation from higher temperatures that offsets increases in precipitation in other regions. Feng and Fu (2013) examined the contributions of precipitation and PET to projected changes in the P/PET ratio, while Scheff and Frierson (2014) found that increases in near-surface vapor deficits (following a constant relative humidity) are the primary cause for PET increases in 14 phase 5 of Coupled Model Intercomparison Project (CMIP5) models under the RCP8.5 high emissions scenario. Recently, Cook et al. (2014) analyzed the PDSI_pm and the standardized precipitation evapotranspiration index (SPEI) using simulations from 15 CMIP5 models under the RCP8.5 scenario and found widespread drying in the twenty-first century because of increased PET everywhere (resulting from increased surface radiation and vapor deficits) and reduced precipitation over subtropical areas. While these previous studies helped quantify the uncertainties in model projections of future drought and examined some of the major causes, they did not fully address two outstanding questions: 1) whether the spatial pattern and the magnitude of the drought changes revealed by the PDSI_pm and SM- and R-based indices are consistent with each other given the differences in their intended purpose and 2) what the driving factors or causes for the drought changes based on each of these three indices. Since most of the recent drought analyses (e.g., Feng and Fu 2013; Cook et al. 2014; Prudhomme et al. 2014; Scheff and Frierson 2014) have examined drought or aridity changes under the high emissions scenario RCP8.5, here we will focus on drought changes under the low–moderate scenario RCP4.5 (van Vuuren et al. 2011; also see http://sedac.ipcc-data.org/ddc/ar4_scenario_process/RCPs.html). To further address these two questions and examine the causes for the drought changes based on the three types of drought indices, here we analyze the relationship among changes in sc_PDSI_pm, soil moisture content, and runoff and their underlying driving factors using the model output from CMIP5 (Taylor et al. 2012). The goal is to improve our understanding about the magnitude, causes, and relationships of the changes in agricultural and hydrological droughts in the twenty-first century. Here, we focus on the mean response to GHG-induced warming under a low–moderate emissions scenario across multiple models, which effectively removes natural climate variability. The uncertainties associated with different emissions scenarios (Taylor et al. 2013) and natural climate variations are not addressed in this study.

This paper is organized as follows: Section 2 provides a brief description of the model data and analysis method. Drought and other hydroclimatic changes in the twenty-first century over global land and in several hotspot regions are discussed in section 3. Section 4 examines the magnitude and causes of the drought changes in the twenty-first century. A summary and conclusions are presented in section 5.

2. Data and method
a. Data, PDSI calculations, and drought definition

The CMIP5 simulations from 14 coupled global climate models (Table 1; other models were unavailable at the time we started the analysis) were analyzed in this study. They include the historical simulations with specified anthropogenic and natural external forcing from 1850 to 2005 and the future projections of the GHGs and anthropogenic aerosols following the RCP4.5 for 2006–99 (van Vuuren et al. 2011; Taylor et al. 2012). Only the first ensemble run (“r1i1p1”) was used here if a model has a multiple ensemble simulations. The monthly data for precipitation, surface air temperature, net radiation, specific humidity, wind speed, air pressure, top 10-cm layer SM content, and total R were first regridded onto a 2.5° grid using a scheme that conserves the quantity locally and globally. This was done by first assigning the value of each original grid cell to all tiny grid cells (e.g., at 0.1°) within the original grid cell and then averaging the values over all the tiny grid cells within each 2.5° target grid cell to derive the value on the target grid; then, the values on the 2.5° grid were scaled by the ratio of the global means on the original and the target grids.

The regridded model variables were used to calculate the Penman–Monteith PET and sc_PDSI_pm at each grid box following Dai (2011b). The monthly PET and sc_PDSI_pm from 1900 to 2099 were computed for each of the model runs and then averaged over the model runs to derive the multimodel ensemble-mean sc_PDSI_pm. The drought frequencies based on the sc_PDSI_pm, SM and R were derived for each model run first and then averaged over the models to derive the multimodel ensemble-mean change. For all the variables, the monthly climatology for 1970–99 was subtracted from the monthly data at each grid box before regional averaging and other analysis. Comparisons between our analysis and the IPCC Fifth Assessment Report (AR5; Collins et al. 2014) that used more model runs showed broadly similar change patterns for many climate fields (temperature, precipitation, evapotranspiration, soil moisture, etc.). Thus, our results are representative of the CMIP5 model simulations.

In some previous studies (viz., Dai 2011a, 2013), multimodel averaged climate data were used to compute the PDSI, which was then used to examine its future
Because the multimodel averaging reduces the variability in the forcing data for the recent decades, over which the PDSI was calibrated, this reduced variability effectively enlarge the GHG-induced future PDSI changes by a factor of about 3 in Dai (2011a, 2013) compared with the PDSI averaged over the individual models used here. Thus, while the change patterns are similar, the magnitude of the PDSI changes reported in Dai (2011a, 2013) should be reduced by a factor of about 3. As in previous analysis (e.g., Dai 2011a,b, 2013; Taylor et al. 2013), we defined drought events as periods with a monthly drought index below the value corresponding to the 20th (regular drought) or 10th (severe drought) percentile of the current (1970–99) climate at each grid box. Using the local percentile value, instead of a uniform threshold everywhere, improves the spatial comparability of drought frequencies. Since the mean and variance for SM and \( R \) vary greatly in space, we converted the SM and \( R \) anomalies into units of local standard deviation of the 1970–99 period and used the normalized anomalies to define the agricultural and hydrological drought (based on the percentile thresholds), respectively. The \( sc_{\text{PDSI} \_ \text{pm}} \) values, which were already normalized in their calculation, were used to define the agricultural drought using the percentile threshold, rather than the conventional fixed threshold (Palmer 1965; Dai 2011a).

### b. Attribution analysis method

To analyze how the \( sc_{\text{PDSI} \_ \text{pm}} \) varies because of changes in individual meteorological forcing, we calculated the \( sc_{\text{PDSI} \_ \text{pm}} \) separately for each model run and for each case in which only one forcing factor was allowed to change while all others were kept at the values of the 1970s for any decades outside the calibration period (1950–79), during which all the variables were allowed to vary as in the all-forcing case. In other words, any decade outside 1950–79 had the same forcing data as for 1970–79 (from the model run) for all the forcing variables except for the one being examined. This setup ensures that the variability in the forcing data during the calibration period (1950–79) was the same as in the all-forcing case (important for future PDSI changes) and that the forcing data for all the variables (except the one being examined) are the same with realistic variations during the current (1970–99) and future (2070–99) periods (so that the difference between the two periods is entirely due to changes in the factor being examined). Cook et al. (2014) applied a similar approach (but not the same setup) to examine the impacts of changes in precipitation, surface vapor deficits, and net radiation on the PDSI \( \text{pm} \).

Our PDSI model also computes PET using the Penman–Monteith equation (Shuttleworth 1993); thus,
we shall examine the contributions to PET changes from the individual forcings in the same way as for sc$_{\text{PDSI pm}}$. The forcing factors for the Penman–Monteith PET include near-surface vapor deficits (VPD), net longwave (LW) and shortwave (SW) radiation, and wind speed (WS). These factors also affect sc$_{\text{PDSI pm}}$, together with precipitation $P$. We estimate the VPD as $(1 - \text{RH}/100)e_T(T_a)$, where RH is the surface relative humidity (%) and $e_T$ is the saturation vapor pressure (in hPa) computed from the surface air temperature ($T_a$; in °C) using the empirical equation $e_T(T_a) = 6.112 \exp[17.62 \times Ta/(234.12 + Ta)]$ (Dai 2006). For this case, both surface RH and $T_a$ (and thus specific humidity $q$) are allowed to change. The $T_a$ change also influences PET through the $d\varepsilon/dT_a$ slope in the Penman–Monteith equation.

For each of the 14 model runs, we computed the sc$_{\text{PDSI pm}}$ and PET for one all-forcing case and five individual forcing cases (for changes in $P$, $T + q$, LW, SW, and WS), leading to a total of 84 different PDSI and PET datasets. Each of these cases was then ensemble averaged over the 14 models, and the ensemble-mean differences between the current and future periods were used to estimate the mean contributions from individual forcing factors. This is equivalent to examine the contribution in each model and then average the contributions over the models because of the linearity in the averaging.

For the top 10-cm layer SM and actual evapotranspiration ($E$) from the CMIP5 models, the above method is not feasible. Instead, we used the following progressive regression analysis to approximately estimate the contributions from individual drivers for each model run and then averaged the contributions over the multiple models to derive the mean contributions, which were converted into a percentage of the multimodel ensemble mean for 1970–99 before plotting. We used these equations to estimate the contributions to the future changes,

$$\Delta SM = b_1 \Delta P + d_1 \Delta E + f_1 \Delta R + e_1$$  \hspace{1cm} \text{(1)}

$$\Delta E = b_2 \Delta PET + d_2 \Delta SM + e_2,$$  \hspace{1cm} \text{(2)}

where “$\Delta$” denotes the difference of 2070–99 minus 1970–99 in annual mean of the variable and $e_1$, and $e_2$ are the small residual terms. The regression coefficients $(b_1, d_1, f_1, b_2, \text{ and } d_2)$ were estimated as follows: Because precipitation is determined mostly by atmospheric processes that are largely independent of local $E$ and $R$ (i.e., $P$ is mainly a cause for the correlation between $P$ and $E$, and between $P$ and $R$), we considered $P$ as the primary driver and used the following stepwise procedure for each model run to estimate the regression coefficients at each gridpoint in order to remove the effects of the interdependence among $P$, $E$, and $R$. Local annual time series for all the variables were first detrended using the global-mean surface temperature series from the multimodel ensemble mean as the $x$ variable (instead using the time as the $x$ variable) through linear regression. This removes any common components among them induced by the GHG and other forcing. The detrended series were further smoothed using 7-yr moving averaging to remove the interannual to multityear variations. The detrended and smoothed annual precipitation anomaly ($P'$) was first used to linearly regress against the similarly detrended and smoothed annual SM anomaly ($y$) from 1950 to 2099 to obtain the regression coefficients ($a_1$, $b_1$) and the part of SM explained by $P'$ ($y' = a_1 + b_1P'$). The residual SM ($y - y'$) was then fitted against similarly processed annual evapotranspiration anomaly ($E'$) to obtain the regression coefficients ($c_1$ and $d_1$) and the SM part explained solely by $E'$ ($y'' = c_1 + d_1E'$). The remaining SM residual ($y'' - y''$) was further regressed against similarly processed annual runoff anomaly ($R'$) to estimate the regression coefficients ($f_1$ and $g_1$). Regression coefficients ($b_1$, $d_1$, and $f_1$) at some grid boxes are statistically insignificant (i.e., not different from zero) and were set to zero to allow the next variable to contribute to the SM change. For a small number of grid boxes, the regression coefficients had the opposite sign as one would expect based on the physical relation with the SM; in these cases, we set the regression coefficients to zero and let the next variable to explain the SM changes. Similar steps were also applied to Eq. (2).

For $R$, we used two methods to attribute the contributions from $P$ and $E$. The first method used an equation similar to Eq. (1) but replacing SM with $R$ and setting $f_1 = 0$ and similar progressive regression steps as for SM. The second method assumes that long-term changes in land water storage are negligible, so that the following $\Delta R = \Delta PET - \Delta SM$ can be used. The two methods yielded very similar results; here we only show the results from the second method.

For $E$, the limiting factors include the atmospheric demand of moisture (i.e., PET) and the availability of near-surface moisture (i.e., SM). We found that the results are similar whether $\Delta PET$ or $\Delta SM$ is chosen as the first primary driver. Below we only show the results with $\Delta PET$ as the first driver.

Given that the regression coefficients were derived from decadal to centennial variations over 1950–99, we applied them in Eqs. (1) and (2) to estimate the response of the SM, $R$, and $E$ to the long-term changes in their corresponding driving factors. As shown below, this approach seems to work reasonably well as it is able to identify the main contributors to the future changes in SM, $R$, and $E$.

The use of 7-yr moving averaged, detrended anomalies in estimating the regression coefficients allows us to
focus on the decadal to centennial variations and changes, which are the focus of this analysis. However, our tests showed that results without the smoothing are similar. This suggests that the relationships among the short-term variations and long-term changes are similar.

3. Hydroclimatic and drought changes in the twenty-first century

a. Hydroclimatic changes

Before we discuss drought changes, it is helpful to briefly examine the model-simulated hydroclimatic changes, which are summarized in Figs. 1–3. Figure 1a shows that under the RCP4.5 scenario annual precipitation ($P$) will increase by 10%–30% from 1970–99 to 2070–99 over most Eurasia, North America, and central to northern Africa but decrease by 3%–15% over most Australia, southern Africa, the regions around the Mediterranean and the Amazon, Central America, and southwestern North America. These broad change patterns are very similar in higher emissions scenarios except for larger magnitudes (Collins et al. 2014). The precipitation decreases over subtropical land areas are part of the larger subtropical drying zones that extend to the oceans (Collins et al. 2014). The decreases of subtropical precipitation result from poleward expansion of the subtropical subsidence zone (e.g., Lu et al. 2007; Scheff and Frierson 2012) as well as the increased drying by the subsidence of the Hadley circulation because of increased vertical humidity gradient in a warmer climate (Chou et al. 2009).

Figure 1 shows that the pattern and magnitude of changes in surface $E$ largely follow those for precipitation, while near-surface SM decreases over most land areas, including northern Europe, most of North America, and many parts of Asia, which all receive more precipitation. The increased surface drying in spite of increased precipitation over many land areas is consistent
with the fact that most of the precipitation increase comes from increases in heavy precipitation, while the frequency of precipitation events decrease (Trenberth et al. 2003; Sun et al. 2007), resulting in more dry spells in a warmer climate (Meehl et al. 2007), although a large increase in evaporative demand could also offset most or all of the precipitation increases. The $R$ change patterns based on the 12 models used here (Fig. 1d) are broadly consistent with those based on more models (Collins et al. 2014); however, Fig. 1d shows larger decreases over the northwest United States, central Africa, and northern Australia than in Collins et al. (2014). Nevertheless, the $R$ change patterns roughly follow those of precipitation, with decreases over most of Australia, southern Africa, the Amazon, southern and central Europe, and the central and western United States. Overall, Figs. 1b,d suggest that future agricultural drought may become more widespread while hydrological drought may increase only over limited areas. This is expected because increased evaporative demand of moisture by a warmer atmosphere (Fig. 2) will reduce soil moisture content, while increased precipitation (especially intense precipitation) will lead to higher runoff in spite of more dry days. The mean $R$ change patterns are broadly consistent with the streamflow changes simulated by a high-resolution river routing model forced with daily runoff fields from CMIP5 models (Koirala et al. 2014). However, they appear to be inconsistent with the large increases in hydrological drought frequency over most land areas (including many areas in Eurasia) reported by Prudhomme et al. (2014). We will examine this issue further in section 3d.

We emphasize, however, that the soil moisture and runoff changes among individual CMIP5 model runs vary greatly, especially over Asia and central and northern Africa (Fig. 1). Further, we notice that, while the broad change patterns are very similar between the CMIP5 and the previous CMIP3 results (Meehl et al. 2007) for precipitation, the decreases in soil moisture over central and eastern Australia, midlatitude Europe, and North America are more widespread in the CMIP5 simulations than those in CMIP3 models (Wang 2005; Meehl et al. 2007). These changes are likely due to recent changes in land surface models (e.g., Oleson et al. 2008). The large spread among the model-simulated soil moisture changes also illustrates the need for offline calculations of other drought conditions.
measures for quantifying future hydroclimatic changes (Prudhomme et al. 2014).

The change patterns in near-surface soil moisture (Fig. 1b) from the CMIP5 models are similar to those of the sc_PDSI_pm (Fig. 2a) calculated offline using the CMIP5 model output, as noticed previously by Dai (2013). The quantitative relationship between the drought changes defined by these two measures is further examined below. Figure 2b shows that PET calculated using the Penman–Monteith equation (Shuttleworth 1993) increases everywhere over land in the twenty-first century by 5%–15% at low latitudes and by 10%–20% at northern middle to high latitudes, consistent with previous reports (Feng and Fu 2013; Scheff and Frierson 2014). This leads to a reduction of 0.03 to 0.15 in the \( \frac{P}{PET} \) ratio over many land areas (Fig. 2c), as shown previously by Feng and Fu (2013), mostly over the regions with decreasing soil moisture and sc_PDSI_pm. The consistency of the drying patterns among these three measures of aridity (soil moisture, sc_PDSI_pm, and \( \frac{P}{PET} \)) improves our confidence in the future drying patterns revealed by Figs. 1b and 2a,c. Again, we emphasize that the magnitude of the sc_PDSI_pm changes reported in Dai (2011a, 2013) is enlarged by a factor of about 3 compared with that shown in Fig. 2a because of the suppressed variability in the ensemble-mean forcing data used in these previous studies.

Runoff ratio (\( \frac{R}{P} \)) is a key parameter in hydrology. Figure 2d shows that this ratio will decrease slightly by 0.02–0.06 over northern mid- to high-latitudes land areas, where precipitation increases faster than runoff (Fig. 1), whereas it will increase slightly or changes little over low latitudes and the Southern Hemisphere. Averaged over global (60°S–75°N) land areas, runoff ratio (Fig. 3) does not change significantly over the twenty-first century, as the global land \( P, R, \) and \( E \) show similar percentage increases of 4%–5% by the end of the twenty-first century under the RCP4.5 scenario. We notice an accelerated increase in \( R \) during the 1990s that leads to a slightly elevated runoff ratio compared to the previous decades (Fig. 3). The interannual to multiyear percentage variations in \( R \) are larger than those in \( P \) and \( E \) (Fig. 3). This can be explained by the approximate relationship among the three terms on annual to longer time scales: \( \Delta \frac{P}{P_o} \approx \left( \frac{E_o}{P_o} \right) \Delta \frac{E}{E_o} + \left( \frac{R_o}{P_o} \right) \Delta \frac{R}{R_o} \), where subscript \( o \) denotes the 1950–79 mean. Since \( \frac{E_o}{P_o} \approx 0.7 \), \( \frac{R_o}{P_o} \approx 0.3 \), and \( \Delta \frac{E}{E_o} \) is smaller than \( \Delta \frac{P}{P_o} \) for the short-term variations (Fig. 3), this equation suggests that \( \Delta \frac{R}{R_o} \) has to be much larger than \( \Delta \frac{P}{P_o} \) and \( \Delta \frac{E}{E_o} \) for the year-to-year variations.

Given the widespread drying reflected in soil moisture, sc_PDSI_pm, and \( \frac{P}{PET} \) fields (Figs. 1 and 2), it is a bit surprising to see that the runoff ratio does not
decrease substantially over many land areas with significant surface drying (e.g., southwestern North America, northern South America, most of Australia; Fig. 2). One possible reason is that future precipitation becomes more intense but less frequency (Sun et al. 2007), which could help increase the mean runoff ratio and offset the negative impact of drying soils. Another possible mechanism is the increased water use efficiency by plants under elevated CO₂ levels (which was included in most of the models used here), which could lead to reduced transpiration and increased R (Betts et al. 2007; Cruz et al. 2010).

b. Consistency among different drought measures

While the change patterns are broadly consistent among SM, sc_PDSI_pm, and P/PET, as noticed above and previously (e.g., Dai 2013), the magnitude of the drought changes as measured by these different indices has not been examined in detail, and some previous studies (e.g., Burke and Brown 2008; Burke 2011; Hoerling et al. 2012) showed some inconsistencies in the magnitude of drying as measured by different drought indices. Here we revisit this issue, with a focus on the quantitative comparison between near-surface soil moisture and sc_PDSI_pm changes.

Figure 4 shows the multimodel averaged scatterplots of regionally averaged monthly anomalies of sc_PDSI_pm, SM, and R during 1970–99 and 2070–99 for the western United States, southern Europe, southern Africa, and the Amazon, all of which are expected to experience large drying in the twenty-first century (Figs. 1 and 2). Relatively strong correlations (r = 0.37–0.75) exist between the sc_PDSI_pm and SM anomalies, while the sc_PDSI_pm versus R and R versus SM correlations are lower albeit positive. Besides showing the clear decreases from 1970–99 to 2070–99 in SM and sc_PDSI_pm and some decreases in R, Fig. 4 also shows that the statistical relationship (i.e., the slope and correlation) between the SM and sc_PDSI_pm anomalies does not differ greatly between the recent and future periods. However, the relationship between each pair of the variables varies substantially among the models, as reflected by the variations in the correlation coefficients (Fig. 4). These observations are also true for the sc_PDSI_pm versus R and R versus SM relationships. Figure 5 shows that overall the relationships among these three measures of drought in the future will remain similar to those in the current climate and that, for a given amount of SM decrease, the sc_PDSI_pm may decrease a similar amount during 1970–99 and 2070–99 over most land areas, including the contiguous United States (CONUS). This is in contrast to Hoerling et al. (2012), who found that the traditional PDSI using the Thornthwaite PET decreases more in the future than in the present climate for a given SM decrease.

c. Changes in the PDFs

Since drought is defined at the left tail of the probability distribution function (PDF) of a drought index, a small decrease (e.g., 3%–10%; Fig. 1b) in the long-term mean (e.g., of soil moisture) can lead to a large (e.g., >20%) increase in drought frequencies. To illustrate this, we compare (Fig. 6) the multimodel averaged, smoothed histograms of monthly anomalies of regionally averaged sc_PDSI_pm, top 10-cm layer SM, and total R during the current (1970–99) and future (2070–99) periods for the four regions outlined in Fig. 1a. To improve the spatial comparability, we divided the local SM and R anomalies (relative to the 1970–99 mean) for both the current and future periods by their standard deviation (STD) of 1970–99. It is clear that the sc_PDSI_pm, SM and R anomalies largely follow Gaussian distributions. The SM histograms become flatter with a reduced peak and increased spread during 2070–99 than 1970–99. To a lesser degree, these changes are also evident for the sc_PDSI_pm and R (Fig. 6). The warm-season PDFs show shifts to the left (drying) similar to the yearly mean, although the decrease of the peak is smaller than the yearly mean for many of the cases shown in Fig. 6.

Figure 6 clearly shows that a small decrease in the mean (i.e., a small shift of the peak to the left) can lead to a large increase in the frequency of drought, usually defined below the 20th percentile of the current distribution. The percentage increase is even larger for severe drought (<10th percentile). The flattening of the PDFs, especially for SM, greatly enhances the increase of drought. The drought frequency increases are comparable based on the sc_PDSI_pm and normalized SM, while the change based on the normalized R is relatively small for these hotspot regions (Fig. 6).

Figure 7 shows that the PDFs of the SM and R flatten while their peaks decrease over most land areas from 1970–99 to 2070–99. This is also true for sc_PDSI_pm except for most areas in Australia, southern CONUS, South America, southern Africa, and the Mediterranean region, where the shape of the local PDFs of sc_PDSI_pm does not change greatly. Our examination of the PDFs at select individual grid boxes (denoted by the stars in Fig. 7a) confirmed the results shown in Figs. 6 and 7. A systematic flattening of the PDFs, combined with a decrease in the mean (Figs. 1, 2, and 6), would lead to large increases in the frequency of dry (i.e., drought) conditions in the future over many land areas. On the other hand, the decrease in the mean greatly reduces the frequency of wet spells, while the PDF flattening offsets some of the decreases. Although previous studies (e.g., Kharin et al. 2013) showed that extreme temperature and precipitation events will increase in the twenty-first century, few studies examined the changes in the shape of the PDFs, as shown in Figs. 6 and 7.
Changes in drought frequency, defined as the percentage of the time in drought conditions, from 1970–99 to 2070–99 based on the sc_PDSI_pm, normalized SM and $R$ anomalies are further quantified in Fig. 8. We define drought events as months with the drought index below the value corresponding to either the 20th or 10th percentile of the 1970–99 period. The spatial pattern and magnitude of the drought frequency changes are comparable for the two percentile criteria; in a relative sense, however, the frequency of the severe drought
(<10th percentile) increases nearly twice as faster as the moderate drought (<20th percentile). This is because, by definition, the mean drought frequency is 10% and 20% for these cases during 1970–99. Figure 8 shows that all the three drought measures suggest increased drought frequency over most of the Americas, Europe, Australia, southern Africa, and many parts of Asia. The normalized SM anomalies from most CMIP5 models show the largest and most widespread increases (by 10%–20% of the time) in drought frequency over most
land areas except some regions in northern, central, and southern Asia; northern Africa and the Middle East; and southeast South America (Figs. 8c,d). The changes based on the sc_PDSI_pm are similar to those based on the SM but with slightly lower magnitude (of 5%–15%; Figs. 8a,b), while the frequency change of the R-based moderated (severe) drought is relatively small, within 2%–10% (1%–5%) over most land areas. Nevertheless,
the widespread increases in the frequency of the $R$-based hydrological drought shown in Figs. 8e,f are consistent with those shown by Prudhomme et al. (2014). However, they appear to be inconsistent with the increases in the mean runoff and low streamflow rates seen over many areas in Eurasia and North America (Fig. 1d; Collins et al. 2014; Koirala et al. 2014). One possible explanation could be that the drying effect of the PDF flattening (Figs. 6 and 7e,) exceeds the wetting effect of the small mean increases in $R$ over these areas.

**Figure 9** shows the temporal evolution of the percentage global land area under drought conditions defined using the local sc_PDSI_pm, normalized (i.e., divided by local standard deviation of 1970–99) SM and $R$ indices and the 10th or 20th percentile, together with the time series of the global (60°S–75°N) mean of these (unnormalized) variables. Consistent with Fig. 8, the global drought area increases fastest (from 20% to about 30% from 1970–99 to 2070–99 for the moderate drought) for agricultural drought defined using the normalized SM,
followed by agricultural drought defined by sc_PDSI_pm with increases from 20% to about 28% (Fig. 9a). The area of the hydrological drought does show noticeable changes for the moderate drought. For the severe drought (<10th percentile), the global area increases from 10% to about 20% for the SM-based, from 10% to 16% for the sc_PDSI_pm-based agricultural drought, and from 10% to 14% for the hydrological drought (Fig. 9a). This slight increase in severe hydrological drought occurs despite the increases in the global-mean runoff (Fig. 9b). Global-mean values of the SM and sc_PDSI_pm also decrease only slightly, by ∼3% for SM and ∼0.24 for sc_PDSI_pm (Fig. 9b), yet the drought areas defined by them show much larger increases. These results further demonstrate that changes in the extremes (such as drought) may differ from the trends in the mean (e.g., in the R case) or have much larger magnitudes than in the mean.

The warm-season drought areas (Figs. 9c,e) also show similar trends with slightly larger magnitudes. Further, drought areas seem to be stabilized after about year 2065 over the Northern Hemisphere (and for the globe to a less degree) for all three types of drought, as the global-mean values for SM, sc_PDSI_pm, and R stabilize after year 2065 (Figs. 9b,d,f) because of the stabilization of the
RCP4.5 scenario at \( \sim 4 \text{ W m}^{-2} \) after about 2065 (van Vuuren et al. 2011).

The above results show that while the spatial patterns of the drought changes from 1970–99 to 2070–99 based on the sc_PDSI_pm, normalized soil moisture and runoff anomalies are broadly comparable (Fig. 8), the magnitude of the changes differs substantially. In particular, the drought frequency and area changes based on the normalized top 10-cm SM (agricultural drought) show the largest increases, closely followed by those based on the sc_PDSI_pm. This is in contrast to Taylor et al. (2013), who showed larger increases in the drought frequency based on sc_PDSI_pm than those based on the unnormalized top 1-m layer soil moisture anomalies from the Hadley Centre model. Our relatively small changes in R-based hydrological drought are consistent with Taylor et al. (2013), and the change patterns are also consistent with those of Prudhomme et al. (2014). We found that the normalization of the SM had only small effects on our results. Thus, we suspect that the differences between our results and Taylor et al. (2013) for agricultural drought changes are due to the use of...
different soil layers (top 10-cm versus top 1-m layers) and different models (14 CMIP5 models versus 1 Hadley Centre model). It should also be emphasized that the hydrological drought may become more frequent over most land areas even though the mean runoff may increase over many of these areas in Eurasia and other regions, presumably because of the drying impact of flattening PDFs.

4. Attribution of the drought changes

a. Contributions to sc_PDSI_pm changes

Figure 10 shows that changes in precipitation and surface vapor deficits (associated with warming) cause the largest sc_PDSI_pm changes, followed by changes in shortwave radiation, while surface wind speed and longwave radiation do not contribute much to the sc_PDSI_pm change. Following the precipitation change patterns shown in Fig. 1a, sc_PDSI_pm increases by 1–2 units (i.e., fewer droughts) over most of Asia, northern and central Europe, most of North America (except the southwest), and central Africa, whereas it decreases (i.e., more droughts) over Australia, southern Africa, the Mediterranean region, most of South America, Central America, and southwestern North America (Fig. 10a). On the other hand, the effect of increased surface vapor deficits leads to ubiquitous decreases of sc_PDSI_pm by 0.25–2.0 units (Fig. 10b). The large impacts of changes in precipitation and vapor deficits on sc_PDSI_pm shown in Fig. 10 are consistent with those found by Cook et al. (2014).

Surprisingly, changes in surface net LW radiation have very small impacts on sc_PDSI_pm (within about ±0.25 units), while increases in surface solar radiation have considerable drying effects over most land areas (Figs. 10c,d). Decreasing near-surface wind speed over North America and Eurasia leads to small increases (<0.25) in sc_PDSI_pm over these areas (Fig. 10c). The sum (Fig. 10f) of the sc_PDSI_pm changes from these individual forcing cases is very similar to that (Fig. 10g) from the case with all forcing included. This suggests that the effects of the individual forcings on the sc_PDSI_pm are additive. Figure 10 shows that the sc_PDSI_pm decrease (drying) results mainly from increased surface vapor deficits, with additional drying from increased solar radiation, whereas increased precipitation over most of Eurasia and North America leads to wetter conditions over many areas in these regions.

b. Contributions to SM changes

Based on Eq. (1), Fig. 11 shows the contributions of the ΔP, ΔE, and ΔR to SM changes from 1970–99 to 2070–99. It is clear that the ΔP is the most important driver that accounts for many of the positive and negative SM changes, and it is largely responsible for the SM decreases over Australia, most of South America, the Mediterranean region, and southern Africa. On the other hand, increased E enhances the drying over most land areas and it contributes the SM decreases over most Europe, North America, and parts of Asia, although the combined SM change (Fig. 11d) is still dominated by the dP-induced change. Changes in R have very small impacts on SM (Fig. 11c). The spatial patterns of the combined SM change (Fig. 11d) from the linear attribution analysis are significantly correlated (r = 0.62) with those in the actual SM change (Fig. 11e), although the combined SM change is biased toward wetter conditions compared the actual SM change (Fig. 11e).

Another way to examine the dominant contribution to the SM long-term changes is to find the main factor that can explain most (>80%) of the SM trend in the twenty-first century for each grid box with physically consistent sign of changes (e.g., if SM decreases and P increases, then the SM trend cannot be explained by the P changes). This analysis was done using the multimodel ensemble mean, as SM trends vary greatly among individual models. The result of this simple attribution is shown in Fig. 11f. As expected, most of the SM decreases over South America, southern Africa, Australia, southwestern North America, and the Mediterranean region are due to precipitation decreases. The SM increases over parts of Asia, Africa, and northern North America are also due to precipitation increases. On the other hand, E increases account for the SM decreases over the rest of the land areas, except for a few spotty locations where R changes may play a big role (Fig. 11f).

c. Contributions to the runoff changes

Figure 12 shows that precipitation change accounts for most of the runoff change (ΔR) over land, with large negative contributions from E increases only over northern mid- to high-latitude land areas. The E increases offset a large portion of the precipitation-induced runoff increases over Asia and northern North America, bringing the combined ΔR (Fig. 12c) very close to the actual ΔR (Fig. 12d) with a pattern correlation of 0.93. In other words, runoff would have increased substantially more over Asia, northern Europe, and northern North America (cf. Figs. 12a,d) and would have decreased considerably less in the Mediterranean region, the continental United States, and other areas than Fig. 12d shows if there were no increases in E. Thus, the negative impact of increased E on future runoff is nonnegligible even though precipitation change is the primary cause for ΔR.
FIG. 10. Attribution of the sc_PDSI_pm changes from 1970–99 to 2070–99 to changes in an individual forcing with all other variables set to the values of 1970–79 for decades outside the calibration period (1950–79). The individual forcing cases were done for each model run, and the resulting sc_PDSI_pm was averaged over the 14 models. The 2070–99 minus 1970–99 difference in the ensemble-mean sc_PDSI_pm for each forcing is shown here. The individual forcings include changes in (a) precipitation (ΔP), (b) near-surface air temperature and specific humidity [Δ(T + q)], (c) net surface longwave radiation (ΔLW), (d) net surface shortwave radiation (ΔSW), and (e) near-surface wind speed (ΔW). (f) The sum of the sc_PDSI_pm changes induced by all these forcings, which is compared with (g) the actual sc_PDSI_pm change from 1970–99 to 2070–99 in the all-forcing case for each model and then averaged over all the models. The pattern correlation (r = 0.98) between (g) the actual and (f) the attributed change is shown in (f). The stippling indicates at least 80% of the models agreeing on the sign of change.
d. Attribution of potential evapotranspiration changes $\Delta$PET

PET is important for quantifying drought because it represents the evaporative demand from the atmosphere. The widespread drying over the late twentieth and early twenty-first centuries result, to a large extent, from increasing PET driven by rising temperatures (e.g., Dai et al. 2004; Dai 2013). Thus, understanding what factors drive future PET changes may help understand the changes in future evaporation and drought. Our PET attribution analysis is similar to Scheff and Frierson (2014), except that we further separated the net radiation into LW and SW components and considered temperature and humidity changes together as these two are tightly coupled.

Figure 13a shows that changes in surface vapor deficits associated with rising temperatures contribute the most (~73% globally) to the large increases in PET (by 0.2–0.7 mm day$^{-1}$ or 10%–20%; see Fig. 2b) from 1970–99 to 2070–99. Much smaller PET increases are induced by increased surface net SW and LW radiation over many
land areas (Figs. 13b,c). Effects of wind speed changes are very small (Fig. 13d). It is often argued that enhanced downward LW radiation from increased GHGs can lead more radiative heating and thus higher PET, but the CMIP5 models suggest that the net surface LW radiation changes are small and thus their impacts on PET and sc_PDSI_pm are small. In fact, increases in surface SW radiation are more important than net LW radiation changes over many areas. This finding is consistent with Trenberth and Fasullo (2009), who found that global surface warming by the late twenty-first century in CMIP3 models comes mainly from increased SW, not LW, radiation. The dominant effect of increased vapor deficits on PET is also in agreement with Scheff and Frierson (2014), who reproduced the PET changes by scaling the vapor deficit under a constant relative humidity.

e. Attribution of actual evapotranspiration changes $\Delta E$

Since we already examined the factors contributing to PET changes $\Delta PET$, here we consider $E$ changes $\Delta E$ as driven by changes either in PET (atmospheric demand of moisture) or SM (supply of moisture). Figure 14 shows that the increased PET is the main cause for the $E$ increase over most of Eurasia, North America (except for its southwest), and central Africa, whereas the SM decrease is the primary cause for the reduced $E$ over Australia, southern Africa, northeast South America, and southwestern North America. Globally averaged, the PET change accounts for most (66%–78%) of the $E$ change, while the SM’s contribution is around 14%–27%; regionally, however, these contributions differ considerably.

5. Summary and conclusions

To examine the consistency and differences among the changes in agricultural and hydrological droughts by the late twenty-first century, we analyzed the changes in sc_PDSI_pm, top 10-cm layer soil moisture content (SM), and total runoff ($R$) from 14 CMIP5 models under the low–moderate emissions scenario, RCP4.5. Attribution analyses were also performed to identify major factors contributing to these changes as well as changes in potential evapotranspiration (PET) and actual evapotranspiration ($E$). We focused on the multimodel ensemble averaged contributions in the drought attribution analysis, which was done for each model run and then averaged over the models. The main findings are summarized below.

While $R$ change patterns are controlled primarily by precipitation ($P$) changes with decreases in many
subtropical land areas and increases over most Asia and northern North America, SM changes are determined by both $P$ and $E$ changes. Large increases in precipitation over Asia and northern North America lead to increases in $sc\_PDSI\_pm$ (i.e., wetter conditions) over many areas in these regions, while increases in PET results in decreased $sc\_PDSI\_pm$ (i.e., drying) over most of the Americas (except Alaska and northern Canada), Europe (except Scandinavia), Africa, and Australia. Decreased precipitation over many subtropical areas also enhances the drying there. Increased surface solar radiation also leads to considerable drying over most land areas, while changes in net surface LW radiation have little effect. These $sc\_PDSI\_pm$ results are consistent with those of Cook et al. (2014), although we further examined the effects of the SW and LW radiation components rather than the effect of the total net radiation changes.

Consistent with previous studies (Feng and Fu 2013; Scheff and Frierson 2014), we found that PET increases over all land areas and by 10%–20% from 1970–99 to 2070–99 under the RCP4.5 scenario over most land areas, especially over Europe, Russia, Canada, and the Amazon. The ubiquitous PET increase results primarily from the effects of rising surface temperatures and vapor deficits, with small contributions from increasing surface solar and LW radiation. Surprisingly, we found that changes in surface net longwave radiation do not play a major role for the PET increase under rising GHGs. Changes in surface wind speed also have very small

![Image](image_url)

**Fig. 13.** As in Fig. 10, but for the attribution of the PET (in mm day$^{-1}$) change estimated using the Penman–Monteith equation (Shuttleworth 1993). See Fig. 2b for percentage changes in PET. The pattern correlation ($r = 0.99$) between (f) the actual and (e) the attributed changes is shown in (e).
effects on PET. Combined with precipitation changes, the $P$/PET ratio (a measure of aridity) is projected to decrease (i.e., drying) by 0.05–0.20 over southern Europe, northern and central South America, most of North and Central America except Alaska and northern Canada, and Australia. The runoff ratio ($R/P$) is projected to decrease slightly (by 0.02–0.04) over most Eurasia (except South Asia), the northern contiguous United States, and Canada but change little or increase slightly over other regions. As a result, global-mean runoff ratio changes little while global-mean $P$, $E$, and $R$ all increase by about 4%–5% in the twenty-first century under the RCP 4.5 scenario.

We found that the anomaly relationship between SM and the sc_PDSI_pm is similar for the current and future climates, in contrast to the changing anomaly relationship between SM and the traditional PDSI found by Hoerling et al. (2012) over the central United States. The relationships between sc_PDSI_pm and $R$ and between SM and $R$ also do not change significantly in the current and future climates. Further, the probability density functions (PDFs) of these variables, especially for SM and $R$, are projected to flatten over most land areas, with increased standard deviations (STD) and reduced peaks in addition to a shift in the mean of the PDFs. These PDF changes result in more drought, whose occurrence is further enhanced by the decreases in the mean for SM and sc_PDSI_pm over many land areas. The flattening of the PDF for $R$ is the main reason for the increased hydrological drought frequency over most land areas found here and also by Prudhomme et al. (2014), despite the increase in the mean $R$ over many of these areas.

The occurrence frequency for the SM-based moderate (severe) agricultural drought, defined as below the 20th (10th) percentile, is projected to increase greatly by about 50%–100% (100%–200%) in a relative sense over most land areas by the late twenty-first century, while the frequency increases for the $R$-based moderate (severe) hydrological drought are smaller (both within ~50%). The increases in the drought frequencies are largest over South America (except Uruguay and central Argentina), Central and North America (except Alaska and northern Canada), Europe, southern Africa, and Australia. In contrast to Taylor et al. (2013), we found that the agricultural drought defined using the normalized SM content in the top 10-cm layer from the CMIP5 models increases the most, closely followed by the agricultural drought defined by the sc_PDSI_pm. Global land areas under drought (severe drought)

![Fig. 14](image-url)
conditions are projected to increase by about 50% (100%) by the end of the twenty-first century for the SM-based agricultural drought, increase by about 40% (60%) for the PDSI-based agricultural drought, and increase by about 5% (30%) for the hydrological drought, despite that the global-mean SM and sc_PDSI_pm decreases only slightly by about 3% and 0.24, respectively, and global-mean R increases by 4%-5% from 1970–99 to 2070–99. The changes in warm-season drought areas are similar to the annual mean, except that over the Northern Hemisphere the warm-season drought areas stabilize after about year 2065 because of the stabilization of the radiative forcing in the RCP4.5 scenario. To a lesser degree, this is also true for the annual-mean case.

In conclusion, our results are consistent with previous studies (Burke et al. 2006; Burke and Brown 2008; Dai 2011a, 2013; Taylor et al. 2013; Cook et al. 2014; Prudhomme et al. 2014), although the magnitude of the sc_PDSI_pm change of Dai (2011a, 2013) needs to be reduced by a factor of about 3 because of the use of the multimodel ensemble-mean forcing data in these two studies. The results show that the broad change patterns are consistent among the three different types of drought defined using the current percentile values of the sc_PDSI_pm and normalized SM and R anomalies, although large differences exist in their change magnitude, which is not surprising given that these are measures of different types of drought. Further, the relationships among these three drought indices are comparable in the current and future climates, suggesting that these indices are likely to be valid for measuring future droughts. All these indices suggest large increases (up to 50%–200% in a relative sense) in frequency for future moderate and severe drought over most of the Americas, Europe, southern Africa, and Australia. Our findings here confirm the dire projections reported previously by Dai (2011a, 2013), Cook et al. (2014), Prudhomme et al. (2014), and others, despite our use of a low–moderate emissions scenario.

Our findings also suggest that the drying under GHG-induced global warming results mainly from the effect of rising surface temperatures and vapor deficits on PET, while the effect of changes in surface radiation and wind speed is small. Given that the GHG forcings during the last several decades are much smaller than those in the twenty-first century used by the CMIP5 models, this result implies that any changes in historical radiation and wind speed are unlikely due to historical GHG forcing. Rather, they likely resulted from natural climate variability or other factors. Thus, the impacts of historical radiation and wind speed changes need to be separated from the effect of GHG-induced climate change and may not be relevant for GHG-induced future changes.

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REFERENCES


