



No projected global drylands expansion under greenhouse warming

Alexis Berg¹✉ and Kaighin A. McColl^{1,2}

Drylands, comprising land regions characterized by water-limited, sparse vegetation, have commonly been projected to expand globally under climate warming. Such projections, however, rely on an atmospheric proxy for drylands, the aridity index, which has recently been shown to yield qualitatively incorrect projections of various components of the terrestrial water cycle. Here, we use an alternative index of drylands, based directly on relevant ecohydrological variables, and compare projections of both indices in Coupled Model Intercomparison Project Phase 5 climate models as well as Dynamic Global Vegetation Models. The aridity index overestimates simulated ecohydrological index changes. This divergence reflects different index sensitivities to hydroclimate change and opposite responses to the physiological effect on vegetation of increasing atmospheric CO₂. Atmospheric aridity is thus not an accurate proxy of the future extent of drylands. Despite greater uncertainties than in atmospheric projections, climate model ecohydrological projections indicate no global drylands expansion under greenhouse warming, contrary to previous claims based on atmospheric aridity.

Global drylands are regions of the world where ecosystems are water-limited, soils are often relatively infertile and vegetation cover is sparse^{1,2}. They encompass water-limited ecosystems such as deserts, grasslands, shrublands and savanna woodlands and currently cover around 40% of the land surface¹. They also host nearly 40% of the global population³, supporting the livelihood of large rural populations. As climate warms, potential increases in the aridity of existing drylands and in their spatial extent may thus have profound adverse human and socio-economic impacts. In addition to their importance for the human population and economy, recent research has shown the critical global ecological role played by drylands⁴.

To study drylands, a quantitative definition of these regions is needed. Regions conventionally defined as drylands span a range of land environments sharing some similar climatological and ecological characteristics: dry climate, water limitation and scarce vegetation. As such, there is no single atmospheric or land surface variable that can be used to quantitatively identify these regions—instead, a multivariate index must be employed. The most common definition is based on the aridity index (AI)—that is, the ratio of mean annual precipitation (P) to potential evapotranspiration (PET, representing the evaporative demand of the air near the surface; Methods). Under the Middleton and Thomas⁵ scheme, adopted by the United Nations, drylands are regions where $AI < 0.65$. This definition is based on the long-standing observation that similar AI values correspond to broadly similar vegetation types around the world, with lower values corresponding to drier ecosystems, as evaporative demand exceeds precipitation⁶. This definition also only requires atmospheric observations, which have historically been easier to obtain than hydrological or ecosystem measurements.

Building on that definition, an expanding body of literature based on the AI calculated from climate model output suggests that as climate warms, drylands will expand globally, perhaps dramatically, as continental PET increases faster than P ^{7–16}. Such projections are often used to inform ecological impact assessments of future climate change¹⁷.

However, the rationale for using the AI in climate projections to assess future drylands dynamics is debatable. First, land surface data limitations are no longer a concern when using climate model outputs rather than real-world observations. More physically meaningful measures of aridity are directly available from climate model land surface outputs, such as soil moisture or vegetation, eliminating the need for offline indices such as the AI. Second, the AI, as an atmosphere-based metric, is only a proxy for the actual land characteristics associated with drylands, such as limited water availability and low vegetation density. A crucial but seldom evaluated assumption in AI-based studies is that this proxy relationship, established over present-day climate⁵, is stationary under climate change^{17,18}. However, recent research has demonstrated problems with this assumption, showing the AI to be a negatively biased (that is, too arid) estimator of model-simulated future changes in various land surface variables, such as global water cycle and carbon cycle changes^{19,20}. A salient issue is that common calculations of Penman–Monteith PET used in future AI estimates probably overestimate the future evaporative demand, in part by neglecting changes in vegetation physiology under higher CO₂ (refs. ^{21,22}), thus leading to excessively arid future AI values (all other things being equal). Additionally, the approach does not account for environmental effects that may alter the relationship between climate and land characteristics, such as the CO₂ fertilization effect²³.

Although these problems with the AI will probably affect future drylands assessments²⁰, the potential implications for projections of drylands expansion are unknown. Here, we address this critical gap by revisiting projections of future drylands using analyses that are independent of the AI. Using Coupled Model Intercomparison Project Phase 5 (CMIP5) models, we derive an alternative index of drylands, the ecohydrological index (EI), directly based on land surface ecohydrological properties. We compare drylands projections in climate change projections using both the AI and the EI. Furthermore, we analyse the causes of the differential responses of both metrics (AI and EI) to greenhouse warming, focusing in

¹Department of Earth and Planetary Sciences, Harvard University, Cambridge, MA, USA. ²School of Engineering and Applied Sciences, Harvard University, Cambridge, MA, USA. ✉e-mail: alexis_berg@fas.harvard.edu

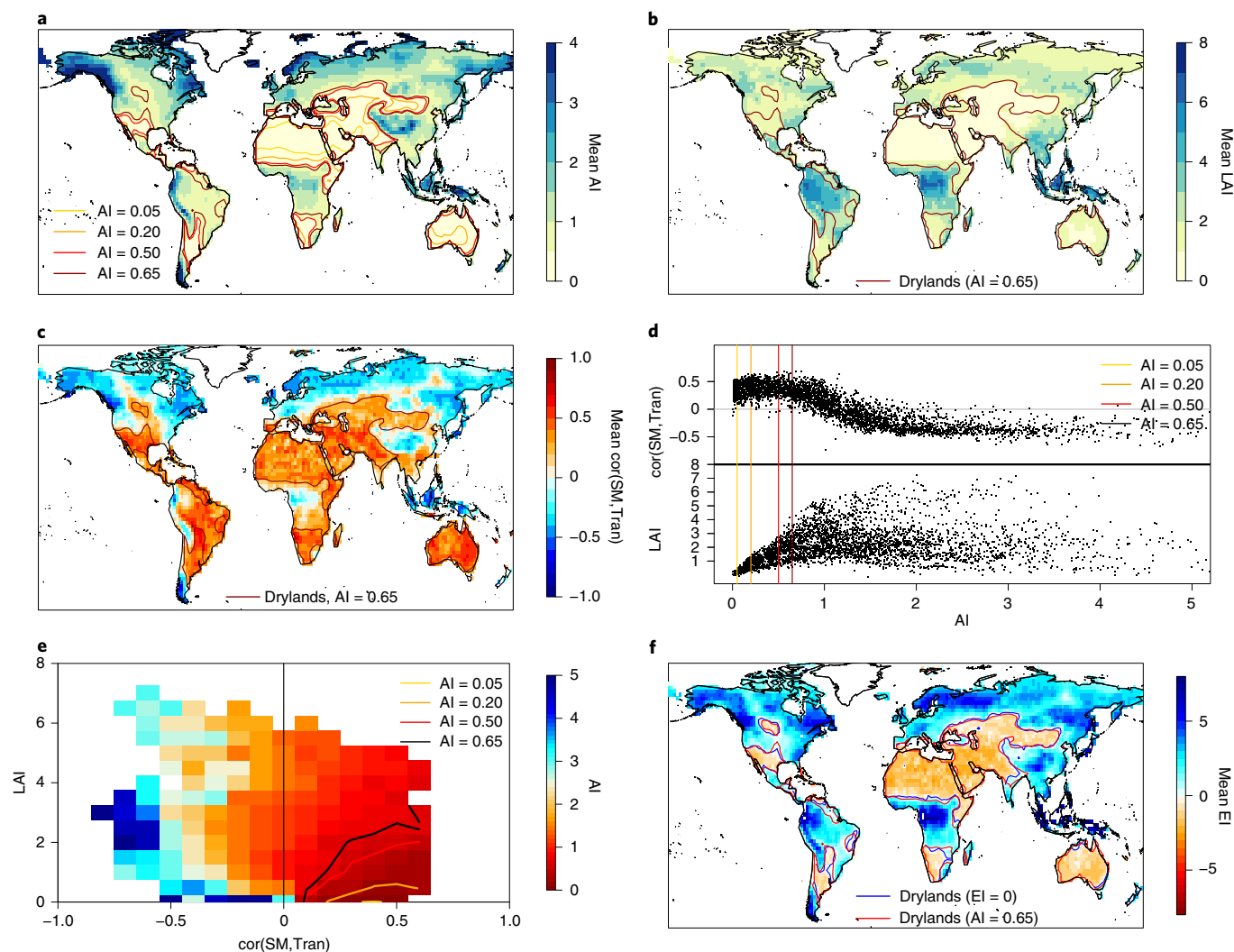


Fig. 1 | Establishing an EI of drylands in CMIP5 models. **a**, Multimodel mean AI in 12 CMIP5 models (Methods and Supplementary Table 1) and corresponding drylands classification⁹ over 1971–2000: hyperarid ($AI < 0.05$), arid ($0.05 < AI < 0.2$), semi-arid ($0.2 < AI < 0.5$) and dry subhumid ($0.5 < AI < 0.65$). **b**, Multimodel mean annual LAI; the contour lines represent drylands according to the AI-based definition ($AI < 0.65$). **c**, Multimodel mean $cor(SM, Tran)$; the contour lines are the same as in **b**. **d**, Relationship over global land between the AI and LAI or $cor(SM, Tran)$, from **a–c**; the vertical lines correspond to the AI thresholds denoted in **a**. **e**, Multimodel mean AI binned as a function of mean $cor(SM, Tran)$ and mean LAI. **f**, Multimodel mean EI (Methods); the contour lines indicate drylands based on the AI and EI definitions.

particular on the role of vegetation physiological responses under higher atmospheric CO_2 .

An EI of drylands

The global pattern of the AI simulated in CMIP5 models for present-day climate includes higher values (less arid) in tropical and high latitudes, and lower (more arid) values in subtropical latitudes⁹. Drylands, as defined on the basis of the AI criteria ($AI < 0.65$), occupy large parts of the continental subtropics (Fig. 1a).

Definitions of drylands—excluding those based on the AI—focus on the determining role of water availability in controlling ecosystem productivity and other plant processes¹; this water limitation is also reflected in sparse vegetation². In the same CMIP5 models, we characterize these two defining characteristics by the simulated correlation between annual mean surface soil moisture (Methods) and transpiration ($cor(SM, Tran)$) and by the leaf area index (LAI), respectively. Positive values of $cor(SM, Tran)$ indicate a soil-moisture-limited transpiration regime; negative values reflect an energy-limited regime²⁴. We focus on soil moisture limitation

instead of absolute soil water content because soil moisture limitation is more directly relevant to the functional definition of drylands as water-limited ecosystems¹, especially under a changing climate (Discussion and conclusions).

In present-day climate, a broad spatial relationship exists in CMIP5 models between AI-defined drylands and regions exhibiting low simulated vegetation and positive $cor(SM, Tran)$ (Fig. 1b–d). The AI thus spatially overlaps with key ecohydrological aspects of drylands, justifying its use as a proxy for drylands under present-day climate. However, some regions exhibit both high LAI and positive soil moisture limitation (for example, the Amazon and Southeast Asia), while others exhibit low LAI but no moisture limitation (high latitudes). Figure 1e shows that AI-defined drylands can be equated with regions with both low vegetation cover and water-limited transpiration, illustrating that both quantities are central to the ecohydrological definition of drylands. On the basis of this finding, we define an EI of drylands as a linear function of LAI and $cor(SM, Tran)$, which is specifically designed to be negative in drylands (Methods). As opposed to the AI, which characterizes

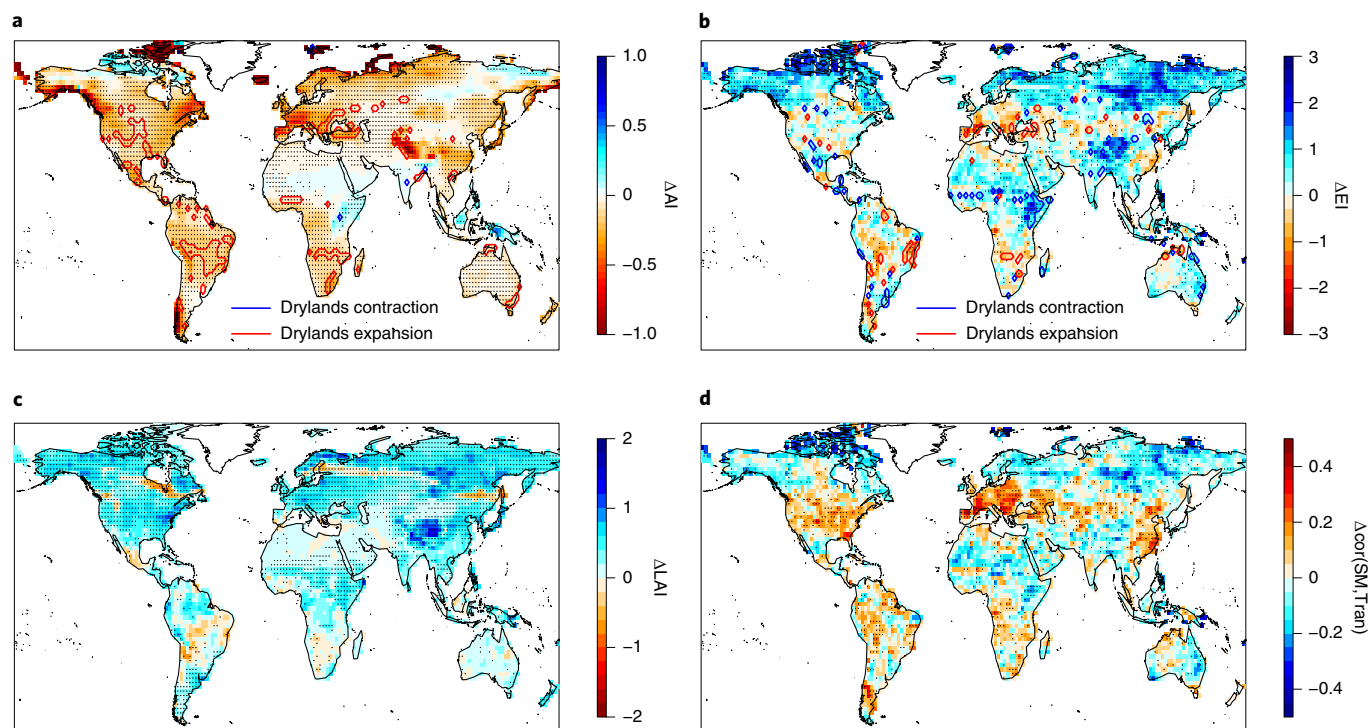


Fig. 2 | Divergent AI and EI projections under climate change in CMIP5 models. **a**, Mean change in AI between 1971–2000 and 2071–2100 in the RCP8.5 scenario. The contour lines indicate changes in drylands defined on the basis of the AI. **b**, Same as **a**, for the EI. **c**, Mean change in LAI. **d**, Change in $\text{cor}(\text{SM}, \text{Tran})$. The stippling indicates where more than three-quarters of models agree on the sign of the change.

atmospheric aridity, the EI is an index of ecohydrological aridity: lower EI values correspond to more water-limited vegetation and lower vegetation density. We emphasize that this index is empirically derived from climate models, by matching simulated AI-defined drylands with relevant simulated land surface outputs (Fig. 1e,f). We thus do not seek to justify the exact index formulation with observational or theoretical considerations. Rather, the index is introduced as a tool to test the hypothesis that drylands are truly expanding in climate model projections.

Divergence between AI and EI projections

Under a high-emission scenario (Representative Concentration Pathway 8.5 (RCP8.5)), the projected AI values in climate models decrease over most of the land surface, indicating a global increase in atmospheric aridity^{7–16}; consequently, AI-defined drylands expand in most places (Fig. 2a). However, land surface outputs from the same CMIP5 models project more balanced changes in ecohydrological conditions, with the EI decreasing in some regions (that is, trending towards more water-limited and/or sparser vegetation) and increasing in others (that is, trending towards less water-limited and/or denser vegetation) (Fig. 2b). Accordingly, EI-defined drylands expand but also contract in various regions (for example, East Africa). In regions where AI-defined drylands expand, EI changes are often positive (Supplementary Fig. 1).

This EI response emerges from a combination of responses in LAI and soil moisture limitation both less uniformly negative than the AI (Fig. 2c,d). CMIP5 LAI projections show widespread increases²⁵, except in some limited subtropical regions and in a narrow band at high latitudes, where a few models project LAI decrease, presumably because of the loss of boreal forests under warming. Soil moisture limitation on transpiration exhibits more contrasted patterns, with increased water limitation in Northern Hemisphere midlatitude regions in particular (North America, Europe and eastern China). In parts of these regions, increased water limitation

dominates the LAI increase in EI changes, leading to a decrease in the EI; however, most often the LAI increase dominates, leading to positive EI changes. Many regions (for example, high latitudes, East Africa and South Asia) show both LAI increases and decreased water limitation.

The discrepancy between projected atmospheric and ecohydrological indices demonstrates that, while the AI may be a proxy for drylands under the current climate, it does not accurately capture projected changes in the ecohydrological conditions associated with drylands. This discrepancy is further reflected in the non-stationarity of the relationship between the AI and ecohydrological properties: under future climate, AI-defined drylands encompass a broader, less ecohydrologically arid set of LAI and water limitation values than under present climate (Supplementary Fig. 2).

Climatic drivers of the AI–EI divergence

The AI decreases in a warmer climate are primarily driven by a warming-induced increase in PET, which dominates the smaller increase in P over land^{8,9,26}. Increased atmospheric aridity can thus occur even when P increases (Fig. 3a); the interpretation is that greater increases in evaporative demand will eventually dry out the land surface by depleting land moisture. However, under such conditions, ecohydrological aridity decreases in CMIP5 models (Fig. 3b); the EI tends to decrease only when P decreases. This response reflects a broadly similar behaviour in both LAI and soil moisture limitation (Supplementary Fig. 3). Soil moisture limitation does increase in some regions with moderate P increases and larger PET increases (Supplementary Fig. 3b); however, vegetation still increases in such regions, indicating that this increased water limitation does not come at the expense of vegetation growth. Figure 3 suggests a dominant role of P changes, rather than PET, in driving changes in ecohydrological conditions in climate models. Furthermore, the joint distribution of ΔPET and ΔP (Supplementary Fig. 3c) also indicates some level of coupling between both quantities: the more

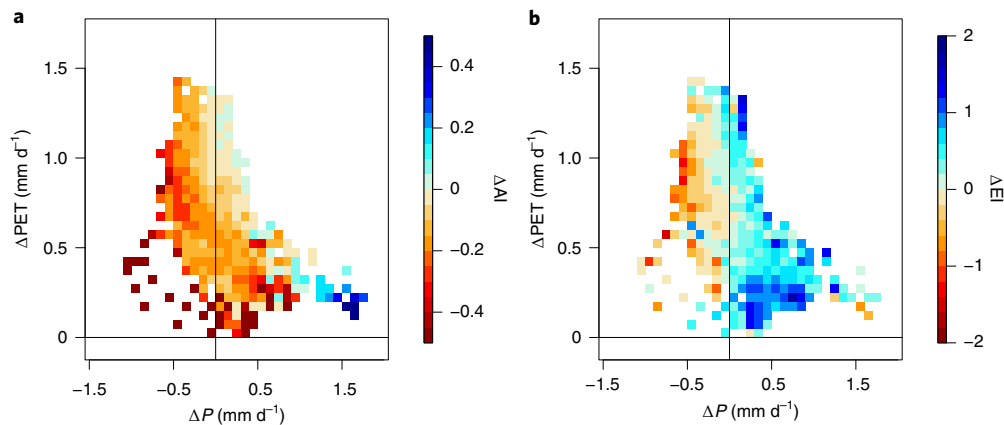


Fig. 3 | Different sensitivities of the EI and the AI to hydroclimatic changes. **a**, Changes in AI in CMIP5 models in RCP8.5 (2071–2100 minus 1971–2000) binned according to corresponding changes in P and PET. **b**, Same as **a**, for the EI. The associated density plot is shown in Supplementary Fig. 3.

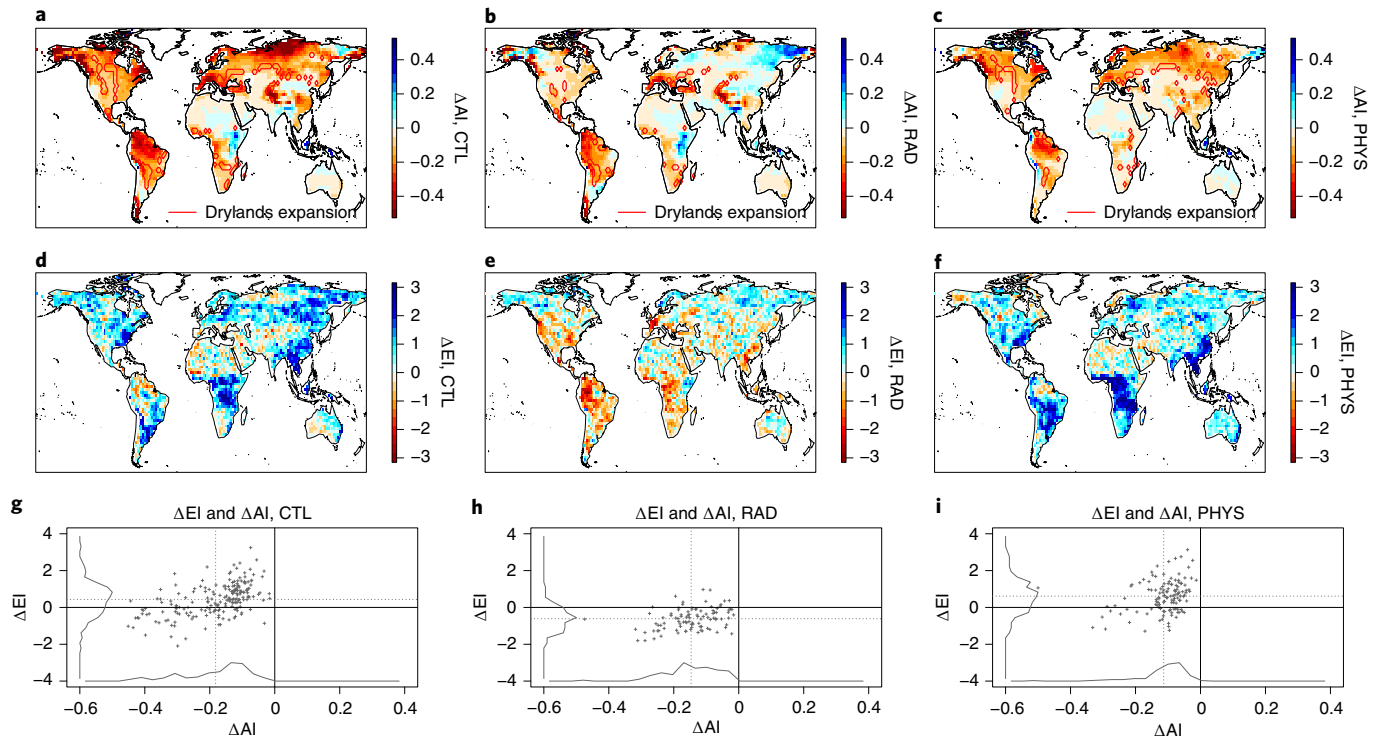


Fig. 4 | Plant physiology decouples AI and EI projections. **a–c**, Changes in AI in CTL (**a**), RAD (**b**) and PHYS (**c**) simulations; the red contour lines indicate drylands expansion under the AI definition. **d–f**, Changes in EI in CTL (**d**), RAD (**e**) and PHYS (**f**) simulations. **g–i**, Changes in EI versus AI in regions where AI-defined drylands expand (shown in **a–c**) in CTL (**g**), RAD (**h**) and PHYS (**i**) simulations. The dotted lines indicate the mean AI and EI values over these regions. The solid lines on the x axis and y axis show the distributions of EI and AI values (the values are normalized so that the maximum of the distribution has a value of 1 on the y axis for the AI and 0.1 on the x axis for the EI).

negative ΔP , the greater average ΔPET . This suggests that part of the increase in PET must actually be interpreted as a response to ΔP , mediated in part by land–atmosphere feedbacks^{27,28}.

The slight overall increase in the EI globally in Fig. 2b (+0.29) is thus consistent with the slight projected increase in land P (+0.15 mm d^{−1}, or +6.3%). The AI response (−0.13 globally in Fig. 2a) is dominated by the larger global PET increase (+0.66 mm d^{−1}, or +19%). The different sensitivities of the EI and the AI to contrasted P and PET changes thus explain some of the divergence in the AI and EI responses to climate change.

Physiological drivers of the AI–EI divergence

Differences in climatic sensitivity do not fully explain the discrepancy between AI and EI projections for drylands. A major forcing of the simulated ecohydrological response to greenhouse warming is the increase in plant water-use efficiency with increased atmospheric CO₂, which increases net primary productivity while reducing stomatal conductance^{23,29,30}, thus potentially modulating plant water constraints³¹. To better understand the role of vegetation physiology in the response of drylands, we analyse CMIP5 Earth System Model simulations that separate the

radiative effect of CO₂ on climate from its physiological effect on vegetation (Methods).

Projections for the control (CTL) simulations, which include both the radiative and physiological effects of four-time-increased CO₂, show a similar behaviour as the broader CMIP5 ensemble (Fig. 4a,d,g): widespread decrease in the AI and associated drylands expansion, even as the EI shows widespread increases, indicating denser and/or less water-limited vegetation. When only the radiative effect of CO₂ on climate is considered (RAD), however, the AI and EI projections are in better qualitative agreement, with mean changes of the same sign both globally (Fig. 4b,e) and over AI-defined expanded drylands specifically (Fig. 4h). In other words, suppressing the physiological effect of CO₂ substantially reduces the discrepancy between AI and EI changes. Consistently, the physiological effect of increased CO₂ (isolated in PHYS) induces a large EI increase (Fig. 4f), suggesting that EI changes in CTL (Fig. 4d) are dominated by plant physiology. The contrasted EI responses in PHYS and RAD predominantly reflect changes in LAI: as shown in previous studies^{32,33}, LAI increases in CMIP5 models are largely driven by CO₂ fertilization, especially in the tropics and subtropics, where climate change alone otherwise induces vegetation decrease (Supplementary Fig. 4a–c). While more muted, changes in water limitation show qualitatively consistent changes, with water limitation tending to increase in RAD and decrease in PHYS (Supplementary Fig. 4d–f). Increased atmospheric CO₂ thus reduces ecohydrological aridity both by increasing biomass and by reducing water limitation.

In addition to the EI increase, the response of vegetation to CO₂ in PHYS also leads to widespread AI decreases (Fig. 4c). These are driven both by decreases in *P* and by increases in PET, contributing, respectively, 25% and 75% of the total AI change (Supplementary Fig. 5 and Methods). Both are induced by land–atmosphere feedbacks caused by the decreases in plant transpiration occurring in models under higher atmospheric CO₂, as bulk stomatal conductance decreases (even as total LAI increases; Supplementary Fig. 4). While physiological feedbacks on surface climate have been analysed before^{32,34–36}, here we show that the combined effect on the AI is very large: the globally averaged AI decrease in PHYS represents 52% of that in CTL, leading to an apparent expansion in AI-defined drylands equivalent to 60% of that in CTL. As the EI otherwise increases (Fig. 4f), changes in the AI and EI in PHYS over new AI-defined drylands are of opposite signs (Fig. 4i). The physiological response of vegetation to CO₂ thus partially decouples atmospheric and ecohydrological aridity trends under climate change, as it simultaneously reduces ecohydrological aridity and enhances atmospheric aridity through associated land–atmosphere feedbacks. This divergence fundamentally undermines the justification for using the AI as a proxy for drylands expansion.

Projections of future drylands extent

Under the AI definition, the average global drylands area across our CMIP5 ensemble increases by 6% in the multimodel mean (from 40% to 46%; Fig. 5) and by 5.5% (from 42.9% to 48.4%) in the mean of individual model changes (+4.8% in the median). These results are qualitatively consistent with previous publications^{7,10,13} (Methods). In contrast, under the EI-based definition of drylands, the global drylands extent remains essentially unchanged: –0.7% (from 35.8% to 35.1%) in the multimodel mean (–1.7% in the mean of model changes and –2.4% in the median), with regional contraction offsetting expansion (Fig. 2b). Despite larger model spread (Fig. 5), future changes in the EI remain smaller (–2.9% to +2.6%) than those in the AI (+3.7% to +7.2%) across all models. AI-based assessments thus lead to an overestimation of future global drylands expansion when compared with ecohydrological projections.

Climate models may underestimate present-day climate aridity in current drylands¹⁰; furthermore, vegetation projections from

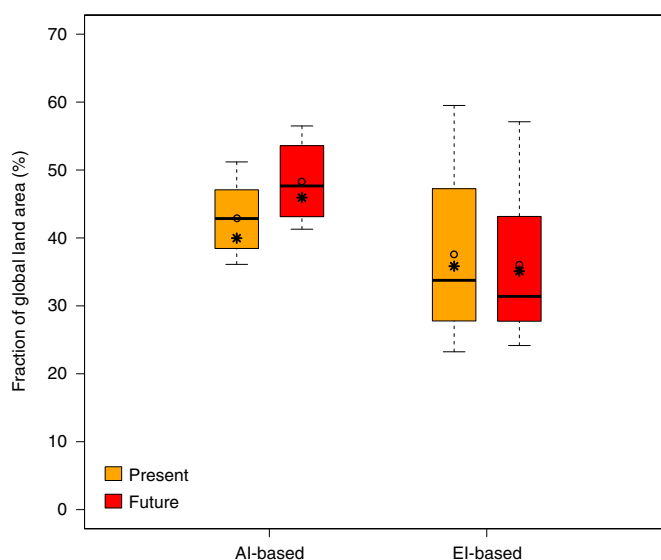


Fig. 5 | Changes in drylands area in CMIP5 models under the AI and EI definitions. Distribution of the global fraction of drylands in CMIP5 models in the present (1971–2000) and future (2071–2100, RCP8.5), based on either the AI definition (left) or the EI definition (right). The box edges represent the first and third quartiles of the CMIP5 distribution, the centre line represents the median, the dot represents the mean and the whiskers represent the entire range. The star indicates the drylands fraction estimated using the multimodel mean (shown in Fig. 2).

climate models often remain constrained by model configuration, allowing, for instance, interactive phenology locally but not changes in vegetation spatial distribution. We therefore also evaluate EI-based drylands changes in projections from three state-of-the-art Dynamic Global Vegetation Models (DGVMs), forced by multimodel climate projections under scenario RCP6.0 in phase 2b of the Inter-sectoral Impact Model Intercomparison Project (ISIMIP³⁷; Methods).

Across the climate model/DGVM ensemble, the EI-based global drylands area remains unchanged (–0.1% of global land from the multimodel/DGVM mean; +0.7% (–0.9%) from the mean (median) of individual model/DGVM changes; Fig. 6c). The spatial patterns are broadly similar to the CMIP5 results (Fig. 6a). Removing the CO₂ effect on vegetation leads to much more negative EI changes (Fig. 6b). Regions of drylands increase thus tend to show greater expansion (for example, central United States), and the associated increase in global drylands is larger (+3.2% of global land from the multimodel/DGVM mean; +3.1% (+2.7%) from the mean (median) of individual changes; Fig. 6c). The ISIMIP results thus confirm the CMIP5 results regarding the quasi-invariance of the global drylands extent to global warming and the key role of CO₂ fertilization in this response.

Discussion and conclusions

Even though the usual definition of drylands relies on the AI, here we showed that the modelled AI is actually a poor predictor of projected changes in drylands from climate model land surface outputs. Whereas AI projections indicate large future drylands expansion, EI projections suggest very limited areal changes in the global mean. This is consistent with previous studies showing the AI to be a negatively biased metric of modelled global land surface changes under greenhouse warming^{19,20}, despite its popularity as a climate impact metric^{7–17}. Our study further highlights relevant mechanisms: AI-based assessments overemphasize the role of PET compared with *P* as a driver of ecohydrological impacts over land, do not account

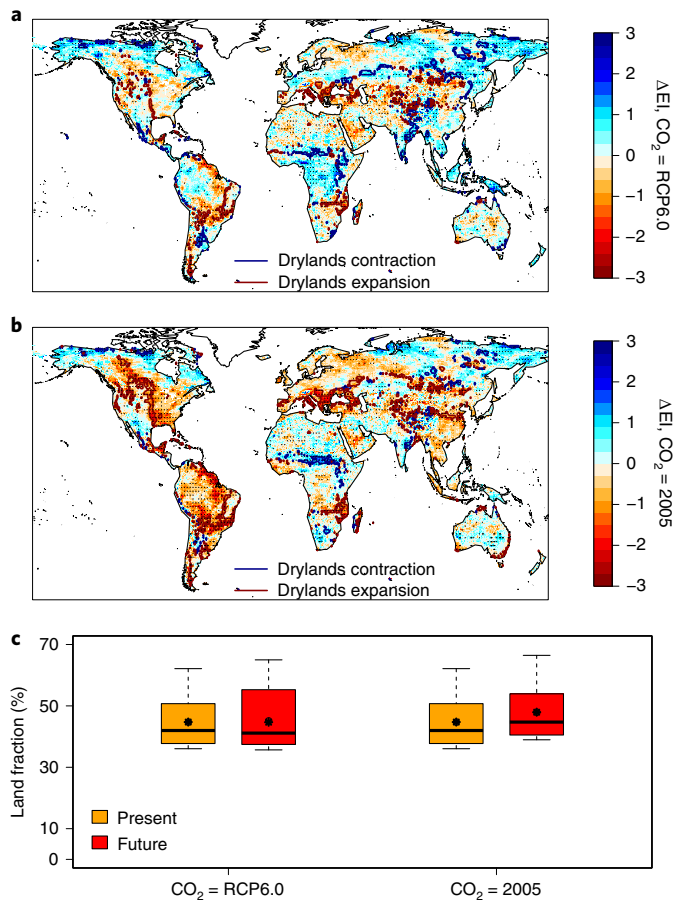


Fig. 6 | Changes in drylands in ISIMIP. a, Model mean change (across all combinations of DGVMs and climate models) in EI under the RCP6.0 scenario between the present (1971–2000) and future (2070–2099), with atmospheric CO₂ seen by vegetation following RCP6.0 values. The contour lines represent changes in drylands under the EI definition. **b**, Same as **a**, but with CO₂ concentrations seen by vegetation held constant after 2005. The stippling indicates where more than three-quarters of combinations of DGVMs and climate models agree on the sign of the change (for visibility, while the ISIMIP outputs are at a 0.5° × 0.5° resolution, the stippling is plotted at a 2° × 2° resolution). **c**, Distribution of drylands area (as a percentage of global land) in different DGVM/climate model combinations, in the present and future, with (left) and without (right) vegetation experiencing atmospheric CO₂ increase after 2005. The box plots have the same structure as in Fig. 5.

for the effect of CO₂ fertilization and neglect the role of land–atmosphere feedbacks associated with vegetation physiology in AI trends themselves. The latter result is consistent with similar issues identified in projections from other PET-based metrics³¹. Including a proposed correction²² in PET calculations to account for plant stomatal responses to CO₂ does not resolve the discrepancy between the AI and EI drylands projections, highlighting fundamental issues with the AI beyond PET calculation (Supplementary Discussion 1 and Methods). We expect such issues to also apply in the latest modelling results of CMIP6.

While we did not seek here to explicitly evaluate AI and EI trends in observations, we note that the AI has predominantly decreased over land over the past 50 years¹⁰, while vegetation has been increasing globally³⁸. Over drylands specifically, little correlation is found between changes in the AI and vegetation density over recent decades³⁹. A dominant role of land use or land management changes is found instead, consistent with a limited influence of ongoing

climatic trends on drylands conditions^{40,41}. Recent observations therefore do not seem to support the role of the AI as an indicator of drylands temporal dynamics either.

Climate models project widespread decreases in surface soil moisture⁴², seemingly consistent with AI projections and thus drylands expansion²⁸ (Supplementary Fig. 8a). However, decreases in surface soil moisture are not consistently associated with increases in water limitation on transpiration in models: while changes in both quantities are spatially correlated ($r = -0.41$), 35% of the land surface shows decreases in surface soil moisture without increases in $\text{cor}(\text{SM}, \text{Tran})$ (Supplementary Fig. 8b). Decreasing soil moisture in wet environments (such as the tropics and high latitudes) may not directly impact transpiration; additionally, because of increased plant water-use efficiency under higher atmospheric CO₂, decreases in absolute soil water content may not translate to greater constraints on transpiration. Projected decreases in soil moisture in many midlatitude regions are also directly caused by climate-driven and CO₂-driven vegetation growth⁴³ and are thus not necessarily indicative of increased water stress in the models. These differences justify a focus on soil water limitation rather than absolute water content. Nevertheless, even tentatively defining drylands solely as regions with low surface soil moisture yields more modest drylands expansion than with the AI (+3%, Supplementary Fig. 9); a similar analysis applied to total-column soil moisture, which shows less negative projected changes than surface soil moisture⁴², leads to a more modest increase (+1.9%, Supplementary Fig. 10). Finally, replacing $\text{cor}(\text{SM}, \text{Tran})$ with surface soil moisture in combination with LAI in an alternative EI (EI*; Supplementary Discussion 2) leads to no substantial drylands expansion, consistent with our initial results (+0.6% in the multimodel mean; Supplementary Fig. 11).

The realism of projected vegetation increases in climate models, however, may be questioned. On the one hand, available CO₂-enrichment experiments do show enhanced vegetation growth under elevated CO₂ (ref. 23), with no clear evidence that models systematically overestimate this effect⁴⁴; and model-simulated historical LAI trends are broadly consistent with the global vegetation increase observed in recent decades^{38,45}. On the other hand, key limiting processes in a changing climate, such as increased water stress, nutrient limitation or increased fire risks^{46,47}, are represented simplistically in models or are entirely omitted. Models may thus overestimate future vegetation growth. We therefore design another alternative index to the EI that does not include LAI changes but focuses on precipitation and soil moisture limitation instead (EI'). The results obtained using this alternative index are still inconsistent with strong global drylands expansion (Supplementary Discussion 3 and Supplementary Figs. 12–14). We emphasize that, while model projections of future vegetation may be overestimated, evaluating the realism of such projections is not a goal of our study; rather, our study aims to accurately analyse and interpret the information that existing model projections provide, regardless of possible biases.

Land aridity is a complex, multidimensional hydroclimatic concept, of which the AI is but one metric. Similarly, the concept of drylands encompasses multiple climatic, hydrological and ecological characteristics¹. A consequence of the AI-based definition of drylands and associated studies^{7–17} is that both concepts have become somewhat conflated—further confounding their definition. Our study clarifies that the AI is best understood as a measure of atmospheric aridity (which does increase with climate change), while the concept of drylands is primarily based on land ecohydrological conditions. We use the EI as a tool to demonstrate that drylands show more nuanced changes under greenhouse warming, which cannot be equated with atmospheric aridity trends. However, we stress that the EI necessarily remains a simple metric, which does not encompass all drylands aspects, such as soil biogeochemistry and ecological composition¹. Further work is needed to fully characterize the responses of all different facets of drylands. By further highlighting

the complex trends in the land–atmosphere system under climate change^{19,20,28}, our study joins calls for caution in the use of imprecise concepts such as aridity and drylands in climate impact studies, and for careful definition of the concepts and variables analysed⁴⁸. In particular, our study highlights the dangers of relying on simple atmosphere-based metrics, such as the AI, as proxies to assess climate impacts on land systems. This approach is sometimes justified by the large structural uncertainties otherwise plaguing land surface outputs from climate models, such as soil moisture, runoff and vegetation⁴⁹ (for example, Fig. 5). However, here differences go beyond model spread: the AI-based assessments of future changes in drylands are qualitatively different from the modelled ecohydrological trends. Uncertainties and limitations in land model simulations undoubtedly complicate our assessment and interpretation of projected ecohydrological trends, and preclude high confidence in model EI projections. However, we argue that enough is known about ecohydrological processes that these uncertainties do not justify relying on a demonstrably flawed atmospheric proxy that is qualitatively at odds with these projections. Finally, we stress that our study does not question the many documented adverse impacts of climate change on different hydrological and biological land systems; however, we argue that an objective assessment of climate model projections indicates little evidence for global drylands expansion under anthropogenic climate change.

Online content

Any methods, additional references, Nature Research reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at <https://doi.org/10.1038/s41558-021-01007-8>.

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Methods

EI of drylands. Our criteria for defining the EI included simplicity (for example, the smallest number of variables possible), accessibility from usual climate model outputs and overlap with the AI-based definition under present-day climate. The EI of drylands is defined as

$$EI = LAI - (a \times \text{cor}(\text{SM}, \text{Tran}) + b) \quad (1)$$

where LAI and $\text{cor}(\text{SM}, \text{Tran})$ are unitless, and a and b are parameters. The parameters are estimated by fitting the line $LAI = a \times \text{cor}(\text{SM}, \text{Tran}) + b$ to the black contour line in Fig. 1e. The estimated values used in this study are $a = 4.72$ and $b = 0.15$. By design, drylands (regions in the present climate in which $AI < 0.65$) then approximately correspond to regions where $EI < 0$. As opposed to the AI, which is an index of atmospheric aridity, we consider the EI as an index of ecohydrological aridity: lower EI values correspond to more arid conditions from an ecohydrological standpoint (that is, to lower vegetation density and more water-limited vegetation). We used surface soil moisture here (variable mrso from CMIP5) for simplicity, as it represents the same depth for all models (even if absolute moisture levels still vary between models). The spatial pattern and magnitude of $\text{cor}(\text{SM}, \text{Tran})$ are similar for surface and total soil moisture⁵⁰ (reflecting consistent interannual variability in both quantities).

CMIP5 simulations. We used publicly available simulations from CMIP5. Supplementary Table 1 lists the models analysed for the different experiments used in our study—using CMIP5 nomenclature: HIST, RCP8.5, 1pctCO₂ (renamed CTL in our study), esmFdbk1 (renamed RAD) and esmFixClim1 (renamed PHYS). To calculate multimodel means, the models were regridded to a common $2^\circ \times 2^\circ$ resolution.

Pre-industrial, historical and future climate simulations. HIST and RCP8.5 are simulations covering the historical period (1850–2005) and twenty-first century under a high-emissions scenario (2006–2100), respectively. We analyse 30-year periods in each, 1971–2000 and 2071–2100, respectively. CO₂ concentrations in the RCP8.5 scenario reach around 935 ppm by the year 2100. Only 12 models were available with the outputs necessary to calculate PET (see below), as well as surface soil moisture and transpiration, and for which LAI was computed interactively with climate (as opposed to being prescribed; Supplementary Table 1).

Experiments separating CO₂ physiological and radiative effects. CTL, PHYS and RAD are idealized single-forcing CMIP5 experiments for coupled carbon–climate Earth System models, meant to study carbon cycle feedbacks. More precisely, they are meant to separate the effect of atmospheric CO₂ increase on climate and the carbon cycle into the radiative effect of CO₂ on the atmosphere and the physiological effect of CO₂ on vegetation. In CTL, both the atmospheric model and the land surface scheme of a climate model are subjected to a 1% annual increase of atmospheric CO₂ starting from pre-industrial levels (284 ppm) and lasting 140 years (ending at 1,132 ppm). In PHYS, only the vegetation module experiences the increase in CO₂, while the atmosphere continuously experiences pre-industrial CO₂ levels. Conversely, in RAD, only the atmosphere experiences the increase in CO₂, while vegetation continuously experiences pre-industrial CO₂ levels. For our purposes, PHYS thus isolates the impact of CO₂ increase on climate and hydrology through the physiological effect of CO₂ on vegetation, while RAD isolates only the radiative effect of CO₂ increase. These simulations and the corresponding decomposition of CO₂ effects into physiological and radiative parts in CMIP5 models have been used in previous hydroclimate studies^{31–33,35,36}. Eight models took part in these experiments; only four models provided both LAI and the necessary outputs to calculate PET (Supplementary Table 1). For each run, we analyse the first 20 years and the last 20 years of the simulations to obtain the corresponding changes.

ISIMIP simulations. Under phase 2b of ISIMIP³⁷, impact models from various sectors (for example, hydrology, vegetation, human health and biodiversity) were driven in a consistent modelling framework by climate projections from a set of climate models and climate scenarios from the CMIP5 experiment. The ISIMIP climate dataset covers the period from 1860 through to 2099 on a horizontal grid with $0.5^\circ \times 0.5^\circ$ resolution; where necessary, climate model output was spatially interpolated. The data were bias-corrected to ensure long-term statistical agreement with the observation-based dataset EWEMBI (E2OBS, WFDEI and ERAI data merged and bias-corrected for ISIMIP³⁷) over the period 1960–1999, while also preserving projected absolute trends in temperature and relative trends in P and all other variables.

For our analysis, we use monthly LAI, soil moisture and transpiration outputs from three DGVMs forced by a set of four climate models (GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR and MIROC5). We computed annual means from monthly outputs. We focused on scenario RCP6.0 for future projections, as counterpart experiments without CO₂ change were available for that scenario (which was not the case for RCP8.5). Three DGVMs (ORCHIDEE, LPJ-GUESS and CARAIB) were available that included historical simulations and future projections with and without CO₂ change. In the historical

simulations, CO₂ was prescribed according to historical values. For the historical period (1860–2005), historical land-use change was also prescribed. For RCP6.0 projections (both with and without CO₂ changes), land use was fixed at 2005 values; thus, the differences between present (1971–2000) and future (2071–2100) values focus on the impact of climate change (and CO₂ for simulations that include CO₂ change).

In the ISIMIP experiment, soil moisture outputs were not standardized to a common depth. The three DGVMs used here have different soil schemes and depths. We use the sum of the first nine layers in ORCHIDEE (equivalent to ~0.7 m deep) and the first layer in LPJ-GUESS (0.5 m); CARAIB had only one layer available, whose actual depth varies depending on rooting depth around the world, starting at 0.7 m.

Calculation of PET and AI. We use monthly outputs of P and of near-surface temperature, specific humidity, wind speed, surface pressure, and latent and sensible heat flux to calculate PET according to the Penman–Monteith equation (see below). The AI was then defined as the ratio of annual mean P to annual mean PET. Drylands expansion is then estimated as the increase in land fraction (not including Greenland and Antarctica) where $AI < 0.65$ between 1971–2000 and 2071–2100; this yields an expansion of ~6% in the mean of the CMIP5 models we analysed, consistent with previous studies^{5,10,13} (note that Huang et al.¹⁰ apply a bias correction to AI calculations from CMIP5 model simulations, which results in larger drylands expansion in their analysis, up to +23%; however, their non-corrected values are also on the order of +6%).

PET represents the evaporative demand of the air near the surface. To calculate PET, we used the open-water formulation, as in Milly and Dunne²¹. This assumes that stomatal resistance is zero (and thus doesn't change over the course of the twenty-first century); it also assumes an aerodynamic roughness of the surface of 0.00137 m (consistent with open water). It computes PET (mm d^{-1}) as:

$$\lambda \text{PET} = \frac{sR_n + 6.43(1 + 0.53u)\gamma D}{s + \gamma},$$

where s is the gradient of the saturation vapour pressure with respect to temperature (Pa K^{-1}), R_n is net radiation minus the ground heat flux (which was calculated as the sum of latent and sensible heat flux), γ is the psychrometric constant (Pa K^{-1}), u is the wind speed at 2 m height (m s^{-1}), D is the vapour pressure deficit of the air at 2 m height (the difference between the saturated vapour pressure and the actual vapour pressure (Pa)) and λ is the latent heat of vaporization (J kg^{-1}), which is calculated as a function of air temperature²¹.

We also calculate PET using the formulation proposed by Yang et al.²² to account for changes in stomatal resistance. It is based on the 'FAO-56 reference crop' formulation, which was modified to include changes in stomatal conductance as a function of atmospheric CO₂ (estimated from CMIP5 climate projections)²²:

$$\text{PET} = \frac{0.408sR_n + \gamma \frac{900}{T+273} uD}{s + \gamma \{1 + u[0.34 + 2.4 \times 10^{-4}([CO_2] - 300)]\}},$$

where T is the 2 m temperature and $[CO_2]$ is the atmospheric CO₂ concentration (in ppmv).

Decomposition of P/PET changes in the PHYS experiment. According to error propagation rules, the fractional change in $AI = P/\text{PET}$ can be approximated by the fractional change in P and in PET as follows:

$$\frac{\Delta\left(\frac{P}{\text{PET}}\right)}{\frac{P}{\text{PET}}} \approx \frac{\Delta P}{P} - \frac{\Delta \text{PET}}{\text{PET}},$$

where Δ refers to the future-minus-present change and the values in the denominator are present-day means. Thus, we have:

$$\Delta\left(\frac{P}{\text{PET}}\right) \approx \frac{\Delta P}{P} \frac{P}{\text{PET}} - \frac{\Delta \text{PET}}{\text{PET}} \frac{P}{\text{PET}};$$

that is, the change in P/PET , $\Delta(P/\text{PET})$, can be approximated by the difference between a P -change-induced term:

$$\frac{\Delta P}{P} \frac{P}{\text{PET}}$$

and a PET-change-induced term:

$$\frac{\Delta \text{PET}}{\text{PET}} \frac{P}{\text{PET}}.$$

We compute area-weighted averages of each term in experiment PHYS. We calculate the global change in P/PET to be -0.071 (unitless); the P -change-induced term and PET-change-induced term are -0.019 and $+0.059$, respectively (thus, their difference is -0.078). We therefore assess the change in AI in PHYS attributable to changes in P to be $1.9/7.8 \approx 25\%$; and the change in AI attributable to changes in PET, $5.9/7.8 \approx 75\%$.

Data availability

All climate model simulations used in the Article are from CMIP5 and are publicly available—for instance, at <https://esgf-node.llnl.gov/search/cmip5/>. All ISIMIP simulations are freely available as well—for example, at <https://esg.pik-potsdam.de/search/isimip/>. All calculated data generated from these sources are available from the corresponding author upon request.

Code availability

The custom R code written to read and analyse the data and generate the figures is available on GitHub at <https://doi.org/10.5281/zenodo.4490414> (ref. ⁵¹).

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Author contributions

A.B. and K.A.M. designed the study. A.B. conducted the analysis and wrote the manuscript. K.A.M. advised on the interpretation of the results and contributed to the manuscript preparation.

Competing interests

The authors declare no competing interests.

Additional information

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Correspondence and requests for materials should be addressed to A.B.

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