

JGR Biogeosciences



RESEARCH ARTICLE

10.1029/2021JG006735

Key Points:

- Increase in mean rainfall and its seasonality affects ecosystem productivity
- Changes in rainfall structure at fine temporal scales only affect water partitioning, not ecosystem productivity
- Field experiments manipulate rainfall outside convection-permitting model projections and can overestimate ecosystem responses

Supporting Information:

Supporting Information may be found in the online version of this article.

Correspondence to:

Y. Moustakis,
i.moustakis18@imperial.ac.uk

Citation:

Moustakis, Y., Fatichi, S., Onof, C., & Paschalis, A. (2022). Insensitivity of ecosystem productivity to predicted changes in fine-scale rainfall variability. *Journal of Geophysical Research: Biogeosciences*, 127, e2021JG006735. <https://doi.org/10.1029/2021JG006735>

Received 29 NOV 2021

Accepted 14 JAN 2022

Author Contributions:

Conceptualization: Yiannis Moustakis, Athanasios Paschalis

Data curation: Yiannis Moustakis

Formal analysis: Yiannis Moustakis

Funding acquisition: Athanasios Paschalis

Investigation: Yiannis Moustakis, Simone Fatichi, Athanasios Paschalis

Methodology: Yiannis Moustakis, Simone Fatichi, Athanasios Paschalis

Project Administration: Yiannis Moustakis, Athanasios Paschalis

Resources: Athanasios Paschalis

Software: Yiannis Moustakis, Simone Fatichi, Athanasios Paschalis

© 2022 The Authors.

This is an open access article under the terms of the [Creative Commons Attribution-NonCommercial License](https://creativecommons.org/licenses/by-nc/4.0/), which permits use, distribution and reproduction in any medium, provided the original work is properly cited and is not used for commercial purposes.

Insensitivity of Ecosystem Productivity to Predicted Changes in Fine-Scale Rainfall Variability

Yiannis Moustakis¹ , Simone Fatichi² , Christian Onof¹, and Athanasios Paschalis¹ 

¹Department of Civil and Environmental Engineering, Imperial College London, London, UK, ²Department of Civil and Environmental Engineering, National University of Singapore, Singapore, Singapore

Abstract Changes in rainfall associated with climate change are expected to affect the tightly coupled water-carbon ecosystem dynamics. Here, we study the effects of altered rainfall at 33 sites in North America, as projected by the high-resolution/high-fidelity (~4 km, 1 hr) continental-wide Weather Research Forecasting (WRF) convection-permitting model under a high-emission scenario (RCP 8.5). We make use of a stochastic weather generator to extend WRF outputs, accounting for natural variability and simultaneously separate the changes in total rainfall, its seasonality, and its intraseasonal pattern. We used these rainfall scenarios to study ecosystem responses with the state-of-the-art Tethys-Chloris terrestrial biosphere model. Model simulations suggest that increases in mean annual rainfall dominate ecosystem responses at dry sites, while wet sites are less sensitive to rainfall changes. Sites of intermediate wetness face reductions in productivity, due to reduced growing season rainfall and increased water losses under altered seasonality, which outpace any possible benefits induced by increases in mean annual totals. Changes in the fine-scale temporal structure of rainfall have an insignificant impact on ecosystem productivity and only alter hydrological dynamics, contradicting expectations based on some field experiments, which, however, are not tailored to directly quantify climate change impacts, but rather to understand the mechanisms leading to ecosystem responses. We further demonstrate how approaches following the “fewer but larger rainfall events” concept might exacerbate ecosystem responses.

Plain Language Summary Rainfall is expected to change with global warming and this can affect ecosystems. Here, we investigate the impacts of changes in rainfall over 33 North American ecosystems, based on high-resolution projections of future end-of-century climate. We extend these projections with the use of statistical tools to study their effects on ecosystem response with a state-of-the-art model. In dry ecosystems where naturally water demand far exceeds water supply, an increase in mean annual rainfall alleviates chronic water stress and stimulates vegetation productivity. In wet ecosystems rarely facing water stress, the increase in mean annual rainfall does not affect vegetation and water is mostly lost as runoff, or recharges the aquifers. In ecosystems where water supply roughly equals water demand, rainfall during the growing season—when water is much needed—is reduced, due to changes in the monthly distribution of rainfall and, hence, vegetation productivity is negatively affected. We also demonstrate that changes in storm characteristics and frequency do not significantly modify vegetation productivity, but are more important for runoff generation and aquifer recharge.

1. Introduction

Rainfall is expected to change under a warmer climate (Allan et al., 2020; Fischer et al., 2013; Fischer & Knutti, 2016). At the global scale, projected changes in mean annual precipitation (Pendergrass et al., 2017; Zhang & Delworth, 2018) are most likely constrained by the surface energy budget at ~3%/K (Allen & Ingram, 2002). Climate models also project changes in the seasonality (monthly rainfall climatology) of rainfall (Pascale et al., 2016). Observations (Markonis et al., 2019; Papalexio & Montanari, 2019) and high-resolution modeling outputs (Prein, Liu, Ikeda, Bullock, et al., 2017; Prein, Rasmussen, et al., 2017) suggest that the temporal structure of rainfall at finer scales (i.e., frequency, intensity, storm profile, and duration) also changes. Precipitation extremes will likely intensify on average at ~7%/K (Clausius-Clapeyron relation; Molnar et al., 2015; Moustakis et al., 2020), with topography, larger-scale dynamics, and local features of atmospheric convection being also important (Chen et al., 2021; Moustakis et al., 2020). Changes in frequency, seasonality, duration, and spatial structure of storms are also expected (Chen et al., 2021; Moustakis et al., 2021).

Supervision: Christian Onof, Athanasios Paschalis

Validation: Yiannis Moustakis, Simone Fatichi, Athanasios Paschalis

Visualization: Yiannis Moustakis

Writing – original draft: Yiannis Moustakis, Athanasios Paschalis

Writing – review & editing: Yiannis Moustakis, Simone Fatichi, Christian Onof

All biomes are sensitive to some degree to most characteristics of rainfall variability (Robertson et al., 2009; Wang et al., 2020), and hence changes in mean annual rainfall, seasonality, and temporal structure can jointly shape ecosystem responses. Future mean annual precipitation increases could stimulate productivity, especially over drier sites (Knapp et al., 2017). Changes in seasonality affecting total growing season rainfall and snow accumulation and melt processes can also affect ecosystem productivity (Bai et al., 2004; Guan et al., 2014; Robinson et al., 2013; Swemmer et al., 2007). Inter-annual rainfall variability also has an effect on ecosystem productivity (Gherardi & Sala, 2015; Knapp et al., 2017) and runoff generation (Markonis et al., 2018).

The various characteristics of rainfall temporal structure (i.e., frequency, intensity, storm profile, and duration) control soil moisture availability, and can, thus, affect ecosystem productivity (D'Onofrio et al., 2019; Fang et al., 2005; Griffin-Nolan et al., 2021; Ritter et al., 2020). Changes in rainfall temporal structure can modify soil moisture dynamics (Porporato et al., 2002, 2004) and plant water availability, and even affect ecosystems that are rarely water limited. Increased vegetation stress can reduce photosynthetic and plant transpiration rates (Fatichi, Pappas, & Ivanov, 2016; Manzoni et al., 2013), and even lead to plant mortality (Preisler et al., 2021). Temporal structure can be particularly important for shallow rooted herbaceous species, which are highly responsive to rainfall pulses (Verbruggen et al., 2021), due to their lack of access to deep water stores. However, even forested ecosystems have been found to be sensitive to changes in rainfall temporal structure, since drought conditions can trigger a number of processes in trees, such as growth limitation, reduction of carbon and water fluxes, and even carbon starvation and hydraulic failure, leading to tree mortality (McDowell, 2011).

Under more extreme precipitation plant canopies can intercept water less efficiently and reduce evaporative losses (Knapp et al., 2008; Porporato et al., 2002). This is the case as under more intense canopy throughfall, water penetrates the soil more deeply and reaches depths where it is sheltered from ground evaporation (Fay et al., 2003; Knapp et al., 2008; Lehmann et al., 2019). It thereby becomes increasingly available to plants as long as their root system is deep enough (Kulmatiski & Beard, 2013). However, under extreme rainfall, water can also be lost as runoff, or propagate further into the soil at depths inaccessible to plants and be slowly lost as deep leakage (Felton et al., 2020), that recharges aquifers.

Numerous field experiments have been performed to understand the importance of changing rainfall in ecosystem dynamics (e.g., Fay et al., 2011; Gherardi & Sala, 2015; Harper et al., 2005; Heisler-White et al., 2009; Knapp et al., 2002, 2008; W. J. Liu et al., 2017; Miranda et al., 2009; Power et al., 2016; Thomey et al., 2011; Zhang et al., 2021). In such field experiments, rainfall is totally or partially excluded with the use of shelters to simulate drought conditions, or supplemented with irrigation. The vast majority of experiments have studied the effect of changes in mean annual rainfall, usually by manipulating the total amount of rainfall during the growing season (J. Liu et al., 2020; Wang et al., 2021).

It has been remarked that experiments usually impose heavy alterations on precipitation variability not experienced in the historical records (Nippert et al., 2006), with annual precipitation changes that can go far beyond General Circulation Model (GCM) projections (Korell et al., 2020b; Song et al., 2019). Moreover, due to their short time-span (typically <4 yr; Wang et al., 2021), field experiments cannot fully account for the stochastic nature of rainfall (Fatichi, Ivanov, et al., 2016). Additionally, given the different experimental setups, intensities of manipulation, and inherent limitations of each study (J. Liu et al., 2020; Song et al., 2019), synthesis of results from multiple studies is not straightforward.

The impacts of changes in fine-scale rainfall temporal structure have been less common in field experiments, which have been mostly conducted in grasslands and shrubland dominated ecosystems (Deng et al., 2018; Fay et al., 2008, 2011; Felton et al., 2020; Gao et al., 2015; Heisler-White et al., 2008, 2009; Knapp et al., 2002, 2008; W. J. Liu et al., 2017; J. Liu et al., 2020; Miranda et al., 2009; Zhang et al., 2021). When studied in an experimental setup, the changes in temporal structure are commonly summarized under the “fewer but larger events” scheme, with more large rainfall events occurring at the expense of lighter/medium events, which also implies increased interstorm periods (e.g., Heisler-White et al., 2008; Knapp et al., 2002; W. J. Liu et al., 2017; Zhang et al., 2021). However, the extent to which the “fewer but larger events” concept relates to realistic projections has not been quantified yet. This is because only recently we are having in our disposal robust climate simulations that can quantify these changes in rainfall structure, overcoming the well-known problems of large-scale GCMs in simulating rainfall (Prein et al., 2015; Stephens et al., 2010).

In summary, disentangling the effects of the multiple facets of realistic rainfall changes on water/carbon dynamics still represents a challenge due to: (a) climate model biases and shortcomings regarding projections of rainfall intensification, (b) the uncertainties inherent to the stochastic variability of weather (especially rainfall), which cannot be captured by field manipulation experiments typically lasting <4 yr, and (c) difficulties in constructing multi-factorial field experiments designed to implement realistic scenarios of rainfall changes, and effectively disentangle the effects of concurrent changes in mean annual rainfall, seasonality, and temporal structure.

In this study, we make use of continental-wide high-resolution (~4 km, 1 hr) outputs of convection-permitting models (CPMs) that have recently been employed, yielding very promising results in simulating fine-scale rainfall statistics (Jacob et al., 2014; Kotlarski et al., 2014; Prein et al., 2015). Using this new stream of data and a weather generator we disentangle the changes in mean annual rainfall, rainfall seasonality, and fine-scale temporal structure of rainfall, and with the use of a state-of-the-art terrestrial biosphere model, we quantify how those changes impact the coupled water/carbon dynamics in various ecosystems in the United States.

The specific questions addressed in this study are: (a) How is altered rainfall under realistic climate change scenarios expected to affect different ecosystems across climates? (b) What is the relative importance of the different components of changes in rainfall (mean annual rainfall, seasonality, and temporal structure) on water and carbon fluxes across different ecosystems? (c) How do realistic convection-permitting projections of rainfall temporal structure differ from manipulations following the “fewer but larger events” concept commonly employed in field experiments?

2. Materials and Methods

2.1. Numerical Experiment Overview

High-fidelity rainfall projections from the Weather Research Forecasting (WRF)—CPM simulations under a high emission scenario (Representative Concentration Pathway [RCP] 8.5; see Section 2.3) are extracted (C. Liu et al., 2017) for 33 locations in the United States and Canada (see Section 2.4.1). Due to their short record (13 yr), the projections are extended with the use of a stochastic weather generator (see Section 2.2.2), and 100-yr long rainfall for 11 rainfall change scenarios are generated for each location (see Section 2.4.2). These scenarios are used as an input to the state-of-the-art terrestrial biosphere model Tethys-Chloris (TC; Fatichi et al., 2012a, 2012b) operating at the hourly scale, to study their impacts on ecosystem scale water/carbon dynamics (see Section 2.2.1). Each rainfall scenario serves to isolate the effects of the different aspects of rainfall change (mean annual rainfall, seasonality, and temporal structure; see Section 2.4.2). Scenarios where rainfall is manipulated following common field experiment protocols are also constructed to compare with the ones driven by WRF projections (see Section 2.4.2).

Percentage changes (%) of key variables and fluxes at the annual scale between the current climate scenario (c_i) and any of the future scenarios (f_i) for each site i , and each ecohydrological variable Y , are expressed as:

$$\Delta^i(Y)(\%) = 100 \cdot \frac{\overline{Y_{fi}} - \overline{Y_{ci}}}{\overline{Y_{ci}}} \quad (1)$$

Statistical significance at the 5% level between the control and future scenarios is inferred based on a two-sample Kolmogorov-Smirnov test modified to take into account the lag-1 auto-correlation for each variable (see Supplemental Methods and Figure S1 in Supporting Information S1). To facilitate comparisons between sites, all water flux variables were normalized by the site's annual rainfall, and changes (%) are expressed as:

$$\Delta r^i(Y)(\%) = 100 \cdot \left(\frac{\overline{Y_{fi}}}{\overline{P_{fi}}} - \frac{\overline{Y_{ci}}}{\overline{P_{ci}}} \right), \quad (2)$$

where P_{ci} and P_{fi} are the site's precipitation under the control c_i and future f_i scenarios respectively.

2.2. Models

2.2.1. Tethys-Chloris

The state-of-the-art terrestrial biosphere model TC (Fatichi et al., 2012a, 2012b) is a mechanistic model that represents at the hourly scale essential physical, biophysical, and biogeochemical land surface processes.

The hydrological component of TC resolves all relevant hydrological processes including canopy interception and throughfall, which are a function of precipitation intensity, and leaf and stem area index. TC represents snow hydrology in detail, accounting for snow interception, solving the snowpack energy and mass balances, and estimating snow accumulation, melt, and associated albedo changes. Vadose zone dynamics are represented with the 1D Richards equation, and infiltration excess and saturation excess runoff are also computed. A sink term representing water uptake by the plants depending on the vertical distribution of root biomass profile is included.

The surface energy balance is based on the commonly used resistance analogue including resistance terms for aerodynamic, leaf boundary layer, under-canopy, soil, and stomatal resistances. Amongst all resistance terms the two most important for this study are the stomatal resistance, which is based on the Leuning (1995) model, and the soil resistance modeled according to Shahraeeni et al. (2012). A “two-big-leaves” scheme and the two stream approximation are used to solve for canopy radiative transfer, which in turn is used to solve the land surface energy budget. Scaling from leaf to canopy is based on the vertical distribution of nitrogen and light in the canopy.

In terms of vegetation physiology, the biochemical model of leaf photosynthesis employed in TC is based on modifications of the Farquhar et al. (1980) model (Bonan et al., 2014; Collatz et al., 1991, 1992; Dai et al., 2004; Kattge & Knorr, 2007; Leuning, 1995; Sellers et al., 1996), and it is essential to solve for stomatal resistance. Assimilated carbon which is not respired, is partitioned among five pools (leaves, living sapwood, fine roots, carbohydrate reserves, and flower and fruits), following a semi-empirical allocation scheme. Carbon can be subsequently converted into heartwood and standing dead leaves, and undergo turnover as a function of tissue age, drought, and cold temperature stresses. Vegetation phenology is simulated through empirical formulae based on root zone temperature, photoperiod length, and soil moisture content.

Plant water stress is parameterized with the use of a simple stress factor β , which is directly applied to the gross assimilation rate, and is a function of leaf water potential and two parameters Ψ_{st} and $\Psi_{50\%}$ which relate to the beginning, and 50% of stomatal closure respectively.

TC has been thoroughly validated against observational and experimental data in previous studies, and has been found to perform well across a larger range of biomes and climates (e.g., Fatichi & Ivanov, 2014; Mastrotheodoros et al., 2020; Paschalis et al., 2015, 2017).

2.2.2. Advanced Weather Generator (AWE-GEN)

Synthetic meteorological data are generated with the AWE-GEN stochastic weather generator (Fatichi et al., 2011; Peleg et al., 2017) in order to extend the 13-yr WRF simulations to a 100 yr-long simulation of “stationary” climate. This is necessary to better understand interannual variability effects. The generator simulates precipitation, air temperature, air humidity, cloudiness, wind speed, and shortwave radiation time series at the hourly scale, while preserving the mean and higher-order statistics for all variables, as well as to a large extent their dependencies (e.g., synchronous and lagged cross-correlations). Rainfall is computed first and, based on the known occurrence of rainfall, the other atmospheric variables are computed maintaining physical consistency among variables (e.g., lower radiation and a smoother temperature cycle in a cloudy day).

AWE-GEN computes rainfall using the Neyman-Scott Rectangular Pulse Model (Paschalis et al., 2014). The parameters of the model include the storm arrival rate, the number of cells in a storm, the within-storm rainfall cell arrival rate, and the parameters that describe the probability distributions of the rainfall cell duration and intensity. All model parameters vary with the calendar month. Possible biases in replacing WRF rainfall with AWE-GEN simulated rainfall have a negligible impact on simulated water/carbon dynamics (Supplemental Methods and Figure S2 in Supporting Information S1).

2.3. Data

The current and future climate scenarios for each site location are based on the continental-wide simulations of the WRF CPM, operating at a ~ 4 km, 1-hr resolution over North America (C. Liu et al., 2017). The CTL-WRF simulation is a 13-yr retrospective simulation of the present climate driven by ERA-Interim reanalysis data. The future climate projection (PGW-WRF) is a 13-yr simulation of the future end-of-century climate under a high-emissions scenario (RCP8.5), and was generated with a pseudo global warming approach, using the multi-model (19 GCMs, Coupled Model Intercomparison Project Phase 5 [CMIP5]) ensemble-mean change from 1976–2005 to 2071–2100 (C. Liu et al., 2017). The performance of the WRF simulations in representing rainfall has been evaluated and the projected rainfall intensification has been thoroughly documented in previous studies (Cannon & Innocenti, 2019; Dai et al., 2020; C. Liu et al., 2017; Moustakis et al., 2021; Prein, Liu, Ikeda, Bullcock, et al., 2017; Prein, Liu, Ikeda, Trier, et al., 2017; Prein, Rasmussen, et al., 2017; Rasmussen et al., 2020; Scaff et al., 2019).

For each site of interest, all atmospheric variables are extracted from CTL-WRF. Present and projected rainfall are extracted from CTL- and PGW-WRF. Statistics extracted from the WRF simulations are used to parameterize the weather generator. One statistic that is very important but difficult to estimate robustly due to the short length of the WRF simulations is the coefficient of variation of annual rainfall, and its change from the current to the future climate. To obtain this estimate, the relative change from the current to the future climate is estimated based on CMIP5 RCP8.5 mean multi-model (32 climate models), multi-ensemble estimates ($5.4\% \pm 3.8\%$ [mean $\% \pm \%$ standard deviation] increase of coefficient of variation across all sites). Such changes in the coefficient of variation of rainfall are generally insufficient to affect the variability of productivity (Figure S3 in Supporting Information S1).

2.4. Rainfall Scenarios and Case Studies

2.4.1. Case Studies

The 33 sites used in this study cover a wide range of climates and biomes over North America (Figure 1 and Data Set S1). TC has been parameterized and validated over these 33 sites in previous studies and has been found to reproduce well observations (Fatichi & Pappas, 2017; Paschalis et al., 2018; also in Figures S4–S9 and Supplemental Methods in Supporting Information S1). Tropical biomes are not represented in this study, as the extent of the WRF simulations does not cover any region in the tropics.

The wetness index (WI) of each site is expressed as the ratio of mean annual rainfall to Potential Evapotranspiration, approximated as $\lambda^{-1}R_n$ (Roderick et al., 2014), where λ is the latent heat of vapourization, and R_n is the modeled net radiation. Based on WI, we define sites as dry ($WI < 0.65$), wet ($WI > 1.1$), and intermediate (in between).

2.4.2. Experiments

Time series with a length of 100 yr of stationary climate were found to be a good compromise between computational time and the sample size needed to robustly quantify interannual variability with confidence (Supplemental Methods and Figure S10 in Supporting Information S1). Throughout the 100-yr hourly simulations, CO_2 is held constant at 409.8 ppm (2019 global mean average). As the focus of the present study is purely changes in rainfall, we did not opt for a multi-factorial experiment, and all atmospheric variables other than rainfall refer to the current climate, and are computed based on CTL-WRF statistics fed to AWE-GEN. In a strict sense, pairing future rainfall with current climatic conditions violates the global energy and water budget, but this is unavoidable in any setup that tries to isolate the effect of a specific driver of change. Nevertheless, as we use AWE-GEN to generate the meteorological forcing, the variables remain physically consistent and are influenced by the occurrence of rainfall (see Section 2.2.2), and therefore a given rainfall scenario. A flat terrain is assumed and simulations are essentially one-dimensional in the vertical direction. The experiments are as follows:

2.4.2.1. Control Rainfall and Future Rainfall

In the control (future) rainfall scenario, NSRPM is calibrated based on CTL-WRF (PGW-WRF) rainfall.

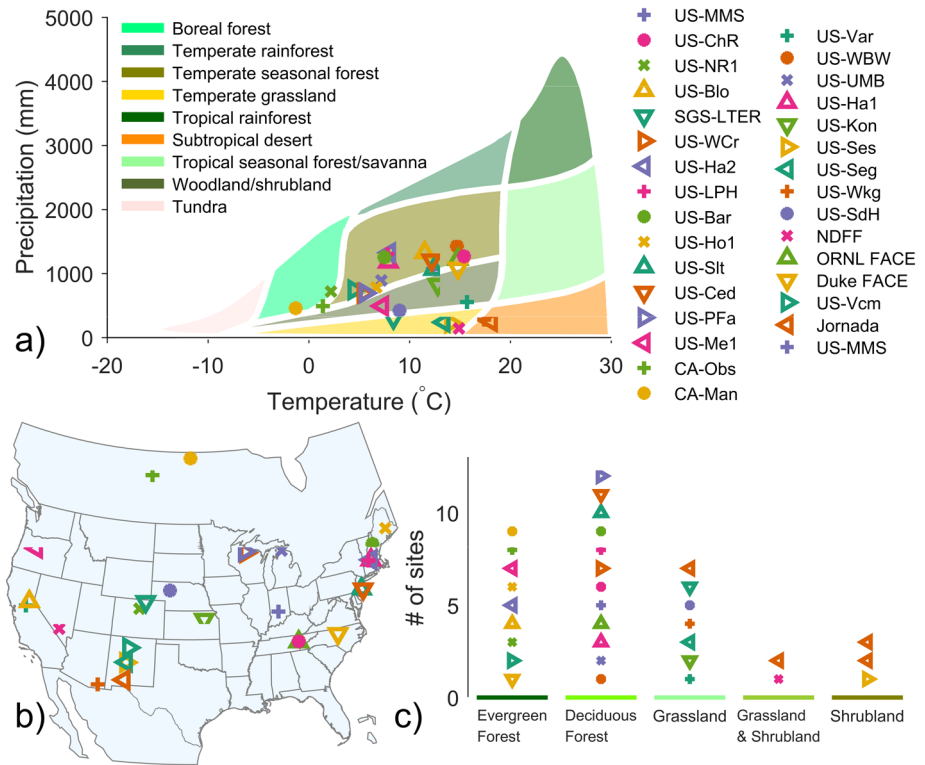


Figure 1. Sites used in this study: This figure shows the sites used in this study scattered over: (a) The Whittaker Biome Diagram. (b) A map covering the North American region. (c) A graph showing the dominant vegetation type at each site is also shown. Each site is represented by a colored symbol as indicated in the legend. A list of site details and the corresponding abbreviations can be found in Data Set S1.

2.4.2.2. Mean Annual Rainfall Change

Only the PGW-WRF projected mean annual rainfall changes are applied to the rainfall time series, while seasonality and temporal structure refer to CTL-WRF. To do so, NSRPM is calibrated based on CTL-WRF, as in the control scenario. The simulated non-zero rainfall values are then re-scaled by a multiplicative factor to match the desired long term mean annual rainfall, as in Equation 3:

$$P = P^1 \cdot \frac{MAP_f}{MAP_c}, \quad (3)$$

where P and P^1 are the adjusted and originally simulated rainfall time series respectively. MAP_f and MAP_c are the future and control mean annual precipitation, respectively.

2.4.2.3. Seasonality Change

Only the PGW-WRF projected seasonality changes are applied, while mean annual rainfall and temporal structure refer to CTL-WRF. NSRPM is calibrated based on CTL-WRF. The simulated non-zero rainfall values are then re-scaled by a multiplicative factor to match the desired long term seasonality, as in Equation 4:

$$P^i = P^{1,i} \cdot \frac{\overline{FUT^i}}{\overline{CTL^i}} \cdot \frac{MAP_c}{MAP_f}, \quad (4)$$

where P^i and $P^{1,i}$ are the adjusted and originally simulated rainfall for each month i , and $\overline{FUT^i}$ and $\overline{CTL^i}$ are the mean monthly amounts for the corresponding month.

2.4.2.4. Temporal Structure Change

Only the PGW-WRF projected changes in the temporal structure of rainfall are applied, while mean annual rainfall and seasonality refer to CTL-WRF. NSRPM is calibrated based on PGW-WRF. The simulated non-zero rainfall values are then re-scaled by a multiplicative factor to match the desired long term mean annual rainfall and seasonality, as in Equation 5:

$$P^i = P^{1,i} \cdot \frac{\overline{CTL^i}}{\overline{FUT^i}}, \quad (5)$$

where P^i and $P^{1,i}$ are the adjusted and originally simulated rainfall for each month i , and $\overline{CTL^i}$ and $\overline{FUT^i}$ are the mean monthly control and future amounts for the corresponding month.

By re-scaling rainfall, we purposely alter intensities, however the other features of the temporal structure of rainfall (i.e., storm structure, duration, and frequency) remain almost intact. Hence, such an approach was preferred, since preserving the rainfall structure is a major focus of this study. Additionally, the separation of the different drivers of rainfall change performed here is meaningful, as confirmed by the isolated effects of mean annual rainfall, seasonality, and temporal structure of rainfall, which additively yield almost the same ecosystem responses of the case with totally altered rainfall (Figure S11 in Supporting Information S1), highlighting the robustness of the approach.

2.4.2.5. Fixed Dry Intervals (D)

In those scenarios, we follow common field practices applied in ecology where the consequences of the “fewer but larger events” scheme are investigated. We modify the Control simulations by applying a fixed 5, 15, or 30-day dry interval, but preserving the total amount of rainfall and seasonality, and create the $D5$, $D15$, and $D30$ scenarios, respectively (Figure 2). The levels of manipulation imposed here are chosen to be comparable with the levels used in the literature (Figure 2). After each dry interval the corresponding cumulative rainfall obtained from the Control scenario in that period is applied at a constant rate. This rate is determined as the minimum among an assumed sprinkler capacity (10 mm/hr), the 0.995th quantile of modeled non-zero rainfall, and the saturated soil hydraulic conductivity, in order to avoid excessive water losses through surface runoff (see Supplemental Methods), which are unlikely to occur in real experiments.

Rainfall is always applied from 09:00 a.m. to follow common field practices and avoid very high or low evaporative demand that could affect the results. Atmospheric variables which are physically correlated and affected by rainfall occurrence (i.e., cloudiness, shortwave radiation, air temperature, and humidity) are not recomputed after the manipulation. This mimics the mismatch that inevitably occurs in a real experimental setup. For example, manipulated rainfall is allowed to occur under clear-sky conditions.

2.4.2.6. Removal of Fixed Percentage of Events (R)

Storm profile, duration, and volume characteristics are completely distorted under the fixed dry-intervals (D) scenarios and a less disruptive manipulation protocol is also employed as an alternative. This approach preserves storm characteristics and the changes in frequency and intensity are effectively isolated. The creation of scenarios $R25$, $R50$, and $R75$ is composed of randomly removing 25%, 50%, or 75% of Control rainfall events (>1 mm), respectively. Events are removed in any given month, and their amounts are equally redistributed to the remaining events by re-scaling them without changing their temporal structure. The remaining events are then randomly reallocated within the month based on a Poisson process with a rate of arrival (i.e., number of occurrences per unit of time) λ that is estimated as $\lambda = n/m$, where n is the number of remaining events, and m is the number of hours in each month. The inter-arrival time in a Poisson process is an exponentially distributed random variable with mean $1/\lambda$. A minimum 4-hr dry interval is assumed to define statistically independent rainfall events. Mean annual rainfall and seasonality are preserved in this setup. Based on the modified rainfall occurrence, all atmospheric variables are then recomputed with AWE-GEN to maintain physical consistency.

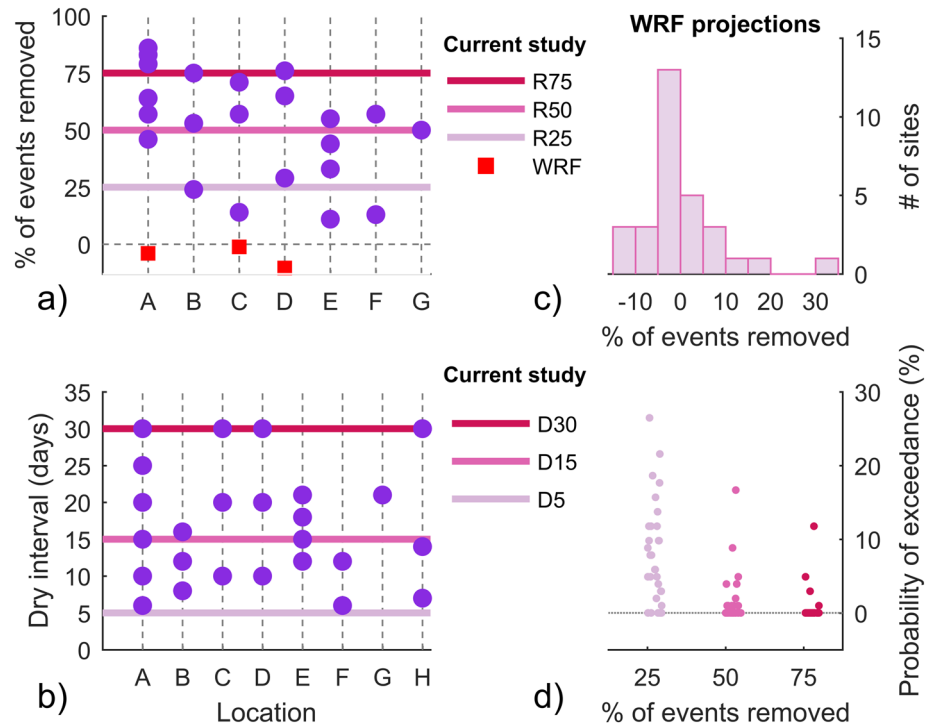


Figure 2. An overview of rainfall manipulation field experiments which studied the “fewer but larger events” hypothesis, found in the literature, with the intensity of rainfall manipulation being expressed as: (a) Percentage (%) of rainfall events removed. (b) Fixed dry intervals (days). (c) A histogram of the distribution of WRF-projected reductions in rainfall events for the 33 sites used in this study. Negative values indicate an increase in the number of events. (d) Probability that a year in the Future scenario exhibits a number of events corresponding to an event removal exceeding 25%, 50%, and 75% from mean Control conditions for each site. Manipulations are grouped based on field experiments conducted over **A**: Konza Prairie Biological Station, Manhattan, KS, USA (Fay et al., 2008, 2011; Felton et al., 2020; Harper et al., 2005; Heisler-White et al., 2009; Knapp et al., 2002), **B**: Inner Mongolian Grassland Ecosystem Research Station, Inner Mongolia, China (W. J. Liu et al., 2017), **C**: Central Plains Experimental Range, Nunn, CO, USA (Heisler-White et al., 2008, 2009), **D**: Agricultural Research Center-Hays, Hays, KS, USA (Heisler-White et al., 2009), **E**: Songen Grassland Ecological Research Station, Inner Mongolia, China (Zhang et al., 2021), **F**: Ordos Sandland Ecological Research Station, Inner Mongolia, China (Gao et al., 2015), **G**: DRI-Grass Experimental Platform, Richmond, NSW, Australia (Power et al., 2016), and **H**: Southeastern Spain (Miranda et al., 2009). In subplot (a) and (b) the *D* and *R* manipulations employed in this study are also shown. WRF-projected event reduction (%) is also shown in subplot (a) for sites A, C, and D which are located within the WRF domain (see Supplemental Methods).

3. Results

3.1. Ecosystem Responses Under Altered Rainfall

Dry, intermediate, and wet sites respond differently to projected changes in mean annual rainfall, rainfall seasonality, and temporal structure of rainfall at finer temporal scales.

The effects of the different components of rainfall intensification are largely additive (Figure S11 in Supporting Information S1) as demonstrated in Figure 3, where the average effects of the total rainfall changes are shown, expressed as percentage changes following Equation 1 (Figures 3a–3c) and Equation 2 (Figures 3d–3h). In Figure 4, the effect of the interannual variability of rainfall on net primary productivity, NPP, and the interannual variability of NPP for all treatments are shown. Detailed ecosystem responses (%) for all relevant ecohydrological variables, along with *p*-values of the two-sided Kolmogorov-Smirnov test regarding the distribution similarity between future and control scenarios for all sites are listed in detail in the table that supplements this work (Data Set S1).

Mean annual rainfall increases dominate responses at dry sites. In particular, annual NPP increases by +5.76%, being driven primarily by mean annual rainfall increases (+7.59% increase in NPP; Figure 3a), and is only slightly affected by changes in seasonality (−0.64%) and temporal structure (−0.48%), which however seem to

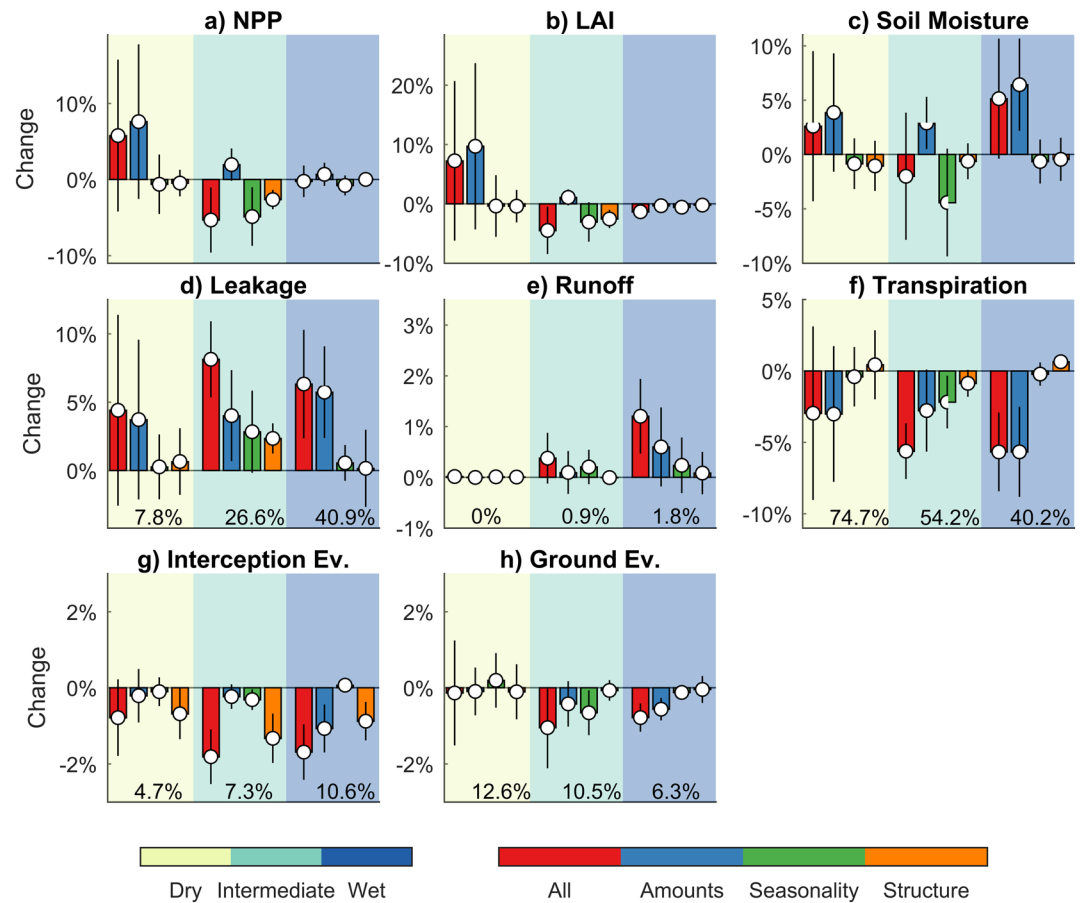


Figure 3. Partitioning the effects of the different components of rainfall intensification: Bar graphs summarizing the effects of the different aspects of rainfall changes on (a) NPP, (b) LAI, (c) soil moisture, (d) leakage to bedrock, (e) runoff, (f) transpiration, (g) evaporation from water intercepted by vegetation canopy (interception Ev.), and (h) evaporation from the ground (ground Ev.) for all sites lumped across the aridity gradient indicated by the colorbar on the bottom left. Changes in (a)–(c) are mean percentage changes relative to the control scenario, following Equation 1. Changes in the water fluxes (d)–(h) are expressed as mean percentage changes in the fractions of the total precipitated water, following Equation 2 (see Section 2.1). The numbers at the bottom refer to the mean values under the Control scenario. The different components of rainfall changes (i.e., total change (all), mean annual rainfall amounts, seasonality, and temporal structure) are indicated by the colorbar at the bottom right. The black solid vertical lines indicate the mean $\pm$ (standard deviation) range.

offset the signal that would result from the mean annual rainfall change alone (Figures S12–S15 in Supporting Information S1). The total increase in NPP is concurrent with a total increase of +7.25% in Leaf Area Index, LAI (Figure 3b). Similarly, the increase in growing season soil moisture θ (+2.59%) is also mostly affected by increases in mean annual rainfall (which contributed +3.85%; Figure 3c), explaining the pattern of NPP, as plant water stress is dependent on θ . Regarding the hydrological cycle, the ratio of Leakage to total precipitated water, L_t/P , increases by +4.40%, which can mostly be attributed to the contribution from mean annual rainfall (+3.72%; Figure 3d). The ratio of transpiration to total precipitated water T/P decreases by –2.97%, driven mostly by the contribution from mean annual rainfall increase (–3.02%), as transpiration increases not as much as precipitation, even though its absolute amount in the future scenario is larger than in the control (Figure 3f).

Changes in seasonality dominate responses at intermediate sites, due to a reduction in mean growing season rainfall (Figure S16 in Supporting Information S1), mostly over deciduous forests (Figure S17 in Supporting Information S1). More specifically, NPP and θ are reduced by –5.34% and –2.01%, respectively, with reductions being mostly attributed to changes in seasonality, where seasonality induced θ decrease is –4.43% and for NPP is –4.89% (Figures 3a and 3c and Figures S12–S15 in Supporting Information S1). Mean annual rainfall increase stimulates NPP (+1.94%; Figure 3a and Figure S13 in Supporting Information S1), while the temporal structure

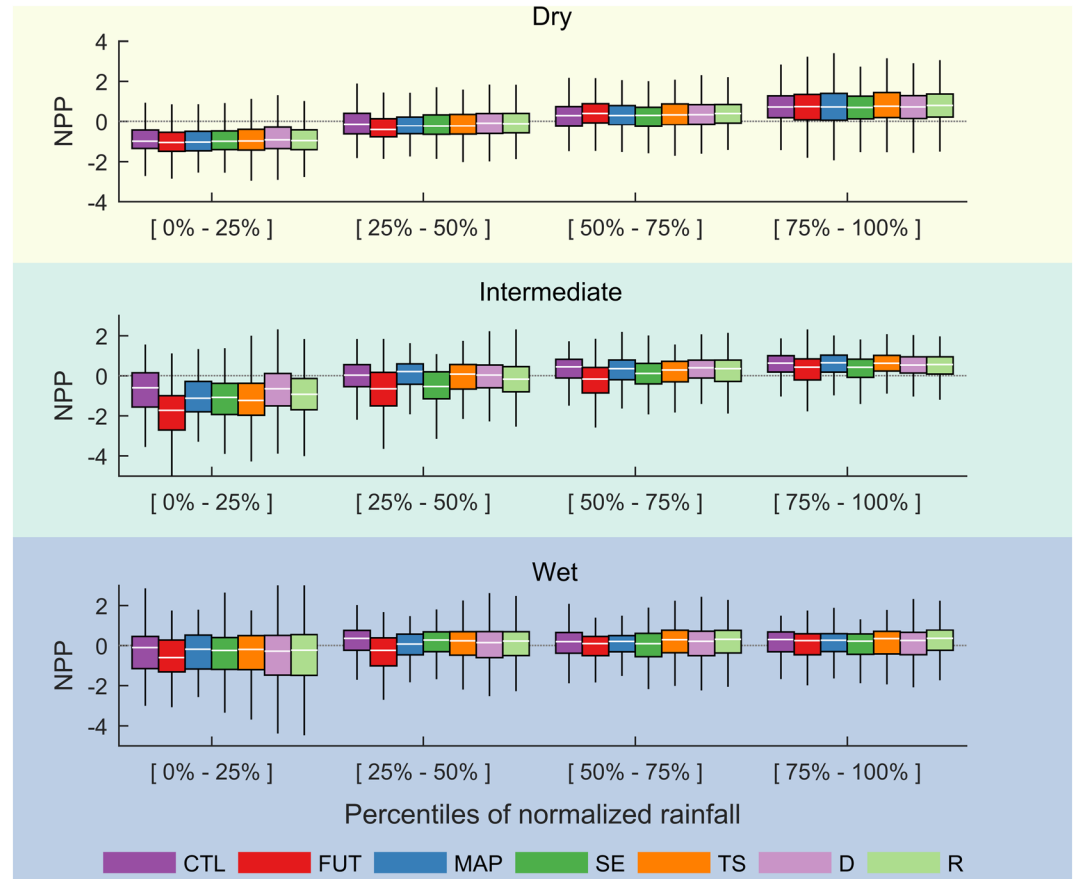


Figure 4. Interannual variability and variability between scenarios: Boxplots showing NPP responses to different levels of annual rainfall, for different scenarios, over dry, intermediate, and wet sites. For each year, class of sites, and treatment, NPP is expressed as z -scores, with respect to the mean and standard deviation of NPP of the Control scenario corresponding to each site, respectively. For each treatment, all z -scores are grouped based on wetness index (dry, intermediate, and wet sites), and on rainfall bins, defined by the quartiles of normalized annual rainfall. The different scenarios are indicated by the colors shown in the colorbar. The scenarios are abbreviated as; CTL (Control), FUT (Future), MAP (only mean annual precipitation changes), SE (only seasonality changes), TS (only temporal structure changes), D (lumped $D5$, $D15$, and $D30$), and R (lumped $R25$, $R50$, and $R75$).

of rainfall reduces NPP (-2.66% ; Figure 3a and Figure S15 in Supporting Information S1). The total decrease in NPP is consistent with a total decrease of -4.49% in LAI (Figure 3b).

The hydrological cycle also changes at intermediate sites, with marked increases in L_k/P , and T/P reductions. In particular, the marked L_k/P increase ($+8.13\%$) is mostly attributed to mean annual rainfall changes ($+4.01\%$), while seasonality and rainfall temporal structure contribute to a lower extent ($+2.83\%$ and $+2.34\%$; Figure 3d). Mean annual rainfall and seasonality changes jointly lead to a small increase in the ratio of runoff to total precipitated water R/P ($+0.37\%$), while changes in the temporal structure of rainfall do not affect R/P (Figure 3e). Total T/P is reduced under future rainfall (-5.62%), due to increases in mean annual rainfall and changes in seasonality. In particular, under increased mean annual rainfall T/P is reduced (-2.78%), due to less than proportional increase of transpiration than precipitation (Figure S13 in Supporting Information S1). Under altered seasonality T/P is also reduced (-2.19%), since T is reduced in absolute amounts, following NPP and LAI reductions (Figure 3e and Figure S14 in Supporting Information S1).

At wet sites, vegetation dynamics are largely insensitive to changes in rainfall, and changes in rainfall mostly affect the water fluxes. In particular, despite a marked increase in θ ($+5.13\%$) attributed to the increase in mean annual rainfall ($+6.41\%$), NPP is not affected significantly (-0.25% ; Figures 3a–3c and Figure S12–S15 in Supporting Information S1). On the contrary the hydrological cycle is considerably altered with increased L_k/P

(+6.32%) and R/P (+1.20%), primarily due to changes in mean annual rainfall (L_k/P + 5.73%, R/P + 0.60%), and to a smaller degree to changes in rainfall seasonality (R/P + 0.23%).

A strong correlation between the amount of water that is totally lost due to leakage and runoff, and NPP exists, explaining ~86% of NPP variance under altered seasonality, and ~36% of NPP variance under altered rainfall temporal structure (Figure S18 in Supporting Information S1).

On average, the ratio of water intercepted by canopy and evaporated to total precipitated water In_e/P , and the ratio of water evaporated from the ground to total rainfall Gr_e/P slightly decrease, while the ratio of transpiration to total evapotranspiration T/ET remains stable. In particular, across all climates, expected changes in rainfall structure alone will decrease In_e/P by -0.91%. Increases in mean annual rainfall can stimulate productivity and lead to increases in LAI which by itself could increase In_e/P . However, by re-scaling current rainfall to match future rainfall amounts, we effectively increase rainfall intensities and, hence, In_e/P is also reduced under increased mean annual rainfall (-0.43%; Figure 3g). Gr_e/P is reduced at intermediate (-1.05%) and wet (-0.79%) sites, mostly driven by changes in mean annual rainfall (-0.43% and -0.57%), and to a smaller degree in seasonality (-0.66% and -0.13%; Figure 3h). Changes in rainfall structure alone increase T/ET (+1.48%; Figures S12 and S13 in Supporting Information S1), contrary to the increases in annual precipitation that decrease T/ET at a similar magnitude (-1.02%), leading to an overall stable ratio (+0.35%) when all rainfall changes are considered.

Interannual variability of rainfall also impacts vegetation dynamics, and the interannual variability of NPP associated with the interannual variability of rainfall is considerably larger than the variability of NPP induced by the various treatments at dry and intermediate sites (Figure 4). In fact, for comparable annual rainfall levels there is a significant overlap in the distributions of annual NPP responses among different treatments (Figure 4). At dry sites, where vegetation is water limited, productivity is substantially higher during wet years and lower in dry years (Figure 4), while at intermediate ones, the relationship between annual rainfall and NPP is saturating as rainfall increases, and productivity does not benefit from additional water during wetter years. At wet sites, which are not water limited, the interannual variability of rainfall does not affect NPP, but is important in shaping the interannual variability of the water cycle.

The future increases in mean annual rainfall suggest an increase in the frequency of wet years, with respect to the current climate. Given the sensitivities of NPP to the interannual variability of rainfall, this increase in frequency of wet years leads to an overall increase in mean NPP at dry sites. At intermediate sites, as mean annual rainfall increases, dry years (with respect to the control rainfall amounts) become less frequent and this enhances plant productivity.

3.2. CPM Driven Responses Versus Rainfall Manipulation Experiments

Under the scenarios of fixed dry-intervals (D) and removal of fixed percentage of events (R), mimicking the “fewer but larger events” scheme commonly employed in field experiments, stronger ecosystem responses are simulated, compared to the ecosystem responses to WRF-projected temporal structure of rainfall presented in Section 3.1 (Figure 5, and Figure S19–24 in Supporting Information S1, and Data Set S1).

At dry sites productivity is slightly stimulated and marked L_k/P and R/P increases are reported, while In_e/P and Gr_e/P are reduced. In particular, NPP increases only by +1.81% under $D30$, and +1.75% under $R75$, however in most cases changes are statistically insignificant (Figure 5a), while θ changes are also small (+1.63% under $D30$ and -1.49% under $R75$; Figure 5c). Variability is strong for the heavier manipulations $D30$ and $R75$. L_k/P increases with D scenarios (+2.93% under $D30$) and the changes are stronger than in the R simulations (+1.62% under $R75$; Figure 5d). T/P also increases in the R scenarios (+4.31% under $R75$), responding more notably than for the D scenarios (+1.95% under $D30$; Figure 5f). Simulated changes in L_k/P and T/P in the heavier manipulations are stronger than those simulated with the WRF-projected rainfall temporal structure changes. In_e/P (-3.43% under $D30$) and Gr_e/P (-1.58% under $D30$) also decrease more than in the simulations with WRF-projected rainfall temporal structure changes (Figures 5g and 5h).

At intermediate sites NPP is reduced, L_k/P and R/P are found to increase, while In_e/P and Gr_e/P are reduced. In particular, the vegetation dynamics show a mixed signal of mostly minor responses under the lighter rainfall manipulations (Figures 5a, 5b, and Figure S19–S24 in Supporting Information S1). However, the heavier manipulations yield a clearer signal of a statistically significant decrease of NPP (-2.24% under $D30$ and -4.13% under

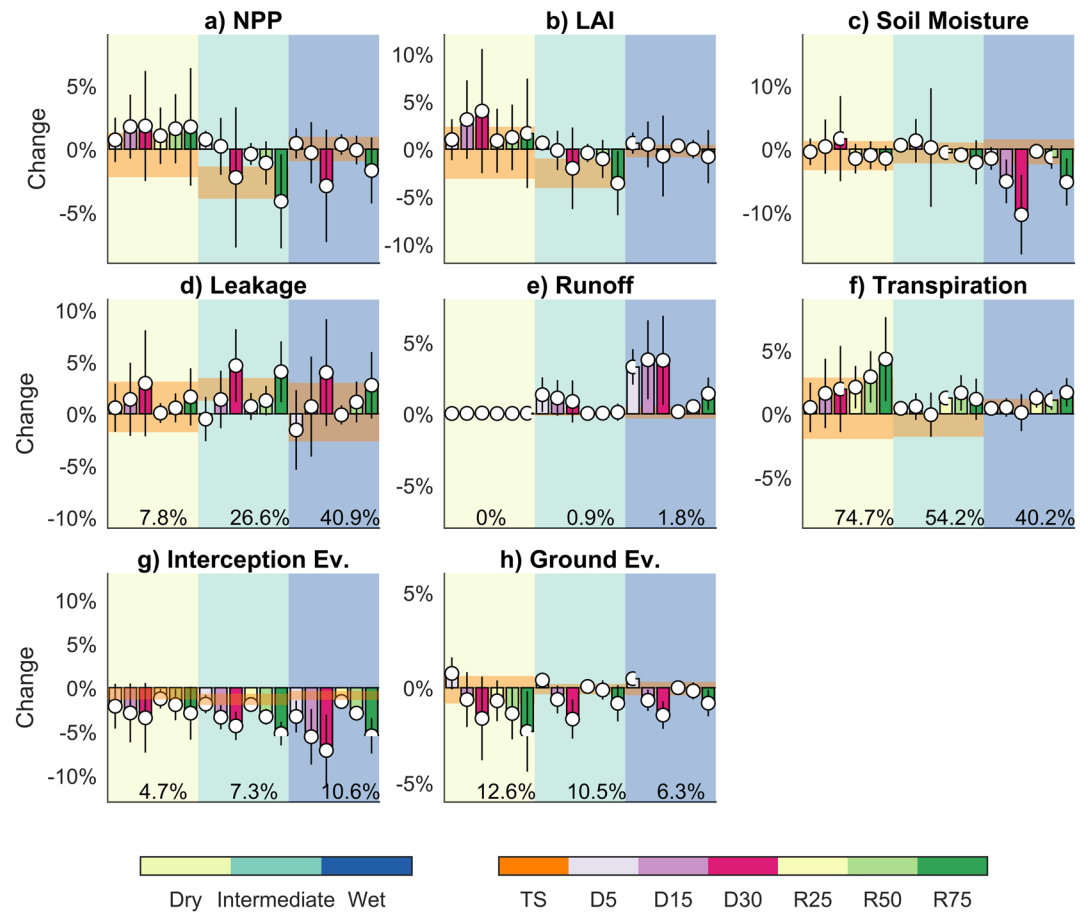


Figure 5. Impacts of heavy manipulations of rainfall temporal structure: Same as Figure 3, but for the *D* and *R* scenarios. For each variable, the orange patches indicate the mean $\pm$ (standard deviation) of ecosystem responses under the scenario simulated with WRF-projected changes in the temporal structure of rainfall (TS).

R75), which far exceeds any impacts obtained by WRF-projected changes in rainfall temporal structure (Figures 5a and 5b). Most hydrological fluxes are also significantly altered in the *R* and *D* scenarios (Figures 5d–5h). L_e/P increases more strongly under *D30* (+4.63%) and *R75* (+4.04%; Figure 5d). R/P increases (+0.86% under *D30* and +0.10% under *R75*), while I_e/P also decreases (–4.35% under *D30* and –5.23% under *R75*; Figures 5e and 5g). G_e/P decreases under *D30* (–1.65%; Figure 5h), with statistically insignificant mixed responses under lighter manipulations. Statistically insignificant T/P increases are obtained under *R* scenarios (+1.14% under *R75*; Figure 5f).

Wet sites respond similarly to intermediate ones, albeit with stronger increases in R/P . In particular, NPP decreases significantly under the heavier *D30* (–2.91%) and *R75* (–1.70%) manipulations, combined with a LAI and θ decrease (Figures 5a–5c and Figures S19–S24 in Supporting Information S1). R/P increases more strongly (+3.74% under *D30* and +1.40% under *R75*) and I_e is more strongly reduced (–7.14% under *D30* and –5.48% under *R75*) compared to intermediate sites (Figures 5e, 5g, and Figure S22 in Supporting Information S1).

A correlation between the amount of water, that is, totally lost due to leakage and runoff and NPP explains ~30% to 36% of NPP variance for *D15*, *D30*, *R50*, and *R75* (Figure S25 in Supporting Information S1). Deciduous forests respond more strongly than evergreen forests (Figure S26 in Supporting Information S1), while shrublands, grasslands, and mixed shrublands/grasslands appear to be overall less responsive to manipulations (Figure S26 in Supporting Information S1). T/ET generally increases with the increase becoming stronger as wetness and manipulation intensity increases, reaching up to a 10% increase (Figures S19–S24 in Supporting Information S1).

The heavier *D30* and *R75* scenarios yield responses of comparable or even stronger magnitude in all water fluxes, when compared to the experiments reported in Section 3.1 (Figure S27 in Supporting Information S1). Regarding NPP responses, the effect of *D30* (+1.81%) and *R75* (+1.75%) scenarios is less important at dry sites, where mean annual rainfall changes remain dominant (+7.59% effect on NPP; Figure S27 in Supporting Information S1). At intermediate sites, changes in NPP under *D30* (−2.24%) and *R75* (−4.13%) are comparable with the impact of seasonality changes (−4.89% effect on NPP; Figure S27 in Supporting Information S1). At wetter sites, NPP is reduced by −2.91% in *D30* and by −1.70% in *R75*, contrary to the negligible impacts of total rainfall change (−0.25% effect on NPP; Figure S27 in Supporting Information S1).

4. Discussion

4.1. Expected Changes in Ecosystem Dynamics Under Changing Rainfall

The overall simulated pattern suggests that with projected rainfall changes, vegetation is stimulated at dry sites, and suppressed at intermediate ones, while plants at wet sites are largely insensitive to these changes (Figure 3). Water losses as L_e/P and R/P increase at the expense of the other water fluxes, mostly T/P . Despite ecosystem responses to changes in each aspect of rainfall variability have been studied separately, it remains unclear the relative importance of all those components under realistic high-resolution rainfall projections. Disentangling total ecosystem responses to the separate effects of changes in mean annual rainfall, seasonality, and temporal structure, is detailed here.

Mean annual rainfall increases are found to dominate water-limited sites, with the WRF-projected changes in seasonality having no marked effect. At the same time, changes in seasonality dominate the responses at intermediate sites, and more prominently in deciduous forests, offsetting any possible gains by increased mean annual rainfall (Figure 3). The reductions reported here are linked to a strong decrease in growing season rainfall (Figure S16 in Supporting Information S1), and a consequent increase in water losses (Figure S18 in Supporting Information S1). This demonstrates that seasonality changes can be very important at intermediate sites which, despite not experiencing chronic water stress, still lie near the boundaries of water-limitation in certain periods of the year, and are sensitive to changes in the seasonal rainfall distribution. Even though seasonality changes can potentially affect wetter ecosystems where sensitivity of productivity to annual precipitation is low (Baldocchi et al., 2018; Ritter et al., 2020; Wang et al., 2020), our results suggest that WRF-projected seasonality changes are not sufficient to affect these wet sites (Figure 3).

Importantly, the results suggest that WRF-projected changes in the fine-scale temporal structure of rainfall have a negligible impact across sites, irrespective of climate and vegetation type. This highlights the importance of mean annual rainfall and seasonality in driving productivity, as compared with changes in temporal structure, which are less relevant in this regard. The footprint of changes in temporal structure only emerges in the hydrological components, with a consistent reduction in I_n/P across sites, and R/P increases at wetter ones (Porporato et al., 2002). Our results confirm some previous studies on semi-arid sites (Densmore-McCulloch et al., 2016; Hao et al., 2017; W. J. Liu et al., 2017; Miranda et al., 2009), and contradict the observational findings of others, where statistically significant changes in productivity have been reported (Fay et al., 2003, 2008, 2011; Gao et al., 2015; Harper et al., 2005; Heisler-White et al., 2008, 2009; Knapp et al., 2002; Thomey et al., 2011; Zhang et al., 2021). However, diverging results have been reported throughout the literature depending on different experimental setups, locations, climate, vegetation types, and treatment protocols (Wilcox et al., 2015), and therefore it is not unlikely that the simulated negligible effects of rainfall temporal structure are realistic.

4.2. Rainfall Temporal Structure Manipulation and Ecosystem Responses

Even though WRF projections of changes in temporal structure have a negligible impact on NPP, stronger ecosystem responses emerge under the numerical experiments where rainfall is manipulated following protocols commonly applied in field experiments (Figure 5). It should be noted that a direct comparison between the 100-yr simulations used here and field experiments, which typically last <4 yr (Wang et al., 2021), is not attempted in this study. However, we do quantify how extreme rainfall manipulation schemes such as the “fewer but larger events” concept affect ecosystems, in comparison with high-resolution realistic rainfall temporal structure projections.

The emerging pattern (Figure 5) seems to agree with the conceptualization of Knapp et al. (2008), according to which amplified soil moisture fluctuations under “fewer but larger events” with prolonged dry-out periods alleviate water stress and benefit arid ecosystems, while at wetter ecosystems water thresholds for deep percolation are expected to be crossed more often, reducing water in the root zone and thus, vegetation productivity (Fay et al., 2003; Knapp et al., 2008).

However, our results also show a strong variability in responses among sites. On the one hand, this suggests that ecosystems with different vegetation, climates, and soil types respond differently to altered temporal structure (Heisler-White et al., 2009; W. J. Liu et al., 2017; Miranda et al., 2009). On the other hand, this indicates that even though the conceptual single-bucket model proposed by Knapp et al. (2008) can be informative for shallow-rooted grasses, it cannot represent the complex root-water-soil dynamics when woody species are considered, which typically have deeper roots and access multiple soil layers (Ross et al., 2012).

It is important to note that the “fixed Dry-intervals” (*D*) scenarios, which do not preserve storm characteristics largely agree with the “Removal of fixed percentage of events” (*R*) scenarios on productivity related responses (e.g., NPP and LAI). However, they diverge on the magnitude of changes in the hydrological components, especially for runoff. This indicates that even under extreme conditions, storm temporal characteristics at such fine temporal scales are not directly felt by plants. In other words, it is the storm total depth that is more important for ecosystem response (Post & Knapp, 2021).

This finding, along with the dominance of WRF-projected changes in mean annual rainfall and rainfall seasonality over changes in the temporal structure of rainfall, coincides with previous research that reported the ability of ecosystems to dampen high-frequency rainfall variability (Stoy et al., 2009). Water precipitated at the fine-scale is buffered by soils and can remain available to plants for longer periods (McColl et al., 2017) and, hence, high-frequency rainfall variability is essentially integrated over coarser temporal scales in the root zone (Paschalis et al., 2015; Verbruggen et al., 2021).

4.3. The Realism of the “Fewer but Larger Events” Scheme in the Light of Rainfall Projections

In most field experiments changes in the temporal structure of rainfall are imposed under the “fewer but larger events” scheme, where heavy rainfall events become more frequent at the expense of light/medium ones, with a concurrent reduction in wet days (Knapp et al., 2008). The “fewer but larger events” concept employed in field experiments is commonly obtained through sheltered plots which capture naturally occurring rainfall, which is irrigated back to the plots after a fixed dry-interval, usually at a constant rate (see Section 2.4.2).

However, under such schemes, not only are storm characteristics distorted, but also the dry-intervals applied far-exceed model projections (Figure 2), even though some more realistic approaches based on the Clausius-Clapeyron scaling of rainfall have also been used (Holdrege et al., 2021). In particular, WRF-projected changes show on average only a ~5% reduction in number of rainfall events over North America (Dai et al., 2020), and a median of ~1% reduction over the sites used here (as increases also occur), which is far from typical experiments under which the number of rainfall events is reduced up to 80% (Figure 2). This divergence holds irrespective of how rainfall events are defined (4 hr dry interval, >1 mm). The probability with which years with number of events corresponding to 25%, 50%, and 75% removal can occur is quantified in Figure 2d, indicating that only 8%, 1.5%, and 0.7% of years on average exceed such levels of event reduction. This illustrates that such manipulation levels are too extreme and not in line with high-resolution convection-permitting projections.

The “fewer but larger events” concept is not only too extreme, but also quite different from rainfall change observations (Markonis et al., 2019). This compensation mechanism between heavier and lighter events at the local scale that is implied under the “fewer but larger events” concept might possibly occur regionally rather than temporally, with rainfall decrease in some areas compensating for the intensification of heavy events in others (Markonis et al., 2019). In fact, theoretical expectations and realistic projections suggest changes much more complex in nature, expressed with shifts and increases in the rainfall distributions (Dai et al., 2020; Markonis et al., 2019; Pendergrass & Hartmann, 2014), changes in storm duration, volumes, frequency, seasonality (Moustakis et al., 2021), and spatial extent (Chen et al., 2021), with different quantiles of precipitation (which are usually linked to different storm types) responding differently to climate change (Dai et al., 2020; Moustakis et al., 2021).

The scenarios following the “fewer but larger events” concept suggest that such schemes are not only unrealistic from a strictly hydrological point of view, but also that such biases are relevant from an ecohydrological perspective as well, since they likely overestimate ecosystem responses, especially the different water fluxes, when compared to realistic WRF-projections of changes in the temporal structure of rainfall (Figure 5). In some cases, responses under numerical experiments where rainfall is manipulated are comparable or even greater than the effect of the total rainfall change, as projected by WRF (Figure S27 in Supporting Information S1). This means that field experiments implementing more realistic rainfall changes in line with projections are also needed (Korell et al., 2020b).

However, it should be highlighted that extreme manipulation experiments, pushing ecosystems toward their boundaries, usually do not aim to directly quantify climate change, but to understand the mechanisms leading to ecosystem responses. Hence, extreme manipulations are still undoubtedly very useful in this regard (De Boeck et al., 2020; Kayler et al., 2015; Korell et al., 2020a; Muller et al., 2020), and can also help further improve and parameterize terrestrial biosphere models, but they should be interpreted in this way, with the scope to increase mechanistic understanding, rather than making realistic projections.

4.4. Outlook for Best Combination of Field and Numerical Experiments

The presented results reveal a remarkable dominance of interannual variability of rainfall over the variability between different treatments at dry and intermediate sites (Figure 4). This suggests that field experiments, which typically last <4 yr (Wang et al., 2021), are largely affected by interannual variability of rainfall, which can mask or exacerbate the true signal of imposed rainfall changes in ecosystem responses. This might be related to the remarks of Leuzinger et al. (2011), who reported that ecosystem responses to changes in various environmental drivers decrease as the duration of experiments increases. There is also a significant overlap in the distributions of NPP responses among different treatments (Figure 4), indicating that the responses are weak and large samples are needed for the signal to emerge. It should also be noted that within-treatment variability remains high even for comparable amounts of rainfall (Figure 4), remarking that rainfall is not the sole explanatory variable of NPP variability. This irreducible uncertainty is related not only to the inherent stochasticity of NPP (Huenneke et al., 2002), but also to the stochastic variability of all climatic variables (i.e., radiation, temperature, and humidity) which comes into play. This variability is unavoidable, and cannot be taken into account even in experimental setups with many replicates, and different levels of rainfall manipulation, as it will affect meteorological forcing other than rainfall in the same way in all replicates.

Given the above arguments, we highlight that a proper consideration of the stochastic nature of rainfall and other climatic variables is urgently needed, and can be achieved with multi-year numerical experiments with properly constrained models, which can complement shorter-term field manipulation experiments. Numerical experiments, due to their relative strengths can serve as a test bed for hypotheses formulated based on field experimental results, and as a tool to extend the statistical significance by simulating longer periods and a larger range of conditions. Conducting more field experiments to separate treatment signal from the noise generated by the chaotic nature of climate would also be helpful in this regard.

4.5. Limits of the Interpretation

CPMs are computationally expensive and their simulations are constrained to short records and few—if any—ensemble members, making them difficult to use directly, if weather stochasticity is relevant for the question of interest. However, they can still provide useful insight into the expected signal and magnitude of changes in higher-order rainfall statistics, and at fine spatiotemporal scales. It should also be noted that the simulations used here refer to a high-end emissions scenario (RCP8.5). This implies that under lower emission scenarios, where changes in rainfall can be milder than the ones reported here, ecosystem responses could also be weaker. For example, smaller mean annual rainfall increases would stimulate water-limited sites less, while changes in the temporal structure, which already have a negligible impact under RCP8.5, would have an even smaller effect. Hence, more multi-ensemble continental-wide CPM simulations for different emission pathways are definitely needed to better capture the signal and uncertainty of rainfall changes (Moustakis et al., 2021).

In this study, only a single model—the TC terrestrial biosphere model—has been employed and, hence, the results are affected by the model structure (e.g., parameterization of vegetation water stress). In a recent model

intercomparison the performance of terrestrial biosphere models in simulating rainfall manipulation experiments was assessed (Paschalis et al., 2020). Models, mostly due to uncertainties in estimating water stress and long-term leaf area dynamics exhibited a positive bias in simulating the sensitivity of productivity to rainfall (Paschalis et al., 2020; Ukkola et al., 2021). However, most models were able to properly estimate the sign of change, even though there was disagreement in the magnitude. Nevertheless, model improvements in representing soil-plant hydraulics are definitely necessary to refine the estimate of NPP responses to rainfall changes (Y. Liu et al., 2020).

Plant succession dynamics, which are not currently simulated in TC, can play an important role in regulating ecosystem responses in the long-term. Shallow-rooted grasses rapidly respond to rainfall (Verbruggen et al., 2021), while woody plants with deeper roots may benefit under increased water content in deeper soil layers, and out-compete shorter plants for light, favoring encroachment (Gherardi & Sala, 2015; Holdrege et al., 2021). Plants can also exhibit a strong plasticity in response to altered rainfall, by changing their root characteristics (Engelhardt et al., 2021; Mueller et al., 2018; Padilla et al., 2013), growth, and reproductive strategies, in order to maximize water uptake through the roots, capture more light, and maintain reproductive effort (Gao et al., 2015; Wilcox et al., 2017). However, uncertainty remains over such strategies (Byrne et al., 2013; Griffin-Nolan et al., 2021; Post & Knapp, 2021; Wilcox et al., 2017), which are unlikely captured by the simple carbon allocation scheme used in TC.

The soil biogeochemistry module of TC representing soil microbiology and nitrogen, phosphorus, and potassium dynamics (Botter et al., 2021; Fatichi et al., 2019) was deactivated in this study, as local parameterizations of soil biogeochemical processes are still challenging. Hence, the various soil carbon and nutrient dynamics triggered by altered rainfall, which can co-regulate productivity, are not accounted for (Austin et al., 2004; Engelhardt et al., 2021; Hu et al., 2018; Huxman et al., 2004; Manzoni et al., 2012).

Water redistribution via overland flow, lateral subsurface flows and hillslope orientation can alter water and energy limitations in ecosystems (Fan et al., 2019; Peters et al., 2012; Tai et al., 2021), but such effects are unaccounted for in our experiments, where a flat terrain is assumed. Finally, it should be noted that TC only resolves land surface processes, and land-atmosphere feedbacks (Berg et al., 2016; Santanello et al., 2018) are not represented here.

5. Conclusion

Future rainfall projected by CPMs is shown to considerably affect the carbon and water cycles over a wide range of North American biomes, mostly due to changes in mean annual rainfall and seasonality. Changes in annual rainfall are dominant at dry ecosystems, however, at intermediate ones, changes in seasonality outpace the benefits of increase in mean annual rainfall. Projected changes in the fine-scale temporal variability of rainfall have a negligible impact on ecosystem productivity, and their footprint only emerges on the components of the water cycle. Soils tend to cushion rainfall variability at such fine scales and integrate it over coarser temporal scales and, hence, storm characteristics, frequency, and precipitation extremes are shown to be less relevant for ecosystem productivity. However, when rainfall is unrealistically manipulated, as often happens in field experiments, ecosystem responses are likely exacerbated.

Our study showcases how numerical experiments with a terrestrial biosphere model can benefit from high-resolution continental-wide CPM simulations which have recently been employed, and have provided, for the first time, realistic rainfall projections at fine spatiotemporal scales relevant to ecohydrological dynamics, without the need for employing downscaling, or debiasing techniques. Such multi-year numerical experiments can complement field experiments and help quantify the uncertainties related to the interannual variability of climate and rainfall in particular, thus isolating the signal of ecosystem responses induced by various components of long-term rainfall changes.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The High Resolution Weather Research and Forecasting (WRF) Simulations of the Current and Future Climate of North America is obtained by the Research Data Archive (RDA) of the National Center for Atmospheric Research (NCAR; <https://rda.ucar.edu/datasets/ds612.0/>). The details and DOIs of the sites used are listed in Data Set S1. The MATLAB code for the TC terrestrial biosphere model is freely available and can be found at <https://doi.org/10.24433/CO.0905087.v2>. The MATLAB code for the stochastic weather generator AWEGEN is freely available and can be found at <https://hyd.ifu.ethz.ch/research-data-models/awe-gen.html>.

Acknowledgments

Yiannis Moustakis acknowledges funding from the Skempton Fellowship of the Department of Civil and Environmental Engineering, Imperial College London. Athanasios Paschalis acknowledges funding from NERC (NE/S003495/1). Simone Faticchi acknowledges the support of the Singapore Ministry of Education Academic Research Fund Tier 1 through the project “Bridging scales from below: The role of heterogeneities in the global water and carbon budgets.”

References

- Allan, R. P., Barlow, M., Byrne, M. P., Cherchi, A., Douville, H., Fowler, H. J., et al. (2020). Advances in understanding large-scale responses of the water cycle to climate change. *Annals of the New York Academy of Sciences*, 1472(1), 49–75. <https://doi.org/10.1111/nyas.14337>
- Allen, M. R., & Ingram, W. J. (2002). Constraints on future changes in climate and the hydrologic cycle. *Nature*, 419(6903), 224–232. <https://doi.org/10.1038/nature01092>
- Austin, A. T., Yahdjian, L., Stark, J. M., Belnap, J., Porporato, A., Norton, U., et al. (2004). Water pulses and biogeochemical cycles in arid and semiarid ecosystems. *Oecologia*, 141(2), 221–235. <https://doi.org/10.1007/s00442-004-1519-1>
- Bai, Y., Han, X., Wu, J., Chen, Z., & Li, L. (2004). Ecosystem stability and compensatory effects in the Inner Mongolia grassland. *Nature*, 431(7005), 181–184. <https://doi.org/10.1038/nature02850>
- Baldocchi, D., Chu, H., & Reichstein, M. (2018). Inter-annual variability of net and gross ecosystem carbon fluxes: A review. *Agricultural and Forest Meteorology*, 249, 520–533. <https://doi.org/10.1016/j.agrformet.2017.05.015>
- Berg, A., Findell, K., Lintner, B., Giannini, A., Seneviratne, S. I., van den Hurk, B., et al. (2016). Land–atmosphere feedbacks amplify aridity increase over land under global warming. *Nature Climate Change*, 6(9), 869–874. <https://doi.org/10.1038/nclimate3029>
- Bonan, G. B., Williams, M., Fisher, R. A., & Oleson, K. W. (2014). Modeling stomatal conductance in the earth system: Linking leaf water-use efficiency and water transport along the soil–plant–atmosphere continuum. *Geoscientific Model Development*, 7(5), 2193–2222. <https://doi.org/10.5194/gmd-7-2193-2014>
- Botter, M., Zeeman, M., Burlando, P., & Faticchi, S. (2021). Impacts of fertilization on grassland productivity and water quality across the European Alps under current and warming climate: Insights from a mechanistic model. *Biogeosciences*, 18(6), 1917–1939. <https://doi.org/10.5194/bg-18-1917-2021>
- Byrne, K. M., Lauenroth, W. K., & Adler, P. B. (2013). Contrasting effects of precipitation manipulations on production in two sites within the central grassland region, USA. *Ecosystems*, 16(6), 1039–1051. <https://doi.org/10.1007/s10021-013-9666-z>
- Cannon, A. J., & Innocenti, S. (2019). Projected intensification of sub-daily and daily rainfall extremes in convection-permitting climate model simulations over North America: Implications for future intensity–duration–frequency curves. *Natural Hazards and Earth System Sciences*, 19(2), 421–440. <https://doi.org/10.5194/nhess-19-421-2019>
- Chen, Y., Paschalis, A., Kendon, E., Kim, D., & Onof, C. (2021). Changing spatial structure of summer heavy rainfall, using convection-permitting ensemble. *Geophysical Research Letters*, 48(3), e2020GL090903. <https://doi.org/10.1029/2020GL090903>
- Collatz, G. J., Ball, J. T., Grivet, C., & Berry, J. A. (1991). Physiological and environmental regulation of stomatal conductance, photosynthesis and transpiration: A model that includes a laminar boundary layer. *Agricultural and Forest Meteorology*, 54(2), 107–136. [https://doi.org/10.1016/0168-1923\(91\)90002-8](https://doi.org/10.1016/0168-1923(91)90002-8)
- Collatz, G. J., Ribas-Carbo, M., & Berry, J. A. (1992). Coupled photosynthesis–stomatal conductance model for leaves of C4 plants. *Functional Plant Biology*, 19(5), 519–538. <https://doi.org/10.1071/pp9920519>
- Dai, A., Rasmussen, R. M., Liu, C., Ikeda, K., & Prein, A. F. (2020). A new mechanism for warm-season precipitation response to global warming based on convection-permitting simulations. *Climate Dynamics*, 55, 343–368. <https://doi.org/10.1007/s00382-017-3787-6>
- Dai, Y., Dickinson, R. E., & Wang, Y.-P. (2004). A two-big-leaf model for canopy temperature, photosynthesis, and stomatal conductance. *Journal of Climate*, 17(12), 2281–2299. [https://doi.org/10.1175/1520-0442\(2004\)017<2281:ATMFCT>2.0.CO;2](https://doi.org/10.1175/1520-0442(2004)017<2281:ATMFCT>2.0.CO;2)
- De Boeck, H. J., Bloor, J. M. G., Aerts, R., Bahn, M., Beier, C., Emmett, B. A., et al. (2020). Understanding ecosystems of the future will require more than realistic climate change experiments – A response to Korell et al. *Global Change Biology*, 26(2), e6–e7. <https://doi.org/10.1111/gcb.14854>
- Deng, Q., Zhang, D., Han, X., Chu, G., Zhang, Q., & Hui, D. (2018). Changing rainfall frequency rather than drought rapidly alters annual soil respiration in a tropical forest. *Soil Biology and Biochemistry*, 121, 8–15. <https://doi.org/10.1016/j.soilbio.2018.02.023>
- Densmore-McCulloch, J. A., Thompson, D. L., & Fraser, L. H. (2016). Short-term effects of changing precipitation patterns on shrub-steppe grasslands: Seasonal watering is more important than frequency of watering events. *PLoS One*, 11(12), e0168663. <https://doi.org/10.1371/journal.pone.0168663>
- D’Onofrio, D., Sweeney, L., von Hardenberg, J., & Baudena, M. (2019). Grass and tree cover responses to intra-seasonal rainfall variability vary along a rainfall gradient in African tropical grassy biomes. *Scientific Reports*, 9(1), 2334. <https://doi.org/10.1038/s41598-019-38933-9>
- Engelhardt, I. C., Niklaus, P. A., Bizouard, F., Breuil, M.-C., Rouard, N., Deau, F., et al. (2021). Precipitation patterns and N availability alter plant–soil microbial C and N dynamics. *Plant and Soil*, 466(1). <https://doi.org/10.1007/s11104-021-05015-7>
- Fan, Y., Clark, M., Lawrence, D. M., Swenson, S., Band, L. E., Brantley, S. L., et al. (2019). Hillslope hydrology in global change research and earth system modeling. *Water Resources Research*, 55(2), 1737–1772. <https://doi.org/10.1029/2018WR023903>
- Fang, J., Piao, S., Zhou, L., He, J., Wei, F., Myneni, R. B., et al. (2005). Precipitation patterns alter growth of temperate vegetation. *Geophysical Research Letters*, 32(21). <https://doi.org/10.1029/2005GL024231>
- Farquhar, G. D., von Caemmerer, S. V., & Berry, J. A. (1980). A biochemical model of photosynthetic CO₂ assimilation in leaves of C₃ species. *Planta*, 149(1), 78–90. <https://doi.org/10.1007/BF00386231>
- Faticchi, S., & Ivanov, V. Y. (2014). Interannual variability of evapotranspiration and vegetation productivity. *Water Resources Research*, 50(4), 3275–3294. <https://doi.org/10.1002/2013WR015044>
- Faticchi, S., Ivanov, V. Y., & Caporali, E. (2011). Simulation of future climate scenarios with a weather generator. *Advances in Water Resources*, 34(4), 448–467. <https://doi.org/10.1016/j.advwatres.2010.12.013>

- Fatichi, S., Ivanov, V. Y., & Caporali, E. (2012a). A mechanistic ecohydrological model to investigate complex interactions in cold and warm water-controlled environments: 1. Theoretical framework and plot-scale analysis. *Journal of Advances in Modeling Earth Systems*, 4(2). <https://doi.org/10.1029/2011MS000086>
- Fatichi, S., Ivanov, V. Y., & Caporali, E. (2012b). A mechanistic ecohydrological model to investigate complex interactions in cold and warm water-controlled environments: 2. Spatiotemporal analyses. *Journal of Advances in Modeling Earth Systems*, 4(5). <https://doi.org/10.1029/2011MS000087>
- Fatichi, S., Ivanov, V. Y., Paschalis, A., Peleg, N., Molnar, P., Rimkus, S., et al. (2016). Uncertainty partition challenges the predictability of vital details of climate change. *Earth's Future*, 4(5), 240–251. <https://doi.org/10.1002/2015EF000336>
- Fatichi, S., Manzoni, S., Or, D., & Paschalis, A. (2019). A mechanistic model of microbially mediated soil biogeochemical processes: A reality check. *Global Biogeochemical Cycles*, 33(6), 620–648. <https://doi.org/10.1029/2018GB006077>
- Fatichi, S., & Pappas, C. (2017). Constrained variability of modeled T:ET ratio across biomes. *Geophysical Research Letters*, 44(13), 6795–6803. <https://doi.org/10.1002/2017GL074041>
- Fatichi, S., Pappas, C., & Ivanov, V. Y. (2016). Modeling plant-water interactions: An ecohydrological overview from the cell to the global scale. *Water*, 3(3), 327–368. <https://doi.org/10.1002/wat2.1125>
- Fay, P. A., Blair, J. M., Smith, M. D., Nippert, J. B., Carlisle, J. D., & Knapp, A. K. (2011). Relative effects of precipitation variability and warming on tallgrass prairie ecosystem function. *Biogeosciences*, 8(10), 3053–3068. <https://doi.org/10.5194/bg-8-3053-2011>
- Fay, P. A., Carlisle, J. D., Knapp, A. K., Blair, J. M., & Collins, S. L. (2003). Productivity responses to altered rainfall patterns in a C4-dominated grassland. *Oecologia*, 137(2), 245–251. <https://doi.org/10.1007/s00442-003-1331-3>
- Fay, P. A., Kaufman, D. M., Nippert, J. B., Carlisle, J. D., & Harper, C. W. (2008). Changes in grassland ecosystem function due to extreme rainfall events: Implications for responses to climate change. *Global Change Biology*, 14(7), 1600–1608. <https://doi.org/10.1111/j.1365-2486.2008.01605.x>
- Felton, A. J., Slette, I. J., Smith, M. D., & Knapp, A. K. (2020). Precipitation amount and event size interact to reduce ecosystem functioning during dry years in a mesic grassland. *Global Change Biology*, 26(2), 658–668. <https://doi.org/10.1111/gcb.14789>
- Fischer, E. M., Beyerle, U., & Knutti, R. (2013). Robust spatially aggregated projections of climate extremes. *Nature Climate Change*, 3(12), 1033–1038. <https://doi.org/10.1038/nclimate2051>
- Fischer, E. M., & Knutti, R. (2016). Observed heavy precipitation increase confirms theory and early models. *Nature Climate Change*, 6(11), 986–991. <https://doi.org/10.1038/nclimate3110>
- Gao, R., Yang, X., Liu, G., Huang, Z., & Walck, J. L. (2015). Effects of rainfall pattern on the growth and fecundity of a dominant dune annual in a semi-arid ecosystem. *Plant and Soil*, 389(1), 335–347. <https://doi.org/10.1007/s11104-014-2366-4>
- Gherardi, L. A., & Sala, O. E. (2015). Enhanced precipitation variability decreases grass- and increases shrub-productivity. *Proceedings of the National Academy of Sciences of the United States of America*, 112(41), 12735–12740. <https://doi.org/10.1073/pnas.1506433112>
- Griffin-Nolan, R. J., Slette, I. J., & Knapp, A. K. (2021). Deconstructing precipitation variability: Rainfall event size and timing uniquely alter ecosystem dynamics. *Journal of Ecology*, 109(6237). <https://doi.org/10.1111/1365-2745.13724>
- Guan, K., Good, S. P., Caylor, K. K., Sato, H., Wood, E. F., & Li, H. (2014). Continental-scale impacts of intra-seasonal rainfall variability on simulated ecosystem responses in Africa. *Biogeosciences*, 11(23), 6939–6954. <https://doi.org/10.5194/bg-11-6939-2014>
- Hao, Y. B., Chaoting, Z., Liu, W. J., Li, L. F., Kang, X. M., Jiang, L. L., et al. (2017). Aboveground net primary productivity and carbon balance remain stable under extreme precipitation events in a semiarid steppe ecosystem. *Agricultural and Forest Meteorology*, 247, 356–364. <https://doi.org/10.1016/j.agrformet.2017.03.006>
- Harper, C. W., Blair, J. M., Fay, P. A., Knapp, A. K., & Carlisle, J. D. (2005). Increased rainfall variability and reduced rainfall amount decreases soil CO₂ flux in a grassland ecosystem. *Global Change Biology*, 11(2), 322–334. <https://doi.org/10.1111/j.1365-2486.2005.00899.x>
- Heisler-White, J. L., Blair, J. M., Kelly, E. F., Harms, K., & Knapp, A. K. (2009). Contingent productivity responses to more extreme rainfall regimes across a grassland biome. *Global Change Biology*, 15(12), 2894–2904. <https://doi.org/10.1111/j.1365-2486.2009.01961.x>
- Heisler-White, J. L., Knapp, A. K., & Kelly, E. F. (2008). Increasing precipitation event size increases aboveground net primary productivity in a semi-arid grassland. *Oecologia*, 158(1), 129–140. <https://doi.org/10.1007/s00442-008-1116-9>
- Holdrege, M. C., Beard, K. H., & Kulmatiski, A. (2021). Woody plant growth increases with precipitation intensity in a cold semiarid system. *Ecology*, 102(1), e03212. <https://doi.org/10.1002/ecy.3212>
- Hu, Z., Guo, Q., Li, S., Piao, S., Knapp, A. K., Ciais, P., et al. (2018). Shifts in the dynamics of productivity signal ecosystem state transitions at the biome-scale. *Ecology Letters*, 21(10), 1457–1466. <https://doi.org/10.1111/ele.13126>
- Hueneke, L. F., Anderson, J. P., Remmenga, M., & Schlesinger, W. H. (2002). Desertification alters patterns of aboveground net primary production in Chihuahuan ecosystems. *Global Change Biology*, 8(3). <https://doi.org/10.1046/j.1365-2486.2002.00473.x>
- Huxman, T. E., Snyder, K. A., Tissue, D., Leffler, A. J., Ogle, K., Pockman, W. T., et al. (2004). Precipitation pulses and carbon fluxes in semiarid and arid ecosystems. *Oecologia*, 141(2), 254–268. <https://doi.org/10.1007/s00442-004-1682-4>
- Jacob, D., Petersen, J., Eggert, B., Alias, A., Christensen, O. B., Bouwer, L. M., et al. (2014). EURO-CORDEX: New high-resolution climate change projections for European impact research. *Regional Environmental Change*, 14(2). <https://doi.org/10.1007/s10113-013-0499-2>
- Kattge, J., & Knorr, W. (2007). Temperature acclimation in a biochemical model of photosynthesis: A reanalysis of data from 36 species. *Plant, Cell and Environment*, 30(9), 1176–1190. <https://doi.org/10.1111/j.1365-3040.2007.01690.x>
- Kayler, Z. E., Boeck, H. J. D., Fatichi, S., Grünzweig, J. M., Merbold, L., Beier, C., et al. (2015). Experiments to confront the environmental extremes of climate change. *Frontiers in Ecology and the Environment*, 13(4), 219–225. <https://doi.org/10.1890/140174>
- Knapp, A. K., Beier, C., Briske, D. D., Classen, A. T., Luo, Y., Reichstein, M., et al. (2008). Consequences of more extreme precipitation regimes for terrestrial ecosystems. *BioScience*, 58(9), 811–821. <https://doi.org/10.1641/B580908>
- Knapp, A. K., Ciais, P., & Smith, M. D. (2017). Reconciling inconsistencies in precipitation–productivity relationships: Implications for climate change. *New Phytologist*, 214(1), 41–47. <https://doi.org/10.1111/nph.14381>
- Knapp, A. K., Fay, P. A., Blair, J. M., Collins, S. L., Smith, M. D., Carlisle, J. D., et al. (2002). Rainfall variability, carbon cycling, and plant species diversity in a mesic grassland. *Science*, 298(5601), 2202–2205. <https://doi.org/10.1126/science.1076347>
- Korell, L., Auge, H., Chase, J. M., Harpole, W. S., & Knight, T. M. (2020a). Understanding plant communities of the future requires filling knowledge gaps. *Global Change Biology*, 26(2), 328–329. <https://doi.org/10.1111/gcb.14920>
- Korell, L., Auge, H., Chase, J. M., Harpole, W. S., & Knight, T. M. (2020b). We need more realistic climate change experiments for understanding ecosystems of the future. *Global Change Biology*, 26(2), 325–327. <https://doi.org/10.1111/gcb.14797>
- Kotlarski, S., Keuler, K., Christensen, O. B., Colette, A., Déqué, M., Gobiet, A., et al. (2014). Regional climate modeling on European scales: A joint standard evaluation of the EURO-CORDEX RCM ensemble. *Geoscientific Model Development*, 7(4), 1297–1333. <https://doi.org/10.5194/gmd-7-1297-2014>

- Kulmatiski, A., & Beard, K. H. (2013). Woody plant encroachment facilitated by increased precipitation intensity. *Nature Climate Change*, 3(9), 833–837. <https://doi.org/10.1038/nclimate1904>
- Lehmann, P., Berli, M., Koonce, J. E., & Or, D. (2019). Surface evaporation in arid regions: Insights from lysimeter decadal record and global application of a surface evaporation capacitor (SEC) model. *Geophysical Research Letters*, 46(16), 9648–9657. <https://doi.org/10.1029/2019GL083932>
- Leuning, R. (1995). A critical appraisal of a combined stomatal-photosynthesis model for C3 plants. *Plant, Cell and Environment*, 18(4), 339–355. <https://doi.org/10.1111/j.1365-3040.1995.tb00370.x>
- Leuzinger, S., Luo, Y., Beier, C., Dieleman, W., Vicca, S., & Körner, C. (2011). Do global change experiments overestimate impacts on terrestrial ecosystems? *Trends in Ecology & Evolution*, 26(5), 236–241. <https://doi.org/10.1016/j.tree.2011.02.011>
- Liu, C., Ikeda, K., Rasmussen, R., Barlage, M., Newman, A. J., Prein, A. F., et al. (2017). Continental-scale convection-permitting modeling of the current and future climate of North America. *Climate Dynamics*, 49(1–2), 71–95. <https://doi.org/10.1007/s00382-016-3327-9>
- Liu, J., Ma, X., Duan, Z., Jiang, J., Reichstein, M., & Jung, M. (2020). Impact of temporal precipitation variability on ecosystem productivity. *WIREs Water*, 7(6), e1481. [10.1002/wat2.1481](https://doi.org/10.1002/wat2.1481)
- Liu, W. J., Li, L. F., Biederman, J. A., Hao, Y. B., Zhang, H., Kang, X. M., et al. (2017). Repackaging precipitation into fewer, larger storms reduces ecosystem exchanges of CO₂ and H₂O in a semiarid steppe. *Agricultural and Forest Meteorology*, 247, 356–364. <https://doi.org/10.1016/j.agrformet.2017.08.029>
- Liu, Y., Kumar, M., Katul, G. G., Feng, X., & Konings, A. G. (2020). Plant hydraulics accentuates the effect of atmospheric moisture stress on transpiration. *Nature Climate Change*, 10(7), 691–695. <https://doi.org/10.1038/s41558-020-0781-5>
- Manzoni, S., Schimel, J. P., & Porporato, A. (2012). Responses of soil microbial communities to water stress: Results from a meta-analysis. *Ecology*, 93(4), 930–938. <https://doi.org/10.1890/11-0026.1>
- Manzoni, S., Vico, G., Katul, G., Palmroth, S., Jackson, R. B., & Porporato, A. (2013). Hydraulic limits on maximum plant transpiration and the emergence of the safety–efficiency trade-off. *New Phytologist*, 198(1), 169–178. <https://doi.org/10.1111/nph.12126>
- Markonis, Y., Moustakis, Y., Nasika, C., Sychova, P., Dimitriadis, P., Hanel, M., et al. (2018). Global estimation of long-term persistence in annual river runoff. *Advances in Water Resources*, 113, 1–12. <https://doi.org/10.1016/j.advwatres.2018.01.003>
- Markonis, Y., Papalexiou, S. M., Martinkova, M., & Hanel, M. (2019). Assessment of water cycle intensification over land using a multisource global gridded precipitation dataset. *Journal of Geophysical Research: Atmospheres*, 124(3). <https://doi.org/10.1029/2019JD030855>
- Mastrotheodoros, T., Pappas, C., Molnar, P., Burlando, P., Manoli, G., Parajka, J., et al. (2020). More green and less blue water in the Alps during warmer summers. *Nature Climate Change*, 10(2), 155–161. <https://doi.org/10.1038/s41558-019-0676-5>
- McColl, K. A., Alemohammad, S. H., Akbar, R., Konings, A. G., Yueh, S., & Entekhabi, D. (2017). The global distribution and dynamics of surface soil moisture. *Nature Geoscience*, 10(2). <https://doi.org/10.1038/ngeo2868>
- McDowell, N. G. (2011). Mechanisms linking drought, hydraulics, carbon metabolism, and vegetation mortality. *Plant Physiology*, 155(3), 1051–1059. <https://doi.org/10.1104/pp.110.170704>
- Miranda, J. D. D., Padilla, F. M., Lázaro, R., & Pugnaire, F. I. (2009). Do changes in rainfall patterns affect semiarid annual plant communities? *Journal of Vegetation Science*, 20(2), 269–276. <https://doi.org/10.1111/j.1654-1103.2009.05680.x>
- Molnar, P., Fatichi, S., Gaál, L., Szolgy, J., & Burlando, P. (2015). Storm type effects on super Clausius–Clapeyron scaling of intense rainfall properties with air temperature. *Hydrology and Earth System Sciences*, 19(4), 1753–1766. <https://doi.org/10.5194/hess-19-1753-2015>
- Moustakis, Y., Onof, C. J., & Paschalis, A. (2020). Atmospheric convection, dynamics and topography shape the scaling pattern of hourly rainfall extremes with temperature globally. *Communications Earth & Environment*, 1(1), 11. <https://doi.org/10.1038/s43247-020-0003-0>
- Moustakis, Y., Papalexiou, S. M., Onof, C. J., & Paschalis, A. (2021). Seasonality, intensity, and duration of rainfall extremes change in a warmer climate. *Earth's Future*, 9(3), e2020EF001824. <https://doi.org/10.1029/2020EF001824>
- Mueller, K. E., LeCain, D. R., McCormack, M. L., Pendall, E., Carlson, M., & Blumenthal, D. M. (2018). Root responses to elevated CO₂, warming and irrigation in a semi-arid grassland: Integrating biomass, length and life span in a 5-year field experiment. *Journal of Ecology*, 106(6), 2176–2189. <https://doi.org/10.1111/1365-2745.12993>
- Muller, L. A. H., Ballhausen, M.-B., Lakovic, M., & Rillig, M. C. (2020). Response to the editor: Assessing the robustness of communities and ecosystems in global change research. *Global Change Biology*, 26(2), e4–e5. <https://doi.org/10.1111/gcb.14853>
- Nippert, J. B., Knapp, A. K., & Briggs, J. M. (2006). Intra-annual rainfall variability and grassland productivity: Can the past predict the future? *Plant Ecology*, 184(1), 65–74. <https://doi.org/10.1007/s11258-005-9052-9>
- Padilla, F. M., Aarts, B. H. J., Roijendijk, Y. O. A., de Caluwe, H., Mommer, L., Visser, E. J. W., et al. (2013). Root plasticity maintains growth of temperate grassland species under pulsed water supply. *Plant and Soil*, 369(1), 377–386. <https://doi.org/10.1007/s11104-012-1584-x>
- Papalexiou, S. M., & Montanari, A. (2019). Global and regional increase of precipitation extremes under global warming. *Water Resources Research*, 55(6), 4901–4914. <https://doi.org/10.1029/2018WR024067>
- Pascale, S., Lucarini, V., Feng, X., Porporato, A., & ul Hasson, S. (2016). Projected changes of rainfall seasonality and dry spells in a high greenhouse gas emissions scenario. *Climate Dynamics*, 46(3), 1331–1350. <https://doi.org/10.1007/s00382-015-2648-4>
- Paschalis, A., Fatichi, S., Katul, G. G., & Ivanov, V. Y. (2015). Cross-scale impact of climate temporal variability on ecosystem water and carbon fluxes. *Journal of Geophysical Research: Biogeosciences*, 120(9), 1716–1740. <https://doi.org/10.1002/2015JG003002>
- Paschalis, A., Fatichi, S., Pappas, C., & Or, D. (2018). Covariation of vegetation and climate constrains present and future T/ET variability. *Environmental Research Letters*, 13(10), 104012. <https://doi.org/10.1088/1748-9326/aae267>
- Paschalis, A., Fatichi, S., Zscheischler, J., Ciais, P., Bahn, M., Boysen, L., et al. (2020). Rainfall-manipulation experiments as simulated by terrestrial biosphere models: Where do we stand? *Global Change Biology*, 26(6), 3336–3355. <https://doi.org/10.1111/gcb.15024>
- Paschalis, A., Katul, G. G., Fatichi, S., Palmroth, S., & Way, D. (2017). On the variability of the ecosystem response to elevated atmospheric CO₂ across spatial and temporal scales at the Duke Forest FACE experiment. *Agricultural and Forest Meteorology*, 232, 367–383. <https://doi.org/10.1016/j.agrformet.2016.09.003>
- Paschalis, A., Molnar, P., Fatichi, S., & Burlando, P. (2014). On temporal stochastic modeling of precipitation, nesting models across scales. *Advances in Water Resources*, 63, 152–166. <https://doi.org/10.1016/j.advwatres.2013.11.006>
- Peleg, N., Fatichi, S., Paschalis, A., Molnar, P., & Burlando, P. (2017). An advanced stochastic weather generator for simulating 2-D high-resolution climate variables. *Journal of Advances in Modeling Earth Systems*, 9(3), 1595–1627. <https://doi.org/10.1002/2016MS000854>
- Pendergrass, A. G., & Hartmann, D. L. (2014). Two modes of change of the distribution of rain. *Journal of Climate*, 27(22), 8357–8371. <https://doi.org/10.1175/JCLI-D-14-00182.1>
- Pendergrass, A. G., Knutti, R., Lehner, F., Deser, C., & Sanderson, B. M. (2017). Precipitation variability increases in a warmer climate. *Scientific Reports*, 7(1), 17966. <https://doi.org/10.1038/s41598-017-17966-y>
- Peters, D. P. C., Yao, J., Sala, O. E., & Anderson, J. P. (2012). Directional climate change and potential reversal of desertification in arid and semiarid ecosystems. *Global Change Biology*, 18(1), 151–163. <https://doi.org/10.1111/j.1365-2486.2011.02498.x>

- Porporato, A., Daly, E., & Rodriguez-Iturbe, I. (2004). Soil water balance and ecosystem response to climate change. *The American Naturalist*, 164(5), 625–632. <https://doi.org/10.1086/424970>
- Porporato, A., D'Odorico, P., Laio, F., Ridolfi, L., & Rodriguez-Iturbe, I. (2002). Ecohydrology of water-controlled ecosystems. *Advances in Water Resources*, 25(8), 1335–1348. [10.1017/CBO9780511535727](https://doi.org/10.1017/CBO9780511535727)
- Post, A. K., & Knapp, A. K. (2021). How big is big enough? Surprising responses of a semiarid grassland to increasing deluge size. *Global Change Biology*, 27(6), 1157–1169. <https://doi.org/10.1111/gcb.15479>
- Power, S. A., Barnett, K. L., Ochoa-Hueso, R., Facey, S. L., Gibson-Forty, E. V. J., Hartley, S. E., et al. (2016). DRI-Grass: A new experimental platform for addressing grassland ecosystem responses to future precipitation scenarios in South-East Australia. *Frontiers of Plant Science*, 7, 1373. <https://doi.org/10.3389/fpls.2016.01373>
- Prein, A. F., Langhans, W., Fosser, G., Ferrone, A., Ban, N., Goergen, K., et al. (2015). A review on regional convection-permitting climate modeling: Demonstrations, prospects, and challenges. *Reviews of Geophysics*, 53(2), 323–361. <https://doi.org/10.1002/2014RG000475>
- Prein, A. F., Liu, C., Ikeda, K., Bullock, R., Rasmussen, R. M., Holland, G. J., et al. (2017). Simulating North American mesoscale convective systems with a convection-permitting climate model. *Climate Dynamics*, 7(6), e1481. <https://doi.org/10.1007/s00382-017-3993-2>
- Prein, A. F., Liu, C., Ikeda, K., Trier, S. B., Rasmussen, R. M., Holland, G. J., et al. (2017). Increased rainfall volume from future convective storms in the US. *Nature Climate Change*, 7(12), 880–884. <https://doi.org/10.1038/s41558-017-0007-7>
- Prein, A. F., Rasmussen, R. M., Ikeda, K., Liu, C., Clark, M. P., & Holland, G. J. (2017). The future intensification of hourly precipitation extremes. *Nature Climate Change*, 7(1), 48–52. <https://doi.org/10.1038/nclimate3168>
- Preisler, Y., Tatarinov, F., Grünzweig, J. M., & Yakir, D. (2021). Seeking the “point of no return” in the sequence of events leading to mortality of mature trees. *Plant, Cell and Environment*, 44(5), 1315–1328. <https://doi.org/10.1111/pce.13942>
- Rasmussen, K. L., Prein, A. F., Rasmussen, R. M., Ikeda, K., & Liu, C. (2020). Changes in the convective population and thermodynamic environments in convection-permitting regional climate simulations over the United States. *Climate Dynamics*, 55, 383–408. <https://doi.org/10.1007/s00382-017-4000-7>
- Ritter, F., Berkelhammer, M., & Garcia-Eidell, C. (2020). Distinct response of gross primary productivity in five terrestrial biomes to precipitation variability. *Communications Earth & Environment*, 1, 34. <https://doi.org/10.1038/s43247-020-00034-1>
- Robertson, T. R., Bell, C. W., Zak, J. C., & Tissue, D. T. (2009). Precipitation timing and magnitude differentially affect aboveground annual net primary productivity in three perennial species in a Chihuahuan Desert grassland. *New Phytologist*, 181(1), 230–242. <https://doi.org/10.1111/j.1469-8137.2008.02643.x>
- Robinson, T. M. P., Pierre, K. J. L., Vadeboncoeur, M. A., Byrne, K. M., Thomey, M. L., & Colby, S. E. (2013). Seasonal, not annual precipitation drives community productivity across ecosystems. *Oikos*, 122(5), 727–738. <https://doi.org/10.1111/j.1600-0706.2012.02655.x>
- Roderick, M. L., Sun, F., Lim, W. H., & Farquhar, G. D. (2014). A general framework for understanding the response of the water cycle to global warming over land and ocean. *Hydrology and Earth System Sciences*, 18(5), 1575–1589. <https://doi.org/10.5194/hess-18-1575-2014>
- Ross, I., Misson, L., Rambal, S., Arneeth, A., Scott, R. L., Carrara, A., et al. (2012). How do variations in the temporal distribution of rainfall events affect ecosystem fluxes in seasonally water-limited Northern Hemisphere shrublands and forests? *Biogeosciences*, 9(3), 1007–1024. <https://doi.org/10.5194/bg-9-1007-2012>
- Santanello, J. A., Dirmeyer, P. A., Ferguson, C. R., Findell, K. L., Tawfik, A. B., Berg, A., et al. (2018). Land-atmosphere interactions: The loco perspective. *Bulletin of the American Meteorological Society*, 99(6), 1253–1272. <https://doi.org/10.1175/BAMS-D-17-0001.1>
- Scaff, L., Prein, A. F., Li, Y., Liu, C., Rasmussen, R., & Ikeda, K. (2019). Simulating the convective precipitation diurnal cycle in North America's current and future climate. *Climate Dynamics*, 55(1–2). <https://doi.org/10.1007/s00382-019-04754-9>
- Sellers, P. J., Randall, D. A., Collatz, G. J., Berry, J. A., Field, C. B., Dazlich, D. A., et al. (1996). A revised land surface parameterization (SiB2) for atmospheric GCMs. Part I: Model formulation. *Journal of Climate*, 9(4), 676–705. [https://doi.org/10.1175/1520-0442\(1996\)009<0676:ARLSPF>2.0.CO;2](https://doi.org/10.1175/1520-0442(1996)009<0676:ARLSPF>2.0.CO;2)
- Shahraeeni, E., Lehmann, P., & Or, D. (2012). Coupling of evaporative fluxes from drying porous surfaces with air boundary layer: Characteristics of evaporation from discrete pores. *Water Resources Research*, 48(9). <https://doi.org/10.1029/2012WR011857>
- Song, J., Wan, S., Piao, S., Knapp, A. K., Classen, A. T., Vicca, S., et al. (2019). A meta-analysis of 1,119 manipulative experiments on terrestrial carbon-cycling responses to global change. *Nature Ecology & Evolution*, 3(9), 1309–1320. <https://doi.org/10.1038/s41559-019-0958-3>
- Stephens, G. L., L'Ecuier, T., Forbes, R., Gettleman, A., Golaz, J. C., Bodas-Salcedo, A., et al. (2010). Dreary state of precipitation in global models. *Journal of Geophysical Research*, 115(D24). <https://doi.org/10.1029/2010JD014532>
- Stoy, P. C., Richardson, A. D., Baldocchi, D. D., Katul, G. G., Stanovick, J., Mahecha, M. D., et al. (2009). Biosphere-atmosphere exchange of CO₂ in relation to climate: A cross-biome analysis across multiple time scales. *Biogeosciences*, 6(10), 2297–2312. <https://doi.org/10.5194/bg-6-2297-2009>
- Swemmer, A. M., Knapp, A. K., & Snyman, H. A. (2007). Intra-seasonal precipitation patterns and above-ground productivity in three perennial grasslands. *Journal of Ecology*, 95(4), 780–788. <https://doi.org/10.1111/j.1365-2745.2007.01237.x>
- Tai, X., Venturas, M., Mackay, S., Brooks, P., & Flanagan, L. B. (2021). Lateral subsurface flow modulates forest mortality risk to future climate and elevated CO₂. *Environmental Research Letters*, 16, 084015. <https://doi.org/10.1088/1748-9326/ac1135>
- Thomey, M. L., Collins, S. L., Vargas, R., Johnson, J. E., Brown, R. F., Natvig, D. O., et al. (2011). Effect of precipitation variability on net primary production and soil respiration in a Chihuahuan Desert grassland. *Global Change Biology*, 17(4), 1505–1515. <https://doi.org/10.1111/j.1365-2486.2010.02363.x>
- Ukkola, A. M., Kauwe, M. G. D., Roderick, M. L., Burrell, A., Lehmann, P., & Pitman, A. J. (2021). Annual precipitation explains variability in dryland vegetation greenness globally but not locally. *Global Change Biology*, 27(18), 4367–4380. <https://doi.org/10.1111/gcb.15729>
- Verbruggen, W., Schurgers, G., Horion, S., Ardö, J., Bernardino, P. N., Cappelaere, B., et al. (2021). Contrasting responses of woody and herbaceous vegetation to altered rainfall characteristics in the Sahel. *Biogeosciences*, 18(1), 77–93. <https://doi.org/10.5194/bg-18-77-2021>
- Wang, J., Tian, D., Knapp, A. K., Chen, H. Y. H., Luo, Y., Li, Z., et al. (2021). Precipitation manipulation and terrestrial carbon cycling: The roles of treatment magnitude, experimental duration and local climate. *Global Ecology and Biogeography*, 30(9), 1909–1921. <https://doi.org/10.1111/gcb.13356>
- Wang, Z., He, Y., Niu, B., Wu, J., Zhang, X., Zu, J., et al. (2020). Sensitivity of terrestrial carbon cycle to changes in precipitation regimes. *Ecological Indicators*, 113, 106223. <https://doi.org/10.1016/j.ecolind.2020.106223>
- Wilcox, K. R., Fischer, J. C. V., Muscha, J. M., Petersen, M. K., & Knapp, A. K. (2015). Contrasting above- and belowground sensitivity of three Great Plains grasslands to altered rainfall regimes. *Global Change Biology*, 21(1), 335–344. <https://doi.org/10.1111/gcb.12673>
- Wilcox, K. R., Shi, Z., Gherardi, L. A., Lemoine, N. P., Koerner, S. E., Hoover, D. L., et al. (2017). Asymmetric responses of primary productivity to precipitation extremes: A synthesis of grassland precipitation manipulation experiments. *Global Change Biology*, 23(10), 4376–4385. <https://doi.org/10.1111/gcb.13706>

- Zhang, H., & Delworth, T. L. (2018). Robustness of anthropogenically forced decadal precipitation changes projected for the 21st century. *Nature Communications*, 9(1), 1150. <https://doi.org/10.1038/s41467-018-03611-3>
- Zhang, J., Shen, X., Mu, B., Shi, Y., Yang, Y., Wu, X., et al. (2021). Moderately prolonged dry intervals between precipitation events promote production in *Leymus chinensis* in a semi-arid grassland of Northeast China. *BMC Plant Biology*, 21(1), 147. <https://doi.org/10.1186/s12870-021-02920-y>

References From the Supporting Information

- Fatichi, S., Leuzinger, S., Paschalis, A., Langley, J. A., Donnellan Barraclough, A., & Hovenden, M. J. (2016). Partitioning direct and indirect effects reveals the response of water-limited ecosystems to elevated CO₂. *Proceedings of the National Academy of Sciences of the United States of America*, 113(45), 12757–12762. <https://doi.org/10.1073/pnas.1605036113>
- Hovenden, M. J., Leuzinger, S., Newton, P. C. D., Fletcher, A., Fatichi, S., Lüscher, A., et al. (2019). Globally consistent influences of seasonal precipitation limit grassland biomass response to elevated CO₂. *Nature Plants*, 5(2), 167–173. <https://doi.org/10.1038/s41477-018-0356-x>
- Jung, M., Koirala, S., Weber, U., Ichii, K., Gans, F., Camps-Valls, G., et al. (2019). The FLUXCOM ensemble of global land-atmosphere energy fluxes. *Scientific Data*, 6(1), 74. <https://doi.org/10.1038/s41597-019-0076-8>
- Lanzante, J. R. (2021). Testing for differences between two distributions in the presence of serial correlation using the Kolmogorov–Smirnov and Kuiper's tests. *International Journal of Climatology*, 41(14), 6314–6323. <https://doi.org/10.1002/joc.7196>
- Pastorello, G. (2020). The FLUXNET2015 dataset and the ONEFlux processing pipeline for eddy covariance data. *Scientific Data*, 7(1), 225. <https://doi.org/10.1038/s41597-020-0534-3>