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Competing influences of anthropogenic warming, ENSO, and plant physiology on future terrestrial aridity

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Abstract

The 2011–2016 Californian drought illustrates that drought-prone areas do not always experience relief once a favorable phase of El Niño–Southern Oscillation (ENSO) returns. In the 21st century, such an expectation is unrealistic in regions where global warming induces an increase in terrestrial aridity larger than the aridity changes driven by ENSO variability. This premise is also flawed in areas where precipitation supply cannot offset the global warming-induced increased evaporative demand. Here, atmosphere-only experiments are analyzed to identify land regions in which aridity is currently sensitive to ENSO, and where projected future changes in mean aridity exceed the range caused by ENSO variability. Insights into the drivers of these aridity changes are obtained in simulations with incremental addition of three different factors to current climate: ocean warming, vegetation response to elevated CO₂ levels, and intensified CO₂ radiative forcing. The effect of ocean warming overwhelms the range of ENSO-driven temperature variability worldwide, increasing potential evapotranspiration (PET) in most ENSO-sensitive regions. Additionally, ~39% of the regions currently sensitive to ENSO receive less precipitation in the future, independent of the ENSO phase. Aridity increases consequently in 67–72% of the ENSO-sensitive area. When both radiative and physiological effects are considered, the area affected by aridity rises to 75–79% when using PET-derived measures of aridity, but declines to 41% when total soil moisture aridity indicator is employed. This reduction mainly occurs because plant stomatal resistance increases under enhanced CO₂ concentrations, which results in improved plant water use efficiency, and hence reduced evapotranspiration and soil desiccation. Imposing CO₂-invariant stomatal resistance may overestimate future drying in PET-derived indices.

1. Introduction

Observed climate change arises from the combined effects of external forcings – both anthropogenic and natural – and chaotic internal climate variability. To assess the vulnerability of different managed systems (e.g., energy, agriculture, and water supply) to future climate change, and to inform sound adaptation strategies, it is essential to examine

changes in the mean state and background variability jointly, rather than individually. This is particularly important for evaluating perturbations to the hydrological cycle, where inherent variability and expected mean state changes are spatially and seasonally complex.

a. Changes in Precipitation

The globally averaged tropospheric radiative cooling rate is balanced by surface sensible heat fluxes and by the latent heating released during precipitation formation. This balance provides a fundamental constraint on the changes in global mean precipitation (hereafter P) (Allen and Ingram 2002; Pendergrass and Hartmann 2014; Thorpe and Andrews 2014; Trenberth 2011). The P response to future climate change can be divided into two components: a “fast” response associated with the atmospheric component of CO₂ radiative forcing; and a “slow” response to the global surface warming independent of the forcing mechanism (Andrews et al. 2011; Andrews et al. 2010; Myhre et al. 2016). The “fast” response arises because increased CO₂ concentrations lead to an immediate decrease in atmospheric longwave radiative cooling (Pendergrass and Hartmann 2014) and an increase in tropospheric heating, which is largely balanced by a rapid decrease in latent heating and hence global P (Bony et al. 2013; Colman 2015; Kamae et al. 2015; Richardson et al. 2016; Samset et al. 2016; Sherwood 2015; Tian et al. 2016). The “slow” response occurs because global warming enhances longwave radiative cooling by the atmosphere, which is largely balanced by additional latent heating and precipitation, both of which increases by roughly 2–3% per Kelvin of global warming (Allen and Ingram 2002; Andrews et al. 2010; Bala et al. 2010; DeAngelis et al. 2016).

On a regional scale, the fast P response to CO₂ forcing can be complex (e.g., Richardson et al. 2016). The warming-induced changes in P are also complex, driven by multiple physical mechanisms. These include the “wet-get-wetter” mechanism associated with an increase in tropospheric water vapor (Held and Soden 2006), and the “warmer-get-wetter” mechanism linking the patterns of tropical sea surface temperature (SST) changes with rainfall changes (Xie et al. 2010). A poleward displacement of current zonal-mean wet/dry patterns is also expected as a result of shifts in atmospheric circulation (Marvel and Bonfils 2013; Polson et al. 2013; Seidel et al. 2008), while terrestrial moisture recycling introduces meridional structure in the patterns of P change over land (Greve et al. 2014). This meridional structure is largely absent in the zonal changes over oceans (Durack et al. 2012). The resulting forced pattern of P change differs markedly from patterns arising from changes in P variability alone (Power et al. 2013; Zhou et al. 2014).

Given the spatial complexity of changes in the mean state and variability of P, and in view of potential interactions between forced and unforced changes (Maher et al. 2014), it is important to quantify the relative importance of different contributory factors to future P changes. Such an analysis was performed by Bonfils et al. (2015), who decomposed the 21st century P response into the sum of three components: 1) the long-term change in mean P; 2) the historical, 20th-century P response to ENSO variability; and 3) an intensification of ENSO-driven P responses in the 21st century. Understanding where and when the projected changes in P will rise above the historical range of ENSO-driven variability can be of great

benefit for assessing the potential vulnerability of agriculture, water resources, and certain energy sectors (such as hydropower) to climate change.

b. Changes in Evapotranspiration

In drought research, understanding changes in the mean and variability of P only informs the “supply side”. It is equally important to assess the behavior of actual evapotranspiration¹ (ET). On timescales longer than a few months, global mean ET increases at 2–3% per Kelvin of global warming to be in balance with changes in P. Over oceans, where there is an infinite moisture source, the fast response to rising CO₂ concentrations is an increase in low-level atmospheric stability and near-surface humidity, which lead to a suppression of ET (Cao et al. 2012; Kamae and Watanabe 2012). In contrast, the warming of the land surface decreases vertical stability of the lower atmosphere, increases the export of moisture flux from the boundary layer, and enhances convection. These changes tend to increase ET and P (Cao et al. 2012), particularly in tropical regions (Richardson et al. 2016).

Over land, however, an important competing mechanism exists, involving transpiration of water by vegetation (Schlesinger and Jasechko 2014). Plant stomata regulate transpiration; the degree of regulation depends on the availability of energy (in the form of radiation), water (in the soil and as atmospheric moisture) and CO₂ (Farquhar and Sharkey 1982).

c. Impact of vegetation on changes in P and ET

Under elevated atmospheric CO₂ levels, plants optimize photosynthesis and water loss per unit leaf area by reducing the opening of stomata in their leaves. Elevated CO₂ induces an increase in water use efficiency (WUE), which is the amount of CO₂ absorbed by photosynthesis per amount of water lost during transpiration (Goudriaan and Unsworth 1990)². The reduced transpiration and surface latent heat flux to the atmosphere lead to a significant drying and warming of the boundary layer over land, and a decrease in P (Andrews et al. 2011; Cao et al. 2012; Dong et al. 2009; Doutriaux-Boucher et al. 2009). These physiological effects can also modulate the relative strengths of latent and sensible heat flux responses to increased CO₂, thereby influencing the net atmospheric heating itself, and hence the “fast” response of P to CO₂ (DeAngelis et al. 2016). While substantial progress has been made in understanding these mechanisms, their contributions to recent observed changes in ET remain uncertain. For example, the recent multi-year decline in global terrestrial ET has been ascribed to both a persistent reduction in soil water availability (Jung et al. 2010) and to a transition to El Niño conditions (Miralles et al. 2014), with a very recent recovery in ET attributed to vegetation greening (Zhang et al. 2015).

d. PET and changes in aridity

The message from the research described above is that the mechanisms driving future changes in P and ET are complex, and are not easily partitioned into contributions from background variability, mean state changes, and changes in variability. In contrast, most

¹the actual amount of water removed from the surface through soil land canopy evaporation and transpiration.

²Increasing CO₂ can lead to increased photosynthesis but to similar transpiration in regions where plants are limited by water availability. Where plants are limited by energy availability, increased CO₂ may cause little or no increase in photosynthesis, but a decrease in transpiration (Goudriaan and Unsworth 1990). In both cases, there is an increase in WUE.

climate projections show a common signal of 21st century increases in atmospheric moisture demand and aridity in response to CO₂-induced warming. These projections, however, often rely on aridity metrics based on potential evaporation (PE) (Burke and Brown 2008; Burke et al. 2006; Dai 2011a, 2011b, 2013; Sheffield et al. 2012; Zhao and Dai 2015) or on potential evapotranspiration (PET) (Berg et al. 2016; Cook et al. 2014; Cook et al. 2015; Feng and Fu 2013; Fu and Feng 2014; McCabe and Wolock 2015; Scheff and Frierson 2014; Scheff and Frierson 2015; Swann et al. 2016) rather than on ET. PET represents the atmospheric evaporative demand from a well-watered reference grass. In contrast, PE is the maximum amount of evaporation that would occur from an open-water surface.

In most projection studies, PE and PET estimates assume a space- and time-invariant value for the stomatal resistance r_s (Allen et al. 1998; Sheffield et al. 2012). While this is standard practice because it avoids problems associated with calibration, vegetation mixture and morphology, this assumption does not account for the sensitivity of PET to plant adaptation in a CO₂-enriched atmosphere. Recent scientific literature suggests that in simulations investigating the plant physiological response to elevated CO₂, the choice of aridity index can have considerable influence on the estimated future drying. Drying can be enhanced by the use of aridity indices based primarily on atmospheric variables (such as surface relative humidity, the Palmer Drought Severity Index (PDSI) or P/PET; Swann et al. 2016, Berg et al. 2016). Alternatively, use of aridity indices based mainly on hydrological variables or vegetation properties (such as P minus ET, or runoff; Swann et al. 2016, (Roderick et al. 2015) can reduce the estimated future drying.

Independently, Milly and Dunne (2016) show that PE and PET estimators based on time-invariant r_s may severely over-predict the changes in aridity in non-water stressed regions. The assumed space- and time-invariance of r_s is therefore questionable. Whether this over-prediction in aridity is systematic is unclear. Mixed results are found in studies comparing future drying trends over 21st century North America obtained with either offline PET-derived PDSI or model soil moisture estimates (which implicitly account for the variations in r_s). While the drying trends predicted with PDSI and near-surface soil moistures are similar (Cook et al. 2015), disparities across regions and models exist when PDSI and full-column soil moisture trends are compared (Feng et al. 2016; Smerdon et al. 2015). These mixed results highlight important uncertainties across different aridity predictors. The likely cause of such disparities is that we have relatively poor observational constraints on the impacts of CO₂-induced structural and physiological changes in vegetation on soil moisture, runoff, and water resources (Frank et al. 2015; Ukkola et al. 2016).

e. The recent California drought

The 2011–2016 drought in California can be used to study the relative importance of interannual and long-term changes in P, ET and PET. The rainfall deficit over California has at least three proposed causes: (1) a purely internal mechanism initiated by equatorial Pacific SST fluctuations (Seager and Henderson 2016); 2) a human-induced, non-uniform change in geopotential height (Swain et al. 2016); and 3) a response to Arctic sea-ice loss (Sewall 2005; Sewall and Sloan 2004). These explanations are not mutually exclusive. Other California drought studies, based on PDSI indices require a contribution from human-

induced increases in evaporative demand (Diffenbaugh et al. 2015; Williams et al. 2015). Although progressive forest canopy water loss has been observed over 2011–2015 (Asner et al. 2016), the role of vegetation in explaining the Californian drought is presently unclear.

Despite these scientific uncertainties, the 2015/16 “super El Niño”³ (as it was referred to in media headlines) was expected to provide much-needed drought relief in California⁴. Instead, the State received only near-average P during the event, which resulted in a worsening of the drought (as of December 2016, roughly 73% of California was still experiencing drought conditions). In contrast, the weak La Niña of 2016/17 has unexpectedly been associated with near-record rainfall and snowfall, bringing drought relief throughout California by April 2017. These two unusual years merit more scientific scrutiny. As they clearly illustrate, the expectation that a particular ENSO phase will almost always be a regional source of relief is significantly challenged by the limited predictability of the “far-fetched” responses to ENSO.

f. Goal

In this study, we use different sets of atmospheric model simulations to identify regions where projected changes in aridity are large enough to overwhelm the effect of local drying/moistening associated with ENSO variability. To provide a comprehensive assessment of relative contributions to future drought, we consider a variety of hydroclimatic variables, including changes in P, PET and ET, and several aridity indices. The latter are based on soil moisture, runoff, or on combinations of P and PET or P and ET. For each variable, the combined effects arising from mean-state changes and ENSO variability are examined for three components of greenhouse warming: 1) the “slow” ocean warming (+SST); 2) the ocean warming and the response of plant physiology to rising atmospheric CO₂ levels (+SST+Veg); and 3) ocean warming and plant physiology effects, together with the radiative forcing from enhanced CO₂ (+SST+Veg+Rad). These sets of simulations are used to estimate the individual contributions of different factors and processes to future droughts.

2. Methods

a. Description of experiments

We use results from six different sets of numerical experiments (Table 1) available in the CMIP-database (Taylor et al. 2012). Our objectives are as follows: 1) identify regions where a projected change in aridity exists; 2) determine whether this change exceeds the effect of local drying/moistening associated with ENSO variability; 3) examine the robustness of results to model uncertainties; 4) assess the sensitivity of results to the choice of aridity indices; and 5) determine the relative contributions of ocean warming, plant physiology, and CO₂-induced radiative forcing to future aridity changes. We focus on ENSO and ENSO season (January–March) for two reasons: ENSO is the primary contributor to internal

³The Oceanic Niño Index (ONI; http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ensoyears.shtml) computed over the Niño3.4 region indicates that “super El Niño” events have occurred in 1982–83 (ONI=2.1) and 1997–98 (ONI=2.3) and 2015–16 (ONI=2.2).

⁴Most seasonal forecast models predicted a wetter-than-average California winter in 2015–16.

variability in P; and ENSO-induced P effects have significant global socio-economic impacts.

In estimating these relative contributions, we consider the incremental inclusion of: a) SST warming of 4K (+SST); b) the "fast" carbon cycle response associated with the impact on plant physiology of an imposed global increase of CO₂ concentration (+Veg); and c) the "fast" radiative responses to rising CO₂ (+Rad). Atmosphere-only model experiments amip and amipFuture are used to address objectives 1–4. Three other types of atmosphere-only simulations (amip4×CO₂, sstClim, sstClim4×CO₂) are analyzed to address objective 5. Although these five experiments are nominally a part of the Cloud Feedback Model Intercomparison Project (CFMIP), they have also been very useful for studying changes in the hydrological cycle (Bony et al. 2013; Chadwick 2016; Chadwick et al. 2014; DeAngelis et al. 2016).

Brief details of these simulations are as follows:

1. The **amip** experiment (Hist) is forced by observed time-varying SST and sea-ice changes over 1979–2008, and the CO₂-equivalent concentration is set at 345 ppmv (Gates et al. 1999).
2. The **amipFuture** experiment (Hist+SST) is almost identical to the amip simulation, with the exception that a composite SST warming pattern (Appendix A) scaled to a global mean of 4K is added to the time-varying SST observations over the 1979–2008 period. Atmospheric constituents are held fixed at their amip values.
3. The **amip4×CO₂** experiment (Hist+Rad) is almost identical to the amip simulation; the sole difference is that the atmospheric CO₂ concentration “seen” by the radiative scheme is quadrupled. The vegetation, however, only experiences the 1×CO₂ value.
4. The **sstClim** experiment (PI) is driven by prescribed climatological preindustrial SSTs, which vary over the seasonal cycle, but not interannually. Sea ice and atmospheric constituents are taken from each model’s own pre-industrial control run. The simulation is 30-year long; the radiation and vegetation schemes use the pre-industrial value of equivalent CO₂.
5. The **sstClim4×CO₂** experiment (PI+Veg+Rad) is almost identical to the sstClim simulation, with the exception that atmospheric CO₂ concentration is quadrupled. Both the radiative and the vegetation schemes “see” the increase in CO₂.

In all simulations, the dynamic vegetation schemes are turned off (i.e. the spatial distribution of vegetation is fixed). The vegetation, however, can respond to climate variations by altering leaf area, modifying stomatal resistance, and modifying productivity. We estimate the slow ocean-warming response by computing the (amipFuture–amip) anomalies:

$$(Hist + SST) - Hist = + SST \quad [1]$$

We estimate the fast CO₂-induced plant responses by computing the [(sstClim4×CO₂–sstClim)–(amip4×CO₂–amip)] anomalies:

$$((PI + Veg + Rad) - PI) - ((Hist + Rad) - Hist) = +Veg \quad [2]$$

The first part of this operation (sstClim4×CO₂–sstClim) allows the combined effect of vegetation and radiative responses to elevated CO₂ to be inferred:

$$(PI + Veg + Rad) - PI = +Veg + Rad \quad [3]$$

A total of four models (HadGEM2-ES, IPSL-CM5A-LR, MPI-ESM-LR, MPI-ESM-MR) in the CMIP5 archive (Table 2) have contributed simulations and output variables suitable for addressing our objectives (with one single realization per model). Prior to analysis, all model data were regridded to a common 72×144 latitude/longitude grid using an area-conserving scheme. The significant advantages of using atmosphere-only simulations instead of coupled ocean-atmosphere simulations are described in Appendix A.

b. Analysis of the amip and amipFuture experiments

Our analysis begins with the amip and amipFuture experiments, which isolate the effects of the change in mean climate and the variability induced by the “slow” ocean warming alone (+SST). We use model composites to identify the spatial patterns of land surface climate response to the two different phases of ENSO. Model composite response patterns are calculated both before to and after applying the SST warming. For the historical (Hist) climate, and for each variable of interest, we first identify the region R_1 that is sensitive to ENSO. The R_1 region is defined with two simple criteria. It encompasses continental grid cells: 1) showing a sign change in anomalies between the two ENSO phases; and 2) with a minimum temporal correlation of |0.15| with the model Niño 3.4 SST time series. R_1 is expressed as an area-weighted fraction of the total land area between 60°S and 75°N (this excludes the large glaciated land masses of Greenland and Antarctica). We then estimate how this fraction will be altered by a future change in the mean state. For further details, see Appendix B.

c. Analysis of the amip4×CO₂, sstClim and sstClim4×CO₂ experiments

We add the +Veg and +Veg+Rad anomalies to the Hist+SST data to test the sensitivity of our results to the incremental inclusion of the “fast” physiological and radiative responses to imposed quadrupling of CO₂. This adjustment involves adding the local monthly climatological anomaly of +Veg or +Veg+Rad to each month on each grid cell of the Hist +SST output. The +Veg anomalies are added to estimate the additional responses imposed by changes in CO₂ due to plant physiology, yielding Hist+SST+Veg. The +Veg+Rad anomalies are added to provide information on the role of both radiative and physiological responses, yielding Hist+SST+Veg+Rad.

d. Aridity indices

We measure terrestrial aridity using six indices: the Climate Moisture Index (CMI, Appendix C), $P/(P+PET)$, PDSI, surface soil moisture (10-cm depth), total soil moisture (summed over all soil layers, with a full depth ranging between 3–7m. across models; Table 2), and total runoff. CMI (Willmott and Feddema 1992) is a dimensionless drought indicator of the potential water availability, often used by the World Bank to assess the risks of climate change. $P/(P+PET)$ is a modified version of P/PET , the aridity index adopted by the United Nations Environment Programme (UNEP) (Middleton and Thomas 1992), but it is, better suited for analyzing future aridity in a warming world (Scheff and Frierson 2015). PDSI (Palmer 1965) is a widely used operational meteorological drought index based on both water supply and demand. The near-surface and full-column soil moisture variables are indicators of hydrological and agricultural droughts that incorporate different root zone depths. The two soil domains interact differently with the atmosphere (e.g., deeper soil moisture pool interacts mainly through plant transpiration, and has a longer memory than the shallow soil layer, which is exposed to bare soil evaporation). Runoff, a primary concern for water managers, is directly related to terrestrial hydrological conditions; it can be affected by both CO_2 -induced structural ('greening') and physiological change in vegetation (e.g., Ukkola et al. 2016).

Here, soil moisture and runoff are direct outputs from the AMIP-style simulations and depend on actual ET calculated in the model. In contrast, CMI, $P/(P+PET)$ and PDSI are indices derived from both P and PET, where P denotes the water supply (a direct output of the simulations), and PET represents the atmospheric demand. PET is not supplied as model output and needs to be estimated. For this purpose, we used the Penman-Monteith equation (Appendix C), as recommended by the United Nations Food and Agriculture Organization (Allen et al. 1998). As in many drought projection studies (see Introduction), our calculation of PET employs the CO_2 -invariant stomatal resistance (r_s) of a reference grass. The implications of increasing r_s and reducing PET in a CO_2 -enriched atmosphere (by an increase in the denominator of the Penman-Monteith equation) will be further addressed in section 3f.

3. Results

a. Changes in T in response to ocean warming

The two panels of Figure 1a show the present-day land surface temperature responses (or teleconnections) to El Niño and La Niña events (H_h)⁵, derived from the multi-model composite analysis of the Hist simulations. Only regions where the temperature anomaly changes sign between the two ENSO phases are displayed (region R_1). This region represents 60% of the continental surface between 60°S and 75°N. Similar teleconnections patterns are found in the future (Hist+SST) in response to the ocean warming (Fig. 1b; F_f)⁵. Note that in both figure 1a and figure 1b, only region R_1 from the Hist simulations is

⁵The notation H_h should be interpreted as follows: “H” indicates that this is a change in some variable (e.g., temperature, precipitation), “H” indicates that the quantity considered is from the historical period, and “h” indicates that the historical mean value of that quantity is removed to obtain an anomaly. We will present other combinations, such as F_f and F_h , where “F” and “f” refer to the simulations of idealized future conditions.

displayed. Figure 1c shows the corresponding temperature responses to El Niño and La Niña events in the Hist+SST simulations expressed relative to the present-day mean state (F_h). By the end of the 21st century, warming dwarfs temperature changes associated with ENSO. The phase of ENSO modulates the amplitude of warming everywhere but does not reverse the sign of the mean changes in temperature. In the southwest U.S., for example, the slight cooling during El Niño events does not fully compensate for the warming induced by the large increase in SSTs.

b. Changes in P and PET in response to ocean warming

From the Hist simulations, we find that only 41% of the continental surface between 60°S and 75°N exhibits P responses that change sign between the two ENSO phases (Fig. 2a; Table 3, column 1). Meteorological droughts (P deficits) associated with El Niño events occur during boreal winter in western Australia, India, Indonesia, Brazil, southeastern Africa, Central America, and the northwestern U.S. In contrast, La Niña events are characterized by drier than normal P conditions along the west coast of tropical South America, and at subtropical latitudes of North America and South America. Regions with positive T anomalies (Fig. 1a) are often co-located with regions experiencing negative P anomalies (Fig. 2a). Model expectations regarding the future behavior of precipitation are spatially more complex than with temperature, which generally shows a strong latitudinal dependence in all models. Estimates of the ENSO-driven P responses in the future relative to the present-day mean state (F_h , Figs. 2c) suggest that most regions north of 30°N will become wetter, independent of the phase of ENSO. In contrast, many subtropical regions will become drier, exceeding the range of ENSO-induced variability in P. In the future climate, only 20% of the original region R_1 continues to show P anomalies that change sign with the phase of ENSO.

To highlight the results from ENSO response maps for all variables and experiments⁶, we display them in a more compact graphical and tabular form in Figs. 3–4 and Table 3. Note that Figures 3–4 and Table 3 focus solely on the R_1 regions, which are currently sensitive to ENSO.

The two left-most bars of Figure 3a summarize the precipitation results from Figures 2a and 2c (the right bars are discussed in Section 3d). The R_1 region for P comprises the 41% of the land area with P responses changing sign during the two ENSO phases in the Hist experiments. During historical El Niño events, 56% of the R_1 region is drier (yellow) and 44% is wetter (light-green), as indicated by the Historical bar. The +SST bar in Figure 3a indicates that only one fifth (20%) of the R_1 region continues to be sensitive to ENSO in response to imposed future SST warming (combined light-green and yellow portions of the bar; Table 3, column 6). Nearly 41% (33–44% across models) of the R_1 region becomes wetter (dark-green) independent of the phase of ENSO. Drying (dark-brown) exceeds the range of ENSO-driven P variability in 39% (30–44% across models) of the R_1 region.

⁶Figs 1–2 for T and P, Figs. 7–8 for P/(P+PET) and total soil moisture, Figs. S1–S4 for PET, CMI, PDSI, and surface soil moisture, and Figs. S6–S8 for total runoff, photosynthesis and ET.

Figure 3b repeats the analysis in Figure 3a, but shows results for PET instead of P. In the Hist simulations, the sign of PET anomalies is affected by ENSO variability over 53.5% of the global land surface. Roughly 54% of this R_1 area has higher PET during El Niño events. The PET anomalies (Fig. S1a) correspond closely to the ENSO-driven T anomalies (Fig. 1a): anomalously warm (cool) regions yield anomalously high (low) PET⁷. In the western U.S., for example, warmer than normal conditions during La Niña events induce anomalously high PET and low P; both contribute to drier conditions over the region. In response to ocean warming (+SST), virtually all of the R_1 land (99%) experiences increased PET, exceeding by far the PET changes induced by ENSO variability. The increase in PET is mainly due to the simulated increase in water vapor deficit, as is documented in a number of different studies (e.g., Roderick et al. (2015), Fu and Feng (2014) and Scheff and Frierson (2014)).

c. Changes in aridity indices in response to ocean warming

We now repeat the above-described T and P analyses using five of the six aridity indices: CMI, $P/(P+PET)$, PDSI, surface soil moisture, and total soil moisture (Table 3 and the first two bars in Figs. 3c–g). Across these indices, the percentage of the global land surface area with aridity values sensitive to the phase of ENSO ranges from 39% to 50%. From 57% to 60% of these regions sensitive to ENSO are drier during El Niño events (Hist). This partitioning is consistent with results from Miralles et al. (2014) who found global scale El Niño-induced limitations in terrestrial moisture supply. Ocean-forced warming (+SST) yields a pronounced decrease in the percentages of region R_1 that remain influenced by ENSO variability. Aridity increases overwhelm ENSO-driven variability in 67% to 72% of the R_1 regions (48–72% when all models are considered individually), while only 9% to 17% of the R_1 region experience a decrease in aridity (9–29% when all models are considered individually). Results are relatively insensitive to the choice of aridity index or to model uncertainties (Fig. 3c–h): Preliminary conclusions indicate that both model surface and total soil moisture responses are largely consistent with the three offline, PET-derived aridity responses. Total runoff is the least affected aridity indicator, with 41% (27%) of the “ENSO sensitive” land area experiencing less (more) runoff in response to the ocean warming (+SST).

d. Sensitivity of results to inclusion of physiological and radiative forcings

The above-described changes in aridity in the amipFuture simulations (+SST) occur in response to an imposed ocean warming and in the absence of increasing atmospheric CO_2 . In reality, however, regional hydroclimate responds not only to CO_2 -induced SST increases, but also to the influence of enhanced CO_2 levels on the vertical profile of radiative heating and to altered surface energy fluxes arising from plant responses to increased CO_2 . Including the responses to both the radiative and physiological forcings can therefore lead to substantial changes in projected aridity: CO_2 radiative heating enhances land surface temperature and increases evaporation and precipitation, whereas CO_2 fertilization causes

⁷This close T/PET coupling is well-known in drought research and is attributed to the use of PET formulations that are overly sensitive to temperature (Sheffield et al. 2012), such as the Thornthwaite equation. In our analysis, we find close T/PET coupling even when the Penman-Monteith equation is used for estimating PET (cf. Roderick et al. 2015).

plant stomata to close, increasing stomatal resistance (r_s) and hence reducing terrestrial evapotranspiration (Andrews et al. 2011).

The simulations analyzed here enable us to assess the sensitivity of our results to the individual and combined radiative and physiological effects of increased CO_2 (section 2c). Results for P and PET are synthesized in Figures 3a–b. In the columns marked +SST+Veg, the effect of enhanced water use efficiency of plants is added to the ocean warming effect. The combined effects of SST warming, changes in water use efficiency, and atmospheric radiative forcing are shown in the columns marked +SST+Veg+Rad.

Consider the P results first. Adding the physiological effect of increased CO_2 (+SST+Veg) to ocean warming only (+SST) has minimal impact on the total land area that changes sign during ENSO phases (Fig. 3a yellow+light-green; also compare Figs. 2d–e to Fig. 2c): there is a very small increase in the percentage of land area that receives consistently less precipitation (from 39% to 41%), but this change is smaller in amplitude than the inherent inter-model uncertainties (denoted by the error bars; all models simulate an increase in R_1 except MPI-ESM-MR). This small reduction in precipitation caused by the incorporation of CO_2 -induced plant physiological effects (Fig. 2f) corroborates previous findings (Andrews et al. 2011, Berg et al. 2016; Swann et al. 2016; Cao et al. 2012). Globally, the P reduction caused by the physiological effects is more than offset by the P increase associated with the radiatively-induced fast surface warming and increase in atmospheric water vapor (Fig. 3a; also compare Figs. 2f and 2g). In the case of PET (Fig. 3b, Fig. S1c–e), results are insensitive to the inclusion of the physiological and radiative forcings. In all three sets of simulations (+SST, +SST+Veg and +SST+Veg+Rad), most regions experience an increase in future PET that exceeds ENSO-driven variability.

In terms of PET-derived CMI, $P/(P+PET)$, and PDSI, our results show a very small increase in permanently arid area in response to the inclusion of plant physiological forcing. For CMI, $P/(P+PET)$, and PDSI, the permanently arid area is 69%, 70%, 67% in +SST (respectively), increasing to 70%, 71%, 68% in +SST+Veg (see Figs. 3c–e; Figs. 5, S2–S3, panels c–d). This increase in aridity is in accord with the P/PET and PDSI results of Berg et al. (2016) and Swann et al. (2016), who attributed it primarily to increasing temperature and PET. PET increases even further with the inclusion of radiative forcing alone (e.g., Swann et al. 2016), leading to an additional increase of the proportion of land becoming arid beyond the range of responses induced by ENSO variability (to 78%, 79%, 75% for the CMI, $P/(P+PET)$, and PDSI indices in +SST+Veg+Rad; Figs. 5, S2–S3, panel e). With the exception of MPI-ESM-LR, all models simulate the increase in permanently arid area for all 3 indicators between the +SST and +SST+Veg cases. This increase in arid land in response to the inclusion of the radiative forcing (+SST+Veg+Rad) is robust across all four models considered and the 3 aridity indicators (Table S1). In summary, these three model-averaged PET-derived indices imply that a state of permanent aridity will occur in roughly 75% to 79% of the regions where aridity is currently sensitive to ENSO variability.

e. Sensitivity of surface and total soil moisture changes to inclusion of physiological and radiative responses

In contrast to the case of the three PET-derived aridity indices, the inclusion of plant physiological effects has a pronounced impact on total soil moisture (Fig. 3g, Fig. 6). The percentage of “ENSO sensitive” land area that is permanently arid in response to the imposed 4K warming decreases from 72% in +SST to only 41% in +SST+Veg, a result robust in sign across models⁸. In contrast, the top-10cm soil moisture (Fig. 3f, Fig. S4), which is primarily controlled by soil evaporation rather than by plant transpiration, is much less sensitive to the changes in stomatal closure than to the evaporative demand of the atmosphere. This explains why the shallow soil moisture responses are very similar to those obtained with the PET-based aridity indices (compare Fig. 3f with Figs. 3c–e). In contrast, total soil moisture (Fig. 3g) reflects the deeper root zone soil moisture (the rooting depth for many ecosystems is estimated between 1.5–3 m; (Hagemann and Stacke 2015)), which is directly controlled by ET. The latter decreases during non-drought conditions, sequestering water in the soil, allowing plants to bridge longer dry spells. Owing to this additional soil moisture, runoff increases in many areas (Fig. 3h Fig. S6).

To understand these results in more detail, we analyzed additional terrestrial variables: actual evapotranspiration (ET) and its three components: evaporation from soils (EV_s), evaporation from water intercepted by plants (EV_v), and transpiration (TR). We also examined plant carbon uptake (i.e. gross primary productivity; GPP) and leaf area index (LAI).

Under present-day conditions, water-limited regions with negative P anomalies during El Niño experience negative anomalies in ET, GPP and LAI due to deficits in water availability for plant growth and evapotranspiration. No ENSO-related effects on GPP, LAI and TR occur in regions where growth is limited by temperature, such as the boreal forest (see Fig. 1A of Nemani et al. 2003). In simulations of future warming, inclusion of the plant response to enhanced CO₂ levels (from +SST to +SST+Veg) generally yields: 1) larger land area with more carbon uptake (red, Fig. 4b, red; Figs. S7c–d) and 2) less transpiration (Fig. 4f, dark-brown, Figs. S8c–d) and less ET per unit leaf area associated with increased stomatal resistance. The enhanced carbon uptake also favors more “greening” (Fig. 4c, red) and more canopy layers that can intercept (EV_v , Fig. 4e, dark-brown) and transpire water. Plant transpiration and evaporation (Figs. 4e–f) reacts more strongly than soil evaporation (Fig. 4d) to inclusion of physiological effects (+Veg). The relative magnitudes of changes in soil evaporation (Fig. 4d) and surface soil moisture (Fig. 3f) are in good accord; the same holds for the relative sizes of changes in transpiration (Fig. 4f) and total soil moisture (Fig. 3g). These results support the above-described discussion of the primary drivers of soil moisture changes. The changes in actual evapotranspiration (Fig. 4a) are influenced by changes in both soil evaporation and plant transpiration.

⁸However, this change is much smaller in amplitude in IPSL-CM5A-LR than in other models. Figure S5 shows that IPSL-CM5A-LR, as expected, conserves soil moisture by stomatal closure. In this particular model, the effect is smaller than in other models and is overwhelmed by the increase in aridity induced by ocean warming (+SST case). The smaller preservation of soil moisture in IPSL-CM5-LR (relative to the other three models) is probably attributable to differences in land models, soil structure, root zone depth, vegetation mixture, or morphology.

f. Implications of fixing stomatal resistance in PET-derived aridity estimates

In most studies predicting an increase in aridity under climate change (including this study), the PET-derived aridity metrics assume a stomatal conductance r_s that is invariant to changes in CO_2 . The lack of r_s output in the amip experimental database precludes the use of CO_2 -dependent values of r_s in the PET calculations. As an alternative, we analyze two aridity indices based on actual ET instead of PET: CMIET and $P/(P+ET)$. The reason for choosing these ET-based aridity indices is that ET calculations account for variations in r_s in response to solar radiation, temperature, and humidity, as well as in the response to CO_2 levels imposed by the experimental design. Although not ideal, we use these alternative aridity indices in an attempt to bound the problem by assuming that the “true” projection of terrestrial aridity should lie somewhere between the PET-based indices (the upper bound) and the ET-based indices (the lower bound)⁹.

In the +SST case (Figs. 4g–h), the ET-defined indices imply that more than half of the R_1 region will become more arid in the future, beyond the expected range of ENSO variability (55–57% for CMIET and $P/(P+ET)$), with little change when both the physiological forcing and the fast response to radiative forcing are included (54–57% for CMIET and $P/(P+ET)$). The regions predicted to face more arid climate in the future remain widespread, although these “lower bounds”, as defined by the ET indices show smaller aridity changes than those inferred from the “upper bounds” defined by the PET indices (78–79% for CMI and $P/(P+PET)$). Similar results between PET- and ET-derived indices are found when models are analyzed one by one.

4. Limitations of the study and future directions

The results presented above have several key caveats. First, our analyses do not consider the impact of possible changes in ENSO (in terms of amplitude, frequency or ocean patterns in the tropical Pacific), or how such changes might affect the quantitative partitioning of the different drought influences that we have examined. At our present stage of scientific understanding, there are still significant uncertainties in model projections of future changes in ENSO magnitude and structure (e.g., Bonfils et al. 2015). In view of these uncertainties, our underlying assumption that ENSO characteristics will remain unchanged in the future is not unreasonable.

Another underlying assumption is that the regions defined as “ENSO sensitive” under present-day climate do not change with global warming. There is, however, evidence of an eastward shift of the teleconnection patterns between ENSO and hydroclimate variables in response to ocean warming (Zhou et al. 2014). This suggests that the locations of regions categorized as “ENSO sensitive” are not identical in the present-day and future climate simulations analyzed here (e.g, Figs. 2a–b show opposite El Niño-driven P signals in Mexico and in Southern U.S.). However, we do not expect this small locational shift to substantially alter our results. Although we do not consider the eastward shift in teleconnections identified

⁹Because ET is both limited by P and available soil moisture, using ET in aridity metrics is not ideal. For example, $P/(P+ET)$ or $(P-ET)$ may increase (i.e., indicating “wetter” conditions) because ET declines faster than P. If the decline in ET reflects a reduction in atmospheric demand, the conditions are indeed wetter. However, if the strong reduction in ET is caused by a sharp decline in soil moisture (indicating drier conditions), soil moisture and $P/(P+ET)$ or $(P-ET)$ results are inconsistent.

by Zhou et al. (2014), we do explore an issue they did not examine – the impact of physiological and radiative forcings, which can also impact the strength or position of ENSO teleconnections.

A drawback of the simulations analyzed here is that the slow +SST response did not interact with the fast +Rad and +Veg responses. Additionally, the simulations did not consider the effects of dynamic vegetation, land use or land cover changes, and changes in the nitrogen cycle.

5. Discussion and Conclusion

A number of studies have investigated changes in the mean state of hydroclimatic variables in response to global warming (Allen and Ingram 2002; Held and Soden 2006; Manabe et al. 1981; Marvel and Bonfils 2013; Wetherald 2010; Wetherald and Manabe 2002). The size and physical significance of projected changes in hydrological cycle components should be viewed in the context of an understanding of their intrinsic variability (Wetherald 2010). Such context provides insights into the potential risks of droughts in a warmer climate.

Understanding the likely sign and magnitude of projected changes in regional aridity indices is a challenging scientific problem. In this study, we consider: 1) the relative contributions from changes in P versus evaporative demand; 2) the combined effects of mean-state changes versus variability associated with ENSO; and 3) the sensitivity of results to the “slow” ocean warming, the feedbacks from physiological adaptation of plants to enhanced CO₂, and the “fast” radiative forcing changes caused by elevated CO₂ concentrations.

Using simulations of present-day climate, we identified land surface areas where aridity indices currently change sign between the El Niño and La Niña phases of ENSO. This “ENSO-sensitive” region is calculated for five different meteorological and agricultural aridity indices (three PET-dependent aridity indices and two soil moisture indicators). Depending on the index examined, 57%–60% of the ENSO-sensitive area in the Hist simulation experiences drying during the El Niño phase, whereas the other 40%–43% of the area experiences wetting during the same phase.

Both PET and P anomalies can drive changes in terrestrial aridity. In response to the “slow” global-scale ocean warming alone, we find that changes in meteorological and agricultural aridity are dominated by the increase in atmospheric demand, and that approximately 67%–72% of the ENSO-sensitive region becomes permanently arid. This increase in permanently arid area is not sensitive to the choice of the aridity index employed, and is robust across models. In these regions, even the large ENSO-induced intrinsic variability will no longer completely offset the expected regional-scale warming and drying signals associated with the ocean warming. In contrast, the simulated future changes in total runoff indicate that the projection of increasing hydrological droughts (with 41% of the ENSO-sensitive region) is less dire than that of increasing meteorological and agricultural droughts.

CO₂ forcing alters the surface energy balance, reduces plant ET, increases land surface warming, enhances evaporative demand, and reduces the increase in P that is expected to result from global warming. According to the recent literature, the net impact of this

physiological effect depends on the type of aridity index considered. Inclusion of plant physiology induces more drying in atmosphere-based aridity indices (such as relative and specific humidity, P/PET or PDSI; Andrews et al. 2011, Berg et al. 2016, Milly and Dunne 2016, Swann et al. 2016), but less drying when aridity indices are considered that incorporate information directly relevant to plant growth (e.g. soil moisture, runoff, or P minus ET, Swann et al. 2016; see footnote #5). Over North America, aridity trends over the 21st century estimated with PET-derived PDSI and near-surface soil moisture are in good agreement, but disparities exist when compared to trends in deeper soil moisture (Cook et al. 2016; Cook et al. 2015; Smerdon et al. 2015). The uncertainties in the treatment of land processes can contribute to such disparities. For instance, transpiration may decline with a CO₂-induced stomatal closure, but increase with greening and a lengthening of growing season (Ukkola et al. 2016). The impact of such factors on future aridity is not well understood.

Our results are in agreement with this recent literature: when using the three PET-dependent aridity indices dominated by the behavior of meteorological variables (CMI, P/(P+PET) and PDSI) and 10-cm soil moisture (layer that interacts closely with the atmosphere), we obtained a relatively small increase in permanently arid land area in response to the inclusion of plant physiology feedbacks. The permanently arid area in the +SST simulations (67%–70%) increased by only several percent in +SST+Veg (to 68%–71%). The area affected rises to 75–79% in the +SST+Veg+Rad case, a result consistent across all models and the three aridity indices. Regions where the sign of local response associated with ENSO variability continue to change despite the change in mean state typically include the Northwest U.S., the southeast U.S., or the region at the southeastern border of the Amazon forest (the boundaries of these regions are however spatially sensitive to the choice of aridity index).

We obtained a large reduction in future arid land when total soil moisture (a more plant-based index) is considered (from 72% in +SST to 41% in +SST+Veg). This large reduction mainly arises because the inclusion of CO₂-physiology feedback preserves soil moisture in the root zone. While the differences in future aridity projections between PET-based indices and total soil moisture have a plausible physical explanation, neglecting the increase in stomatal resistance in PET estimators may have led to an overprediction of the future drying estimated with the PET-derived indices. Our results highlight the importance of simulating the biological components of the Earth system in climate change studies, and clearly illustrate that the response of terrestrial aridity to greenhouse warming can be strongly dependent (in both sign and magnitude) on the choice of aridity index.

Model-specific r_s information is not currently used in calculating PET-based aridity indices. There is therefore an inconsistency in the projections of aridity between the model's actual ET-based estimate, and the PET-based estimate that is approximated from the available model standard output (using the FAO's spatially and temporally invariant value of r_s). To reduce biases in terrestrial aridity projections estimated with PET-driven aridity indices, we recommend that modeling groups provide calculated PET as a diagnostic output of the climate model (e.g., using model values of r_s , wind speed and surface net radiation). This

new standard output would represent the simulated atmospheric water demand with greater fidelity than is presently possible in CMIP multi-model studies.

Sound decision-making requires climate-change projections that are based on an understanding of both intrinsic variability and the likely changes in the climatic mean state associated with global warming. This is particularly important in developing climate change adaptation strategies, in assessing agricultural and infrastructure risks, and in managing water resources and land use. In some regions, ENSO variability will continue to be the major determinant of year-to-year changes in aridity. Other regions are likely to experience 21st century changes in mean state that overwhelm the effects of intrinsic variability. The analysis performed here provides a sound scientific basis for identifying regions where societies may be more vulnerable to future climate change, and are likely to face drought conditions well outside of the historical range.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

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APPENDIX A

Advantages of using atmospheric simulations

The use of atmospheric simulations presents certain diagnostic advantages. First, while most coupled climate models consistently project an increase in the frequency of extreme ENSO events in the future climate (Cai et al. 2014; Capotondi 2015), there is considerable model disagreement in projected 21st century changes in the spatial structure and amplitude of ENSO (Bonfils et al. 2015; Coelho and Goddard 2009; Collins et al. 2010; Kao and Yu 2009; Vecchi and Wittenberg 2010). By prescribing the same sequence of observed SSTs in both the amip and amipFuture simulations, we assume identical ENSO evolution, and thus avoid introducing coupled model errors in the pattern and amplitude of ENSO. Second, coupled model biases in zonal P and SST features can obscure robust physical changes in hydroclimate (Marvel and Bonfils 2013). The amip-type simulations alleviate this problem by imposing the same SST changes in all models. This eliminates P errors arising from model-specific biases in SST magnitude and pattern. The use of the ensemble average of these simulations focuses attention on climate change features that are robust across models, and serves to reduce the noise associated with atmospheric internal variability.

The SST warming pattern (Fig. 1b of Zhou et al. 2014) is derived from a normalized composite of 13 individual CMIP3 model SST response patterns, obtained from simulations with a 1%/year increase in atmospheric CO₂. The response pattern was estimated at the time of CO₂ quadrupling. Each model's SST response was divided by its global mean SST change and multiplied by 4 prior to computing the multi-model ensemble mean, ensuring a global-mean SST forcing of 4K (<http://cfmip.metoffice.com/CMIP5.html>).

There may be one minor inconsistency in the experimental design: A quadrupling of CO₂ concentrations from the amip historical value (345 ppm) corresponds to a radiative forcing pathway leading to 8.5 W.m⁻² and 1380 ppm CO₂ by 2100 (van Vuuren et al. 2011). Based on Fig 12.5 of the 5th IPCC report, this radiative forcing is expected to induce a global annual-mean surface warming of about 4K by ~2090. It is not clear whether a SST perturbation of 4K by 2100 in the amipFuture simulation is slightly larger than expected. This possible inconsistency should not, however, alter the main conclusions of our study presented.

APPENDIX B

Analysis Procedure

The main analysis consists of the following 5 steps:

1. For each model and each amip (Hist) simulation, we compute local January–March (JFM) anomalies relative to the climatological seasonal mean of that run (H_h). A similar calculation is performed for each amipFuture (Hist+SST) simulation (F_f).
2. We also calculate each model's future JFM anomaly relative to its respective historical amip climatological value (F_h). (Note: for PDSI, the amipFuture PDSI values are already calculated relative to the amip baseline in the PDSI code).
3. From the H_h , F_f and F_h anomalies, we calculate the multi-model El Niño and La Niña composites, using nine El Niño (1982–83, 1986–87, 1987–88, 1991–92, 1994–95, 1997–98, 2002–03, 2004–05, 2006–07) and eight La Niña events (1983–84, 1984–85, 1988–89, 1998–99, 1999–2000, 2000–01, 2005–06, and 2007–08).
4. We then identify all continental grid cells where the variable of interest is influenced by ENSO variability (the R_1 region). Inclusion in the R_1 region requires that two criteria are fulfilled: first, that the correlation between the hydroclimate variable at this location and the model Niño 3.4 SST time series exceeds a minimum threshold of |0.15|, and second, that the local sign of H_h in the El Niño and La Niña composites changes between these two phases of ENSO. For example, a grid cell would qualify as “sensitive to ENSO” if it satisfies the correlation criteria with Niño3.4 and also has land surface temperatures that are anomalously warm during El Niño and anomalously cold during La Niña. These criteria allow us to investigate whether the projected

changes in mean state are large enough to overwhelm the sign of local response to ENSO variability. These criteria also provide a uniform basis for comparison across all models, simulations and variables.

5. Finally, we identify all continental grid cells where the composited F_h anomalies continue to change sign between the two phases of ENSO (R_2 region). Interpretation of these results is relatively straightforward: while both the R_1 and R_2 regions are primarily dominated by ENSO variability, the climate in the non-overlapping portion of R_1 and R_2 (i.e., the land area present in R_1 but excluded from R_2), exhibits a change in mean state that overwhelms the range of ENSO-driven variability.

We note that steps 1, 3 and 4 closely follow the procedure of (Zhou et al. 2014). By exploring the differences between maps of H_h and F_h , they investigated how large-scale warming may affect the variance in P associated with El Niño-driven teleconnections. In contrast, our goal is to focus on the El Niño and La Niña F_h composite maps, which provide information on the contributions of mean-state change and ENSO variability.

APPENDIX C

CMI and Penman-Monteith Potential Evapotranspiration

The CMI ranges from -1 to $+1$, with wet climates indicated by positive values.

$$CMI = \begin{cases} \frac{P}{PET} - 1 & \text{if } P < PET \\ 1 - \frac{P}{PET} & \text{when } P \geq PET \\ 0 & \text{if } P = PET = 0 \end{cases} \quad [4]$$

The potential evapotranspiration (PET) is not supplied as a model output and thus needs to be calculated. We use the Penman-Monteith equation (FAO; (Allen et al. 1998) for a well-watered reference crop of 0.12 m height:

$$PET = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T_a + 273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + \frac{r_s u_2}{208})} \quad [5]$$

Here R_n is the net radiative energy available at the surface ($\text{MJ m}^{-2} \text{ day}^{-1}$) and G is the heat flux into the soil, which is close to zero on daily or longer time scales. The term $(e_s - e_a)$ is the vapor pressure deficit of the air (kPa), where e_s is the saturation vapor pressure (kPa) at air temperature T_a . $\Delta = de_s/dT$ at T_a is the local slope of the saturation vapor pressure temperature relationship (kPa K^{-1}), and $e_a = R_H^* e_s$ is the actual vapor pressure (kPa). u_2 , the wind speed at 2 m above canopy (m s^{-1}), is fixed at 1 m s^{-1} . $\gamma = (c_p/\epsilon\lambda)$. $P_s = 0.000665$

P_s is the psychrometric constant ($\text{kPa } ^\circ\text{C}^{-1}$) with P_s the atmospheric surface pressure (kPa). R_n , T_a , R_H and P_s are all model outputs.

The factor $u_2/208 = 1/r_a$ where r_a is associated with the friction of air flowing over vegetative surfaces; and r_s is the bulk stomatal resistance that regulates vapor flow through the stomata openings of a reference crop. This reference vegetation is a 0.12 m high green grass, with fixed $r_s = 70 \text{ s m}^{-1}$, and an albedo of 0.23. For assessing future changes in aridity in a warming world, the Penman-Monteith equation is more reliable than other empirically based PET calculations, such as the Thornthwaite equation (Dai 2011c; Sheffield et al. 2012; Wehner et al. 2011) which is excessively sensitive to surface warming. Although using a constant value of r_s in the Penman-Monteith equation is unrealistic under increasing CO_2 levels, this is standard practice in many drought projection studies.

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Figure 1.

a–b): Ensemble-mean surface T anomalies ($^{\circ}\text{C}$) in response to El Niño (left column) and La Niña (right column) events based on historical (H_h) and future (F_f) anomalies, calculated relative to their own mean state. Regions that do not satisfy the two “ENSO-sensitive” criteria (see text) are masked. c–d–e): F_h anomalies in response to ocean warming (+SST), ocean warming and plant physiological effects (+SST+Veg), and ocean warming, plant physiology, and the fast radiative effect (+SST+Veg+Rad). All anomalies are calculated relative to the same (amip) historical baseline. Stippling in c–e highlights all land grid-points where the sign of the variable changes between the two ENSO phases (Note: stippling is not

present in the T figure, because the phase of ENSO only modulates the amplitude of the warming). f–g): Effects of +Veg only and +Rad only.

Figure 2.

a–b): Ensemble-mean precipitation (mm/day) in response to El Niño (left column) and La Niña (right column) events based on historical (H_h) and future (F_f) anomalies, calculated relative to their own mean state. Regions that do not satisfy the two “ENSO-sensitive” criteria (see text) are masked. c–d–e): F_h anomalies in response to ocean warming (+SST), ocean warming and plant physiological effects (+SST+Veg), and ocean warming, plant physiology, and the fast radiative effect (+SST+Veg+Rad). All anomalies are calculated relative to the same (amip) historical baseline. Red stippling in c–e highlights all land grid-

points where the sign of the variable changes between the two ENSO phases. f–g): Effects of +Veg only and +Rad only.

Figure 3.

a–f) Quantitative breakdown (in %) of the historical “ENSO-sensitive” land into 4 different categories. Results are for: a) P; b) PET and six aridity indices; c) CMI; d) P/(P+PET); e) PDSI; f) surface soil moisture; g) total soil moisture; and h) total runoff. Relative to the mean state during the historical period, the four regions distinguished here are either wetter during El Niño events, with positive anomalies for P and the six indices, or negative anomalies for PET (light green shading); drier during El Niño events, with negative anomalies for P and the six indices or positive anomalies for PET (yellow shading); and wetter or drier, irrespective of the ENSO phases (dark green and dark brown shading,

respectively). The percentage of the land area in each of these four categories is calculated for the historical period (H_h), and for the future climate (relative to the historical mean state; F_h). In the latter case, results are given for the response to ocean warming only (+SST), as well as for the inclusion of plant physiological effects (+SST+Veg) and the fast radiative effect (+SST+Veg+Rad). Each individual error bar represents $\pm 1\sigma$ uncertainty estimated from the small (4-model) sampling distribution. The percentage of land between 60°S and 75°N qualifying as sensitive to ENSO (R_1 region) is indicated in the titles. Total runoff outputs are missing for HadGEM2-ES and surface soil moisture is only available for IPSL-CM5A-LR.

Figure 4.

Same as Figure 3 but for: a) ET; b) GPP; c) LAI; d) EV_s ; e) EV_v ; f) TR; g) ET-derived CMI; and h) $P/(P+ET)$. The color convention for panels a), and d-h) is the same as in Figure 3. For panels b) and c), results are partitioned between regions with a positive anomaly (i.e., more leaves, or more carbon uptake) during El Niño events (salmon shading); regions showing a negative anomaly (light-blue shading) during El Niño events; and regions with either positive or negative anomalies, irrespective of the ENSO phase (red and dark-blue shading, respectively). Note that LAI outputs are missing for HadGEM2-ES, and the quantitative breakdown of ET into EV_s , EV_v and TR is only available for IPSL-CM5A-LR.

Figure 5.

a–b): Ensemble-mean $P/(P+PET)$ in response to El Niño (left column) and La Niña (right column) events based on historical (H_h) and future (F_f) anomalies, calculated relative to their own mean state. Regions that do not satisfy the two “ENSO-sensitive” criteria (see text) are masked. c–d–e): F_h anomalies in response to ocean warming (+SST), ocean warming and plant physiological effects (+SST+Veg), and ocean warming, plant physiology, and the fast radiative effect (+SST+Veg+Rad). All anomalies are calculated relative to the same (amip) historical baseline. Red stippling in c–e highlights all land grid-points where the sign

of the variable changes between the two ENSO phases. f–g): Effects of +Veg only and +Rad only.

Figure 6.

a–b): Ensemble-mean total soil moisture in response to El Niño (left column) and La Niña (right column) events based on historical (H_h) and future (F_f) anomalies, calculated relative to their own mean state. Regions that do not satisfy the two “ENSO-sensitive” criteria (see text) are masked. c–d–e): F_h anomalies in response to ocean warming (+SST), ocean warming and plant physiological effects (+SST+Veg), and ocean warming, plant physiology, and the fast radiative effect (+SST+Veg+Rad). All anomalies are calculated relative to the same (amip) historical baseline. Red stippling in c–e highlights all land grid-

points where the sign of the variable changes between the two ENSO phases. f–g): Effects of +Veg only and +Rad only.

Table 1

Description of the experiments

Name	SST and sea ice	CO ₂	Time Period	Vegetative (Veg)/Radiative (Rad)
amip	observed 1979–2008	345ppmv	1979–2008	Rad sees 1×CO ₂
				Veg sees 1×CO ₂
amipFuture	observed 1979–2008+4K	345ppmv	1979–2008	Rad sees 1×CO ₂
				Veg sees 1×CO ₂
amip4×CO₂	observed 1979–2008	4×345ppmv	1979–2008	Rad sees 4×CO ₂
				Veg sees 1×CO ₂
sstClim	monthly-varying from piControl	preindustrial	30 years	Rad sees 1×CO ₂
				Veg sees 1×CO ₂
sstClim4×CO₂	monthly-varying from piControl	4×preindustrial	30 years	Rad sees 4×CO ₂
				Veg sees 4×CO ₂

Atmospheric variables include: Ta, P, Ps, R_n, ET, huss, hurs (hur, hus for models 3,4 when huss and hurs are not available)

Land variables include: GPP (missing for model 1), LAI (missing for models 1), EV_v, TR (missing for model 1), EV_s (missing for models 1,3,4), surface soil moisture (missing for models 3,4), and total soil moisture. For consistency, we analyze GPP, LAI, TR, EV_v, EV_s and surface soil moisture from model 2 only. See Table 2 for model descriptions.

Table 2

Models description

	Coupled model name	Atmospheric / land part	amip	amipFuture	amip4×CO ₂	sstClim	sstClim4×CO ₂	vertical	Lat × lon	horizontal res	No soil layers/maximum
1	HadGEM2-ES	HadGEM2-A MOSES2	20131118	20131118	20131118	ver-1	ver-1	38 level	145×192	1.25×1.875	4/3
2	IPSL-CM5A-LR	LMDZ5A ORCHIDE	20110427	20121106	20110429	ver-1	20110429	39 level	96×96	1.87×3.75	7/3.86
3	MPI-ESM-LR	ECHAM6 JSBACH	2011005	ver-1	2011005	ver-1	ver-1	47 level	96×192	1.87×1.87	5/9.58 (~7 until bed rock)
4	MPI-ESM-MR	ECHAM6 JSBACH	ver-1	ver-1	ver-1	ver-1	ver-1	95 level	96×192	1.87×1.87	5/9.58 (~7 until bedrock)

All simulations are defined as “r11p1” runs

Table 3

Percentage of land sensitive to ENSO between 60°S and 75°N. The R1 region is portioned into: 1) land experiencing drier (or wetter) anomalies during El Niño events during the historical period; 2) land that continues to be sensitive to ENSO in the future; and 3) land that becomes permanently drier (or wetter) beyond historical ENSO variability.

	Historical			+SST			+SST+Veg			+SST+Veg+Rad		
	R ₁ : land sensitive to ENSO	drier with El Niño	wetter with El Niño	always drier	always wetter	remains sensitive to ENSO	always drier	always wetter	remains sensitive to ENSO	always drier	always wetter	remains sensitive to ENSO
P	41.02	55.9	44.1	39.0	41.3	19.7	40.9	38.8	20.3	35.3	42.4	22.2
PET	53.55	53.7	46.3	99.1	0.2	0.7	99.0	0.3	0.7	99.7	0.1	0.2
CMI	45.33	60.0	40.0	68.8	12	19.2	70.0	12.3	17.7	77.8	5.5	16.7
P/(P+PET)	45.66	59.4	40.6	70.3	11.3	18.4	71.3	11.0	17.7	79.2	4.0	16.8
PDSI	50.05	58.8	41.2	66.8	16.9	16.3	68.4	14.3	17.3	74.6	11.1	14.3
Sfc moisture	41.08	58.3	41.7	71.6	10.8	17.6	67.1	15.5	17.4	76.0	10.6	13.4
Total moisture	39.34	57.4	42.6	71.6	9.5	18.9	41.5	34.8	23.7	41.0	33.8	25.2
Total runoff	40.4	43.8	56.2	41.0	26.9	32.1	33.3	39.5	27.2	27.2	42.5	30.3
P/(P+ET)	36.92	54.3	45.7	57.5	14.2	28.3	50.5	19.0	30.5	57.3	14.9	27.8
CMIET	38.77	54.0	46.0	54.6	17.1	28.3	49.8	21.2	29.0	54.3	17.9	27.8