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CO_2-plant effects do not account for the gap between dryness indices and projected dryness impacts in CMIP6 or CMIP5

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Abstract

Recent studies have found that terrestrial dryness indices like the Palmer Drought Severity Index (PDSI), Standardized Precipitation Evapotranspiration Index (SPEI), and Aridity Index calculated from future climate model projections are mostly negative, implying a drying land surface with warming. Yet, the same models' future runoff and bulk soil moisture projections instead show regional signals of varying sign, and their vegetation projections show widespread greening, suggesting that the dryness indices could overstate climate change's direct impacts. Most modeling studies have attributed this gap to the indices' omission of CO_2-driven stomatal closure. However, here we show that the index-impact gap is still wide even in future-like model experiments that switch off CO_2 effects on plants. In these simulations, mean PDSI, Aridity Index, and SPEI still decline broadly with strong warming, while mean runoff, bulk soil moisture, and vegetation still respond more equivocally. This implies that CO_2-plant effects are not the dominant or sole reason for the simulated index-impact gap. We discuss several alternative mechanisms that may explain it.

1. Introduction

Drought is a surface water shortage, usually driven by below-normal precipitation (P), that negatively impacts water resource production (i.e. stream runoff and groundwater recharge) and/or photosynthesis, with societal consequences (e.g. Wilhite and Glantz 1985, AMS Council 2013). *Aridity* is a permanent, climatological lack of enough P to support plentiful regional water resources or vegetation (Budyko and Miller 1974, Middleton and Thomas 1997), which plays a key role in human settlement patterns (e.g. Seager *et al* 2018).

However, because water resource production and photosynthesis are strongly constrained by the evaporative environment as well as P, the most effective methods for quantifying aridity and drought from climate data require both P and potential evaporation E_0. E_0 integrates radiation, temperature, humidity, and wind speed to quantify the rate at which the atmosphere is capable of evaporating surface water (e.g. Hartmann 2016). The aridity index or AI (Transeau 1905, Middleton and Thomas 1997) is the ratio P/E_0 of annual climatological means. The Standardized Precipitation-Evapotranspiration Index or SPEI (Vicente-Serrano *et al* 2010) is the difference $P - E_0$ smoothed to a user-defined timescale and transformed to a normal distribution. The Palmer Drought Severity Index or PDSI (Palmer 1965) is a bucket model of soil moisture forced by monthly P and E_0. Lower AI and more negative PDSI and SPEI values indicate drier conditions, with reduced water resources and vegetation. These indices are widely used and understood.

According to the standard Penman–Monteith equation (Monteith 1981, Allen *et al* 1998), E_0 substantially increases with future greenhouse warming, mainly due to its dependence on temperature (Scheff and Frierson 2014). Since projected changes in land P with warming are much less robust (e.g. IPCC 2013, Greve and Seneviratne 2015), global-scale climate model studies of AI (Feng and Fu 2013, Fu and Feng 2014, Scheff and Frierson 2015, Huang *et al* 2015, Fu *et al* 2016, Zarch *et al* 2017, Park *et al* 2018, Wang *et al* 2021), PDSI (Dai 2013, Cook *et al* 2014, Zhao and Dai 2015, Zhao and Dai 2016, Lehner *et al* 2017), and SPEI (Cook *et al* 2014, Touma *et al* 2015, Naumann *et al* 2018) almost always obtain widespread drying in future high-emission scenarios. The same models also project widespread future declines in near-surface soil moisture SM_s (Dai 2013, IPCC 2013, Berg *et al* 2017) and relative humidity RH (IPCC 2013, Byrne and O'Gorman 2016), which are used to argue for the physical relevance of the AI- or PDSI-based drying projections (e.g. Sherwood and Fu 2014, Dai *et al* 2018).

Yet, as argued above, the core purpose of AI, PDSI, and SPEI, and the main use of SM_s, is to indicate negative impacts to water-resource production and/or photosynthesis (Roderick *et al* 2015, Greve *et al* 2017, Scheff *et al* 2017, Scheff 2018). And, the same models that project widespread global declines in AI, PDSI, SPEI, SM_s, and RH with strong future warming project much more equivocal, two-sided changes in water-resource generation (IPCC 2013, Roderick *et al* 2015, Zhao and Dai 2015, Zhao and Dai 2016, Swann *et al* 2016, Milly and Dunne 2016, Milly and Dunne 2017, Greve *et al* 2017, Scheff *et al* 2017) and deep-layer soil moisture SM_d (Berg *et al* 2017, Berg and Sheffield 2018, Greve *et al* 2019). Furthermore, these models project ubiquitous future *increases* in photosynthesis (Greve *et al* 2017, Greve *et al* 2019, Scheff *et al* 2017, Mankin *et al* 2018) and leaf coverage (Mankin *et al* 2019), a.k.a. 'greening.' Thus, it is not clear if the AI, PDSI, and SPEI projections are actually relevant for warming impacts on water availability, nor (likewise) if the models' prognostic runoff, SM_d, and/or vegetation projections are reliable. Scheff (2018) and Scheff *et al* (2017) show that this 'index-impact gap' is also clear in global *observations* during CO_2-driven climate changes (both recent and geologic), lending it additional credence. However, it is much less pronounced in certain regions, such as the American Southwest (Cook *et al* 2015, Ault *et al* 2016), particularly for SM_d.

What is the reason for this discrepancy? Most of the above studies argue that projected future AI, PDSI and SPEI do not resemble projected climate change impacts in many places mainly because they do not account for the beneficial effect of elevated CO_2 on plant water requirements, which tends to reduce evapotranspiration (ET) and increase photosynthesis (Roderick *et al* 2015, Swann *et al* 2016, Greve *et al* 2017, Greve *et al* 2019, Milly and Dunne 2017, Scheff *et al* 2017). Yang *et al* (2019) and Yang *et al* (2020) modify the standard Penman–Monteith equation to include this stomatal effect and find that the resulting AI and PDSI come much closer to the models' hydrologic projections, and Lemordant *et al* (2018) show that CO_2-plant effects dramatically alter key model hydrologic outputs. Certainly, the bulk of projected future greening would not occur without these simulated CO_2 effects (Arora *et al* 2013, Shao *et al* 2013).

However, many other proposed causes of the index-impact gap in models, especially with regard to hydrologic impacts (i.e. water resources and SM_d), are unrelated to CO_2-plant effects. Zhao and Dai (2015), Dai *et al* (2018) and Mankin *et al* (2018) argue that the gap occurs partly because the increase in instantaneous *P rate* in a warming world drives greater runoff production for the same long-term total *P*. Observed and projected shifts in *P* towards the hydrological wet season (e.g. Chou *et al* 2013, Allen and Anderson 2018) would have the same effect, and Berg *et al* (2017) argue that the gap between SM_d and SM_s also stems from rectification of the seasonal cycle. Massmann *et al* (2019) show that warming itself may reduce ET by closing stomata (Novick *et al* 2016), apart from CO_2. Further, Mankin *et al* (2019) find that in much of the mid-latitudes, the projected increase in growing-season length due to CO_2 and warming cancels any plant water savings from CO_2-induced stomatal closure, so that the net hydrologic impact of plant responses to CO_2 and warming is often negative, not positive. Lehner *et al* (2019) argue that models' prognostic runoff responses to climate change are biased positive, because flaws in the land hydrologic parameterizations cause modeled runoff to be too sensitive to *P*, and not sensitive enough to warming. Finally, Milly and Dunne (2016) and Vicente-Serrano *et al* (2020) argue that Penman–Monteith E_0 (and thus AI, PDSI and SPEI) is not always relevant to real watersheds under climate change, regardless of CO_2 effects.

On the vegetation side, CMIP-type models generally do not include any representation of drought-driven mortality (Anderegg *et al* 2015, Allen *et al* 2015), and often only minimal representations of vegetation heat stress (Peñuelas *et al* 2017, Brodribb *et al* 2020) and nutrient constraints (e.g. Wieder *et al* 2015). Thus, their strong greening projections under high CO_2 are likely overestimates. Mankin *et al* (2018) and Mankin *et al* (2019) argue that a substantial part of the projected greening (and resulting ET increase) is due to warming rather than CO_2 effects, especially in the extratropics where temperature may be a more important limiting factor than moisture. More generally, not all vegetation is vulnerable to water shortage, so even at constant CO_2, vegetation changes would not always be expected given dryness-index changes. Furthermore, with some exceptions (Donohue *et al* 2013, Zhu *et al* 2016), most studies of *observed* vegetation greening to date (e.g. Fensholt *et al* 2012, Mishra *et al* 2015, Ju and Masek 2016) invoke CO_2 changes minimally, or not at all. Instead, they attribute most greening to factors such as temperature and precipitation changes, topographic effects, fire suppression and other disturbance regime changes, land use change, and woody plant encroachment on grasslands.

Thus, it is not at all clear that CO_2-plant effects are the main reason why simulated and observed mean eco-hydrologic impacts of climate change are not as negative as AI, PDSI, or SPEI in many regions. Indeed, Milly and Dunne (2016) found that in one model, the gap between AI and runoff responses persisted even when those effects were switched off, at least in the global average. Here, we extend that comparison to many more models, variables, and regions, showing that even when CO_2-plant effects are suppressed, mean AI, PDSI, and SPEI (index) projections under strong warming scenarios are much more widely negative than mean runoff, SM_d, or vegetation (impact) projections under the same scenarios.

2. Data and methods

We examine monthly output equatorward of 55° from 11 climate models in the Coupled Model Intercomparison Project phase 6 (CMIP6; Eyring *et al* 2016), listed in table S1 in supplementary material (available online at stacks.iop.org/ERL/16/034018/mmedia). We compare the results of two idealized modeling experiments that each start from a constant-forcing control run and then strongly warm the planet by increasing CO_2 1% per year for 140 years, i.e. from 280 ppm in year 1 of the experiment to ≈1130 ppm in year 140 of the experiment, analogous to high-emission future warming scenarios like RCP8.5. In experiment '1pctCO2', both the vegetation and radiation schemes 'see' this large CO_2 increase, as in the experiments discussed in section 1. Experiment '1pctCO2-rad' (Jones *et al* 2016) is identical to 1pctCO2 except that the vegetation schemes instead 'see' a constant 280 ppm of CO_2, so any index-impact gap in 1pctCO2-rad must occur for a reason *other* than simulated CO_2-plant effects. These experiments are solely designed to test the CMIP models' response to high CO_2; they have no forcings other than this idealized 1%-per-year CO_2 increase and they do not directly correspond to any particular real years, though CO_2 levels in the later years of the simulations are comparable to high-emission future scenarios.

For each model, the climatological annual-mean responses of P, E_0, AI, PDSI, SPEI, RH, SM_s, SM_d, water resource generation (i.e. total runoff Q), runoff ratio Q/P, photosynthesis, leaf area index LAI, and evaporative fraction EF are quantified using the difference between years 111–140 (mean CO_2 ≈970 ppm) and years 1–30 (mean CO_2 ≈325 ppm) of the 'r1i1p1' run, except where noted in table S1. (Other runs would be expected to behave similarly; 'r1i1p1' is specified just for reproducibility.) Monthly E_0 is computed using the standard Penman–Monteith equation (Allen *et al* 1998) and AI for each 30-year period is the ratio of 30-year-mean P to 30-year-mean E_0, all as in Scheff *et al* (2017). PDSI and 12-month SPEI are computed from monthly P and E_0 as in Cook *et al* (2014) using years 1–30 as the reference period; SPEI is set to −2.33 (100-year drought) when $P - E_0$ is less than the origin of the reference distribution (S Vicente-Serrano, pers. comm.). As in Scheff *et al* (2017), monthly RH is defined as monthly-mean vapor pressure divided by saturation vapor pressure at monthly-mean temperature, for consistency with the E_0 calculation.

SM_s uses the 'mrsos' output (mm of water in the top 10 cm of the soil), and SM_d is derived by summing the 'mrsol' output (mm of water in each soil layer) to a depth of 2 m, using a fraction of the bottom layer if necessary. They are each converted to volumetric water content ($m^3\ m^{-3}$), by dividing by 100 and 2000 mm respectively. Q is calculated as P minus ET rather than using model runoff output, to emphasize total water-resource generation and avoid inconsistencies in how models defined runoff. Q/P, which AI predicts in the present climate (Gentine *et al* 2012), is the ratio of 30-year means. Photosynthesis is quantified using gross primary productivity (GPP; 'gpp' output), which is the flux of carbon through the stomata (Bonan 2015) and thus the most water-linked metric. EF, a close cousin of the Bowen ratio, is the fraction of the 30-year-mean total turbulent heat flux (LH + SH) made up by the latent heat flux LH; decreases in EF represent drought impacts to the atmosphere.

For each variable, the responses are nearest-neighbor interpolated to a common 3° grid, and multi-model statistics are taken. For SM_d, only nine models are available (table S1); restricting the remainder of the study to only those models does not substantially change the results below. We also conduct a similar analysis on the CMIP5 (Taylor *et al* 2012) 1pctCO2 vs. 'esmFdbk1' experiments, with details and results in supplementary material.

3. Results

Figure 1 maps the median responses to the 'standard' 1pctCO2 experiment, in which both climate and vegetation respond to the large CO_2 increase. The index-impact gap common to coupled-model high-emission experiments is apparent: RH, AI, SPEI, PDSI, and SM_s (figures 1(a)–(e)) robustly and widely decline, but EF, SM_d, Q/P, and Q respond much more heterogeneously (i.e. more like P; figures 1(f)–(j), and LAI and GPP robustly and near-ubiquitously increase (figures 1(k)–(l)). However, EF still resembles PDSI in some places, facially suggesting that PDSI could be relevant for atmospheric impacts (Dai *et al* 2018) despite its dissimilarity to water-resource and ecological impacts. Figure S1 in supplementary material reproduces figure 1 but using standardized changes; results are similar, except that Q and Q/P responses become much weaker than the other metrics, reinforcing the sense of a gap.

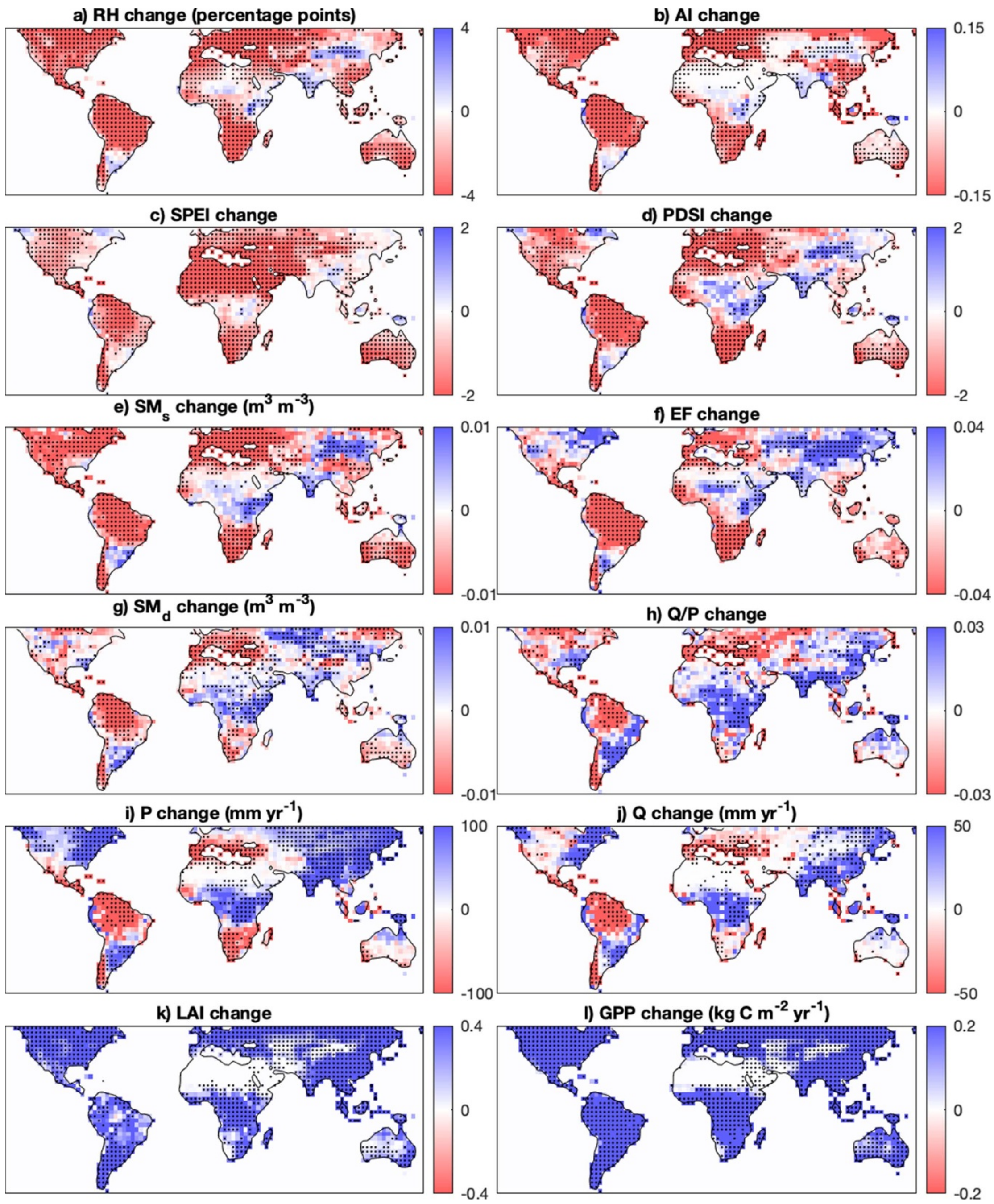

Figure 1. Multi-model median differences between years 111–140 (mean $CO_2 \approx 970$ ppm) and 1–30 (mean $CO_2 \approx 325$ ppm) of the 1pctCO2 CMIP6 experiment, in which vegetation responds to the CO_2 increase. Black dots show where at least 75% of the models agree on the sign of the change (i.e. where the change is robust.) Variables without units given are dimensionless. Year numbers do not directly correspond to any particular real-world years, and differ only in their CO_2 concentration.

Figure 2 maps the responses to the 1pctCO2-rad experiment, in which climate responds to the large CO_2 increase, but vegetation does not. Despite the lack of any CO_2-plant effects, the index-impact gap is still wide, especially for hydrologic impacts: RH, AI, SPEI, PDSI, and SM$_s$ (figures 2(a)–(e)) again show widespread robust declines, but the responses of Q/P (figure 2(h)) and especially Q (figure 2(j)) are again much more two-sided. In particular, the Americas are dominated by AI, SPEI, and PDSI 'drying', yet have less consistent decreases in Q/P, and regional decreases and increases in Q. In Africa and Australia, Q and Q/P increases are actually more extensive than decreases, despite strongly drying AI, PDSI and SPEI. However, in general, the gap is not quite as large as in figure 1, both because RH, AI, SPEI, and PDSI dry slightly less, and because Q and Q/P dry slightly more, consistent with Swann *et al* (2016). Thus, CO_2 effects still appear to cause some of the gap, by reducing ET and thus increasing both E_0 and Q in figure 1 relative to figure 2 (Brutsaert and Parlange 1998, Berg *et al* 2016).

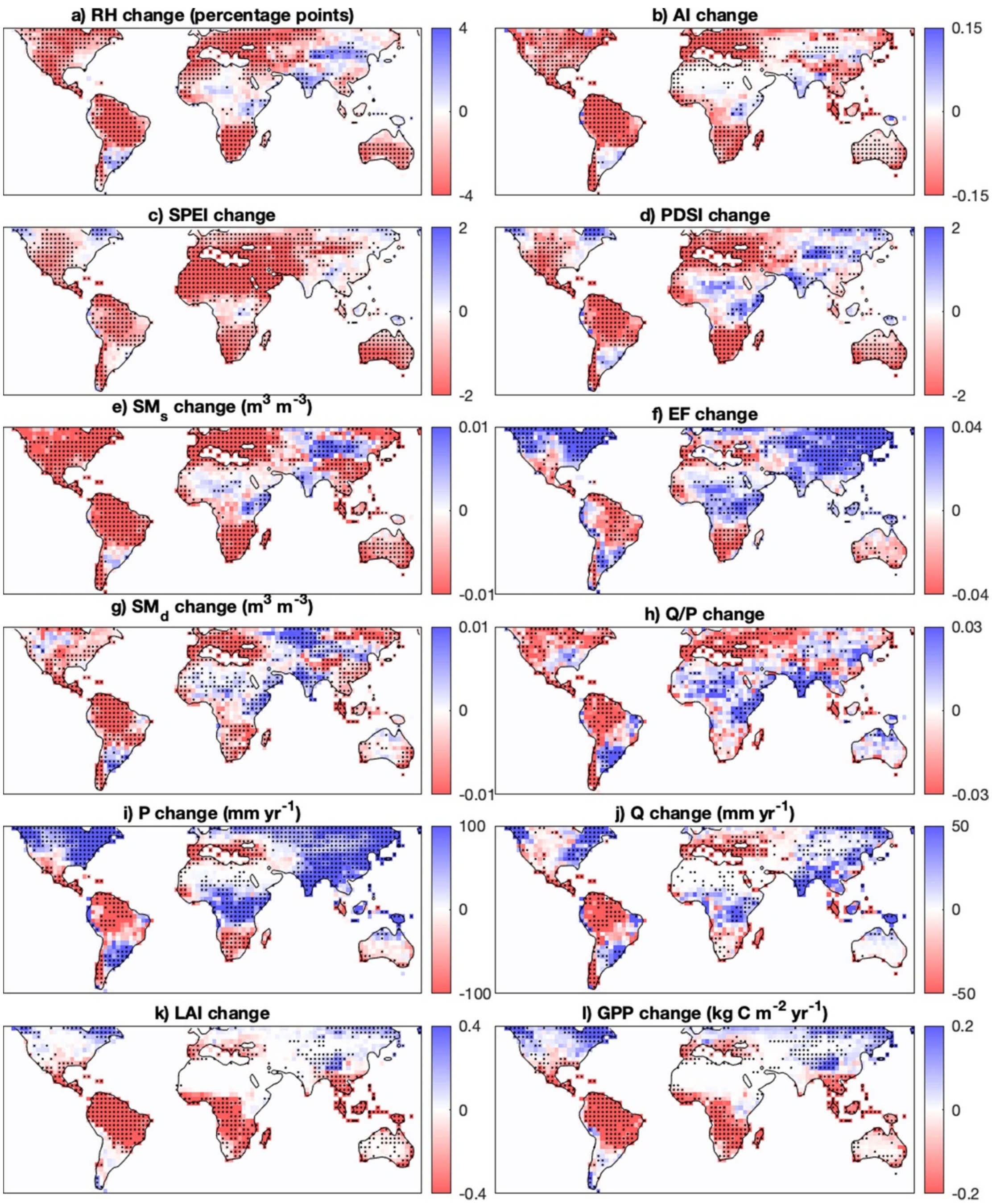

Figure 2. As figure 1, but for the 1pctCO2-rad experiment, in which vegetation does not respond to the CO_2 increase.

SM_d (figure 2(g)) declines more robustly than Q, but not always as robustly as AI or SPEI, especially in Eurasia, North America and Australia. The declines are still weaker and less consistent than those in SM_s (figure 2(e)). Interestingly, EF (figure 2(f)) responds much more like P (figure 2(i)) than like the indices, SM_s, or even SM_d, implying that the relative consistency of EF with PDSI in figure 1 may just be a fortuitous effect of CO_2 reducing ET. Finally, as expected, LAI and GPP (figures 2(k)–(l)) lose their large, near-ubiquitous increases (which are likely overestimates as discussed in section 1) and resemble the indices much more closely, particularly in the tropics and subtropics. This implies that CO_2 effects can explain much of the simulated low-latitude gap between index and vegetation responses in high-emission scenarios. Yet, LAI and GPP still change little (or even increase) in many regions where AI, SPEI and PDSI strongly decline, particularly in the mid-latitudes and Australia. Figure S2 reproduces figure 2 using standardized changes; again the main difference is relative weakening of the Q and Q/P responses.

Figure 3 distills figures 1 and 2 by plotting each panel as a single point in area-with-robust-drying vs. area-with-robust-wetting space, color-coded by type of metric (where 'robust' means stippled on

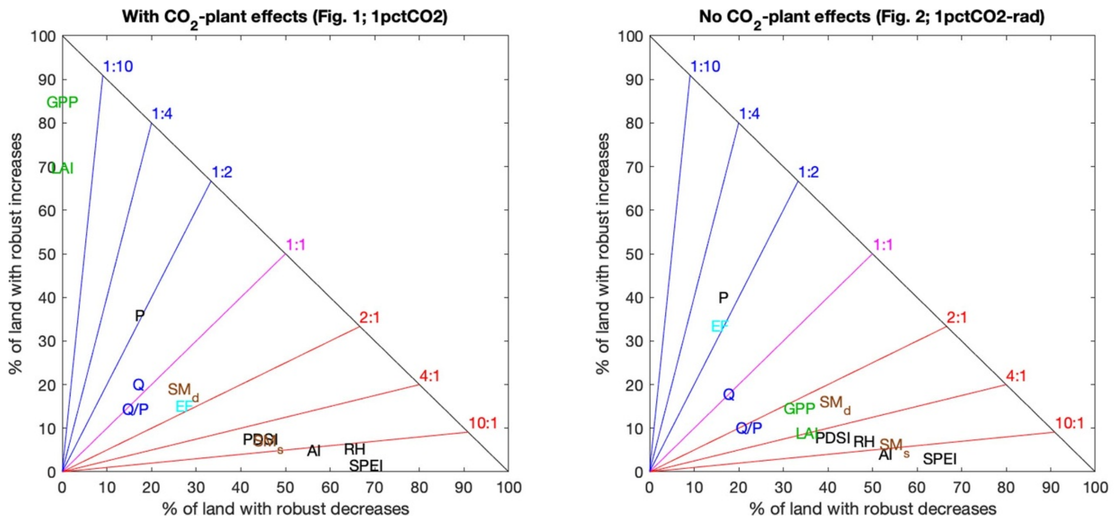

Figure 3. Percent of land area with multi-model robustly projected (i.e. stippled) decreases (x-axis) and increases (y-axis) in each variable on figure 1 (left; vegetation responds to CO_2) and figure 2 (right; vegetation does not respond to CO_2). Climate variables and indices are in black, vegetation impacts in green, water-resource impacts in dark blue, soil moisture impacts in brown, and atmospheric impacts in light blue. Colored lines mark ratios of robust-decrease area to robust-increase area.

figures 1 or 2; that is, ⩾75% intermodel agreement). It is immediately apparent that while the gap between the index (AI, PDSI, SPEI) and hydrologic impact (Q, Q/P) projections under a high-emission scenario is larger with CO_2-plant effects on (left), it is still large even with CO_2-plant effects turned off (right). In the latter case, for PDSI, more than four times as much land area has robust drying as robust wetting, yet the areas of robust Q increase and robust Q decrease are equal (figure 3, right), complicating the interpretation of PDSI as a water-resource proxy under climate change (e.g. Cook *et al* 2009). For AI, more than 10 times as much land area has robust drying as robust wetting, yet the area of robust Q/P decrease is only twice the area of robust Q/P increase, despite the theoretical basis for AI as the primary driver of Q/P variation in the present climate (Budyko and Miller 1974).

For SM_d and (especially) GPP and LAI, the gap from AI, PDSI, and SPEI responses without CO_2-plant effects (right) is much smaller than with CO_2-plant effects (left), mainly because the massive GPP and LAI increases are much reduced. However, the gap is still noticeable: similar to Q/P, robust GPP and SM_d decreases are only about 2–3 times more widespread than respective increases, even though robust PDSI, AI and SPEI decreases are over 4, 10, and 20 times more widespread than respective increases. LAI more strongly tends to decrease, similar to PDSI, but still not as much as AI, SM_s or SPEI. Thus, the indices still do not seem to be particularly reliable proxies for projected future vegetation-related impacts, even in a world where CO_2 does not affect vegetation. As discussed above in the context of figure 2, this is particularly so in parts of the midlatitudes, where growing-season lengthening is an important driver of vegetation increases (e.g. Mankin *et al* 2018, Mankin *et al* 2019). Also, EF is even farther from the indices when CO_2-plant effects are off (right) than on (left), confirming that any apparent relevance of the indices for EF in figure 1 is just a fortuitous consequence of CO_2 effects on transpiration.

We quantify several of the index-impact gaps in greater detail by mapping disagreement between the impact variables (Q, Q/P, SM_d, GPP) and the indices and similar variables (AI, PDSI, SPEI, SM_s) across the multi-model ensemble (figure 4). Specifically, we map the percentage of models that obtain increases in impact variables despite decreases in index-type variables (minus the percentage that do the opposite, which is much smaller). With CO_2-plant effects on (left column), a large proportion of the models simulate hydrologic and vegetation increases despite declining indices, as expected (though there are also regional exceptions). With CO_2-plant effects turned off (right column), this proportion persists, albeit slightly diminished. Again, the gaps between Q and Q/P and the indices (figures 4(a)–(f)) and between SM_d and SM_s (figures 4(g)–(h)) are particularly persistent. (Some very dry regions do have the opposite sign gap, but $Q \approx 0$ in such places.)

In contrast, the prevalence of SM_d increases despite PDSI declines (figure 4(i)) is more noticeably reduced once CO_2 effects are turned off (figure 4(j)), while regions with the opposite sign gap are expanded. This relative agreement makes sense, since PDSI is a fundamentally a model of SM_d. Finally, the very large proportion of models that increase GPP despite index declines (e.g. figure 4(k)) largely vanishes or reverses in the tropics when CO_2 effects are turned off, but still noticeably persists in the mid-latitudes (figure 4(l)); results are similar for LAI. This again

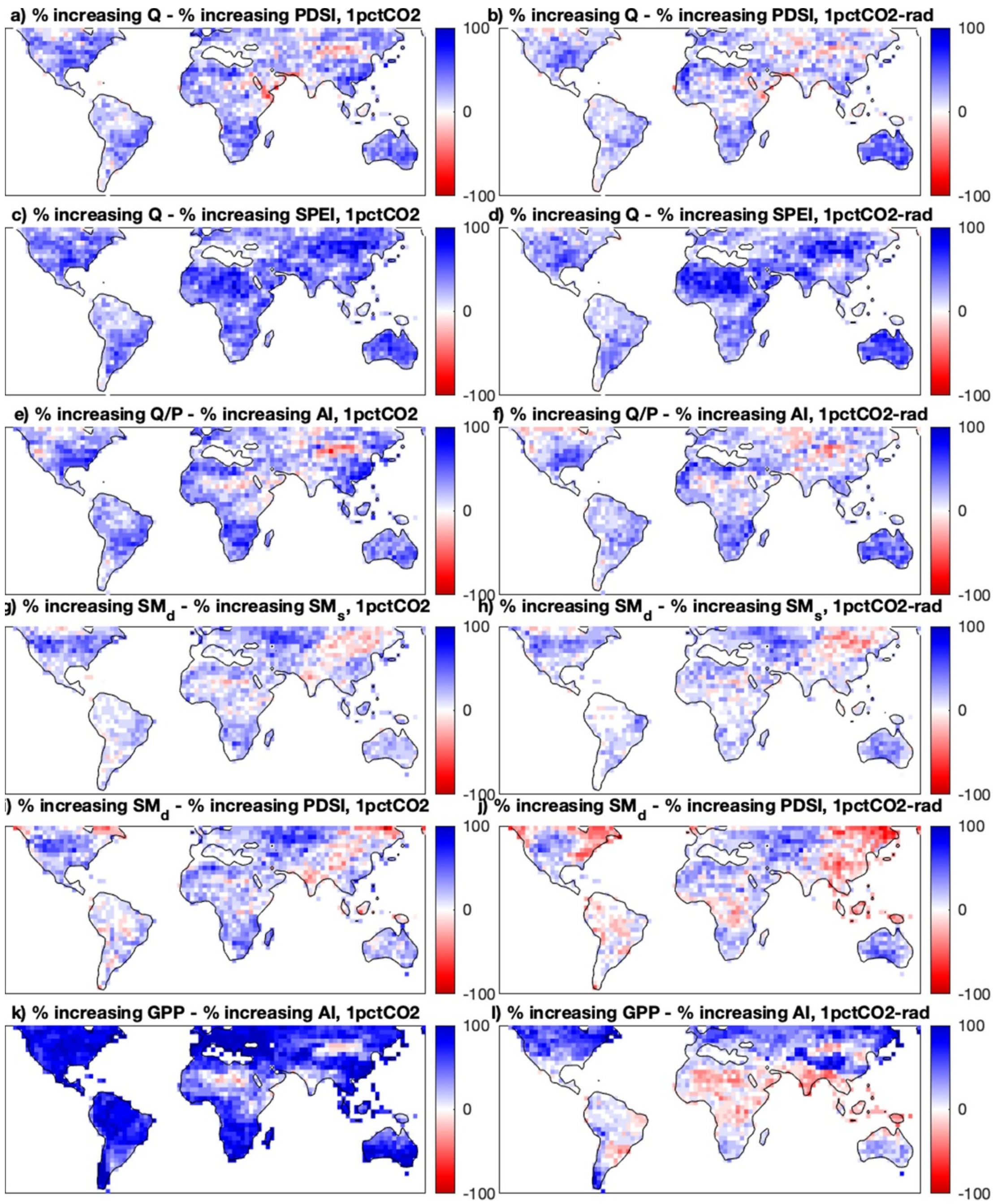

Figure 4. Percent of models with increasing A minus percent of models with increasing B (equivalently, percent of models with increasing A and declining B minus percent of models with increasing B and declining A), for selected pairs of variables A and B. Left: 1pctCO2 (vegetation responds to CO_2). Right: 1pctCO2-rad (vegetation does not respond to CO_2). In panels (g–j), both variables use only the 9 models that had SM_d for both experiments (table S1).

suggests that growing-season lengthening, in addition to CO_2, is a key driver of the gap between index and vegetation responses in the midlatitudes.

Figures S3–S6 reproduce figures 1–4 but using nine CMIP5 models, for cleaner comparison with the literature cited in section 1. The results are very similar, though the index-impact gaps (both with and without CO_2) tend to be even wider in CMIP5 than in CMIP6. Whether this is due to model improvement going from CMIP5 to CMIP6, or just different model selection (tables S1 vs. S2), is unknown. The lack of index-impact gaps in CMIP5 in parts of the American Southwest (Cook *et al* 2015, Ault *et al* 2016) is also apparent in figure S6.

4. Discussion

In short, figures 1–4 and S3–S6 show that while some simulated index-impact gaps under high-emission scenarios are in fact driven by CO_2-plant effects (e.g. low-latitude greening despite index declines, or PDSI declining more than SM_d), most of the others (e.g. Q, Q/P and mid-latitude vegetation increasing despite index declines, and SM_d declining less than

SM_s) persist without any CO_2-plant effects. Thus, contrary to studies like Swann *et al* (2016), Milly and Dunne (2017), Scheff *et al* (2017), and Greve *et al* (2017), but in agreement with Mankin *et al* (2019) and Greve *et al* (2019), we find that CO_2-plant effects are *not* the sole or dominant reason that prognostic impact outputs disagree with PDSI, SPEI, and AI under future global warming scenarios. Instead, other mechanisms must be in play to explain most of these gaps.

What could those other, non-CO_2 factors be? The easiest explanations are that the indices are just simple formulas, and should not be expected to reflect complex climate change impacts in the first place (e.g. Milly and Dunne 2016, Greve *et al* 2019)—and/or that mean changes in runoff and vegetation production are not actually what the indices are built to measure. However, the indices all have long histories of successful use in the present climate as hydrological and ecological impact proxies, continue to be frequently used to quantify future climate change's broad dryness effects (e.g. Lehner *et al* 2017, Naumann *et al* 2018, Wang *et al* 2021), rest on solid theoretical foundations (Penman–Monteith E_0, the Budyko curve, soil moisture modeling, the complementary principle), and do in fact agree with the impact projections in some places (figures 4 and S6; Cook *et al* 2015, Ault *et al* 2016). Where there are disagreements, they are mostly in one direction (indices drier than simulated impacts; figure 4) even with CO_2 effects turned off. Thus, it is important to understand where the differences come from, so as to better assess the relevance and applicability of both types of future projections.

For water-resource (Q and Q/P) responses, there is no shortage of potential non-CO_2 mechanisms by which they could skew more positive than index responses, as detailed in section 1. Again, these include direct closure of leaf stomata by high temperatures and vapor-pressure deficits (Novick *et al* 2016, Massmann *et al* 2019), concentration of P into fewer, heavier events (e.g. Mankin *et al* 2018, Dai *et al* 2018), and concentration of P into the hydrological wet season (e.g. Chou *et al* 2013), all of which are accounted for in the models but not in the indices. Biases in model Q and Q/P sensitivity to P and temperature (Lehner *et al* 2019) could also be important. More broadly, some of the gap between Q and PDSI responses could also simply be that PDSI is a soil-moisture model, despite its frequent tacit use to indicate runoff scarcity. However, there is no similar 'apples and oranges' argument for the large gap between Q/P and AI responses, since Q/P is the quantity that AI classically predicts (Budyko and Miller 1974, Gentine *et al* 2012). Planned offline land-modeling work will test many of the above mechanisms.

For vegetation-related impacts (GPP and LAI), CO_2 clearly causes the simulated departure from the indices in the tropics and subtropics (compare figures 1(d), (l) and 2(d), (l)). However, there is still a large non-CO_2-related gap in parts of the midlatitudes, most easily explained by the lengthening of temperate growing seasons with simulated global warming (e.g. Mankin *et al* 2019), as stated in section 3. Whether a longer growing season could overcome increased future drought stress to cause greening in the real-world midlatitudes absent CO_2 effects is far from certain. However, observations to date (Zhu *et al* 2016) show that greening has been much more prevalent than de-greening at all latitudes, including the mid-latitudes. (As discussed in section 1, many studies also invoke disturbance, mortality, and land-use change processes to explain the observed greening, but those are largely absent from the CMIP warming simulations, so could not be the main causes of the future simulated greening.)

Likewise, the almost total persistence of the gap between SM_d and SM_s responses when CO_2 effects are turned off strongly suggests that its main cause is the seasonal mechanism proposed by Berg *et al* (2017), rather than plant savings of SM_d due to elevated CO_2. Similarly, the gap between EF and index responses is even stronger when CO_2 effects are off, so it must have a non-CO_2 cause, likely the basic thermodynamic EF increase with warming and/or the strong constraint of EF by radiation and P (Scheff 2018).

As a final caveat, these simulations only examine transient climate responses, rather than fully equilibrated climate responses. Thus, it is not clear from this study whether the index-impact gaps, and their attribution to CO_2-plant effects vs. warming, would persist over very long time scales on which vegetation (and thus hydrology) could further evolve. However, since the century-scale transient climate response is most relevant to climate change on human time scales, and since most future simulations are also transient, the simulations examined here are still of immediate relevance.

5. Conclusion

A number of studies find that simple climatic dryness and drought indices, such as the Aridity Index (AI), Palmer Drought Severity Index (PDSI), and Standardized Precipitation-Evapotranspiration Index (SPEI), indicate much more widespread drying under strong future global warming scenarios than implied by high-complexity models of hydrology and vegetation. Many of these studies ascribe these simulated 'index-impact gaps' to the direct effects of very high CO_2 on plant physiology. To the contrary, here we show that for hydrology and for mid-latitude vegetation, these gaps strongly persist even in specialized simulations (CMIP6 1pctCO2-rad; CMIP5 esmFdbk1) in which direct CO_2-plant effects are completely *turned off*. This strongly suggests key non-CO_2 cause(s) for the modeled index-impact gaps for hydrology and for mid-latitude vegetation. Future work will test several candidate causes for the hydrologic index-impact gap from the literature using land-modeling experiments, and will also analyze the index-impact gaps in observations.

Data availability statement

No new data were created or analyzed in this study.

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