Climate change reduces extent of temperate drylands and intensifies drought in deep soils

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Drylands cover 40% of the global terrestrial surface and provide important ecosystem services. While drylands as a whole are expected to increase in extent and aridity in coming decades, temperature and precipitation forecasts vary by latitude and geographic region suggesting different trajectories for tropical, subtropical, and temperate drylands. Uncertainty in the future of tropical and subtropical drylands is well constrained, whereas soil moisture and ecological droughts, which drive vegetation productivity and composition, remain poorly understood in temperate drylands. Here we show that, over the twenty first century, temperate drylands may contract by a third, primarily converting to subtropical drylands, and that deep soil layers could be increasingly dry during the growing season. These changes imply major shifts in vegetation and ecosystem service delivery. Our results illustrate the importance of appropriate drought measures and, as a global study that focuses on temperate drylands, highlight a distinct fate for these highly populated areas.
Global climate models (GCMs) project consistent increases of climatological aridity for the twenty first century1-3. Yet, GCM projections of meteorological droughts are uncertain and suggest robust increases in some but not all regions4,5. This uncertainty could have particularly strong consequences for dryland regions6,7, which are already limited by water9,10. Drylands may respond to climate change in their distribution, driven by aridity, or in ecosystem structure, function, and composition, driven by ecophysiological processes. Global drylands expanded over the twentieth century by 4–8%5,6 and represent currently c. 40% of the global terrestrial surface (refs 2,5). Despite observations of increasing overall aridity, forecasts of extreme drought events in the second half of the twentieth century remain uncertain14,15,16. Model projections largely agree, however, that drylands will likely continue to expand during the twenty first century1–3,5,10 due to increases in evaporative demand and a global hydrological cycle with longer and more severe dry periods10,12,13. A net expansion of drylands may reduce ecosystem services and impact human livelihoods14 through low water scarcity15,16, vegetation die-offs17, and land degradation18 all of which are exacerbated by human land use19. The projected global trend towards increased aridity is largely robust to variation among models and data sources, even though potential evapotranspiration by itself is unsuitable for understanding drying trends11,20,21. However, global temperature and precipitation projections vary geographically and latitudinally1,10 suggesting different outcomes for tropical and subtropical drylands (hereafter subtropical) drylands versus temperate drylands at mid-latitudes5. Of particular concern for dryland ecosystems, trends in meteorological drought and soil moisture are highly uncertain and generally model dependent6,7.

This uncertainty is especially complicated for soil moisture availability, which is dictated by the combination of weather, vegetation, soil and landscape attributes. In dryland ecosystems, soil moisture controls most ecosystem processes8,22. Reduced primary productivity occurs primarily during periods of reduced soil moisture and not directly to an absence of precipitation8,22,23. Conditions that diminish harvest yields due to below-normal levels of soil moisture, particularly during the growing period, have traditionally been called agricultural drought (in contrast, for example, to meteorological drought which is a period of below-normal precipitation5). The notion of reduced soil moisture has been extended to ecosystems and is referred to as ecological drought8. Ecological drought is commonly described as a ‘prolonged and widespread deficit in naturally available water supplies […] that create multiple stresses across ecosystems’ (US Geological Survey, US Climate Science Centers and the Science for Nature and People Partnership) and has recently garnered widespread attention as one of the topics defining twenty first century climate change14. Because of the complexity of the water cycle, soil moisture and ecological drought projections show large uncertainties among GCMs13,6,7. Soil moisture projections and drying trends are better constrained in subtropical drylands because these are closely linked to the well-represented Hadley Circulation1. Much of the existing research on climate change impacts to drylands has focused on climatic aridity and meteorological droughts, or has been restricted to subtropical drylands. As a result, much less is known about impacts of climate change on soil moisture and ecological droughts, and in particular in temperate drylands.

Vegetation responds to and influences soil moisture through transpiration, interception, shading, and hydraulic redistribution8. Despite adaptations of dryland vegetation to ambient aridity levels8,24, responses to increased droughts and warming under climate change remain difficult to constrain. Potential outcomes include plant functional type shifts18,25, woody plant mortality17 and encroachment26, and resistance of some vegetation types24. These vegetation responses vary among plant functional types and depend on seasonal and soil depth dynamics of soil moisture in addition to climate8,22,27. Three plant functional types—shrubs, C3 grasses and C4 grasses—most frequently dominate temperate dryland vegetation. While all types use shallow soil moisture, shrubs can use water from greater depths8,22. Shifts in the relative dominance of plant functional types, particularly those involving woody species, can impact ecosystem water balance by altering water uptake and evapotranspiration26. Woody plant encroachment has been a concern in grass-dominated drylands worldwide during the twentieth century and is projected to increase under climate change26. Changes in vegetation in response to changes in soil moisture may impact ecosystem services in temperate dryland ecosystems globally.

We applied a two-tiered approach to assess consequences of climate change for global temperate, arid and semiarid drylands. First, we quantified zones of contraction, expansion and stability of the distribution of five temperate dryland regions. Second, we estimated impacts of climate change on seasonal and depth patterns of ecological drought, and their consequences for plant water uptake using SOILWAT28,29, an ecosystem water balance simulation model. SOILWAT utilizes site-specific soils and weather data (here we evaluated spatially and temporally downscaled output from 16 GCMs driven by an intermediate and a high emissions scenario), and SOILWAT soil moisture outputs compare very favourably with GCM estimates (see Methods). Furthermore, SOILWAT provides high temporal resolution (daily) information about ecosystem water balance and plant available moisture that reflects the influence of site-specific soil conditions.

Here we illustrate that GCMs for the late twenty first century project a net loss of c. 15% (following the representative concentration pathway (RCP) 4.5 (ref. 1)) to 30% (following RCP8.5) of current temperate dryland extent due to climatic changes. We show that the duration of ecological droughts during growing periods may substantially increase, especially in deeper (>20 cm) soils. Water uptake by vegetation under future climate could be increasingly reliant on surface soil moisture, favouring shallow-rooted over deep-rooted vegetation, which contrasts with previous projections of increasing dryland woody encroachment26. Plant water uptake patterns within and among regions are projected to become more similar, suggesting a homogenization of niche spaces and vegetation composition. Our findings emphasize contrasting spatial trajectories between subtropical and temperate drylands and highlight the need to assess seasonal as well as spatial patterns of soil moisture dynamics to understand factors that shape the future of temperate drylands and the services they provide.

Results

Spatial response of temperate drylands to climate change. The extent of temperate drylands under current climate is 8.3 × 106 km² based on aridity, climate zone, and mean annual temperature (MAT) (Fig. 1 and Supplementary Table 1). This corresponds to c. 5.6% of the global terrestrial surface and to 20–30%, varying by published estimates2,5, of all arid and semiarid areas globally. Changes in aridity, climate zone, and mean annual temperature projected by GCMs will alter the future distribution of temperate drylands, which we defined here climatologically2. By the end of this century, climate change could lead to a net contraction of temperate drylands of up to 2.4 × 106 km² (1.2–3.3 × 106 km² among 16 GCMs following RCP8.5) with considerable variation among regions (Fig. 1 and
Future scenarios (Fig. 2). Our model, driven by soil data and continuously droughts during growing periods, which we estimated as the Duration and distribution of ecological droughts but not in North America (19%; Fig. 1b–f insets). GCMs showed consistency in four regions (32–80% agreement), currently sub-humid areas (Supplementary Table 3). Our temperate drylands, primarily because of increased aridity in 9% (6–20%) of the current extent would be added in the future as subtropical drylands (Supplementary Table 3). An area equal to converted under the considered scenario mainly to warmer (24–51% among GCMs) of current temperate drylands would be subtropical drylands expand. We found that a median of 36% masks our result that temperate drylands may contract while total may increase by 5–23% globally2,5, that general statement

Supplementary Table 2). RCP8.5 represents a ‘business as usual’ scenario, that is, no mitigation to curb climate change, which will not occur if the Paris agreement to keep the global mean temperature ‘well below 2 °C above pre-industrial levels’ is implemented. All results for the intermediate emissions scenario RCP4.5, which assumes a stabilization of emissions without overshoot, are given in Supplementary Figs 1–10 and Supplementary Tables 1–3, 5, 7, and 10, but are qualitatively similar. While other studies indicate that drylands in total may increase by 5–23% globally, that general statement masks our result that temperate drylands may contract while subtropical drylands expand. We found that a median of 36% (24–51% among GCMs) of current temperate drylands would be converted under the considered scenario mainly to warmer subtropical drylands (Supplementary Table 3). An area equal to 9% (6–20%) of the current extent would be added in the future as temperate drylands, primarily because of increased aridity in currently sub-humid areas (Supplementary Table 3). Our assessment of contracting, stable, and expanding zones among GCMs showed consistency in four regions (32–80% agreement), but not in North America (19%; Fig. 1b–f insets).

Duration and distribution of ecological droughts. Ecological droughts during growing periods, which we estimated as the longest snow-free, frost-free period when soil water potential was continuously < −3.0 MPa, could last longer under projected future scenarios (Fig. 2). Our model, driven by soil data and climate inputs from 16 GCMs, projected increasing drought periods in every temperate dryland region, except for parts of Asia, that are not projected to shift in distribution under climate change (Fig. 2 and Supplementary Tables 4–5). Ecological droughts may become longer over 65% (31–96% among GCMs) of the area of temperate drylands in surface soil layers (0–20 cm) and 85% (68–97%) in deeper layers (> 20 cm). This increase in growing season droughts coincided with a reduction of the warm/wet season overlap due to increasing cold-season precipitation (Supplementary Figs 2–6 and Supplementary Tables 6–7). Increasing ecological drought, particularly during the warm and dry season13, is consistent with other evaluations1–4, and will have consequences for dryland vegetation, including elevated plant mortality, more frequent wildfires, and shifts in plant functional types. East Asia is the only region with projections that consistently diverged from the trend of increasing ecological drought, which is consistent with previous studies1. This may be related to East Asia being the only region with a positive warm/wet season overlap (Supplementary Fig. 5). Ecological droughts in East Asia may become shorter instead of longer in over 43% (surface layers) and 26% (deeper layers) of the region.

The projected intensification of ecological droughts is more pronounced for deep layers (+10%, 0–20% corresponding to +18 days, 8–38 days, longer dry periods) than surface layers (0%, −12 to 30%; +2.6 days, −7 to 17 days) particularly for contracting and expanding zones. This result was surprising since increased cold-season precipitation might be expected to enhance
Discussion

Net reductions in the area of temperate drylands occurred in our projections following an intermediate and a high-emission scenario across all five temperate dryland regions and illustrate the different impact of climate change on the distribution of temperate versus subtropical drylands. The latter are projected to expand due to conversions from temperate to subtropical climate in addition to increased aridity in currently sub-humid subtropical regions. Consequences for vegetation of a shift from temperate to subtropical drylands include loss of temperature-controlled seasonal cycle, phenological shifts, increases in frost-intolerant species and dominance of C₄ over C₃ grasses. Furthermore, impacts on ecosystem services could have large consequences for human well-being: aggressive human diseases, including dengue and schistosomiasis, as well as mound-building termites, occur in subtropical climates and could expand as temperate drylands warm, whereas cool season crops such as wheat and potato would no longer be economically viable.

Our findings suggest large and regionally variable shifts in the distribution of temperate drylands under a changing climate, and highlight the complex interplay between seasonal soil water resources and intensified ecological droughts during the growing season that differ with soil depth. While increased water availability at depth would be expected with more cold-season precipitation (favouring woody and deep-rooted species), soil moisture at depth is an important resource for deep-rooted woody species as drought proceeds. Our results suggest instead a soil moisture regime that is increasingly dominated by longer ecological droughts particularly at depth and by available water restricted to surface soils (favouring shallow-rooted herbaceous species) and the cool season (favouring winter annuals, including invasive grasses). Increasing water scarcity in deep soils is relevant for ecosystem function because soil moisture at depth is an important resource for deep-rooted woody species as drought proceeds.

This indicates, for instance, that expected future increases of woody plant encroachment may not be generalizable across all drylands. Our study emphasizes the need to differentiate among drylands and describes intensifications of seasonal and soil depth patterns of drought that could affect temperate dryland plant communities and the services they provide, including water resources, wildlife habitat, soil conservation, agriculture and carbon storage.

Methods

Study area. We identified temperate drylands using three criteria: mean annual temperature (MAT), the Trewartha climate classification scheme, and the FAO/UNEP aridity index (AI) (ref. 36). In addition, we restricted the analysis to areas with soils of less than 90% sand content. We classified temperate areas if

![Figure 2 | Duration of ecological droughts during growing season.](image-url)
climate dependent, we determined the study area under current climate and for each future climate scenario.

We applied a geographic raster with 0.3125° square cells, so that exactly one cell centre of the NCEP/CFSR T382 Gaussian grid\(^4\) fell in each of our cells. Our raster contained 1,152 × 576 cells and had its origin at 90° S and 179.84375° W. We made an initial generous estimate due to lack of complete knowledge about which cells may be identified as temperate drylands. From the total possible 663,552 cells in the raster, we included 20,021 cells for running simulations. After completing simulation runs, we determined that 12,638 out of the 20,021 raster cells classified as temperate drylands under either current climate or at least one future scenario. We considered only this subset of cells for further analysis.

We grouped the 12,638 raster cells in six geographic regions (Fig. 1) based on the UN geoscheme (United Nations Statistics Division: Composition of macro geographical (continental) regions, geographical sub-regions, and selected economic and other groupings; available at http://unstats.un.org/unsd/methods/m49/m49regin.htm; accessed on 4 Feb 2014). 'South America' (< 15° N & > 25° W); 'Southern Africa' (< 0° N & > 0° & < 55° E)—we omitted Southern Africa from further analysis because only one cell under a few climate conditions was identified as temperate dryland; 'Eastern Asia' including the eastern portion of Southern Asia (along border of Afghanistan/Pakistan except area around city of Quetta) and the eastern portion of Eastern Europe (≥ 87° E starting about at the border point of Russia, Kazakhstan, and China); 'Western and Central Asia’ including the western portion of Southern Asia (along border of Afghanistan/Pakistan plus area around city of Quetta) and western portion of Eastern Europe (≥ 87° E); 'Western Mediterranean basin’ (W of the Dinaric and Pindus Mountains) including Europe and Northern Africa, but excluding Eastern Europe (≥ 0° N and ≤ 25° W and ≤ 14° E); 'North America' (≥ 25° N and > 50° W).

**Simulation framework.** We utilized SOILWAT, a daily time step, multiple soil layer, process-based, simulation model of ecosystem water balance\(^5\)\(^-\)\(^7\). SOILWAT has been applied and validated in dryland ecosystems including temperate grassland\(^8\)\(^-\)\(^10\), temperate shrub-dominated ecosystems\(^9\)\(^-\)\(^11\) and temperate dry-domain forests\(^12\). Inputs to SOILWAT include daily weather conditions (mean daily maximum and minimum temperature and daily precipitation), mean monthly climate conditions (mean monthly relative humidity, wind speed and cloud cover), latitude, elevation, vegetation (mean monthly live, standing and litter biomass, active root depth profile) and soil properties (texture of each soil layer). SOILWAT estimates processes for each functional plant group including
interception by vegetation and litter, evaporation of intercepted water, transpiration and hydraulic redistribution from each soil layer. Transpiration and evaporation are estimated by limiting potential rates with stress functions of soil water potential, atmospheric demand, seasonal leaf area, rooting distribution, vegetation-specific critical soil moisture values of water extraction and shading of canopy and litter45. This is an approach comparable to the modified Jarvis–Stewart model42,43. SOILWAT estimates hydrological processes including partitioning of precipitation into snowfall and rain, snow accumulation, melt and loss, infiltration into the soil profile, percolation for each soil layer, bare soil evaporation and deep drainage26,39. PET is calculated using the Sellers’ formulation44 of Penman45 which incorporates day length effects. Because estimations of PET with Penman-based equations had a tendency to overestimate PET in some regions46, we corrected our PET estimates by multiplication with 1.2 based on a comparison with PET values for 1961–1990 (FAO global map of monthly reference evapotranspiration—19; available at http://www.fao.org; accessed on 24 Oct 2012).

Our simulation experiment consisted of a total of 20,020 cells, which we subjected to present climate and two RCPs (RCP 4.5 and RCP 8.5) and the resulting climate projections of 16 global circulation models. We executed this experiment on Yellowstone at the National Center for Atmospheric Research–Wyoming Supercomputing Center47 and Advanced Research Computing Center’s Mount Moran/Bighorn facilities at the University of Wyoming.

**Input data for weather conditions and climate scenarios.** We used NCEP/CFSR products38 on a T382 Gaussian grid (resolution of ∼ 0.312 × 0.312°) to simulate current climate conditions (1979–2010; Supplementary Figs 2–6 and Supplementary Tables 6–7). Specifically, we extracted daily maximum and minimum temperature (2 m above ground) and precipitation from the 6-hourly data sets (d093.9 and d093.1 (ref. 48)). We also extracted relative humidity (2 m above ground), wind speed and speed components (10 m above ground) and total cloud cover, which we converted to sky cover via sunshine percent49 from the monthly data set (d093.2 (ref. 48)) and calculated mean monthly values.

We extracted for the centre of each cell 32 projected future climate conditions as monthly time-series for 2069–2099 from 1/2° downscaled and bias-corrected products of the fifth phase of the Climate Model Intercomparison Project50 (CMIP5) of 16 global circulation models (GCMs) for two RCPs51, RCP4.5 and RCP8.5, from the ‘Downscaled CMIP5 and CMIP5 Climate and Hydrology Projections’ archive52 at http://gdo-dcp.ucdavis.edu/downscaled_cmip_projections/ (data accessed on 4 Feb 2014). We combined historical daily data (NCEP/CFSR) with monthly GCM projections of historical and future conditions with a hybrid-delta downsampling approach to obtain future daily forcing34,53. We selected 16 GCMs from all those that participated in CMIP5 that represented the most independent and best performing subset of GCMs53 (Supplementary Table 8).

Changes in annual precipitation across temperate drylands showed an overall median increase of ∼ 48 mm yr⁻¹ (∼13 to 91 mm yr⁻¹); however, there was important variation among regions (∼ 39 mm yr⁻¹ for South America to +58 mm yr⁻¹ for Western and Central Asia) as well as within regions (Supplementary Fig. 2 and Supplementary Tables 6–7). MAT increased consistently across GCMs by ∼ +5.2 °C (3.4–7.3 °C) for all regions except South America, where the lowest increase was ∼ +3.1 °C (Supplementary Fig. 3 and Supplementary Tables 6–7). PET increased similarly consistent with an overall median of +28 mm yr⁻¹ (94–209 mm yr⁻¹) (Supplementary Fig. 4 and Supplementary Tables 6–7). The typical precipitation regime under current conditions was dominated by cold-season precipitation except for Eastern Asia, which showed consistent wet-season precipitation. PET is the sum of mean monthly precipitation of December, January and February on the northern hemisphere, and the sum of mean monthly precipitation of June, July and August on the southern hemisphere. Wet/warm-season overlap is the mean annual PET observed within regions, variation among regions, variation among RCPs, and variation among GCMs. Here, we reported results under RCP8.5, which is closely tracked by recent greenhouse gas emissions76. However, RCP8.5 represents a ‘business as usual’ scenario without mitigation; if the Paris agreement30 to keep the global mean temperature ‘well below 2 °C’ (RCP2.6) could be met, the equivalent scenario for RCP4.5 (Supplementary Information) or RCP2.6 (not simulated) could be more realistic. In the article, we focus on variation among regions and among GCMs (note: overall variation among RCP was for precipitation-related variables as large as variation among GCMs, Supplementary Table 9). The variation among GCMs is due to spatial variation and local vegetation (temperate drylands are defined as a function of climate) and due to within-variation in forcing from the 16 GCMs.

We estimated level of spatial agreement by counting GCMs that classified a cell as temperate dryland. We identified three shifting zones for each GCM: the contracting zone comprises cells with a temperate dryland under current, but not under future climate condition; the stable zone comprises cells with a temperate dryland under current and future conditions; the expanding zone comprises cells with a temperate dryland under future, but not current conditions. We calculated summaries by region and shifting zone in two steps to simultaneously account for both effects of variation among GCMs, and the spatial components. We first calculated for each GCM the target summary statistic among those cells that are part of a zone and region. In a second step, we calculated the

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**Analysis of response variables.** Each SOILWAT simulation run produced daily output for each process and water compartment for the 31-year simulation period discarding the first year as spin-up (see ‘Simulation framework’). On the basis of the daily data, we calculated derived response variables (see next paragraph) and then aggregated temporally across 31 years by mean and standard deviation. We calculated these derived and aggregated variables for the current climate condition and for 16 GCMs under two RCPs. We evaluated the results for each RCP by agreement level of temperate dryland classification and by the selection of study area cells for the aggregation of response variable values (details in ‘Variation of response variables’). Because our simulation experiment was deterministic, we estimated effect sizes and performed an evaluation of simulation results, but no statistical hypothesis testing77. We used R version 3.1.2 (ref. 78) for all analyses and for creating figures; we used the R package ‘maps’ version 3.0.2 to add country borders to figures of geographic data.

We chose two derived response variables to capture ecological constraints on potential vegetation. We estimated the mean annual duration of continuous cold-season droughts (defined as groundwater drought resulting in deep soil layers [T20] to transpiration resulting from water uptake from deep soil layers [T20] to transpiration resulting from water uptake from all soil layers [T]).

**Variation of response variables.** We allowed for variation among rater cells within regions, variation among regions, variation among RCPs, and variation among GCMs. Here, we reported results under RCP8.5, which is closely tracked by recent greenhouse gas emissions76. However, RCP8.5 represents a ‘business as usual’ scenario without mitigation; if the Paris agreement30 to keep the global mean temperature ‘well below 2 °C’ (RCP2.6) could be met, the equivalent scenario for RCP4.5 (Supplementary Information) or RCP2.6 (not simulated) could be more realistic. In the article, we focus on variation among regions and among GCMs (note: overall variation among RCP was for precipitation-related variables as large as variation among GCMs, Supplementary Table 9). The variation among GCMs is due to spatial variation and local vegetation (temperate drylands are defined as a function of climate) and due to within-variation in forcing from the 16 GCMs. We estimated level of spatial agreement by counting GCMs that classified a cell as temperate dryland. We identified three shifting zones for each GCM: the contracting zone comprises cells with a temperate dryland under current, but not future climate condition; the stable zone comprises cells with a temperate dryland under current and future conditions; the expanding zone comprises cells with a temperate dryland under future, but not current conditions. We calculated summaries by region and shifting zone in two steps to simultaneously account for both effects of variation among GCMs, and the spatial components. We first calculated for each GCM the target summary statistic among those cells that are part of a zone and region. In a second step, we calculated the
median value among the 16 GCM summary values and used the minimum–
maximum GCM range as indicator of among GCM variation. We determined for each
shift the contribution of each defining factor and determined whether a cell had
changed the climate classification between temperate and boreal35 (1–3 months
with mean temperature ≥ 10 °C), subtropical36 (≥ 8 months with mean
temperature ≥ 10 °C) or tropical35 (12 months with mean temperature ≥18 °C), and
where the aridity classification36.
We estimated the relative contributions of cells, regions, shifting zones, GCMs,
and RCPs to the variation of two groups of variables: climate inputs/drivers (MAT,
MAI, PET, wet/warm-season overlap) and the derived ecophysiological
response variables. We calculated the uniquely attributable variation based on
additional factors as a percentage of the total variance for each
variable for the extent of the study area for each climate condition. We partitioned
the variation for the absolute variable values under each climate condition and as
difference between future and current conditions. Absolute values indicated that
most of the variation was attributable to among-cell variation (mean ± 1 s.d. are
68 ± 38% for climate drivers, and 63 ± 19% for response variables) and the rest to
among-region variation (Supplementary Table 9). Variation attributable to
among-GCM and among-RCP variation were of similar size, but only relevant for
differences between future and current conditions (20 ± 11% and 22 ± 27% for
climate drivers, and 9 ± 5% and 7 ± 12% for response variables). The large variation
among climate drivers for the attribution of RCP arose because MAI and PET
were primarily driven by variation in RCP whereas other drivers (MAI, PET,
warmer-season overlap) showed larger variation among GCMs.
Comparison of SOILWAT results with other approaches. We compared
projections of GCMs against SOILWAT output of mean monthly soil moisture. The
variable "soil moisture content" was extracted for seven GCMs under historical and future
(RCP4.5 and RCP8.5) scenarios from non-downscaled
data from the ESGF node https://pcmdi.llnl.gov/. We calculated normalized mean
monthly values for the periods of 1980–2005 and 2070–2099 for each of our
simulated raster cells and compared agreement with equivalent soil moisture values
from SOILWAT output. We estimated agreement between models with Duveiller’s Z,
which is the best performing symmetric agreement index82. Z ranges between 0 and
1 where 0 indicates no agreement and 1 is perfect agreement. λ is proportional
to Pearson’s correlation index and accounts for systematic and unsystematic bias.
The comparison is favourable with an overall agreement level for the historical time
period 0.37 ± 0.21, which increased to 0.67 ± 0.09 for the future period under the
RCP8.5 scenario. The regional agreement for the historical time period was run with
observation-based weather data, whereas the GCM output represents hindcasts.
For the future time periods, the representation of climate conditions for our
simulations were based on GCM output. Thus, we expected a higher agreement
between our simulation results and those from GCMs for the future time periods
than for the historic period. Friedman et al. compared GRACE satellite
observations of terrestrial water storage with GCM predictions for 2003–2012 for
the Mississippi River Basin and found good agreement in overall aggregated values,
but considerable GCM deviations spatially and in water flux partitioning. In a
similar exercise, Wu et al. compared GRACE data to GCM predictions to select
GCMs for the historical period. Over their simulations for the historic time period
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Author contributions
D.R.S., J.B.B. and W.K.L. designed the study with the help of all authors. J.B.B. with the help from W.K.L. and D.R.S. organized and led the working group. D.R.S. carried out the simulation experiments. D.R.S. with the help from J.B.B. and W.K.L. analysed the data and wrote the manuscript. All authors contributed towards interpreting the data and improving the manuscript.

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