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The terrestrial water cycle in a warming world

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Climate model projections of the terrestrial water cycle are often described using simple empirical models ("indices") that can mislead. Instead, we should seek to understand climate model projections using simple physical models.

Future changes to droughts, floods, heatwaves and wildfires all depend on changes to the water cycle in a warming world. Changes in these extremes are not just determined by changes in precipitation, but also by changes in land surface water fluxes (including evaporation, transpiration and runoff) and storages (including soil moisture, vegetation and groundwater). In order to depict this future, climate science must rely on models. For example, a climate model can be run under a particular emissions scenario to observe how precipitation, soil moisture or runoff simulated by the model changes with time. Climate scientists should not blindly believe everything the model says, but it provides a physically plausible response, which integrates changes to different hydrological mechanisms in a physically consistent manner.

Instead of directly describing water storages or fluxes simulated by climate models, it has become common in climate change impact studies to use simple empirical models of "dryness", "aridity", or "drought", which are calculated using simulated variables from climate models and are interpreted broadly as proxies for hydrological or ecosystem variables. The main reason for their use is historical: the relative lack of observations of most water storages and fluxes compared with widely-available meteorological data (such as precipitation and temperature) led to the historical development of an array of simple empirical models based on precipitation and temperature. The simple empirical models focused on here are often termed "indices", so we shall use the terms interchangeably, while recognizing that the term "index" can be used more broadly. One prominent example is the "aridity index" (AI), the ratio of precipitation to potential evapotranspiration (also sometimes defined as the reciprocal and called the "dryness index"). The long-standing conceptual model of Budyko[1] relates the AI to the partitioning of precipitation between evapotranspiration and runoff; specifically, a higher AI implies a higher "runoff ratio", the ratio of the long-term mean annual runoff to the long-term mean annual precipitation. However, its scope has broadened significantly and it often seems to be interpreted as a general measure of land surface "dryness": for instance, it is used explicitly in the definition of "drylands" adopted by the United Nations[2], and is regularly compared to other hydrologic variables, such as soil moisture and relative humidity. Other examples of widely-used simple empirical models include the Palmer Drought Severity Index[3], the Standardized Precipitation Evapotranspiration Index[4], and other variants, which undergird key IPCC drought results[5].

Redundancy, bias and ambiguity

We argue that the use of such simple empirical models in describing climate model projections is often undesirable for at least three reasons. First, their use is often redundant. Many indices were originally introduced to circumvent data limitations. However, inside a climate model, data limitations are typically not a problem, since the climate model provides a complete view of the simulated earth system, including land hydrology and ecosystems. If one is interested in how soil moisture might change in a warming world, for example, then it is better to simply examine the soil moisture variable in the climate model making the projection, rather than an index based on other modelled variables that is only approximately related to soil moisture[6–8]. A common response to this point is that land surface models exhibit larger errors than atmospheric models, so, when analyzing climate model outputs, it is preferable to use indices of surface quantities that are based on variables from the atmospheric component of the climate model, like the AI, rather than the land surface component. We agree that land surface models exhibit major uncertainties, but since they are tightly coupled to the atmospheric model, errors in one propagate rapidly to the other near the land surface[9–11]. Thus, there is no reason to favor an atmospheric model over a land surface model near the land surface. The solution to problems with climate models is not to build new offline empirical models on top of them, but to improve climate models[12]. Beyond the AI, the broader point is that parsimony should be valued by eliminating indices that outlive their usefulness and introducing new indices only when there is no reasonable existing alternative.

Second, an index that is a reliable proxy of a particular water storage or flux in the current climate may be substantially biased in future climates. If an index explains spatial variability in the present climate, it is often assumed that it can explain temporal variability as the planet warms, but that assumption (space-for-time substitution) may be badly wrong in a non-stationary environment. An example of this is the non-radiative effect of CO_2 on plants, which causes the leaves of most plants to fix more carbon for a given amount of water loss, all else being equal. CO_2 is well-mixed in the atmosphere meaning that, in the current climate, plants are exposed to roughly similar concentrations of CO_2. Therefore, CO_2 does not explain much spatial variability in transpiration in the current climate, and indices such as the traditional AI do not directly include CO_2 concentrations in their formulation. However, CO_2 rises in a warming world, and non-radiative effects of CO_2 on plants have a first-order impact on changes to the water cycle, at least in model projections[11,13,14]. The AI misses these and other[15] effects and leads to substantially biased projections[8,16]. Specifically, the projected AI declines rapidly in most parts of the world, which should imply rapidly declining runoff ratios; yet the directly simulated runoff ratios do not reflect this and even increase in many parts of the world[8,12,15]. Similarly, the standard definition of a “dryland” is based on the AI, and so models project rapid and widespread expansion of drylands under warming. Yet the same models project substantial plant growth in many of the same regions projected to become drylands based on the AI, which is inconsistent[17,18]. Using an alternative index to define drylands – specifically designed to reproduce the spatial distribution of drylands produced by the AI in the current climate but defined in terms of plant and land surface properties rather than precipitation and temperature – results in projections of no dryland expansion, on average, in a warmer world[18]; in other words, projected global dryland expansion is an artifact of the AI. Beyond the AI, the broader principle is that one should not needlessly extrapolate an empirical index that has been designed for the present climate into the future, just as one should not needlessly extrapolate a statistical model beyond the period for which it was constructed.

Third, indices often introduce definitional ambiguity that slows scientific progress. Concepts such as “dryness”, “aridity”, and “drought” have multiple definitions in the literature, often associated with a particular index. These terms are multifaceted and there is room for different perspectives. However, there is a tendency for definitional ambiguity to creep in, which can render the index unfalsifiable. For example, it is common to compare the AI and other indices to a range of hydrologic and ecosystem variables, even though the AI is only linked mechanistically to the runoff ratio and associated quantities. This is a problem because different hydrologic variables behave differently as the planet warms: for example, global mean surface soil moisture is projected to decrease, whereas global mean runoff is projected to increase[15]. If the AI poorly matches the runoff ratio, it will likely at least qualitatively match another hydrologic variable. The definitional ambiguity allows the AI to then be defended as tracking at least some aspects of “aridity” or other ambiguous terms.

Back to fundamentals

For these reasons, we recommend that simple empirical models not be used in describing climate model projections unless (1) there is no reasonable alternative, and (2) the index is precisely related to a hydrologic flux or storage by clear physical mechanisms, and thus makes testable predictions. For example, the use of the AI in studies of times or places where the runoff ratio has not been measured would satisfy (1), since the AI can be interpreted as a proxy for the runoff ratio; but its use to describe climate model projections of the runoff ratio would not, since the runoff ratio – and, more importantly, the runoff itself -- can be described directly using outputs from the climate model. If the AI is interpreted solely as a proxy for the runoff ratio using Budyko's conceptual model[1], then it arguably satisfies (2); but when interpreted as a broader measure of "aridity", as is common, it does not. In practice, it is almost always better to describe climate model projections in terms of the climate model's simulated water storages and fluxes, rather than using an index.

We have outlined various problems with simple empirical models, but do not suggest that full-complexity climate models are the only useful tool for studying future changes to the water cycle. Indeed, simple physical models – models derived from clear physical arguments that distill a process down to its most fundamental mechanisms -- remain critical to understanding and scientific progress. A complete review is beyond the scope of this comment, but two recent examples are Byrne and O'Gorman's theory of changes in relative humidity over land[20]; and Cerasoli et al.'s simple model of potential net cooling effects from midlatitude afforestation due to clouds[21]. Projected changes to the water cycle simulated by full-complexity climate models are more robust when they can be reproduced, at least qualitatively, by simple physical models[19].

In summary, we do not recommend using simple empirical models to describe full-complexity climate model projections, but do recommend the use of simple physical models to understand them.

Author contributions
K.A.M. wrote the manuscript, with input and edits from M.L.R., A.B., and J.S.

Competing interests
The authors declare no competing interests.

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