## Title
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# Pushing precipitation to the extremes in distributed experiments: recommendations for simulating wet and dry years

Running head: Extreme precipitation experiments

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## Abstract

Intensification of the global hydrological cycle, ranging from larger individual precipitation events to more extreme multi-year droughts, has the potential to cause widespread alterations in ecosystem structure and function. With evidence that the incidence of extreme precipitation years (defined statistically from historical precipitation records) is increasing, there is a clear need to identify ecosystems that are most vulnerable to these changes and understand why some ecosystems are more sensitive to extremes than others. To date, opportunistic studies of naturally occurring extreme precipitation years, combined with results from a relatively small number of experiments, have provided limited mechanistic understanding of differences in ecosystem sensitivity suggesting that new approaches are needed. Coordinated distributed experiments (CDEs) arrayed across multiple ecosystem types and focused on water can enhance our understanding of differential ecosystem sensitivity to precipitation extremes, but there are many design challenges to overcome (e.g., cost, comparability, standardization). Here we evaluate contemporary experimental approaches for manipulating precipitation under field conditions to inform the design of "Drought-Net", a relatively low cost CDE that simulates extreme precipitation years. A common method for imposing both dry and wet years is to alter each ambient precipitation event. We endorse this approach for imposing extreme precipitation years because it simultaneously alters other precipitation characteristics (i.e., event size) consistent with natural precipitation patterns. However, we do not advocate applying identical treatment levels at all sites – a common approach to standardization in CDEs. This is because precipitation variability varies >5-fold globally resulting in a wide range of ecosystem-specific thresholds for defining extreme precipitation years. For CDEs focused on

precipitation extremes, treatments should be based on each site's past climatic characteristics. This approach, though not often used by ecologists, allows ecological responses to be directly compared across disparate ecosystems and climates, facilitating process-level understanding of ecosystem sensitivity to precipitation extremes.

## Introduction

Global climate models forecast a future with more frequent large precipitation events, extended dry periods and an increase in extreme wet *and* dry years (IPCC, 2013; Seneviratne *et al*., 2012; Singh *et al.,* 2013; Fischer *et al.,* 2013). Indeed, recent trends in precipitation have been consistent with this expected intensification of the global hydrological cycle (Frich *et al*., 2002; Trenberth *et al*., 2003; Groisman *et al*., 2005; Huntington, 2006; Marvel & Bonfils, 2013; Donat *et al*., 2016). Extreme precipitation years have been linked to local scale increases in exotic species (Concilio *et al.*, 2015), regional scale mortality in forests (Breshears *et al.*, 2005) and carbon cycle anomalies with global implications (Reichstein *et al*., 2013; Zscheischler *et al*., 2014a,b; Ahlström *et al*., 2015; Ruppert *et al.,* 2015; Haverd *et al.,* 2016). However, because extreme precipitation periods are by definition statistically rare (i.e., as those years exceeding 1$^{st}$ to 10$^{th}$ percentile thresholds based on historical records; Easterling *et al.*, 2000; Jentsch, 2006; Jentsch *et al.*, 2007; Smith, 2011a; Knapp *et al.,* 2015), our understanding of the mechanisms underlying ecological responses and feedbacks to climate extremes is quite limited (Smith, 2011b; Reichstein *et al*., 2013; Kayler *et al*., 2015). Furthermore, because natural climate extremes tend to be especially well studied when substantial ecological consequences are evident, our perception of ecosystem responses to climate extremes may be biased towards extreme ecological responses (Smith, 2011b). Indeed, results from a limited number of field experiments that simulate climate extremes suggest that ecosystem sensitivity can vary substantially, with some types of climate extremes causing relatively minor ecological responses and some ecosystems surprisingly unresponsive to short-term and even multi-year periods of climate extremes (Smith, 2011b; De Boeck *et al.*, 2011; Jentsch *et al.*, 2011; Collins *et al.,* 2012; Hoover *et al.,* 2014; Tielbörger *et al.,* 2014). While experiments are critical for identifying mechanisms underlying ecological responses (Smith, 2011a; Beier *et al*., 2012; Reichstein *et al*., 2013), most climate extremes experiments (and most global change experiments in general, Knapp *et al*., 2012) are conducted with unique approaches and methods, making it a challenge to determine if apparent differences in sensitivity to climate extremes are due to different methodologies or from differences in key ecosystem attributes (Smith, 2011b). This has prompted multiple calls for ecologists to move beyond conducting unique, local-scale studies and initiate multi-site (and multi-biome), coordinated experiments that impose comparable treatments and measure common response variables across all sites (Beier *et al*., 2004, 2012; Smith *et al*., 2009; Luo *et al*., 2011; Smith, 2011b; Vicca *et al*., 2012; Knapp *et al*., 2012; Fraser *et al.,* 2013, Fraser *et al.,* 2015). Such networked experiments (*sensu* the Nutrient Network; Borer *et al*., 2014) have the potential to be especially important for understanding the mechanisms underlying differential ecosystem sensitivity to climate extremes given how infrequently these climatic periods occur naturally (Smith, 2011a, Knapp *et al*., 2015).

Designing coordinated distributed experiments (CDEs) focused on climate can be challenging from a logistical as well as a scientific perspective. Logistically, it can be a significant challenge to keep costs of climate manipulation infrastructure low, maintenance minimal, and sampling expectations reasonable (Marion *et al*., 1997; Fraser *et al*., 2013). Nonetheless, such attributes are key for 1) including experimental sites that are remote and difficult to access and 2) enabling broad participation and collaboration among scientists in both developed and developing countries (Fraser *et al.,* 2013; Borer *et al*., 2014). The latter is particularly important for increasing the geographic coverage of CDEs beyond North

America and Europe and reducing biases associated with experiments largely restricted to certain biomes (Beier *et al*., 2012; Fraser *et al.,* 2013).

From a scientific point of view, designing a network of experiments focused on assessing ecosystem sensitivity to extreme wet or dry years across a range of ecosystem types (e.g., deserts, grasslands, shrublands, forests) poses additional and unique challenges, particularly with imposing treatments that represent extreme years for all sites. In the analyses below, we focus on the dual challenge of determining and implementing treatments to simulate extreme precipitation years in CDEs that can 1) be imposed with a relatively simple and low cost approach, and 2) facilitate comparisons of responses across diverse ecosystems in order to identify mechanisms underlying differential sensitivity. Such analyses are timely given that Drought-Net (http://www.drought-net.org/) a CDE focused on extreme drought is in its initial stage of implementation. We begin by reviewing how ecologists currently manipulate precipitation under field conditions and assess the merits of these approaches for imposing extreme wet and dry years in distributed experiments. We then consider an approach that best meets the attributes of successful CDEs (Fraser *et al.*, 2013) and evaluate how well such an approach captures key precipitation attributes, besides amount, of historically extreme wet and dry years (Knapp *et al*., 2015).

**Contemporary approaches for manipulating precipitation in field experiments**

We conducted a literature review (Web of Science, Thomson Reuters, Manhattan, NY, USA) of peer-reviewed studies that reported results from experiments that either increased and/or reduced precipitation amount under field conditions (agricultural systems excluded). We restricted our analysis to papers published from 2006-2015 to provide a contemporary view of the most common approaches used by ecologists. From the 596 papers returned from a keyword search combining “precipitation”, “drought”, “experiment” and “ecosystem”, we excluded model simulation studies, reviews, meta-analyses, and experiments that manipulated precipitation pattern but not amount. In the remaining 257 papers, we first categorized experiments according to how precipitation was manipulated (**manipulation type**: *passive* = no energy input required to manipulate precipitation amount beyond the initial deployment of infrastructure vs. *active* = energy required to alter precipitation amount during the experimental period). We then focused on the rationale investigators used for selecting precipitation treatments by categorizing experiments into three broad **treatment goals**. These goals were: 1) to alter precipitation by an *absolute* amount (e.g., + or – 200 mm), 2) to impose a *relative* change in precipitation (e.g., + or – 40% of ambient precipitation), or 3) to *match* treatments to a target level of precipitation based on historical records or a future expected scenario (see Fig. 1 legend for more details). Finally, we determined the **type of ecosystem** manipulated for each experiment and grouped these based on a modified Whittaker biome classification system (Whittaker, 1975).

We found that the approaches currently used by ecologists to alter precipitation under field conditions differ considerably between experiments that simulate periods of increased vs. decreased precipitation. For example, ~88% of experiments that increased precipitation used an active approach whereas ~72% of those that reduced precipitation did so passively (Fig. 1). While techniques for increasing precipitation inputs were quite variable among experiments, most experiments imposing passive reductions in precipitation used some form of the rainfall shelters originally designed by Yahdjian and Sala (2002) or a through-fall displacement (TDE) approach (e.g., Wullschleger & Hanson, 2006). With these shelters and the TDE approach, each rainfall event is reduced by a constant proportion.

Differences between precipitation addition vs. reduction experiments also were noted when considering treatment goals (absolute, relative or matched to a target level). Treatments designed to simulate periods with increased precipitation most commonly (~64%) added a fixed or absolute amount of precipitation above ambient or the long-term mean, whereas experiments that decreased precipitation most often (~94%) imposed treatments based on proportional or relative reductions in ambient precipitation amounts (Fig. 1). Treatments designed to match a particular past or future scenario (e.g., IPCC 2013), or a statistical target for precipitation change were relatively uncommon regardless of whether precipitation was increased (22%) or decreased (8%). Combined, this diversity in approaches for how precipitation is altered and the varied rationale for determining treatment levels highlights the challenge of synthesizing results from these experiments (Jentsch *et al*., 2007; Fraser *et al.*, 2013).

There was also substantial variation among biomes in the type of precipitation experiments conducted (Fig. 1, see also Beier *et al.,* 2012). As expected, short-statured (temperate grassland) biomes were home to the greatest number of precipitation manipulation experiments over the last 10 years, with far fewer experiments conducted in forests. There was also a clear pattern of biomes dominated by woody species hosting many more precipitation addition than reduction experiments, with the opposite true in grassland and tundra biomes (Fig. 1). Whether these patterns are driven by logistical challenges (it is difficult and expensive to reduce precipitation inputs from forests, Wullschleger & Hanson, 2006) or ecological relevance (droughts are widely considered a key driver of grassland dynamics, Sala *et al.,* 2012) is difficult to determine. Regardless, the unequal coverage of biomes with respect to precipitation experiments underscores the need for designing CDEs that can be deployed in multiple ecosystem types, particularly in geographic regions underrepresented by past experiments (Beier *et al.* 2012).

## Simulating extreme precipitation years in distributed experiments

Identifying mechanisms underlying differential ecosystem sensitivity to extreme wet or dry years requires careful consideration of treatment levels and how they are selected. Past CDEs have used standardized or fixed treatments across all sites based on the argument that "the power of a distributed experiment lies in identical replication of treatments" (Borer *et al.*, 2014). We do not recommend this approach for a CDE focused on assessing ecosystem sensitivity to extreme precipitation years. This is because an extreme year is defined statistically and is contingent on historical precipitation variability (Jentsch, 2006). However, interannual variability in annual precipitation varies substantially (5-fold) over the globe (Knapp & Smith, 2001; Davidowitz, 2002) and as a result, the statistical thresholds for defining an extreme wet or dry year also differ dramatically among sites. For example, Knapp et al. (2015) analyzed >1600 long-term (100-yr) precipitation records from sites distributed globally and reported that the deviation from mean annual precipitation (MAP) necessary to achieve a statistically extreme dry year varied on average between -30% and -70%, with xeric regions requiring greater deviations than mesic regions. Greater variation was observed when determining the increase in precipitation required to achieve a statistically extreme wet year (ranging from +40% for sites with high MAP to +150% for arid sites, Fig. 2). Even among sites with similar MAP, substantial variation in the precipitation anomalies necessary to achieve extreme precipitation years was evident (Knapp *et al.*, 2015). For example, in more arid regions (MAP < 500 mm) some sites required only a 25% reduction from MAP to achieve a statistically extreme dry year whereas a 75% reduction was necessary in other sites, reflecting a wide range in historic precipitation variability among sites, even in arid biomes (Davidowitz, 2002). Thus, a CDE that reduced precipitation by a fixed or standardized amount for all sites, (for example -40%) would be inappropriate for comparing ecosystem responses and inferring sensitivity to extreme drought because this treatment would be statistically extreme for some sites but not others (Fig. 2).

To insure that all sites in a CDE are experiencing extreme precipitation increases or decreases to a comparable degree, we recommend that treatment levels are matched to historical levels of precipitation variability for each site. This philosophy of selecting treatments to match site-based criteria has been employed infrequently for precipitation manipulation experiments (Fig. 1). However, among other multi-site global change experiments, matching treatments to a target, such as specific IPCC scenarios, is more common. For example, treatments in most FACE sites targeted ~550 μmol mol$^{-1}$ $CO_2$ (Leakey et al., 2009) and the International Tundra Experiment warmed plots by ~ 2 $^{o}$C across a large number of high latitude sites to match IPCC projections (Arft et al., 1999). In these cases, future increases in $CO_2$ and temperature were not expected to vary substantially among sites, thus imposing identical treatments matched to a common target was justified. Adopting a site-specific approach for imposing extreme precipitation treatments is a significant departure from contemporary experimental designs of CDEs and for previous precipitation experiments (Fig. 1). But such a departure is necessary to ensure that comparably extreme levels of precipitation are imposed at all sites (Fig. 2). Fortunately, web tools are available to quantify site-specific statistically extreme precipitation levels based on historical records or interpolated data for terrestrial sites across the globe (Lemoine *et al.*, 2016); thus, treatment levels needed to impose comparable levels of precipitation extremity can be easily determined for most terrestrial ecosystems included in a CDE.

## Imposing extreme precipitation amounts

As noted earlier, to maximize participation and geographic coverage of a CDE focused on ecosystem responses to extreme precipitation years, logistically simple and relatively low-cost experimental infrastructure is needed. While our literature review revealed a great diversity of techniques for altering precipitation inputs under field conditions, the most commonly used approach was originally designed by Yadijian and Sala (2002) to passively reduce precipitation inputs into modestly sized plots (Fig. 1). This low-cost, low maintenance shelter infrastructure consists of a roof with strips of transparent plastic evenly spaced to intercept a proportion of each precipitation event. The amount of precipitation removed by the roof is thus determined by the density of strips and the proportional area they cover. Detailed analyses indicate that the roof suspended over treatment plots only minimally affects key environmental variables such as temperature and light (Yahdjian & Sala, 2002). This passive approach, though frequently modified for site specific applications, is widely used in many types of ecosystems and has even been scaled up and deployed below the tree canopy in forests to displace throughfall (Wullschleger & Hanson, 2006; Nepsted *et al.*, 2007; da Costa *et al.*, 2010, Pangle et al. 2015). Recently, Gherardi and Sala (2013) expanded the capabilities of this infrastructure by coupling precipitation reduction treatments with addition treatments as part of an automated rainfall manipulation system (ARMS). With this system, precipitation intercepted from one plot is transferred to an adjacent plot with a solar-powered pump, permitting extreme wet and dry treatments to be imposed concurrently. Although originally designed for symmetrical treatments (i.e., -50%, +50%), unequal addition and removal treatments (i.e., -50%, +30%) can also be achieved by either applying only a portion of the intercepted precipitation to the addition plot or by using a larger roof to capture additional precipitation to transfer. Importantly, the ARMS was designed to be relatively low cost (depending on the ecosystem type) with minimal electrical demands met by solar cells (Gherardi & Sala, 2013); hence the general design fits the cost criterion of Fraser et al. (2013) for designing a successful CDE.

**Can experiments simulate other important attributes of extreme precipitation years?**

Extreme wet and dry years differ from each other by more than just precipitation amount (Knapp *et al.*, 2015). For example, dry years are usually warmer and have higher radiation inputs than average years (De Boeck *et al.*, 2011; Beier *et al.*, 2012). In addition, in most major terrestrial ecosystems, extreme wet years can be distinguished by the presence of several large (statistically extreme) daily precipitation events; these are lacking in extreme dry years (Knapp *et al.*, 2015). Wet years also have larger average event sizes and more precipitation events than dry years. In contrast, extreme dry years primarily differ from average precipitation years by an increase in the number of dry days between precipitation events (Knapp *et al.*, 2015). While the precipitation manipulation infrastructure described above (Yahdjian & Sala, 2002; Gherardii & Sala, 2103) was not designed to influence temperature, it is important to ensure that this approach realistically alters other key precipitation attributes besides amount. This is particularly true given the growing number of studies indicating that event size, number, seasonality and the length of dry periods can all significantly influence ecosystem function independent of amount (Knapp *et al.*, 2002, 2008; Heisler-White *et al.*, 2009; Thomey *et al.* 2011; Beier *et al.*, 2012; Raz-Yaseef *et al.*, 2012; Walter *et al.*, 2012; Coe & Sparks, 2014; Grant *et al.*, 2014; Zeppel *et al.*, 2014; Wilcox *et al.*, 2015).

We evaluated how realistically precipitation patterns are altered by the ARMS infrastructure (Gherardii & Sala, 2013) by simulating changes in five important precipitation attributes when precipitation is increased or decreased to extreme levels with this approach.

These attributes were: the number of extreme (99th percentile) precipitation events, the average event size, the number of precipitation events, the number of extreme (95th percentile) periods of consecutive dry days (a dry day was defined as one with < 0.3 mm of recorded precipitation), and the average length of dry periods. For three locations representing very different climates and ecosystem types (desert grassland in New Mexico, USA, mesic grassland in Kansas, USA and temperate forest in Massachusetts, USA) we calculated a probability distribution based on 100-yr historical precipitation records and categorized years as average (45-55$^{th}$ percentile), extreme wet (>90$^{th}$ percentile) and extreme dry (<10$^{th}$ percentile; see Knapp *et al*., 2015 for additional details). For each of these three types of years, we calculated each of the five precipitation attributes above from daily precipitation records at the sites. We then simulated treatments imposed by ARMS by manipulating daily precipitation regimes for each average year by 1) removing a proportion of each precipitation event to simulate a statistically extreme dry year, and 2) increasing each daily event by the proportion necessary to achieve a statistically extreme wet year. Precipitation attribute data (the five attributes considered collectively) for average, extreme wet and dry years as well as simulated extreme wet and dry years were visualized with metaMDS (Fig. 3) and differences between simulated rainfall patterns and actual rainfall patterns were assessed using the Vegan package in R (Oksanen *et al*., 2014). To test for differences among centroid means, we ran permanova analysis using the adonis function.

Results from this simulation (Fig. 3) indicate that the simulated extreme dry years were indistinguishable from actual extreme dry years in the forest ($p = 0.155$) and grassland sites ($p=0.103$) and differed only slightly at the desert site ($p=0.039$). Simulated extreme wet years differed more in multivariate space from actual extreme wet years (only in the forest site were they not significantly different, $p = 0.088$) but in all cases these five precipitation attributes collectively were more similar to extreme wet than average years. This matching of attributes between simulated vs. actual extreme wet or dry years occurred because the ARMS approach altered most (but not all) precipitation attributes in ways that are similar to patterns observed during actual extreme precipitation years. For example, the ARMS approach increased the number of large (extreme) precipitation events and event size (but not event number) for simulated extreme wet years. In contrast, the ARMS eliminated extreme large events while decreasing event size and increasing the length of dry periods between events for simulated extreme dry years. The latter occurred because very small daily events were reduced below the 0.3 mm threshold (see Knapp *et al.,* 2015) and thus these effectively became dry days. Overall, our analyses suggest that the ARMS approach is effective at simulating extreme dry and wet years across a broad range of ecosystem types. Although more labor and energy intensive experimental approaches would provide complete control over the timing and size of each precipitation event, more effectively capturing all attributes of actual extreme years, such approaches would not meet the low-cost, low maintenance criteria for successful CDEs (Fraser *et al.*, 2013).

**Conclusions**

The potential for increases in climatic extremes to alter ecosystem structure and function is well recognized, with impacts that may exceed gradual changes in means (Smith, 2011a). Extreme wet and dry years are defined statistically based on historical precipitation records, and this historical perspective is particularly important given that extreme climatic periods can drive strong directional selection over evolutionary time scales, determining the traits found in plant communities and influencing ecosystem function (Gutschick & BassiriRad, 2003). But there is tremendous variability globally in where and how often extreme responses in ecosystem function occur (Xiao *et al*., 2016). Consequently, there is a clear need for coordinated distributed experiments (CDEs) focused on 1) identifying which types of ecosystems are most vulnerable to climate extremes, and 2) understanding why some ecosystems are more sensitive to extremes than others.

Based on our analysis above, we offer two recommendations for the design of extreme precipitation CDE's. First, contrary to most multi-site experiments we recommend that treatment levels vary among sites, reflecting differences in historical precipitation variability. Thus, to impose comparably extreme precipitation treatments at all sites in a CDE, ecosystems with higher historical precipitation variability will require alterations in precipitation that exceed those in ecosystems that have experienced less precipitation variability. Experimental designs that include ecosystem-specific treatments matched to a target (e.g., a 1 in 100 year precipitation amount) are not commonly used by ecologists. But this approach is critical for climatic extremes experiments in order to assess differential sensitivity across multiple ecosystems. Second, given recent recognition of the important role of other precipitation attributes (e. g., event size, event number, event seasonality, and the duration of dry periods between events) for ecosystem functioning, it's imperative that CDEs simulate extreme precipitation years in ways that alter these variables in a manner consistent with patterns observed in naturally occurring wet and dry years. Fortunately, relatively low cost experimental infrastructure capable of altering precipitation amount *and* pattern in realistic ways already exists (Yahdjian & Sala, 2002; Gherardi & Sala, 2013). If other approaches for manipulating precipitation amount are used, we recommend that concurrent changes in key precipitation attributes are also assessed (see Fig. 3) to ensure that "hidden treatments" are not influencing ecological responses. We hope our analyses and recommendations facilitate the design of a new generation of CDEs (such as Drought-Net) focused on manipulating extremes in precipitation. Such experiments will enable ecologists to better understand how and why ecosystems differ in their sensitivity to extremes in precipitation as well as help identify underlying mechanisms. The latter are urgently needed given forecasts for intensification of precipitation regimes globally.


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**Figure legends**

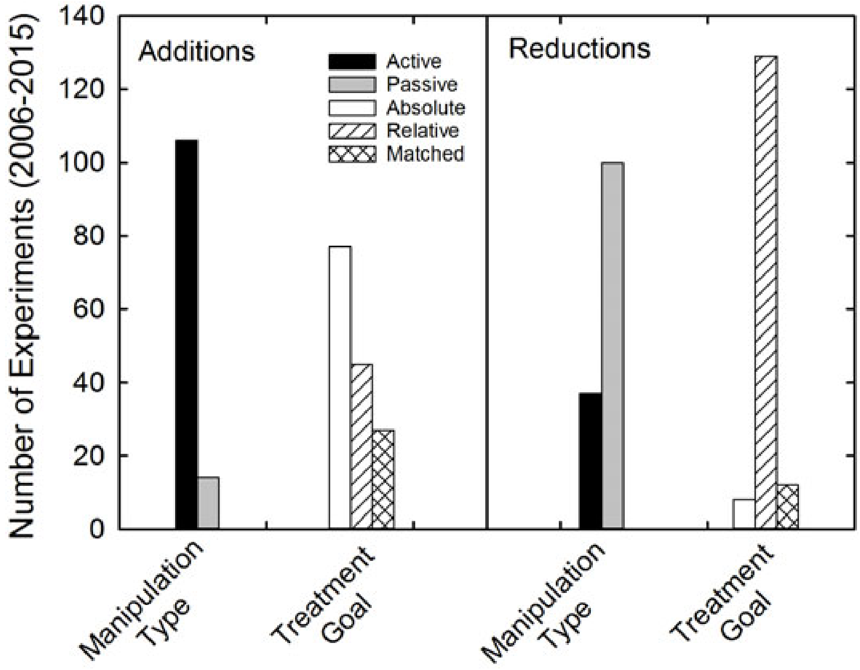
**Fig. 1**. Summary of how and where ecologists have conducted precipitation manipulation experiments based on a Web of Science search of papers published during 2006-2015. Precipitation addition and reduction experiments were assessed separately. Top: experiments categorized based on the type of manipulation (*passive* = no energy input required to manipulate precipitation amount or *active* = energy required to alter

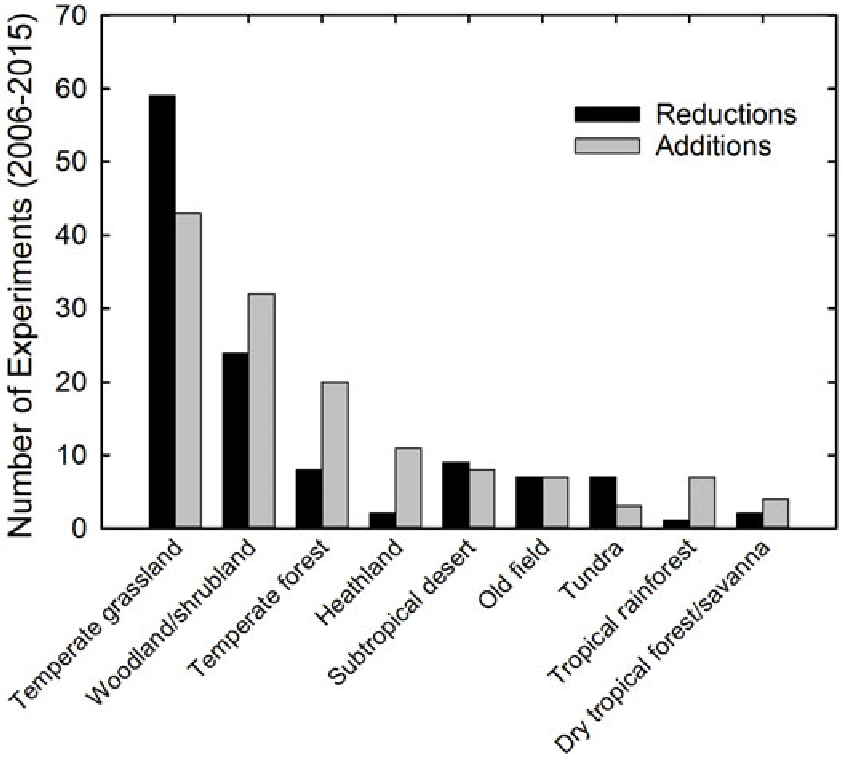
precipitation amount during the experimental period) and the goal of the treatment (to alter precipitation by an *absolute* amount, a *relative* or proportional amount, or to *match* the precipitation treatment to an IPCC scenario or statistical target). Bottom: precipitation reduction and addition experiments summarized according to the types of ecosystems in which they have been conducted. Ecosystem types with less than three experiments are not included. A Boolean search using the key words "precipitation", "drought", "experiment" and "ecosystem" was used to identify the 257 experiments summarized. Note that when a paper reported results from a study that both increased and decreased precipitation, these were counted as two experiments since often the approach used to implement these treatments differed. Moreover, some long-term experiments were included more than once when papers were published based on different periods of data collection.

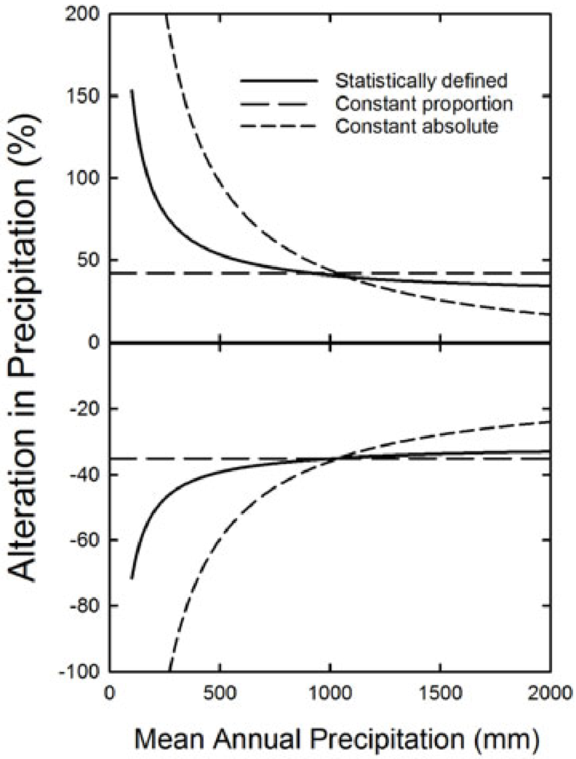
**Fig. 2.** Comparison of three approaches for determining precipitation treatment levels in an experiment distributed across sites that vary in mean annual precipitation (MAP). The solid line depicts how much precipitation must be increased or decreased (on average across sites) to achieve a statistically defined extreme precipitation year based on historical precipitation records (for this example extreme is $\leq 10^{th}$ or $\geq 90^{th}$ percentile; Knapp *et al.,* 2015). Note that to achieve an extreme wet (top) or dry (bottom) year, the mean deviation from average precipitation increases as mean annual precipitation (MAP) decreases. This is because, in general, interannual variability in precipitation increases in more arid regions and thus the thresholds required to achieve statistical extremity also increase. The dashed lines show how treatments based on altering precipitation amount by either a constant absolute or proportional amount compares to that necessary to achieve a statistically extreme wet or dry year. Curves depicting the impact of these

types of treatments are based on determining the value for each that achieved a statistically extreme wet or dry year at 1000 mm MAP and maintaining these treatment levels constant across the MAP gradient. Note that standardizing treatments across all sites, either as an absolute or proportional amount of precipitation added or removed, results in treatments that are not comparably extreme among sites. This is particularly true in more arid regions where identical treatment levels based on proportional or absolute changes substantially under- or overshoot actual extreme levels, respectively.

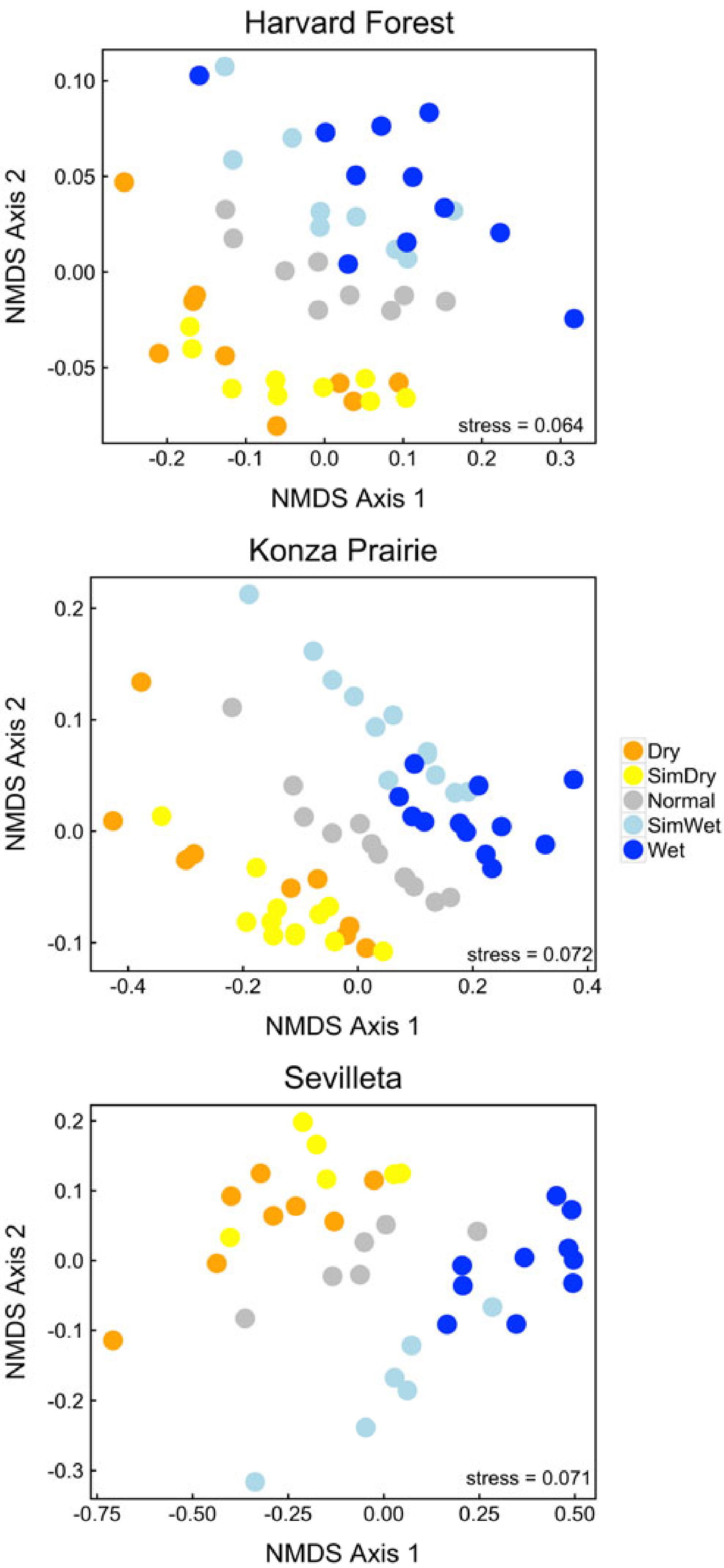
**Fig. 3.** Multidimensional scaling analysis of the impact of simulating extreme dry and wet years by using ARMS (Gherardi & Sala 2013) on five precipitation regime attributes: average precipitation event size, the number of precipitation events, the average length of dry periods between events (a dry day = < 0.3 mm of precipitation), the number of extremely large (99th percentile) precipitation events, and the number of extremely long (95th percentile) periods of consecutive dry days (see Knapp *et al.,* 2015 for more detail). Simulations were performed in three ecosystem types selected to span a wide range of mean annual precipitation levels in the United States (NE Deciduous forest in Massachusetts, central mesic grassland in Kansas, and SW desert grassland in New Mexico). Dry years were simulated by removing a fixed proportion of each precipitation event by the amount necessary to reduce precipitation in normal years to a statistically extreme level. Extreme wet years were simulated by increasing by a constant proportion each precipitation event from normal years. Precipitation attributes from actual extreme dry, wet and normal years are shown as well. Permanova analysis indicated that there were overall significant differences among groups ($p<0.001$) for all sites.


Number of Experiments (2006-2015)
140
120
100
80
60
40
20
0
Additions
Active
Passive
Absolute
Relative
Matched
Reductions
Manipulation Type
Treatment Goal
Manipulation Type
Treatment Goal


Number of Experiments (2006-2015)
70
60
50
40
30
20
10
0
Reductions
Additions
Temperate grassland
Woodland/shrubland
Temperate forest
Heathland
Subtropical desert
Old field
Tundra
Tropical rainforest
Dry tropical forest/savanna



Statistically defined
Constant proportion
Constant absolute
Alteration in Precipitation (%)
200
150
100
50
0
-20
-40
-60
-80
-100
0
500
1000
1500
2000
Mean Annual Precipitation (mm)



Harvard Forest
NMDS Axis 2
0.10
0.05
0.00
-0.05
stress = 0.064
-0.2
-0.1
0.0
0.1
0.2
0.3
NMDS Axis 1
Konza Prairie
NMDS Axis 2
0.2
0.1
0.0
-0.1
stress = 0.072
-0.4
-0.2
0.0
0.2
0.4
NMDS Axis 1
Sevilleta
NMDS Axis 2
0.2
0.1
0.0
-0.1
-0.2
-0.3
stress = 0.071
-0.75
-0.50
-0.25
0.00
0.25
0.50
NMDS Axis 1
Dry
SimDry
Normal
SimWet
Wet