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ABSTRACT

Changes in "blue water", which is the total supply of fresh water available for human extraction over land, are quite closely related to changes in runoff or equivalently precipitation minus evaporation, $P-E$. This article examines how climate change-driven recent past and future changes in the regional water cycle relate to blue water availability and changes in human blue water demand. Although at the largest scales theoretical and numerical model predictions are in broad agreement with observations, at continental scales and below models predict large ranges of possible future $P-E$ and runoff especially at the scale of individual river catchments and for shorter timescale subseasonal floods and droughts. Nevertheless, it is expected that the occurrence and severity of floods will increase and that of droughts may increase, possibly compounded by human-driven non-climatic changes such as changes in land use, dam water impoundment, irrigation and extraction of groundwater. Contemporary assessments predict that increases in 21st century human water extraction in many highly-populated regions are unlikely to be sustainable given projections of future $P-E$. To reduce uncertainty in future predictions, there is an urgent need to improve modeling of atmospheric, land surface and human processes and how these components are coupled. This should be supported by maintaining the observing network and expanding it

Abbreviations: E, Evaporation; E_p, Potential evaporation; GCM, General Circulation Model; GHM, Global Hydrological Model; I, Stream and groundwater inflow; P, Precipitation; P—E, Precipitation minus Evaporation; Q, Runoff; X, Human water demand.

to improve measurements of land surface, oceanic and atmospheric variables. This includes the development of satellite observations stable over multiple decades and suitable for building reanalysis datasets appropriate for model evaluation.

1 | Introduction

Human societies may experience severe water scarcity when extracting a substantial proportion of "blue water", which is the total supply of land surface and groundwater (Greve et al. 2018). Because blue water is difficult to quantify precisely, this article uses changes in Q, or equivalently $P - E$, as a proxy for blue water changes that can be linked to climate processes and climate change in much of its analysis. In the absence of changes in land water storage, precipitation at the Earth's land surface, P, is balanced by evaporation, E, and runoff,Q such that $P - E = Q$. However, because $P - E$ and Q analysis neglects the influence of important hydrological processes such as stream and groundwater flow, and does not accurately reflect short-term changes in water availability where land water storage may be important such as during drought (Peña-Gallardo et al. 2019), we discuss changes in soil moisture and groundwater where observations and modeling allow.

A range of recent work we present has changed our view of past and future blue water change, motivating the need for a new review. Two linked issues stand out. First, as pointed out by (Mankin et al. 2019), older literature held that either warming-driven increases in atmospheric evaporative demand would lead to reductions in future runoff and available blue water, or that stomatal closure due to increases in atmospheric CO_2 would lead to reductions in evapotranspiration, increasing future available blue water. Contemporary assessments recognize that reductions in evapotranspiration due to stomatal closure are opposed by increases in plant leaf area that increase evapotranspiration. Both effects are potentially large but poorly understood, meaning that it is difficult to forecast changes in future blue water in many highly populated regions. Second, although acknowledging that large populations live with severe water scarcity at present, older work did not predict large increases in water stressed populations in most future scenarios, partly linked to the expectation that plant stomatal closure would protect water resources (Oki and Kanae 2006). More recent work predicts that population increases will cause large increases in water scarcity that are not likely to be replenished by increases in water supply (Wada and Bierkens 2014).

We discuss regional water cycle changes and their interaction with societies through five broad topics that focus on progressively smaller spatial scales and shorter timescales. Section 2 asks (1) How well do we understand changes in large-scale multi-decadal mean $P - E$ and how relevant are they below continental scales? Section 3 asks (2) At the hydrological catchment scale most important to humans, how does multi-decadal mean $P - E$ and runoff change and how do changes interact with the land surface? And (3) What are the current issues in theoretical and modeling efforts that predict $P - E$ and blue water and how do these hamper our efforts to constrain future changes? Section 4 asks (4) How well do we understand changes in high and low $P - E$ and runoff subseasonal extremes and longer-term variability and what are their impacts? Section 5 asks (5) Are likely changes in human demand and the impacts of human activities not linked to climate change sustainable given expected climate change-driven changes in blue water supply? In summary, we find that there is broad agreement between observations and model simulations above continental scale and over multi-decadal timescales, and that this is in line with the expectations of basic theory. However, below continental scale and especially for seasonal timescales and below, there are large differences between simulations from different models and between model simulations and observations. This is particularly the case where coupling between atmosphere and land surface are important, such as for drought. Great uncertainty stems from the heterogeneity of the land surface, our lack of knowledge of land surface processes and fundamental differences between whether and how those processes are represented in models and how land and atmosphere models are coupled. As with the use of $P - E$ and Q for estimating changes in blue water availability, specific metrics that are used to assess components of the hydrological cycle may have limitations but their use may be necessary where more accurate options are not available. For example, evaporative demand may be an inadequate proxy for evaporation where land surface processes or moisture availability constrain surface water loss. However, available data or limited understanding may make estimation of true evaporation impractical and hence evaporative demand has been used by many studies including some we describe. All of these large uncertainties make it very difficult to assess whether future changes in human water demand are likely to be met by available supply. Nevertheless, future projections suggest that large increases in human water demand expected in some highly populated regions already under high water stress may not be satisfied by increases in water supply.

In Section 6 we conclude with recommendations for future observational campaigns, and modeling and theoretical work that we believe would improve our understanding of future water cycle changes. We believe that maintaining the existing observing network is vital and argue that it should be extended to improve observation of poorly constrained quantities such as evaporation and precipitation over both land and ocean, and river discharge and water mass balance over land as well as human impacts on land use and water consumption. New modeling and theory that improve representation of small-scale and poorly understood processes are important, including those that take advantage of new developments in kilometer-scale simulations and machine learning. The production and analysis of kilometer-scale simulations are useful not only in themselves but also for the training of low-resolution models or those that use new machine learning techniques and that allow the production of much larger numbers of simulations at lower computational cost.

2 | Changes in the Large-Scale Multi-Decadal Mean Water Cycle

Uncertainty in assessments of future changes in water cycle variables is substantial, and depends on uncertainty in emissions that drive climate change, internal climatic variability, and deficiencies in modeling and observing systems (Douville et al. 2021). In particular, precipitation over land at continental scales and below shows large variations in space and time and can depend on the details of atmospheric circulation and subtle interactions between the atmosphere and the surface.

Projections of regional changes in future climate are made using numerical global climate models (GCMs) (Christensen et al. 2013; Douville et al. 2021). As we discuss below, contemporary GCMs cannot normally be used alone to make reliable forecasts at the spatial scale of hydrological catchments, which are the drainage basins of large, ocean-reaching rivers (Dai et al. 2009), or at the timescale of sub-seasonal extreme water cycle changes. However, they remain primary tools for predicting future changes in large-scale precipitation and atmospheric demand for evaporation, which are fundamental to understanding changes in blue water. An important activity is comparing climate model simulations of the past to observations to improve understanding of both models and observations and to inform our confidence in model projections of the future. In this review, we present results from the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al. 2012) and Phase 6 (CMIP6) (Eyring et al. 2016) experiments, which collate simulations from current climate models.

Changes in future global-mean time-mean $P-E$ are constrained to be small because atmospheric water storage is comparatively small. Changes in separate global-mean P or E are not well-observed. Satellite-based estimates over the ocean have only been available since 1979 and land-based observing stations are not uniformly distributed. Surface observations of E are particularly sparse and not available before the 1990s (Dorigo et al. 2021). Over land, gridded estimates of E are made using water balance models driven by satellite data or using machine learning algorithms trained using point observations. Despite differences between estimates of E, there is broad agreement in multi-annual mean E and $P-Q$ derived from surface-based precipitation and river discharge measurements (Miralles et al. 2016). Changes of both P and E are likely to be of the order of a few % per °C global-mean surface air temperature warming, based on available observations (Adler et al. 2017) and theoretical studies that use energy and water conservation arguments to constrain changes (Fläschner et al. 2016). These conservation arguments are useful down to length scales over which the water and energy cycles can be considered approximately closed—perhaps as small as 4000 km (Muller and O'Gorman 2011; Dagan et al. 2019)—but do not constrain changes at smaller scales, meaning that local P changes in particular could be much larger. Understanding global scale P and E is important for building and evaluating physical models of climate change, but is less relevant to local impacts on human populations. Global-mean changes have been reviewed extensively elsewhere (Hegerl et al. 2015; Allan et al. 2020) and we do not discuss them further.

For multi-decadal mean continental-scale and zonal-mean changes in $P-E$, a body of theory exists that can help to identify useful climate change metrics and highlight areas for improvement in modeling and observing systems. Of particular interest are scalings that link changes in $P-E$ to changes in better observed and better understood quantities such as near surface air temperature, T_S, and specific humidity, q. Zonal-mean large-scale multi-decadal mean $\Delta(P-E)$ over the oceans broadly follows the Held and Soden "wet-get-wetter, dry-get-drier" (WWDD) scaling (Held and Soden 2006) in both modeling and observational studies. By water conservation, $P-E$ must equal the local atmospheric moisture convergence in the time-mean. If changes in horizontal atmospheric moisture flux are dominated by changes in moisture and not changes in winds, and it is assumed that oceanic q increases so as to maintain constant surface relative humidity ($\frac{1}{q}\frac{dq}{dT_S}=\alpha\sim 7$ % per °C at present-day Earth surface temperatures) then it is possible to estimate $\Delta(P-E)$ over ocean as the product $\alpha(P-E)\Delta T_S$. WWDD is a reasonable representation of future multi-decadal mean zonal-mean oceanic changes for climate models (Taylor et al. 2012; Li et al. 2013; Douville et al. 2021) when ΔT_S is known (Figure 1a). Observations of surface salinity since the 1950s are also consistent with this picture (Durack et al. 2012; Grist et al. 2016; Douville and Cheng 2024).

Over land, the wettest and driest percentiles of multi-decadal mean precipitation have also become wetter and drier respectively over the past 30 years (Schurer et al. 2020). However, at geographical locations, WWDD does not apply (Greve et al. 2014). Notably it cannot produce reductions in multi-decadal mean land $P-E$ found in some regions in all CMIP6 models because multi-annual-mean $P-E$ and ΔT_S are always positive over land. Byrne and O'Gorman proposed an extended scaling (Byrne and O'Gorman 2015) accounting for changes in land surface relative humidity, temperature gradients, and how these are mediated by transient atmospheric eddies (cyclones). The extended scaling improves the estimate markedly over land in the extratropics (Figure 1b, green), but less so in the tropics where the neglected influence of changes in mean circulation is important (not shown). Pietschnig et al. (Pietschnig et al. 2019) approximated changes in multi-decadal mean tropical land P through the difference between changes in local and tropical mean relative humidity, effectively parameterizing spatial shifts in the mean circulation. In contrast to Byrne and O'Gorman, they neglected the influence of transient eddies, which are less important to moisture transport in the tropics than in the extratropics. If we further assume that the evaporative index, E/P, is unchanged under climate change—effectively linearising the Budyko relationship (see Box 1) – then $\Delta(P-E)\simeq(1-\beta)\Delta P$, where β is control climatological mean E/P. This yields a reasonable estimate of zonal-mean land $\Delta(P-E)$ in the tropics (Figure 1b, solid red). Note, however, that the fraction of P that becomes E is likely to change in ways that are difficult to predict in future due to uncertain land surface processes, and this is likely to have large impacts on regional blue water availability, as we discuss in the next section.

Another substantial obstacle to both the Pietschnig and Byrne and O'Gorman estimates is our lack of understanding of changes in future relative humidity over land. Progress has been made, however, in estimating associated changes in specific humidity, q. If we assume that oceanic q increases with T_S so as to maintain constant oceanic relative humidity, and atmospheric sources and sinks of q see the same percentage increase as oceanic q, then q over land is expected to increase by the same percentage amount as q from its ultimate oceanic source (Rowell and Jones 2006). The oceanic source is usually taken to be mean oceanic q at the same latitude as the land in question. This method provides good estimates of multi-decadal mean Δq in most land

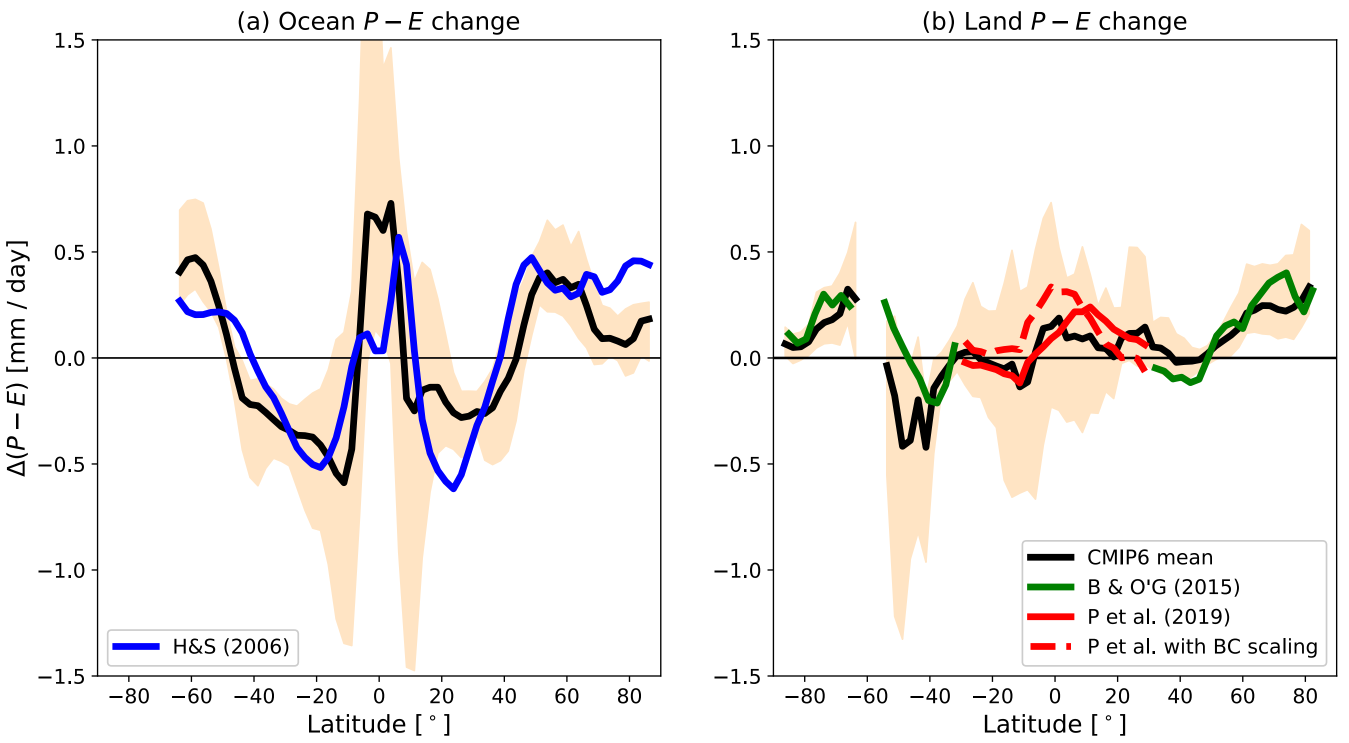


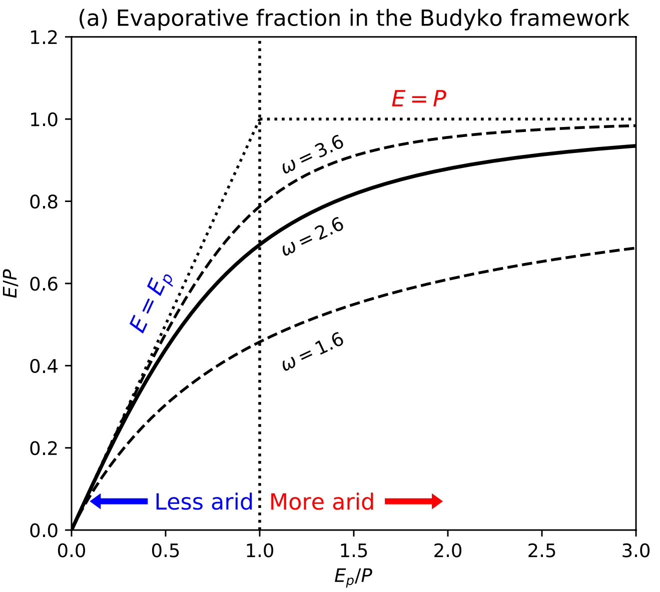
FIGURE 1 | Theoretical estimates of zonal-mean 2081–2100 SSP585 minus 1995–2014 historical $\Delta(P - E)$ compared with model output: Simulation results for 21 CMIP6 models mean (black) and maxima and minima (orange shading), and theoretical estimates of CMIP6 mean from Held and Soden WWDD equation 6 (Held and Soden 2006) (blue), Byrne and O'Gorman equation 7 (Byrne and O'Gorman 2015) (green), Pietschnig et al. equation 3 (Pietschnig et al. 2019) multiplied by $(1 - \beta)$, where β is 30°N—30°S 1995–2014 mean P / E (red), and Pietschnig et al. when changes in q are estimated via oceanic moisture scaling using Chadwick et al. equation 1 (Chadwick et al. 2016b) and taking the oceanic moisture source to be mean near surface oceanic 30°N—30°S q (red-dashed). (a) Ocean-only. The maximum value extends to 2.41 mm day^{-1} in the tropics due to CESM2-WACCM. Other models are below 1.5 mm day^{-1} at all latitudes. (b) Land-only. Due to data availability, the Byrne and O'Gorman extratropical estimate is only available for 11 CMIP6 models. Taking the same model subset for the other results does not make a qualitative difference (not shown). CMIP6 data are described by (Eyring et al. 2016).

regions when compared to observations or future changes projected by climate models (Byrne and O'Gorman 2018; Chadwick et al. 2016b), although there are weaknesses in regions of large changes in land-atmosphere interactions such as Amazonia. Combining this estimate of land q change with the Pietschnig et al. estimate of $\Delta(P - E)$ change yields a reasonable estimate of multi-decadal mean tropical $\Delta(P - E)$, which is useful as a consistency check (Figure 1b, dashed red). A climate model must be used to calculate land ΔT_S, however, as relative humidity depends on both T_S and q. It is important to note that observations suggest a larger decrease in multi-decadal mean land relative humidity than expected from theory or models, although deficiencies in measurements cannot be ruled out (Dunn et al. 2017; Willett et al. 2020; Simpson et al. 2023). It is difficult to determine causes for relative humidity changes using observations alone, but 1979–2014 mean changes in relative humidity appear to be associated with reductions in land evapotranspiration in some regions in addition to oceanic influences (Vicente-Serrano et al. 2018). Oceanic influences include land relative humidity reductions that are expected as the land warms more than the ocean while importing oceanic q that increases only to maintain constant oceanic relative humidity as explained above (Joshi et al. 2008; Byrne and O'Gorman 2013). A GCM study using four CMIP5 GCMs demonstrated that land surface processes linked to soil moisture should tend to increase modeled reductions in multi-decadal mean zonal-mean relative humidity under warming (Berg et al. 2016). We discuss the link between land surface processes, relative humidity and evaporation further in the next section.

An interesting aspect of these large-scale scaling arguments is that they link $\Delta(P - E)$ to changes in temperature but not directly to radiative forcing that drives climate change. Radiative forcing can produce "rapid adjustments" to P and E associated with how forcing is absorbed in the atmosphere and at the surface that produce climate impacts on timescales of a few months to a few years (Richardson et al. 2018). Although changes in large-scale precipitation in climate models are dominated by the surface temperature-driven component, at continental scales and below the direct effects of radiative forcing are more substantial and must be considered separately—even for comparatively spatially-uniform CO_2 forcing (Dunning et al. 2018). Future scaling arguments for regional climate change might therefore also include forcing terms, particularly in regions of strong aerosol forcing. Due to their short lifetime, the radiative effects of aerosol are often regional, driving gradients in atmospheric and surface heating, that can be associated with regional precipitation changes, such as in the monsoon regions (Bollasina et al. 2011) and the Sahel (Zhang et al. 2021), and associated with shifts in the zonal peak of tropical precipitation in the intertropical convergence zone (Rotstayn and Lohmann 2002). A wide

BOX 1 | Aridity Index and the Budyko Framework.

A popular form of the Budyko framework is the Fu equation (Fu 1981), which relates land E to E_p, P and a catchment parameter calibrated to local data, ω. Important physical processes are concealed by ω, such as precipitation frequency, whether precipitation falls as rain or snow, land surface processes such as water transport and vegetation functioning, and timing of water demand versus supply (Padrón et al. 2017). Where these change with climate change, the Budyko framework does not describe catchment level ΔQ and therefore $\Delta(P-E)$ accurately. Nevertheless, the framework does provide a concise description of the relationship between ΔP and ΔQ as a function of aridity index, E_p / P, and assists in the interpretation of the effects of climatological biases in P, E and E_p. (Note that the Budyko framework was originally established to analyze differences between different catchments.



Here we analyze differences due to climate change in individual catchments. This choice is justifiable as we treat each catchment separately and do not calibrate analysis across multiple catchments (Berghuijs and Woods 2016).)

Panel a shows how increases in E_p lead to increases in E at a given value of P, limiting water available for Q and therefore human extraction for three sample values of ω under the Fu equation. Climates with higher E_p / P are termed arid or "water-limited" because evaporation varies principally with precipitation and may approach $E = P$ (dotted horizontal line on panel a). Less arid climates have $E_p < P$ and are termed "energy-limited": precipitation is plentiful and changes in evaporation more strongly resemble $E = E_p$ (dotted diagonal line).

Panel b demonstrates how a bias in precipitation climatology can lead to a large error in the predicted change in evaporation by showing the relationship between evaporation and precipitation at one value of E_p. An increase in precipitation, ΔP, occurs in an arid climate with low P / E_p. This leads to a large increase in E and a small increase in Q, by water conservation, as demand for evaporation is high relative to precipitation supply (red lines). If the same ΔP instead occurs in a non-arid climate with high P / E_p, then the increase in E is slight and the increase in Q will be large as evaporative demand is almost satisfied by climatological rainfall (blue lines).

range of aerosol effects on cloud and hence precipitation have been hypothesized, but their impact remains uncertain (Stier et al. 2024).

Overall, observations, theory and modeling suggest that WWDD adequately describes long-term mean zonal $\Delta(P-E)$ over ocean. Over land, a pattern of tropical and mid-latitude $P-E$ increase and subtropical decrease is still seen, but changes are complicated by changes in relative humidity, atmospheric circulation and the direct effects of radiative forcing, especially below continental scales. Future theoretical work that constrains climate change regionally and on shorter timescales will be useful because current climate models predict substantial but uncertain changes at these scales that can be masked by taking the model ensemble-mean (Chadwick et al. 2016a) and the time-mean (Duan et al. 2023).

3 | Changes in the Time-Mean Catchment-Scale Water Cycle

3.1 | Understanding Observed and Modeled Changes at the Catchment-Scale

River catchments are the drainage basins of large ocean-reaching rivers (Dai et al. 2009). The spatial scale of catchments is local but potentially more relevant to assessments of blue water availability than smaller scales across which water transfers can more easily occur (Schewe et al. 2014). Catchment analysis is also useful for model development and verification because streamflow observations can be used to verify modeled runoff (Dai 2021). At the catchment scale, the Budyko framework can provide a helpful conceptual summary of how E is linked to P and atmospheric demand for evaporation, E_p, when changes in land water storage, land cover and vegetation functioning can be assumed to be negligible (Roderick et al. 2014) (see Box 1). The Budyko framework implies that the evaporative index, E/P, is expected to increase with the aridity index, E_p/P. At low aridity index, P is relatively plentiful, and changes in E are dominated by changes in atmospheric demand, E_p. At high aridity index, P is small compared with E_p and changes in E are dominated by changes in P. Hence, over higher P land regions, increases in aridity index due to greater atmospheric demand for evaporation driven by warming would be expected to reduce runoff and groundwater. Observations of the 20th century, however, show both increases and decreases in aridity index in the time mean (Greve et al. 2014) and few catchments with statistically significant changes in streamflow (Dai 2016, 2021).

A contributing factor in observed changes may be plant physiology, which exerts multiple opposing influences on surface evapotranspiration. Two important effects that occur in response to increases in atmospheric CO_2 concentration are (1) plant stomatal closure, which increases surface resistance to evapotranspiration, reducing E_p and hence E (Swann et al. 2016; Yang et al. 2019), and (2) increases in leaf area which increase evapotranspiration (Mankin et al. 2019; McDermid et al. 2021). Tree ring evidence for the past few decades is inconclusive as to what extent decreases due to stomatal closure or increases due to increased leaf area dominate plant effects on multi-decadal mean evaporation (Douville et al. 2021) with responses differing regionally (van der Sleen et al. 2015; Guerrieri et al. 2019). Meanwhile, observations of Australia for recent decades see streamflow reductions and increases in evapotranspiration (Ukkola, Prentice, et al. 2016; Trancoso et al. 2017), although (Ukkola, Prentice, et al. 2016) note statistically insignificant increases in streamflow and decreases in streamflow in both very wet energy-limited and very arid catchments. Evidence from model simulations is mixed, with some studies finding that changes in stomatal conductance dominate (Swann et al. 2016; Yang et al. 2019), and some finding that changes in leaf area dominate (Mankin et al. 2017, 2018, 2019; McDermid et al. 2021; Verma and Ghosh 2024). A further complication is that increases in leaf area index have been found to increase precipitation by increasing land surface moisture recycling in both recent observations (Cui et al. 2022) and model simulations (Zeng et al. 2018; McDermid et al. 2021; Lesk et al. 2025) leading to increases in $P-E$ with warming in some regions. Multi-decadal mean streamflow changes are also influenced by shorter-term variations in other climate variables. Changes in the seasonality and shorter timescale variations of P, whether P falls as rain or snow and the relationship between the seasonal cycles of P and E_p control streamflow to different degrees in different climate regimes in addition to land surface controls from topography and vegetation (Padrón et al. 2017).

Overall it seems likely that changes in P are the dominant cause of changes in multi-decadal mean $P-E$ in 20th century observations (Yang et al. 2018). P shows both increases and decreases that are strongly related to shifts in atmospheric circulation tied to both climate change and internal climatic variability (Chadwick et al. 2016a; Vicente-Serrano, Dominguez-Castro, et al. 2021; Vicente-Serrano, Garcia-Herrera, et al. 2021). CMIP5 and CMIP6 21st century projections of $\Delta(P-E)$ vary regionally, with increases in the tropics, a muted response or decreases in the mid-latitudes and increases at high latitudes (Swann et al. 2016; Mankin et al. 2017, 2019; McDermid et al. 2021), broadly reflecting the zonal mean shown in Figure 1b. Changes in regional precipitation remain key to $\Delta(P-E)$ (Roderick et al. 2014; Yang et al. 2018), with plant effects amplifying or reducing changes.

The Budyko framework also does not explicitly consider soil moisture. Although, in general, high P low aridity regions would be expected to have high soil moisture and low P high aridity regions would be expected to have low soil moisture in the multi-decadal mean, further insight into climate change responses is gained by analyzing soil moisture directly. In GCMs it has been established that the largest climate change impacts of land-atmosphere interactions are seen in "transitional" environments on the boundary of moisture-limited and energy-limited states (Koster et al. 2004; Seneviratne et al. 2010). Duan et al. analyzed daily-mean 30°N—30°S warm season changes in response to a $4\times CO_2$ increase in CMIP5 and CMIP6 GCMs (Duan et al. 2023). Although there are large inter-model differences, in the model-mean they found that critical soil moisture values that separate energy and moisture limited environments move to lower values of aridity. This leads to large reductions in latent heat flux in transitional regimes even as E_p increases, and larger values of surface temperature increase in transitional regimes compared with all but the most arid desert regimes. The result is an increase in $P-E$ with warming in transitional regimes that occurs because E decreases more strongly than P. The authors emphasized the importance of analyzing daily data because differences in climate change response occur not only in the mean but also through the redistribution of $P-E$ on daily timescales and that redistribution depends on the soil moisture regime. As with long-term mean changes analyzed above, high P energy-limited regimes show increases in $P-E$ dominated by increases in P and low P moisture-limited regimes show only small changes in $P-E$ associated with small changes in P.

3.2 | Numerical Modeling of Future Blue Water Change

Contemporary projections of future blue water change are typically made using detailed numerical land surface global hydrological models (GHMs) that take meteorological driving data from GCMs but are uncoupled from them and the GCMs own land surface schemes (Schewe et al. 2014). On the face of it, this seems a sensible choice, as driving data may be corrected to remove biases that may impact changes in runoff and blue water. However, as we explain here, the use of uncoupled GHMs also has drawbacks.

Although the difference between GHMs and GCM land surface schemes is not well-defined, GHMs typically focus on representing a range of hydrological processes (e.g., infiltration, runoff and streamflow) whilst climate model land surface schemes focus more on the land surface energy and carbon budgets (Haddeland et al. 2011). As above, because GHMs represent surface processes only, simulations of future changes must be driven by estimates of changes in precipitation and other atmospheric variables taken from elsewhere. These are usually provided from GCM output, meaning that

GHM projections of hydrological change will still contain errors associated with climate models. Climate model simulations show errors in predicting the observed time-mean state and long-term historical changes for both relative humidity (Douville and Plazzotta 2017; Dunn et al. 2017) and precipitation (Mehran et al. 2014; Koutroulis et al. 2016; Vicente-Serrano, Dominguez-Castro, et al. 2021; Vicente-Serrano, Garcia-Herrera, et al. 2021). The non-linear form of the Budyko framework shows how even the mean state bias for precipitation has the potential to impact GHM predictions substantially. A precipitation change, ΔP, will produce a larger $\Delta(P - E)$ where the climatological aridity index is low and a smaller $\Delta(P - E)$ where the climatological aridity index is high (see Box 1). Projections of future hydrological change are therefore made by removing biases in climate model output with respect to present day observations before applying the data to GHMs. However, using GHMs driven by bias-corrected GCM data introduces at least two potential problems into GHM predictions as we discuss below: (i) GHMs are tuned to reproduce present day streamflow, meaning that successful validation against recent historical observations may lead to overconfidence in their ability to represent future streamflow changes and (ii) Incompatibilites between representation of physical processes in GHMs and driving GCMs may lead to errors such as double counting of some physical effects.

We analyze an ensemble of runs from three GHMs driven by bias-corrected data from four CMIP5 GCMs (making a total of 12 runs each for a variety of CMIP5-era RCP scenarios) from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) (Warszawski et al. 2014). The three GHMs differ widely in formulation. H08 (Hanasaki et al. 2008) is an extension of the simple Manabe bucket model (Manabe 1969), which represents the land surface as a set of finite capacity buckets whose evaporation is equal to E_P when the buckets are full but decreases once the amount of water in a bucket decreases below some threshold. H08 introduces irrigation, reservoirs and a simple representation of crops through a series of empirical relationships, and has a surface energy budget formulation that is able to represent the diurnal cycle. Hanasaki et al.'s approach was that a relatively simple GHM formulation simplifies parameter estimation and helps avoid overfitting of empirical model components that may lead to overconfidence in hydrological projections. PCR-GLOBWB, on the other hand, is a much more complex model, that additionally simulates a wide range of empirical relationships for snow, inflitration and runoff, transpiration and evaporation, vertical water fluxes, interflow, baseflow and other vegetation and soil processes (Wada et al. 2014). WaterGAP is intermediate in complexity between H08 and PCR-GLOBWB (Müller Schmied et al. 2014).

Contemporary GCM land surface schemes and GHMs are increasingly difficult to differentiate from one another (Haddeland et al. 2011). However, some clear differences remain between sophisticated GHMs such as PCR-GLOBWB and sophisticated land surface schemes such as JULES (Best et al. 2011) and CLM (Lawrence et al. 2019) that were used in CMIP6. First, although containing a simple representation of plants, the GHMs do not consider the land carbon cycle explicitly, either ignoring or representing plant function without reference to conservation of energy or carbon fluxes. This includes the neglect of changes in leaf area and plant stomata, which may increase or decrease evapotranspiration in a high CO_2 climate as discussed above, potentially leading to systematic differences between GHM and GCM predictions that occur in addition to pseudo-random differences introduced by other differences in formulation. Second, GHMs are tuned by catchment to reproduce present day streamflow as closely as possible. GCM land surface models are not. This tuning may lead to an illusory superiority of GHMs over GCMs when comparing simulations of the recent past to observations. In addition, we should note that although GHMs can indeed simulate 20th century evapotranspiration and streamflow interannual variability and trends adequately (Zhang et al. 2016), they are less able to reproduce observed extremes. GHMs show “low to moderate” ability to represent annual seven-day-maxima (Do et al. 2020) and struggle to represent drought frequency and persistence (Tallaksen and Stahl 2014). Performance below continental scale is better when observations-derived input data are used rather than bias-corrected climate model data, however, suggesting the importance of unforced climate variability to 20th century streamflow (Do et al. 2020).

GCM land surface schemes can be run either “offline” driven by but uncoupled from a model atmosphere as in GHM simulations or “online” coupled fully-interactively to a model atmosphere as in GCM simulations. Comparison of the two configurations shows that coupling to the atmosphere can impact predictions of surface water and energy fluxes substantially. Analysis of E_P calculations shows that offline calculations do not reproduce online CMIP5 GCM calculations, even when using a formulation that is conceptually very similar (i.e., Penman-Monteith) (Milly and Dunne 2016, 2017). Laguë et al. made a direct comparison by imposing the same change in the land surface (albedo, evaporative resistance, and roughness) and calculating changes in surface temperature resulting from solving either the surface fluxes and atmospheric state simultaneously in a GCM (online), or the surface fluxes with the atmospheric fields imposed as inputs (offline) (Laguë et al. 2019). Allowing the atmosphere to adjust to changes in the surface as in the online simulation amplifies the temperature responses by more than 50% almost everywhere.

The relevance of the coupling issue to bias-corrected GHM predictions is twofold. First, calculating surface fluxes offline is subject to the inconsistency between the climate state and the expected surface fluxes described above even if the same equations are used. Second, GHMs and GCMs may use different formulations for surface fluxes, which also means that processes included in the atmospheric state are not necessarily included in the offline calculation—especially plant responses as discussed earlier (Milly and Dunne 2016; Swann et al. 2016). This could lead to double counting. For example, if relative humidity decreases due to stomatal closure in a GCM due to its own land surface model, then this is perceived by an offline GHM calculation as a greater atmospheric demand leading to larger evaporation, while in the GCM land surface model, it is actually associated with smaller evaporation. These issues are potentially compounded if the atmospheric information is being bias corrected.

The ISIMIP ensemble allows direct comparison of raw CMIP5 GCM and bias-corrected CMIP5 GCM-driven GHM results (Warszawski et al. 2014). Ensemble-mean GHM predictions show that both positive and negative $P - E$ time-mean changes are expected in the upper mid-range RCP6.0 scenario for a range of large river catchments (Figure 2). Comparing these with ensemble-mean raw projections of the driving CMIP5 models, discrepancies are large in some cases, with CMIP5 predicting increases in $P - E$ where ISIMIP predicts decreases and vice-versa. CMIP5 GCMs show substantial evaporation biases in the present-day land-mean compared with estimates from reanalysis and observations that have been attributed to biases in precipitation, implying aridity biases in CMIP5 output. The GCMs show regions of both positive and negative bias, but the land-mean bias is positive in the large majority of models (Mueller and Seneviratne 2014). Here, we apply a simple aridity index bias correction of the CMIP5 data using the Budyko framework (Osborne and Lambert 2018) that reduces disagreement between CMIP5 and ISIMIP projections for most of the largest differences (Figure 2c). However, the aridity adjusted differences remain substantial, indicating that more than climatological aridity errors in CMIP5 separate CMIP5 and ISIMIP predictions. There also does not appear to be an obvious systematic difference between the ISIMIP and CMIP5 results that could be explained by the fact that ISIMIP GHMs ignore vegetation responses whereas CMIP5 GCMs consider them (Fowler et al. 2019; Yang et al. 2019). Still, the Budyko framework is only one method for attempting to understand and correct model biases. An alternative approach by Lehner et al. used a linear model of the form $\Delta Q = a\Delta P + b\Delta T$, where a and b are constants estimated from observed interannual variability, and a GCM-derived estimate of the vegetation response to changing atmospheric CO_2 concentration is added. They found that estimates of future multi-decadal mean ΔQ derived from CMIP5 ΔP and ΔT and the linear model showed reduced inter-model disagreement in two of three North American catchments they investigated compared with raw GCM estimates (Lehner et al. 2019).

Future climate-driven changes in groundwater, which is a key component of blue water in many parts of the world, have been predicted using both coupled GCMs and offline GHMs. Using the CNRM fully-hydrogeologically coupled GCM, Costantini et al. find that water table depth reduces (approaches the surface indicating a larger supply of groundwater) on average in both historical and future scenario simulations, but with increases in areas that also see reductions in runoff and soil moisture in many CMIP5 and CMIP6 models, such as Western North and South America, the Mediterranean, and parts of East Asia (Costantini et al. 2023). Reinecke et al. used eight ISMIP GHMs driven by four different GCMs to investigate groundwater recharge rate. Crucially, they used not only GHMs with limited representation of vegetation including H08, WaterGAP, and PCR-GLOBWB, but also CLM4.5, JULES, CLM4.5 LPJmL, and MATSIRO, that represent plant effects including changes in stomatal conductance and leaf area index. Ensemble means broadly support the conclusions of (Costantini et al. 2023). However, there are large differences between results from different models, with the choice of GHM rather than the choice of driving GCM typically dominating uncertainty. GHMs that represent plant effects generally show

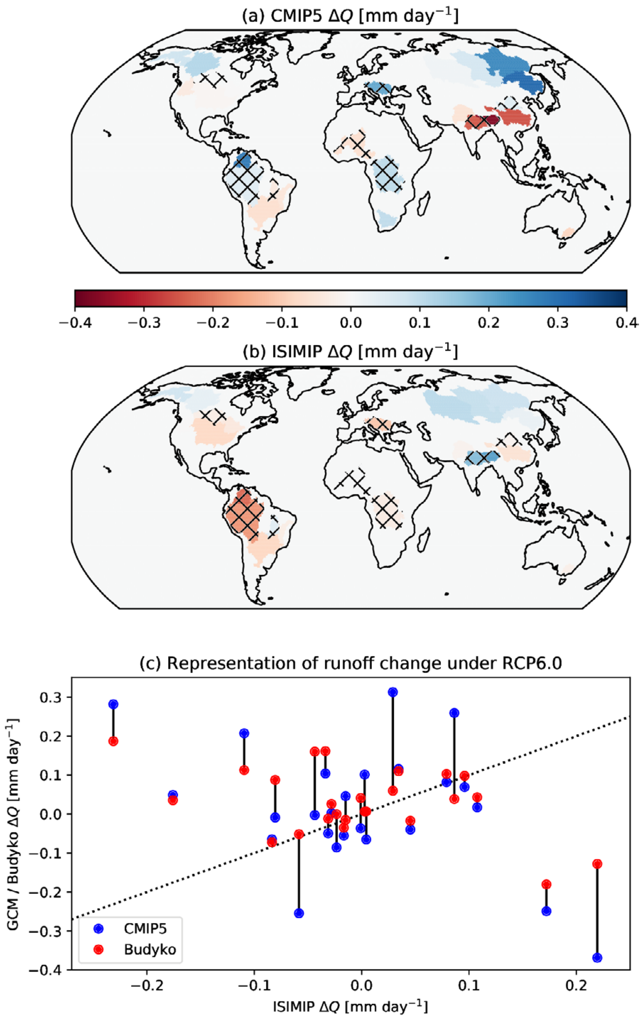


FIGURE 2 | Maps: Raw CMIP5 (top) and ISIMIP (middle) catchment mean changes in RCP6.0 runoff for 2061–2090 with respect to 1961–1990 for the GFDL-ESM2M, IPSL-CM5A-LR, HadGEM2-ES, and MIROC5 CMIP5 models. Catchments for which CMIP5 and ISIMIP means have opposite signs are indicated by hatching. Scatter (bottom): Raw ensemble-mean catchment-mean CMIP5 and Budyko-corrected changes plotted against ISIMIP. Budyko-corrected estimates are calculated using equation 8 from (Osborne and Lambert 2018) and bias-corrected to observations as described in Section 3.2 of the same article. Correction does not substantially improve agreement between raw CMIP5 values and ISIMIP, but some of the largest differences are reduced. CMIP5 data are described by (Taylor et al. 2012) and ISIMIP data are described by (Warszawski et al. 2014).

more positive changes in groundwater recharge than other GHMs, but disagreements between GHMs that represent plant effects are substantial, highlighting the importance of other model uncertainties (Reinecke et al. 2021).

It is clear that continued effort in detailed hydrological modeling, including vegetation representation, and how hydrological models are connected to the atmosphere is important. Although modeling of vegetation responses to increasing CO_2 remains very uncertain (Kolby Smith et al. 2016), the inclusion of plant responses in GHMs will not only improve their representation of physical processes but also their consistency with GCMs that are used to drive them. We have focused on land surface simulation, but deficiencies in atmosphere and ocean modeling are also vital to errors in predicting future blue water change. All models of the Earth's climate solve the equations of thermodynamics and fluid dynamics on a resolved model grid and employ physically motivated but approximate parametrizations to represent poorly understood processes that typically occur below grid scale. Increases in available computing resources have meant that atmospheric models that permit explicit simulation of the key process of atmospheric convection can now be integrated globally (Stevens et al. 2019), but even these models must still parameterize small-scale mixing and microphysical processes.

Contemporary gridded evapotranspiration datasets against which to benchmark models are made either by using machine learning methods to interpolate between sparse point measurements from eddy covariance towers or lysimeters, or by using satellite data to drive simple land surface models (often based on the Penman-Monteith or Priestley-Taylor equations). Global land-mean values are fairly similar across different methods and similar to results found for GCM land surface schemes driven by atmospheric reanalysis data (Pan et al. 2020). All datasets show positive land-mean trends since the 1980s, attributed to increases in leaf area, evaporative demand and precipitation, with leaf area playing the largest role (Yang et al. 2023). However, the magnitude of the trend varies greatly between different observed estimates. Methods that consider plant stomatal effects directly show smaller sensitivity of evaporation increases to leaf area increases (Forzieri et al. 2020), but overall trends over recent decades can be greater or less than for methods that do not consider stomatal effects (Pan et al. 2020; Yang et al. 2023). Land-mean trends predicted by GCM land surface schemes driven by reanalysis data are smaller than most observed estimates for 1982–2011, although agreement between land surface schemes and the Global Land Evaporation Amsterdam Model (GLEAM) (Martens et al. 2017), which shows smaller trends than some other observed estimates, is closer (Pan et al. 2020). Time-mean land-mean values and spatial patterns of E_p calculated using the Penman-Monteith and Priestley-Taylor equations shows broad agreement for the latest CMIP6 GCMs when compared estimates based on reanalysis and observations (Bjarke et al. 2023). Despite this, the latest CMIP6 GCMs still show substantial time-mean biases even with respect to GLEAM (Wang et al. 2020) for evaporation itself that do not appear to have reduced substantially since earlier CMIP5 comparisons (Mueller and Seneviratne 2014). Given these model-observations differences and differences between different observed estimates, the availability of good quality direct evapotranspiration observations remains a concern.

Ultimately, GHMs and GCMs are not the ideal tools for predicting future $P - E$ and blue water change because they cannot represent all relevant processes accurately. However, they are the tools that we have, and we are forced to rely on the range of their predictions conditioned on their ability to represent uncertain observations of the past to give us a measure of uncertainty about the future. While acknowledging great uncertainty in climate model results, we will see in the Section 5 that predicted increases in future human demand for blue water are likely to dwarf climate model predicted changes in blue water supply in many highly-populated regions.

4 | Changes in Water Cycle Variability and Extremes

Sub-seasonal extremes have received substantial attention in the literature, but pose a big challenge for both observations and modeling. This is partly because the rarity of extremes makes it difficult to build large, high quality datasets. A crude expectation is that extreme high precipitation events on timescales of hours to a few days should increase with the supply of local near-surface atmospheric moisture at around 7% per °C. Given that global-mean annual-mean precipitation increases at only a few % per °C in observations and climate models (Adler et al. 2017; Fläschner et al. 2016), the implication is that the temporal intensity distribution of precipitation would see increases in the intensity of high P extremes and decreases in the intensity of less intense P or decreases in precipitation frequency (Trenberth et al. 2003; Pall et al. 2007). Added to this are changes in wind convergence, which can further enhance the most extreme high P events, or changes in relative humidity that tend to reduce high P events over land, and which mean that dewpoint temperature is a more appropriate scaling variable than temperature (Fowler et al. 2021). Analysis of recent observations for Europe (Fischer and Knutti 2016) and Australia (Guerreiro et al. 2018) broadly support these expectations. Climate model results are sensitive to model formulation and experimental design. High-resolution convection permitting models explicitly represent some of the processes relevant to intense mesoscale storms and better represent soil-atmosphere interaction compared with coarse-resolution global climate models, and hence reproduce observations more closely (Marsham et al. 2013; Prein et al. 2015; Kendon et al. 2017; Stevens et al. 2019). Nevertheless, both coarse GCM-resolution and high-resolution climate modeling studies point robustly towards more intense storm hour-mean precipitation (Wasko et al. 2016; Kendon et al. 2017), and associated increases in the severity of low P extremes through increases in the number of multi-day no P events (Kendon et al. 2019). Changes in the spatial size and duration of storms are uncertain, with both increases and decreases found in observations (Fowler et al. 2021). Despite the difficulty of modeling extreme high P events, we note that the robust relationship between extreme high P and near surface air or dewpoint temperature means that simple theory of the kind we have presented for large-scale time-mean precipitation above has the potential to be relevant to extreme high P too. This is because the theory links large-scale time-mean P or $P - E$ to near surface temperature and moisture also.

Turning to effects on the surface, GHMs predict both increases and decreases in seven-day-mean maximum streamflow associated with floods when driven by 21st century climate model projections (although we note again that the ability of GHMs to produce 20th century observations is limited) (Do et al. 2020). When a higher proportion of precipitation falls as extremes, runoff is favored over evapotranspiration in GHMs, meaning that multi-decadal mean runoff can increase in regions of decreases in multi-decadal mean precipitation (Eekhout et al. 2018). These effects would be expected to be enhanced by plant stomatal closure under climate change (Fowler et al. 2019; Kooperman et al. 2018) although stomatal responses are very uncertain (Mankin et al. 2018; van der Sleen et al. 2015; Guerrieri et al. 2019; Singh et al. 2020).

The picture for droughts, which are dry extremes whose characterization depends on the precise definition, is less clear than for high P extremes. We will chiefly consider hydrological drought, which is associated with low streamflow, Q, and low soil moisture. Unlike high P extremes, which tend to occur on hourly to multi-day timescales, hydrological droughts occur on timescales of days or longer. We will focus on multi-day to seasonal timescales, but it is recognized that droughts, such as those associated with long-term sea surface temperature anomalies, can persist for multiple decades (Mishra and Singh 2010). ISIMIP GHMs predict large decreases in time-mean land water storage and associated large increases in hydrological drought days and severity under 21st century climate change in many regions (Pokhrel et al. 2021). But GHMs do not estimate the effects of changes in plant functioning. CMIP5 and CMIP6 climate models that do consider changes in plant functioning also suggest that time-mean near-surface soil moisture is likely to decrease, but that full-column soil moisture including deep soil moisture important to plants will be less impacted due to efficient infiltration of winter rainfall and inefficient summer drying of deeper soils (Berg et al. 2017; Cook et al. 2020). Hence, the severity of hydrological droughts could be reduced by increases in surface resistance to evapotranspiration due to plant stomatal closure that reduce E_p (Swann et al. 2016; Mankin et al. 2018; Yang et al. 2019). However, the effects of increased surface resistance may be counteracted by increased vegetation growth with CO_2 driven climate change that increases the area over which transpiration can occur at the expense of runoff (Mankin et al. 2018; Singh et al. 2020; Vicente-Serrano, Dominguez-Castro, et al. 2021; Vicente-Serrano, Garcia-Herrera, et al. 2021). The net effect of vegetation changes is highly uncertain as increases in evaporation due to increases in vegetation cover are opposed by improved plant tolerance to aridity due to physiological responses to higher atmospheric CO_2. Neither response is well-constrained by observations. On top of plant effects, inadequate representation of soil processes and structure also contribute to model errors in representing present day drought. Notably, evapotranspiration inferred from both streamflow and satellite mass balance observations is frequently found to increase during drought, but this occurs much less in land surface models due to deficiencies in both plant and soil modeling (Ukkola, De Kauwe, et al. 2016; Zhao et al. 2022).

New approaches are looking to improve the modeling of drought through the optimization of plant hydraulics and photosynthesis and their relationship to stomatal conductance (Anderegg and Venturas 2020), but substantial differences in model response at leaf level remain (Sabot et al. 2022). To our knowledge, three CMIP6 GCMs employ hydraulically-optimized stomatal schemes: NCAR CESM2, NorESM2 (both of which use the CLM5 land surface model) and GFDL-ESM4. CESM2 is found to simulate increased evapotranspiration during drought more realistically than GCMs that lack representation of plant hydraulics (Zhao et al. 2022). A future model intercomparison project that explores coupled climate responses when optimized schemes are used would be very useful for determining the remaining uncertainty due to plant effects. Finally on the subject of drought, we note that, although $P - E$ and Q can provide an assessment of long-term blue water changes, below seasonal timescales $P - E$ can show limitations in representing hydrological drought in some catchments due to the influence of surface temperature, and soil and vegetation characteristics among other factors (Peña-Gallardo et al. 2019).

In addition to short term extremes, observations and climate model experiments have been analyzed for better observed, more tractable to model, seasonal to interannual variability. Both observations and models suggest increases in seasonality and amplification of high P and low P events with climate change (Chou et al. 2013; Stephens et al. 2018). CMIP5 models predict that precipitation variability will increase with global-mean temperature (Pendergrass et al. 2017) and global-mean precipitation change (Thackeray et al. 2018). Figure 3 shows changes in $P - E$ variability and extremes in the high-end CMIP6 SSP585 scenario. Shorter temporal means indicate larger changes in future $P - E$ variability on timescales of a few days but also more inter-model disagreement, especially in the tropics (Figure 3, top row). Despite large uncertainty, the bigger changes seen on shorter timescales in climate models are consistent with the expectation that climate change impacts on short timescale events will emerge first (Kendon et al. 2018; Tebaldi et al. 2006).

Another important feature are abrupt transitions between very dry and very wet conditions that show increases in frequency and magnitude in many regions in past and projected future climate change and that affect both subseasonal extremes and longer-term variability. This has been shown both for surplus P over E_p (Chen and Wang 2022; Swain et al. 2025) using the Standardized Precipitation Evapotranspiration Index (SPEI) defined by Vicente-Serrano et al. (2010), for surplus P over E_p where plant effects on evaporation are considered but the effects of unknown land surface moisture storage changes are neglected (Ficklin et al. 2022) and where soil moisture is taken into account (Qing et al. 2023). Analysis of SPEI in reanalysis data suggests that abrupt transitions have increased globally in recent decades (Swain et al. 2025) with more frequent, higher intensity, more rapid transitions occurring in parts of North America, South Brazil, Central Africa, Europe, East Asia and West Australia (Chen and Wang 2022). These studies predict further increases in abrupt transitions in future. Larger swings between flood and drought conditions in a warmer climate are predicted over both land and ocean partly because percentage increases in large P extremes are expected to follow or even exceed percentage increases in atmospheric moisture content while increases in time-mean P increase less strongly constrained by energetic constraints, as discussed above (Swain et al. 2025). However, it is suggested that over land the surface is also able to drive increases in drought-to-flood conditions through surface warming and evaporation that produce convective rainfall in wet energy-limited regions and that drive increased atmospheric convergence in moisture-limited regions (Qing et al. 2023).

Also of interest are the spatial scales over which changes in climate are largest compared with unforced variations. Figure 3, bottom row shows the ratio of SSP585 2080–2099

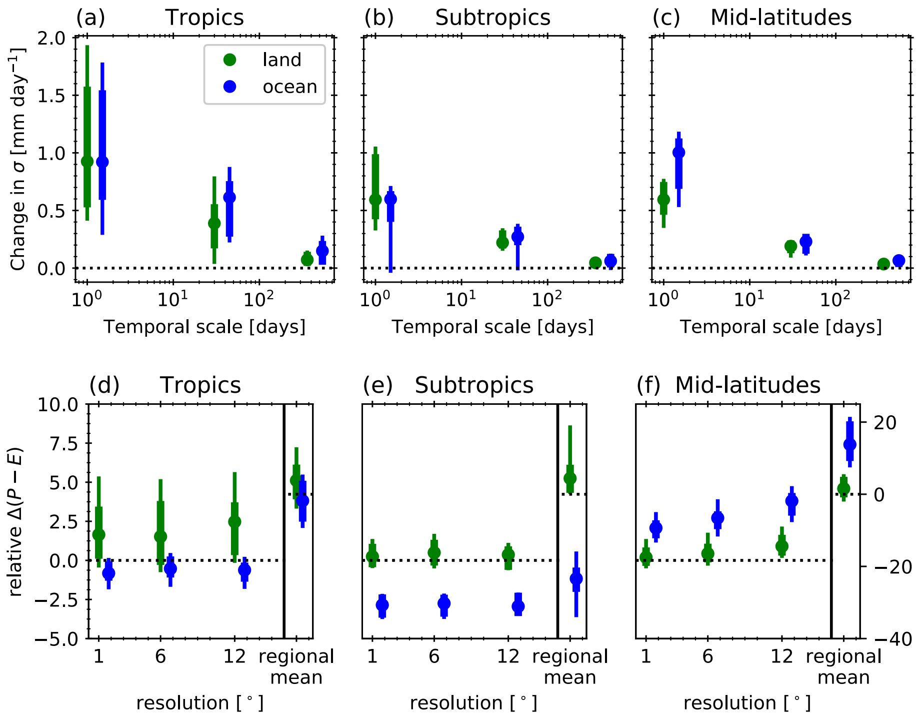


FIGURE 3 | Top row: Change in 2080–2099 $P-E$ standard deviation with respect to 1995–2014 control for 11 CMIP6 models under the SSP585 scenario following the Methods section of Pendergrass et al. (2017). Points are median daily, monthly and yearly temporal mean changes for tropical (20°N—20°S, left), sub-tropical (20°–40° in both hemispheres, middle) and mid-latitude (40°–60° in both hemispheres, right) spatial means. Thick lines are inter-model interquartile ranges, thin lines are interdecile ranges. Bottom row: Future multi-decadal mean $P-E$ changes scaled by unforced $P-E$ unforced variability. Differences between 2080–2099 and 1995–2014 time-mean $P-E$ at each spatial point for each spatial resolution (1°, 5°, 15° and whole latitude band) are taken for 23 CMIP6 models. Twenty identically-calculated unforced differences are prepared by taking the difference between twenty twenty-year time-mean control sections and twenty different twenty-year time-mean control sections. The standard deviation of the twenty differences is then taken at each spatial point. The forced differences at each spatial point are divided by the unforced standard deviations to give ratios whose means are the points on each panel. Thick lines are inter-model interquartile ranges, thin lines are interdecile ranges. Note the different vertical scale for regional means shown on the right-hand side of each panel. CMIP6 data are described by (Eyring et al. 2016).

minus 1995–2014 $P-E$ mean changes to the standard deviation of 20 identically calculated mean changes taken from the control runs for various spatial means in CMIP6 (see the figure caption for details of the method). It turns out that there are few robust responses to the resolution of spatial averaging across models. However, on all spatial scales, oceanic $P-E$ shows decreases in the sub-tropics and increases in the mid-latitudes. This pattern of increases and decreases is consistent with recent historical changes in oceanic multi-decadal mean zonal-mean salinity (Durack et al. 2012; Grist et al. 2016; Douville and Cheng 2024).

Interannual variability and shorter-timescale extremes also interact. The frequency of regional extreme events is strongly influenced by atmospheric circulation patterns related to longer-term unforced climate variability in the current climate, such as the El Niño Southern Oscillation (ENSO) (Allan and Soden 2008; Li et al. 2020) and the North Atlantic Oscillation (NAO) (Fereday et al. 2018). This dominance is expected to continue into the early decades of the 21st century, with interannual variability-driven variations in extremes masking the emergence of the climate change signal (Deser et al. 2017), although these results depend on the magnitude of both model-simulated variability and climate change for the NAO at least (Fereday et al. 2018). The effects of time-mean climate change and variability are also not separate and are expected to interact to produce more intense extremes in the future (Allan and Soden 2008). For example, because changes in the tropical time-mean state lead to a background more favorable to large ENSO events, extreme ENSO events in CMIP5 climate model simulations under high emissions scenarios occur twice as frequently (Cai et al. 2014).

In summary, possible future changes in high and low $P-E$ sub-seasonal extremes associated with floods and droughts are very uncertain. Compared with changes in long-term mean $P-E$, there is less guidance available from theory and predictions must rely more on model parametrizations of processes that occur below the resolved gridscale. Nevertheless, current models robustly predict that changes in climate will emerge on shorter timescales first. Hence, more work with high-resolution models or models that better represent small-scale processes through new techniques such as those from machine learning is needed (Rasp et al. 2018; Beucler et al. 2024; Kochkov et al. 2024).

5 | Non-climatic Effects and the Link Between Supply and Demand

As we have seen in previous sections, climate models predict both increases and decreases in future regional multi-decadal mean $P - E$. These are very uncertain due to deficiencies in model representation of both atmospheric and surface processes (Douville et al. 2021). Also important for future $P - E$ and blue water availability are human non-climatic influences on the land surface and vegetation and the natural succession of vegetation. At present, vegetation is estimated to be responsible for 35%–90% of land evaporation (Miralles et al. 2016; Wei et al. 2017). Hence, although very uncertain, changes in future vegetation that result both from changes in vegetation functioning (Swann et al. 2016; Mankin et al. 2019) and natural succession and human management (Chen et al. 2019), have the potential to alter blue water availability through changes in runoff. Meanwhile, human water management and demand, which now appropriates around 50% of total river discharge (Abbott et al. 2019)—far more than is considered sustainable (Greve et al. 2018)—can itself change the availability of fresh water through mechanisms independent of climate change. Without proper management, non-climatic human activities have the potential to increase hydrological drought severity and even cause hydrological drought (Van Loon et al. 2016). A GHM study predicted that changes in human demand alone may cause large increases in the length and severity of multi-day droughts in parts of Asia, the Middle East and the Mediterranean in the 21st century (Wanders and Wada 2015).

Mounting water scarcity is often addressed through extraction of environmental flows and groundwater, leading to degradation of aquatic ecosystems and biodiversity loss (Pastor et al. 2014), and depletion of groundwater resources leading to land subsidence and saltwater intrusion (Bierkens and Wada 2019). Costantini et al. considered the impact of future increases in human extraction on their predictions of climatically driven changes in water table depth (see Section 3.2). Over most of the land surface, human extraction was not predicted to have a substantial impact on water table depth. However, in Central Africa and areas of South and East Asia, large increases in human populations will drive water extraction that could reverse climate-driven increases in groundwater. In the Mediterranean, Southwestern USA, and Southern Africa, where climate change is expected to reduce groundwater availability, continued water extraction could become very difficult (Costantini et al. 2023).

Changes in land use, such as the conversion of forests and wetlands into crop and grazing lands are estimated to have resulted in a net reduction in time-mean land-mean evaporation of 3500 $km^3 yr^{-1}$ over the 20th century (Sterling et al. 2013). Although most land use change leads to reductions in evaporation, increases in irrigated cropland increase evaporation at the expense of runoff. Between 1900 and 2005, irrigated land area increased from 0.63 to 3.1 million km^2. Results from both CMIP6 simulations and observation-reanalysis products such as GLEAM suggest that although remote effects outside irrigated regions are small, land evaporation in heavily irrigated areas has increased in recent decades due irrigation (Al-Yaari et al. 2022). In Southern Europe, for example, where 80% of all human water use is directed into irrigation, changes in irrigation practices and agricultural intensification along with natural re-vegetation of marginal land dominate observed reductions in long-term mean streamflow (Vicente-Serrano et al. 2019). The same is true of dam water impoundment, estimated as around 10,000 km^3 of water (Wada et al. 2017), which has increased permanent land surface water area by tens of thousands of km^2. Impoundment tends to increase E at the expense of Q: a substantial portion of estimated time-mean evaporation increases of ~30 $km^3\ yr^{-1}$ caused by an increase in global water surface area for 1984–2015 come from losses from artificial reservoirs (Zhan et al. 2019).

Large changes in land cover caused by deforestation have the potential to alter the global hydrological cycle substantially. The Land Use Model Intercomparison Project (LUMIP) deforestation scenario removed 20 million km^2 of forest from the CMIP6 pre-industrial control scenario—similar to the ~33 million km^2 of primary forest estimated to be removed since 850 CE (Hurtt et al. 2020). Global ensemble-mean time-mean changes across participating GCMs (including ocean) in precipitation are around −0.8% (Luo et al. 2022), which is comparable to the decrease that might be expected from 0.5°C of global cooling (Fläschner et al. 2016). Regional changes are much larger, but very uncertain across models. Taking the mean across only the deforested area itself, the GCMs show changes in mean precipitation from −5.9% to +0.1% (Luo et al. 2022). Impacts of this deforestation scenario on runoff are more neutral. Reductions in precipitation cause decreases in runoff, but these are counteracted by increases in runoff that occur because the proportion of rainfall that becomes runoff is increased when forest is replaced by grassland. Reductions in runoff due to decreases in rainfall appear to dominate over more than 60% of global land area, but land-mean changes are not significant if two standard deviations about the mean are considered (Ma et al. 2024). Two caveats should be stated. First, atmospheric CO_2 concentrations were held at pre-industrial levels, therefore ignoring any plant effects on the carbon cycle or resulting CO_2-driven climate change. Second, lost primary forest was converted into grassland, whereas in reality the ~33 million km^2 primary forest lost was partly compensated for by an increase of ~15 million km^2 in secondary forest cover (Hurtt et al. 2020). It is likely that the conversion of primary forest to secondary forest has smaller impacts on climate and the hydrological cycle than conversion to grassland.

The impacts of deforestation on the hydrological cycle have also been explored in more realistic CMIP6 scenarios. Luo et al. examined the effects of deforestation since 1850 through its direct local effects on the land surface and remote effects mediated by the atmosphere. They found that deforestation drives local reductions in evapotranspiration but has only small effects remotely compared with climate-driven effects (Luo et al. 2024). More generally, Zhang et al. found that land use changes—of which deforestation is a major part—cause increases in CMIP6 historical time-mean precipitation in regions of the Northern Hemisphere and decreases in regions of the Southern Hemisphere. Changes in extremes are uncertain in general, but clearest in regions of intense land use change, such as Southern Hemisphere regions where the number of wet days decreases and the number of consecutive dry days increases (Zhang et al. 2024).

Future climate change scenarios used in CMIP6 anticipate further reductions in total primary and secondary forest area. The high greenhouse gas SSP585 scenario removes 0.9 million km^2 between 2015 and 2100; the largest forest removal SSP370 scenario removes 3.4 million km^2 (Hurtt et al. 2020). These changes are smaller than those explored under LUMIP, but still substantial. It is likely that forest loss plays a role in GCM-simulated impacts on climate and water in CMIP6 future scenarios, especially in the areas where forest is removed. One such region is the Amazon basin, for which 4%–13% of mean precipitation decrease by 2100 is attributable to future deforestation across the range of CMIP6 SSP scenarios (Li et al. 2023). More than 40% of reductions in both precipitation and relative humidity were found to be due to the combined effects of plant physiology and deforestation.

Approximately two-thirds of humanity experience severe water scarcity at least 1 month a year under present conditions (Mekonnen and Hoekstra 2016). This is apparent from the water scarcity index (WSI), also know as the use-to-availability ratio, which is the ratio of water demand to supply, $X/(Q+I)$ (Greve et al. 2018; Falkenmark 1997). Here, X is human water demand and I is stream and groundwater inflow into an area. Inflow is typically small and hence the water scarcity index is usually close to $X/(P-E)$ away from major rivers. Nevertheless, even for the present day, WSI estimates are very uncertain due to uncertainties in GHM simulations (Haddeland et al. 2011). Figure 4 (a) and (b) show the 25th and 75th percentiles of near present-day time-mean WSI respectively for 3 joint economic-climate scenarios (SSP1-RCP4.5, SSP2-RCP6.0 and SSP3-RCP6.0) taken from three GHMs driven by input from five climate models (Greve et al. 2018). Uncertainty is clearly large, but even the 25th percentile shows substantial areas of North Africa and Southern and Eastern Asia with WSI > 0.4, which is a crude measure of high water scarcity (Greve et al. 2018), although the human impact of WSI depends greatly on the level of economic development (Falkenmark 1997) and the water supply to which the local population is already adapted (Schewe et al. 2014). These results are in broad agreement with the findings of (Costantini et al. 2023) for groundwater.

Future WSI estimates are further affected by the choice of economic scenario. Panels (c) and (d) show the 25th and 75th percentiles of time-mean WSI changes for the 2050s. Uncertainty is again large, admitting the possibility of both increases and decreases in future WSI. Nevertheless, the majority of ISIMIP ensemble members show increases in future WSI in regions currently under high water stress. In a similar analysis using ISIMIP data at the country scale, Schewe et al. estimated that the percentage of world population under absolute water scarcity ($<500\,\mathrm{m}^{-3}$ capita^{-1}) would increase to roughly 9% under a 2°C increase in global mean temperature, and the percentage under chronic water scarcity ($<1000\,\mathrm{m}^{-3}$ capita^{-1}) would increase to 21%. As above, these numbers are uncertain even in the present day, with 0%–4% of the population estimated to be under absolute water scarcity and 1%–8% under chronic water scarcity, and predictions of the future show areas of both increased and decreased water scarcity (Schewe et al. 2014). Still, our results and those of Schewe et al. concur with the overall balance of evidence that increases in time-mean human water demand predicted in many regions will not be met by increases in time-mean blue water supply (Wada and Bierkens 2014; Greve et al. 2018), implying that extraction will rely increasingly on unsustainable use of stored land surface water. In the absence of appropriate management practices and water infrastructure, this can increase the occurrence and impact of drought (Van Loon et al. 2016).

Human activities not related to climate change or water extraction can also affect water stored in the land surface. In the continental United States, contamination of groundwater by the oil and gas industry is driving the construction of deeper wells for water extraction. This is particularly important as observations show that the transition from fresh to more saline waters

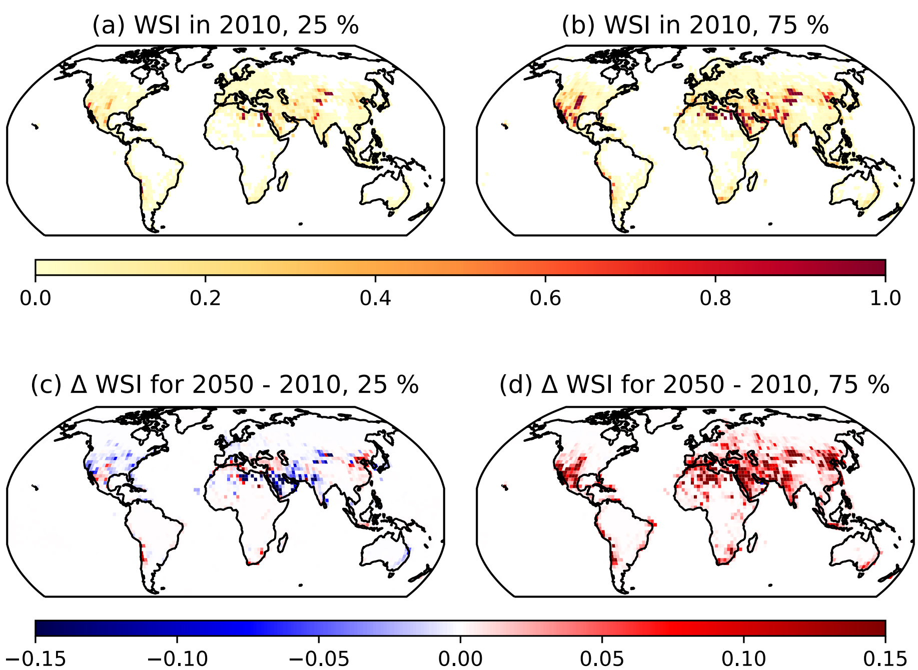


FIGURE 4 | (a) 25th percentile of the water scarcity index (WSI) for 2006–2015 from ISIMIP. (b) 75th percentile. (c) 25th percentile of changes in WSI for 2046–2055 with respect to 2006–2015 predicted by ISIMIP across SSP1-RCP4.5, SSP2-RCP6.0, and SSP3-RCP6.0. (d) 75th percentile. ISIMIP data are described by (Warszawski et al. 2014). WSI values were estimated by (Greve et al. 2018) on a 0.5° longitude-latitude grid. Here we average their data onto a 2.5° grid.

occurs at a shallower depth in the United States than previously expected (Ferguson et al. 2018). If the same is true worldwide, then the store of young (< 50 years old) groundwater may be substantially less than the 0.1–5 million km^3 estimated previously (Gleeson et al. 2016) – equivalent to a layer of water $\sim 0.7 - 34$m deep overlying global land.

Evidently, in many highly populated regions, the effects of future increases in time-mean water demand and non-climatic human impacts may be much greater than time-mean climate change effects on water supply. Climate change-driven changes in shorter time-scale extremes are expected to be large, however, and impact not only blue water supply but also directly disrupt agriculture and communities through flooding (Fowler et al. 2021) and soil erosion (Eekhout et al. 2018). The impacts of increasingly frequent and intense abrupt transitions between drought and flood conditions will also impact blue water availability beyond the isolated effects of individual droughts and floods (Swain et al. 2025). Future projections of changes in abrupt transitions from CMIP6 GCMs for river catchments with large reservoir capacity predict increases in reservoir overspill during precipitation surplus and extended periods of low reservoir levels during drought (Ficklin et al. 2022).

6 | Conclusions and Recommendations for Future Work

In the past few decades there have been considerable advances in the understanding and modeling of future changes in the regional water cycle and its relationship to the availability of blue water for human extraction. Theoretical expectations are in broad agreement with time-mean changes in multi-decadal precipitation minus evaporation, $P - E$, that have been observed or predicted by complex numerical model simulations over both land and ocean on the largest scales, such as in the zonal mean. At continental scales and below, however, there is considerable uncertainty in understanding the past and predicting possible future changes. Changes in precipitation that seem to have dominated historical $P - E$ change are controlled by uncertain changes in atmospheric circulation. Changes in evaporation are further affected by the poorly understood interactions between increasing atmospheric demand for evaporation with warming and plant responses to warming and increases in atmospheric CO_2 that can both suppress and enhance evaporation. Model predictions of the future show opposing signs of predicted future changes in streamflow for large ocean reaching rivers.

A host of human-driven non-climatic effects also cause changes in $P - E$, such as land use change, irrigation, and water impoundment through the building of dams. The combined effect of climatic and non-climatic effects is likely to make a substantial difference to the supply of blue water in the 21st century. However, potentially even more important in the multi-decadal mean are increases in demand for blue water. Despite great uncertainty in future economic-water scenarios and modeling, it seems likely that some highly populated regions will see increases in blue water demand that are not met by increases in supply.

This is not to say that changes in supply are not important. Even if it were the case that time-mean changes in demand dominate changes in supply (and this is by no means certain), changes in the timing of supply are expected to have impacts on flooding and drought that have the potential to cause large impacts on societies. Changes in high $P - E$ extremes linked to storms and flooding in observations and models increase at the expense of lower percentile $P - E$ events with warming. Although there are large uncertainties in model results, this finding broadly follows theory, and is consistent with the expectation that future water cycle changes will emerge at shorter timescales first. Future changes in low $P - E$ extremes linked to subseasonal droughts are very uncertain, again linked to the competing effects of atmospheric demand and plants, but have the potential to cause serious impacts such as increasing the unsustainable extraction of groundwater.

All modeling of changes in Earth's regional climate relies on the parametrization of poorly understood processes that occur below the gridscale at which physical equations are solved. Some processes, such as those involved in cloud microphysics and plant function, seem destined to remain parameterized for the foreseeable future, apparently guaranteeing that predictions of future states that have not been observed will remain uncertain. However, the advent of high-resolution models that physically represent currently parametrized processes and the promise of machine learning methods that make efficient use of available observations, along with recent developments in theory, suggest that we may yet see substantial improvements in predictions of the future water cycle. There is therefore a need for new investment in observations and modeling to best plan for 21st century climate change and water demand. Based on our summary of the literature, we have a number of recommendations for future work.

1. Maintenance and enhancement of observations: Maintenance of the existing observing network is required to monitor 21st century climate change, including surface-based meteorological stations, profiling floats such as Argo that provide near-global salinity measurements, radiosonde observations, and satellites for precipitation, groundwater, soil moisture and sea surface salinity. Enhanced observations of ocean $P - E$, atmospheric transport of water to the continents, estimates of land evaporation and its components from eddy covariance towers and lysimeters, and land water storage including soil moisture, groundwater change and snowpack are also needed (Rodell et al. 2015). There is no direct measurement of oceanic evaporation away from buoys, nor land surface evapotranspiration away from sparse networks of eddy covariance towers and lysimeters. Technological improvements that reduce uncertainty in satellite-derived wind speed, surface temperatures, humidity and vegetation properties used for estimating evaporation are hence important, as are efforts that improve estimates of oceanic precipitation (Behrangi and Song 2020). In addition, the Surface Water and Ocean Topography (SWOT) mission will provide an unprecedented opportunity to monitor surface water and estimate river discharge (Fu et al. 2024). There is

the potential to use data from the Gravity Recovery and Climate Experiment (GRACE) to provide an independent estimate of recent changes in net $P - E$ (Tapley et al. 2004). A substantial challenge is to ensure the long-term stability of satellite observing systems that can provide accurate monitoring of changes in the water cycle over multiple decades and that are therefore also of use for building atmospheric reanalyzes, which are discussed below.

2. Data recovery and use of reanalysis: The number of reporting precipitation gauges has been dropping since the 1990s in many areas (Carvalho 2020) and efforts are needed to counteract this decline. However, data rescue attempts are ongoing that digitize old records, making them available to the community (Brönnimann et al. 2018). It is important to extend these. Atmospheric "reanalyzes" (e.g., ERA5 (Hersbach et al. 2020)), which are model simulations strongly constrained by available observations, are used to monitor poorly observed components of the current hydrological cycle. Future effort is needed to ensure that reanalyzes are useful for understanding climate change, including benchmarking their output against changes in variables not used in reanalysis derivation such as salinity and runoff, ensuring energy and moisture conservation, and quantifying the effect of changes in the observing systems that provide input data to reanalyzes.
3. New model experiments: Although important processes remain unresolved, high-resolution experiments that permit explicit simulation of atmospheric convection have shown their ability to reproduce observed extreme precipitation more faithfully than low-resolution experiments (Kendon et al. 2017). Inclusion of kilometer-scale land surface properties has also been shown to be important for the reduction of model biases (Barlage et al. 2021). Running global experiments is challenging, however, and the production of regional experiments remains important. Producing and analyzing both global and regional kilometer-scale experiments is key for validating our understanding, making predictions, and for training new model parameterizations for low-resolution simulations.
4. Exploitation of new modeling techniques: Even high-resolution simulations continue to parameterize key processes in the atmosphere (e.g., cloud microphysics) and at the surface (e.g., river and groundwater flow). Hence, improvements in modeling may come through new techniques such as those provided by machine learning (Rasp et al. 2018; Beucler et al. 2024; Kochkov et al. 2024) or through targeting reproducing observed relationships for specific processes such as leaf hydraulics or photosynthesis (Sabot et al. 2022).
5. Demand: Continued monitoring, both from space and in situ, of global vegetation, land use change including deforestation, and human consumption of surface water and groundwater reservoirs is needed (Zhao and Ga 2019). Improvements in water demand modeling, aquifer representation, and vegetation modeling will improve understanding of the interaction between demand and supply.
6. Theoretical work that links changes in short timescale variability and extremes to robustly understood and better observed climate variables is needed, as is an understanding of how atmospheric circulation responds to climate change on regional scales, which is key to regional precipitation amounts and hence $P - E$ and blue water availability. This work is particularly important as numerical modeling of key processes depends on physically-motivated but necessarily approximate sub-gridscale parametrizations. Also important is work that connects climate and non-climate impacts on the hydrological cycle to metrics useful to end users.

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Disclosure

The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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