







ARTICLE

Methods, Tools, and Technologies

Infrastructure to factorially manipulate the mean and variance of precipitation in the field

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Extensive ecological research has investigated extreme climate events or long-term changes in average climate variables, but changes in year-to-year (interannual) variability may also cause important biological responses, even if the mean climate is stable. The environmental stochasticity that is a hallmark of climate variability can trigger unexpected biological responses that include tipping points and state transitions, and large differences in weather between consecutive years can also propagate antecedent effects, in which current biological responses depend on responsiveness to past perturbations. However, most studies to date cannot predict ecological responses to rising variance because the study of interannual variance requires empirical platforms that generate long time series. Furthermore, the ecological consequences of increases in climate variance could depend on the mean climate in complex ways; therefore, effective ecological predictions will require determining responses to both nonstationary components of climate distributions: the

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mean and the variance. We introduce a new design to resolve the relative importance of, and interactions between, a drier mean climate and greater climate variance, which are dual components of ongoing climate change in the southwestern United States. The Mean \times Variance Experiment (MVE) adds two novel elements to prior field infrastructure methods: (1) factorial manipulation of variance together with the climate mean and (2) the creation of realistic, stochastic precipitation regimes. Here, we demonstrate the efficacy of the experimental design, including sensor networks and PhenoCams to automate monitoring. We replicated MVE across ecosystem types at the northern edge of the Chihuahuan Desert biome as a central component of the Sevilleta Long-Term Ecological Research Program. Soil sensors detected significant treatment effects on both the mean and interannual variability in soil moisture, and PhenoCam imagery captured change in vegetation cover. Our design advances field methods to newly compare the sensitivities of populations, communities, and ecosystem processes to climate mean \times variance interactions.

KEYWORDS

drought, experiment, legacy effect, precipitation, rainfall, stochasticity, variability

INTRODUCTION

Anticipating the consequences of climate change is arguably the most pressing challenge at the interface of science and society. Not only is the mean temperature rising, but precipitation is also becoming more variable in many regions globally (Armal et al., 2018; Cook et al., 2019; Fischer et al., 2013; IPCC, 2022). Much prior ecological research on climate change has investigated trends in mean climate variables or the impacts of single extreme events (Easterling et al., 2000; Jentsch et al., 2007; Malyshev et al., 2016, e.g., De Boeck et al., 2018); however, robust theory predicts that changes in the variance of climate can also cause important biological responses, even when the mean climate does not change (Ruel & Ayres, 1999; Turelli, 1978; Jensen's Inequality, Pickett et al., 2015). First, increasing climate variance can magnify the influence of environmental stochasticity, i.e., the aspects of climate events that are randomly determined and cannot be predicted precisely (Ridolfi et al., 2011). Second, greater variance can increase the frequency, magnitude, and/or duration of climate extremes that cause ecological tipping points, force transitions to new ecological states, slow the rate of recovery from disturbance, or alternatively, promote community or ecotone stability (Chesson, 2000; Doak & Morris, 2010; Lynch et al., 2014; Peters et al., 2006; Scheffer et al., 2015; Zinnert et al., 2021). Third, as climate variance increases, differences in climate between consecutive years become more dramatic, increasing the potential for antecedent

effects, in which current biological responses depend on responses to past perturbations (Liu et al., 2019; Ogle et al., 2015; Wood et al., 2022). For instance, current primary production may be lessened if the prior year is drier than average (Reichmann et al., 2013).

Confronting variance has transformed other ecological subdisciplines (Carpenter et al., 2015; Ridolfi et al., 2011). For instance, models that incorporated intraspecific trait variance altered predictions of population stability, competitive dynamics, and rates of speciation (Bolnick et al., 2011; Hart et al., 2016). Laboratory studies and process measurements (Borken & Matzner, 2009; Lawson et al., 2015; Sponseller, 2007; Vazquez et al., 2017) indicate that short-term physiological responses to variability in temperature or water availability are common. However, predicting the ecological responses to climate variance at interannual time scales requires observations and experiments that generate long time series because a year is only one data point. Thus, most studies to date cannot predict ecological responses to greater variance in interannual climate (see Hsu & Adler, 2014; Maurer et al., 2020).

Ignoring long-term climate variance could profoundly underestimate or overshoot predicted responses to climate change, depending on whether greater variance in climate poses a net cost or net benefit to the biological response. For example, six years of experimentally increased variability in precipitation had opposite effects on a dominant grass and a co-occurring shrub; greater variance reduced grass biomass by 80%, but boosted

shrub cover nearly 70% (Gherardi & Sala, 2015a, 2015b). Similarly, long-term observations signaled benefits of greater variance in the summer drought index for primary production in a Chihuahuan Desert grassland because small declines in plant biomass during dry summers were more than offset by large biomass gains in years with wet summers. In contrast, evidence indicated costs of greater variance for a nearby Plains grassland, because nonlinear declines in biomass in dry summers were not offset by the small gains in wet summers (Rudgers et al., 2018). Global meta-analyses of observational data revealed a pivot point at ~300 mm mean annual precipitation (MAP), in which the benefits of variance in precipitation for drier-than-300 mm MAP ecosystems flipped to costs of variance for wetter ecosystems (Gherardi & Sala, 2019; Hou et al., 2021).

These examples suggest that climate variance is ecologically important (Benedetti-Cecchi et al., 2006; Bertocci et al., 2005; Rudgers et al., 2018); however, the ecological consequences of climate variance may additionally depend on the climate mean. For example, climate variance may be costly to plant productivity in environments where mean climate conditions are wet and cool because extreme droughts cause large declines in production. Conversely, the influence of variance could reverse to be beneficial under hot, dry conditions, for example, that occur at the southern range limits of northern hemisphere ecosystems, because extreme wet years cause large increases in productivity (see Figure 1; Rudgers et al., 2018). Therefore, climate mean and variance could interactively influence organisms and ecosystem processes in ways that cannot be predicted from separate manipulations of the mean or variance. These interactions could affect systems on multiple levels, from populations of foundation plant species, to diverse communities of consumers, to biogeochemical or biophysical process rates. Therefore, effective ecological forecasts will require that we determine the ecological responses to both nonstationary components of climate distributions: the mean and the variance (Figure 1). However, we currently lack empirical research platforms that test for mean \times variance interactions.

Here, we describe a novel experimental design, modified from prior field infrastructure (Gherardi & Sala, 2013), to test the hypothesis that the effects of variability in precipitation depend on mean precipitation. Our Mean \times Variance Experiment (MVE) adds two new elements to previous designs. First, MVE tests for an interaction between mean and variance in precipitation with a factorial design that crosses a mean treatment (ambient or drier) with a variance treatment (ambient or more variable). Second, MVE adds stochasticity to the variance treatment to allow for possible antecedent

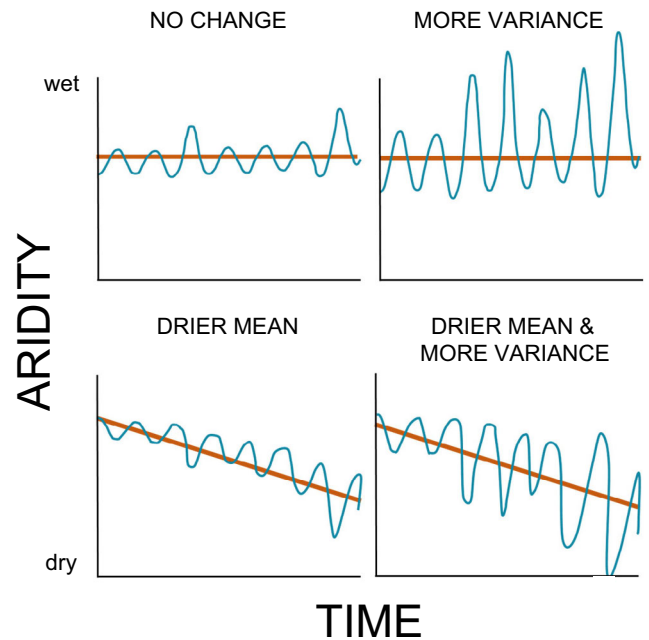


FIGURE 1 Conceptual diagram of future scenarios of climate change considering change in both the mean and variance of aridity. Aridity can be captured by metrics such as the Standardized Precipitation Evapotranspiration Index (Vicente-Serrano et al., 2010).

effects caused by natural stochasticity, rather than regularly alternating between dry and wet years as in the prior design (Gherardi & Sala, 2013). We implemented the new MVE infrastructure in four dryland ecosystem types in the northern Chihuahuan Desert in central New Mexico, USA to compare their susceptibility to interacting changes in the mean and variance of precipitation.

Because drylands have highly variable climates (Collins et al., 2014; Noy-Meir, 1973), they make excellent test beds to advance general understanding of ecological responses to environmental variability. The ecological consequences of changes in both the mean and variance of climate (Figure 1) may also be particularly potent in drylands, where species commonly reach physiological and ecological limits (Allen et al., 2015; Anderegg & Diffenbaugh, 2015). Climate models consistently forecast rising temperatures and greater variance in precipitation for drylands (Feng & Fu, 2013; Zhang et al., 2020), even while long-run mean precipitation trends are notoriously unpredictable (Garfin et al., 2014; Gutzler & Robbins, 2011; Jones & Gutzler, 2016; Seager et al., 2007, 2013). In the Chihuahuan Desert drylands of North America, observational data and models support a pattern of simultaneous change in the mean and variability of aridity. Year-to-year variability in precipitation has increased significantly along with greater aridity (Maurer et al., 2020),

reflecting trends that are consistent with modeled predictions for future climate in this region (Gutzler & Robbins, 2011). In addition to amplified variation in both seasonal and interannual precipitation, meteorological data reveal that droughts have already intensified in this region (Zhang et al., 2021), and a suite of climate models all indicate that the frequency, duration, and intensity of drought will increase in the future (Bradford et al., 2020; Cook et al., 2015). In the *Methods* section, we describe the novel MVE experimental design and report on treatment effectiveness for its longest running installation in the Plains grassland ecosystem in central New Mexico. We address two questions: (1) How much do MVE treatments alter the mean and variance in soil moisture and soil temperature? (2) Does microenvironmental spatial variation influence how much MVE treatments alter soil moisture profiles?

METHODS

Study location

To jointly manipulate the mean and variance of precipitation, we installed infrastructure at the Sevilleta National Wildlife Refuge (SNWR) in central New Mexico at the northern edge of the Chihuahuan Desert biome. The experiment is a central component of the Sevilleta Long-Term Ecological Research Program (SEV-LTER, seviter.unm.edu). Thus far, we have installed the MVE in four ecosystems at SNWR: Plains grassland (34°20'20.40", -106°37'52.36", est. 2019) dominated by blue grama grass (*Bouteloua gracilis*), Chihuahuan Desert grassland (34°20'8.27", -106°43'38.28", est. 2020) dominated by black grama grass (*B. eriopoda*), desert shrubland dominated by creosote bush (*Larrea tridentata*) (34°20'17.73", -106°44'20.86", est. 2021), and juniper savanna dominated by one-seeded juniper (*Juniperus monosperma*) with an understory of blue and black grama grass (34°16'9.05", -106°37'30.84", est. 2022). We report treatment effectiveness from our longest running site in Plains grassland.

Climate context

MAP ranges from ~230 to 330 mm among the four ecosystems, and the majority (~60%) of precipitation falls as rainfall during July–September when the North American Monsoon drives localized convective storms (Notaro et al., 2010). Regional climate models predict warmer winter and summer annual temperatures, more frequent and intense El Niño events (Bhattacharya et al., 2022; Power et al., 2013), declines in winter/spring

precipitation, and more variable monsoon rainfall (Gutzler & Robbins, 2011). However, dryland water availability is determined not only by precipitation inputs but also by the strong influence of temperature on evaporative demand (e.g., Williams et al., 2013). Since 1900, our region has experienced declines in the mean of a commonly used summer drought index, the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010), that accounts for the influence of temperature on water availability. At the same time, variance in SPEI has increased since the 1980s (Rudgers et al., 2018), a scenario of dual change in climate mean and variance (Figure 1).

Experimental design

The MVE design consists of a 2 × 2 factorial manipulation of mean precipitation (ambient or drier) and variance in precipitation (ambient or more) (Figure 2). To alter variance without changing the mean, we used paired plots, one of which received more precipitation and the other less precipitation, thereby amplifying the extremes without changing the mean across the pair. Each set of 6 plots (Figure 2) was spatially blocked, with five blocks and a total of 30 plots per ecosystem type (Appendix S1: Figure S1). Each plot was hydrologically isolated with aluminum flashing buried to 20-cm depth using a gas-powered trencher (Figure 3). Sites were co-located with existing meteorological stations (Moore & Hall, 2022). All construction documents, including price estimates for the first installation (2019), are provided in Zenodo: <https://zenodo.org/record/7996101>.

Drier Mean treatment

To reduce mean soil moisture, we intercepted 25% of precipitation (Figure 2) in our Drier Mean treatment, a moderate forcing within range of likely futures for our region (Seager et al., 2013). Roof panels intercepted precipitation year-round (Figure 3) using a modified and larger version of a published rainout shelter (Yahdjian & Sala, 2002). Plots (5 × 5 m) consisted of nine metal T-posts pounded into the ground ~0.7 m deep, with three posts placed along the center roofline (2.44 m tall) and three shorter posts (1.53 m tall) set along each side to create a peaked roof (Figure 3). All plots were covered in ethyl acrylate shingles (12.7-cm-wide, 244-cm-long, 0.3-cm-thick, Port Plastics, Albuquerque, NM) bent with a heating element into a 45° angle. Shingles were attached to metal conduit using a nut and bolt, with both rubber and aluminum washers placed at both ends of the shingle. Shingles to

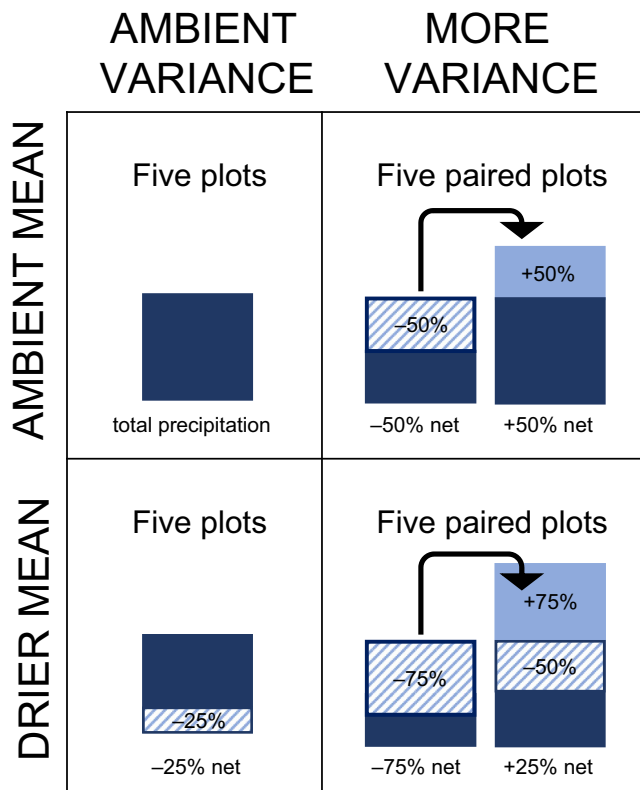


FIGURE 2 Mean \times Variance Experiment design. The Drier Mean treatment reduces total annual precipitation by 25%. For the More Variance treatment, plots are paired, and within each pair, one plot receives 50% less precipitation in a given year, and the other plot receives 50% more precipitation by moving water from the reduction plot, as illustrated in the bar graph. When the Drier Mean treatment is combined with More Variance, one plot receives 75% less precipitation, and the other plot receives 25% more, again by moving water from one plot to the other. To simplify construction, the +25% treatment receives all 75% of removed precipitation from the paired plot, and the shelter intercepts 50% of ambient precipitation to achieve the 25% increase. The numbers of plots indicate replication within each ecosystem type.

capture water were attached in a “ ∇ ” shape, whereas ambient rainfall plots used shingles attached downward (shape = “ \wedge ”) to shed water into the plot but control for potential shelter effects.

More Variance treatment

To increase variance in soil moisture stochastically without changing the mean, we paired plots and amplified their precipitation regimes with a “More Variance” treatment (Figures 2 and 3). Within a pair, one plot received 50% less precipitation and that water was diverted to the other plot in the pair to increase precipitation by 50%. On water reduction plots, water was shed from the clear,

plastic “ ∇ ” shingles (described above) into PVC pipe gutters (diameter 15 cm, length 5 m) that diverted water through black plastic distribution line into a black plastic rain barrel (208 L, Desert Plastics, Albuquerque, NM). A float switch at the bottom of the rain barrel turned on a solar-powered pump that delivered the captured rain to the paired plot using nozzle-head rainfall sprinklers installed along the peaked roof of the shelter. This design delivered water from the barrel into the plot in real time during precipitation events. To create stochastic interannual trajectories for each pair of More Variance plots, once yearly, plots were randomly assigned to either flip the treatment between the plot pair or to maintain the same treatment for the next year. If a flip was assigned, the rainout infrastructure was moved between the plots in the pair during the month of November. In contrast to this stochastic design, Gheradi and Sala (2013, 2015a) alternated between high and low rainfall years in a regular, repeated pattern, which reduces stochasticity and limits the range of possible antecedent effects. Our More Variance treatment instead created stochasticity through random assignments of plots to either extreme high or extreme low precipitation in a given year. Plots receiving both 25% Drier Mean and More Variance (Figure 2) randomly alternated between 75% less precipitation (–25% for Drier Mean and –50% for More Variance) or 25% more precipitation (–25% for Drier Mean and +50% for More Variance).

Sensor network

In a subset of 18 plots per site (three of the five blocks, Appendix S1: Figure S1), we installed sensors to track soil moisture and temperature at three depths (12.5, 22.5, and 37.5 cm; Plains grassland: EC-TM5, Decagon, Pullman, WA; all other sites, TEROS 11, Meter Group, Pullman, WA). Sensors measured volumetric water content (VWC) at a resolution of $0.001 \text{ m}^3/\text{m}^3$ (0.1% VWC) from 0 to 70% VWC in units of cubic meters per cubic meter with a 1 L volume of influence. Sensors were installed up to 12 months in advance of MVE infrastructure installation to capture baseline soil moisture for each plot prior to treatment and to reduce ground disturbance during treatment initiation.

PhenoCams

To detect changes in plant phenology and activity, we deployed digital cameras (“phenocams”) to provide consistent data at fine spatial and temporal resolution (Figure 4). Imagery and data from the cameras are remotely available

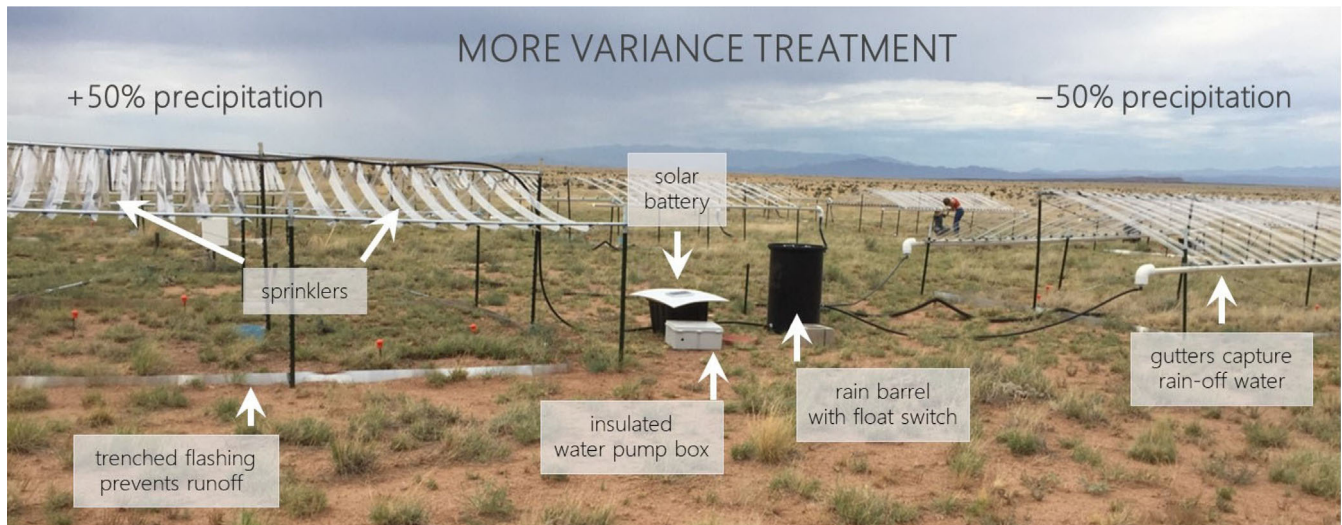


FIGURE 3 The Mean \times Variance Experiment in the Chihuahuan Desert grassland site at the Sevilleta National Wildlife Refuge, Socorro, NM, showing paired plots of the More Variance treatment. On the right, V-shaped shingles catch precipitation on the -50% precipitation plot, which then shunt the water into a black rain barrel through gutters and distribution lines. A float switch in the rain barrel turns on a solar-powered water pump when the barrel fills with water. Overhead sprinklers deliver water to the $+50\%$ precipitation plot during the precipitation event. All plots have the same overhead shelter infrastructure and were trenched with aluminum flashing to prevent runoff and overland flow. Infrastructure was stabilized against high winds with tensioned cables that form an “X” across the plot interior. Photo credit: A. Luketich.

through the PhenoCam Network website: <https://phenocam.nau.edu/webcam/network/search/?sitename=sevmve>. Phenocam imagery provides a continuous visual record of the temporal progression of the experiment; the value of which has been previously demonstrated at the SPRUCE global change experiment in Minnesota (Richardson, Hufkens, Milliman, Aubrecht, Furze, et al., 2018).

Following the standard PhenoCam Network deployment protocol (Richardson, Hufkens, Milliman, Aubrecht, Chen, et al., 2018), prescribed cameras (model NetCam SC SD500BN, StarDot Technologies, Buena Park, CA) were configured using automated scripts (the PhenoCam Installation Tool, or PIT). Cameras were paired with and installed in the 18 plots monitored for soil moisture, spread across three experimental blocks (Appendix S1: Figure S1). Cameras were mounted at a height of 2 m on the southwest center T-post of each plot, with a view down and across the plot, providing the greatest field of view. For protection against weather and animals, cameras were installed inside lightweight, weatherproof housing, which performs reliably in all climates, and all cables were sheathed in PVC split loom conduit. DC power to each camera was provided through a POE-enabled (power-over-ethernet) gigabit switch (model GS108PP, Netgear, San Jose, CA) for each block of cameras. Every 60 min, from 8:00 to 16:00, JPEG images from each camera are sent to the PhenoCam Network server via file transfer protocol (FTP) over the SEV Wireless Research Network. A metadata file containing information about camera settings, exposure time, and

other diagnostic information is uploaded with every image. To reduce the likelihood of synchronized bursts of network traffic, the scheduled camera uploads are staggered with each spatial block and powered on for 10 min with 5-min breaks between blocks, and cameras are start-delayed 1 min among cameras within a block. Cameras were programmed by the PIT to log both visible (red, green, blue [RGB]) and visible infrared (VIS+IR) images, which allows us to calculate “camera NDVI” (Filippa et al., 2018; Petach et al., 2014). Data processing follows previously established protocols for PhenoCam images (Richardson, 2019; Richardson, Hufkens, Milliman, Aubrecht, Chen, et al., 2018; Seyednasrollah et al., 2019) and is conducted nightly for specified regions of interest within the field of view of each camera.

Soil profiles

To evaluate the second question – does microenvironmental spatial variation influence how much MVE treatments alter soil moisture profiles? – we excavated by hand four soil pits (1 m across, 1.5 m long, 1.5–1.8 m deep) in each of the four ecosystem types and also dug smaller pits (to 40-cm depth) in the center of 18 of the 30 plots. All sites had sandy loam to sandy clay loam textured soils, with the top 5–15 cm of soil depth similar in texture across sites. In the Plains grassland, clay content increased at 20–50 cm depth, and we observed a weak to rock-like carbonate buildup beginning at 30–50 cm,

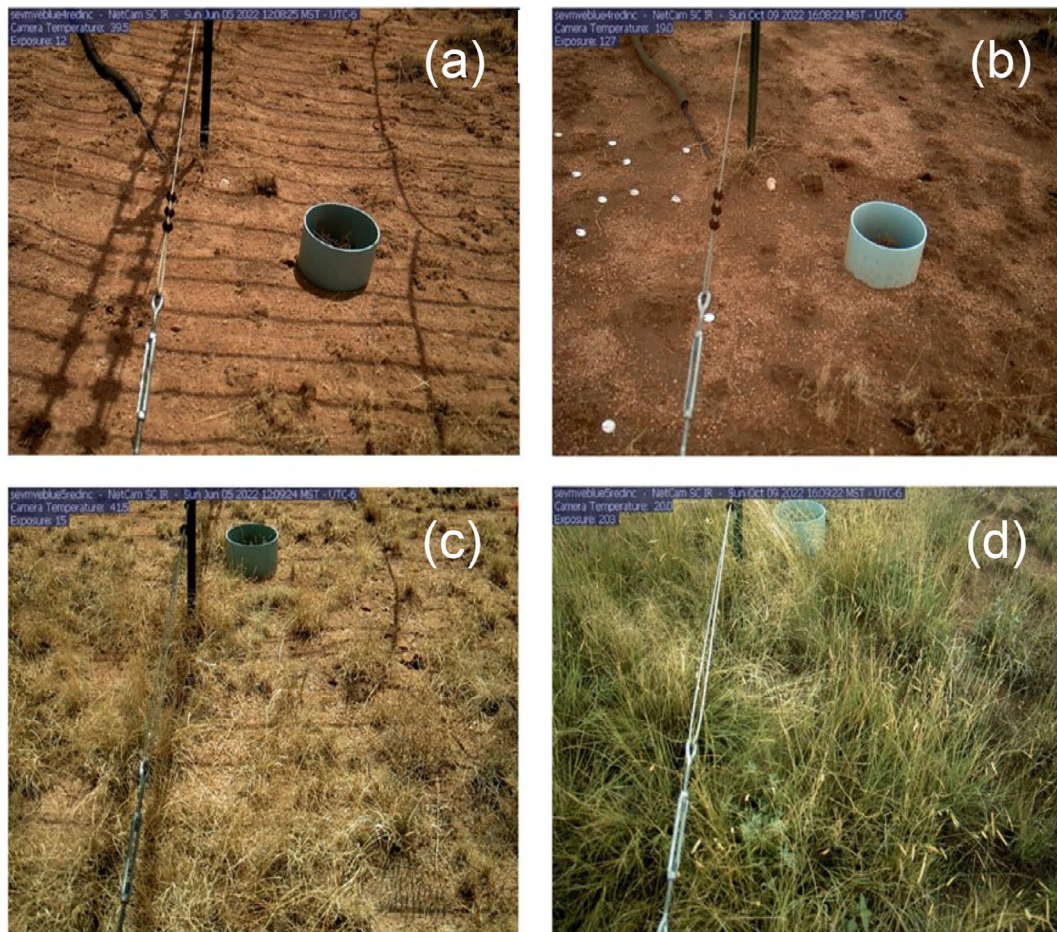


FIGURE 4 PhenoCam images used to calculate the green chromatic coordinate (an index of vegetation “greenness”). Images of one plot pair in the Drier Mean + More Variance treatment at the Plains grassland site at the Sevilleta National Wildlife Refuge, Socorro, NM. Plot 4 (a, b) received 75% less precipitation during October 2021–October 2022, while plot 5 (c, d) received 25% more precipitation during the water year. Images display plots during two phenological stages in June 2022 (a, c) prior to the start of summer monsoon season or October 2022 (b, d) after four months of summer monsoon growth. In the -75% precipitation treatment, GCC was the same for both June (a) and October (b) phenological stages (plot 4 GCC = 0.33). In the $+25\%$ precipitation treatment, GCC was 0.35 in June (c) and increased to 0.39 by October (d). Photo credits: A. Richardson and S. Watson via PhenoCams.

which continued to more than 150 cm in one pit and overlaid a buried soil at 100 cm (i.e., a repeat of the textural sequence described) in the other pit, downslope. The Chihuahuan Desert grassland had a sandy loam to loamy sand soil to 20–40 cm depth over a rock-like soil carbonate horizon that extended deeper than 100 cm. The creosote bush-dominated shrubland had two soil profiles, both with sandy loam for the top 10–15 cm depth. One profile then transitioned to sandy clay loam textures with reworked clasts of rock-like soil carbonate overlying a continuous horizon of rock-like soil carbonate at ~25–40 cm depth. The other profile transitioned from sandy loam textures to redder, sandy clay loam textures at 20–30 cm depth, with dispersed clay soil carbonate buildups that continued to a depth of ~70 cm, after which the profile was sandy loam parent material. Soils at the juniper savanna were largely sandy clay loams. Clay buildup and minor soil carbonate buildup began at

~15–25 cm depth and continued to increase in clay and carbonate content until limestone was met; depth to bedrock ranged from 0 to 90 cm.

Statistical analysis

We used data from soil moisture and temperature sensors at the longest running site, Plains grassland, to address the first question – how much do MVE treatments alter the mean and variance in soil moisture and soil temperature? Because our infrastructure created a gradient from 75% less precipitation to 50% more precipitation within a treatment year (Figure 2), we used a general linear mixed-effects model with the fixed, continuous variable of treatment (-75% , -50% , -25% , 0 , $+25\%$, $+50\%$) interacting with soil depth (12, 22, or 37 cm) (Bates et al., 2015). We included soil depth as a categorical, rather

than continuous, variable because the soil profile information on clay content suggested that soil moisture may not change linearly with depth, which would be assumed if depth were continuous. A separate analysis was used for each water year, which begins 1 October of the prior year, because treatments within the More Variance are re-randomized within each pair in each year to create stochastic trajectories. For Plains grassland, this re-randomization occurred on 30 October 2020, 9 November 2021, and 7 November 2022, and we accommodated minor differences in the date of the flip by analyzing hourly sensor records over each year preceding the date of flip. Our repeated measures statistical models included the random effects of sensor identity nested within plot and plot nested within spatial block (Appendix S1: Figure S1: 3 blocks had sensors, with 6 plots and 18 sensors per block). Because plots varied in initial soil moisture, likely due to variations in the distribution of sand, clay, and soil carbonate with depth (see *Soil profiles*), we included pretreatment mean soil moisture for each sensor (1 November 2018–30 April 2019) as a covariate in the analysis. Models accounted for temporal autocorrelation with an autoregressive 1 (AR1) variance–covariance matrix using the `lme` function in R package `nlme` (Pinheiro et al., 2016), and were fit with maximum likelihood estimation. For each soil depth, we used the `emtrends` function in R package `emmeans` (Lenth, 2018) to test whether the slope (β) of soil moisture against precipitation treatment (−75%, −50%, −25%, 0, +25%, +50%) statistically differed from zero. All R code is publicly available along with the datasets (<https://zenodo.org/record/7996101>).

Our treatments were designed to reduce mean precipitation and increase its variance at the interannual scale, and we estimated the deviation in precipitation received by each plot relative to ambient precipitation on each day (Figure 5). From the daily data, we estimated the mean and CV of estimated daily precipitation received by each plot and treatment combination (Figure 5).

In addition, to evaluate treatment effectiveness for interannual variance in soil moisture, we calculated the mean daily VWC for each sensor in each water year, then used these data to determine the interannual CV across the three water years. A linear model tested whether the interannual CV of soil moisture responded to the fixed factors of Mean treatment (ambient/more) and Variance treatment (ambient/more) using the function `lm` in base R (R Core Team, 2022). Three years is a narrow window to detect a response in the interannual variation in precipitation, and the treatments are designed to run for many years (not only three). However, this analysis provided an initial assessment of the MVE to alter variance without changing the mean.

RESULTS

How much do MVE manipulations alter the mean and variance in soil moisture and temperature?

Mean precipitation gradient

MVE infrastructure to impose a gradient from 75% less precipitation to 50% more precipitation (Figures 2 and 5) significantly altered mean soil moisture in all years at our longest running site in Plains grassland (Figure 6, water year 2020: $\chi^2 = 38.2$, $p < 0.0001$; 2021: $\chi^2 = 14.0$, $p = 0.0002$; 2022: $\chi^2 = 11.17$, $p = 0.0008$). From the −75% treatment to the +50% treatment, average soil moisture differed by 44%–50% at the shallowest soil depth (12 cm) (Figure 6a). Treatment effects on soil moisture were similarly strong at 22-cm depth, with 41%–56% greater moisture in the +50% addition treatment compared with −75% removal (Figure 6b). MVE treatment effects on soil moisture were somewhat weaker at 37-cm depth (26%–48%, Figure 6c), likely because many rain events are too small to reach deep soil, but the MVE treatment did not significantly interact with soil depth in the first two water years (2020: $\chi^2 = 4.3$, $p = 0.11$; 2021: $\chi^2 = 2.1$, $p = 0.36$). Although the effects of MVE infrastructure on soil moisture were generally consistent across soil depths, in water year 2022, soil moisture did not significantly respond to the MVE precipitation gradient at 37-cm depth (Figure 6c; 2022: treatment \times depth, $\chi^2 = 26.1$, $p < 0.001$).

Stochastic variance in precipitation

The More Variance treatment amplified the CV in soil moisture by ~25% relative to ambient climate variance during 2019–2022 (Figure 7, $\chi^2 = 7.0$, $p = 0.039$) similar to its estimated effects on the CV of daily precipitation (Figure 5). Effects on CV in soil moisture were statistically invariant across soil depths (variance treatment \times depth, $\chi^2 = 0.3$, $p = 0.73$), ranging from 24% larger CV in the More Variance treatment than under ambient variance at the shallowest depth to 27% larger CV for the deepest sensor (Figure 7). By design, the More Variance treatment did not significantly alter mean soil moisture at any depth ($\chi^2 = 2.05$, $p = 0.20$, variance treatment \times depth, $\chi^2 = 0.3$, $p = 0.75$).

Soil temperature

The MVE precipitation gradient from −75% to +50% did not have any nontarget effects on soil temperature during

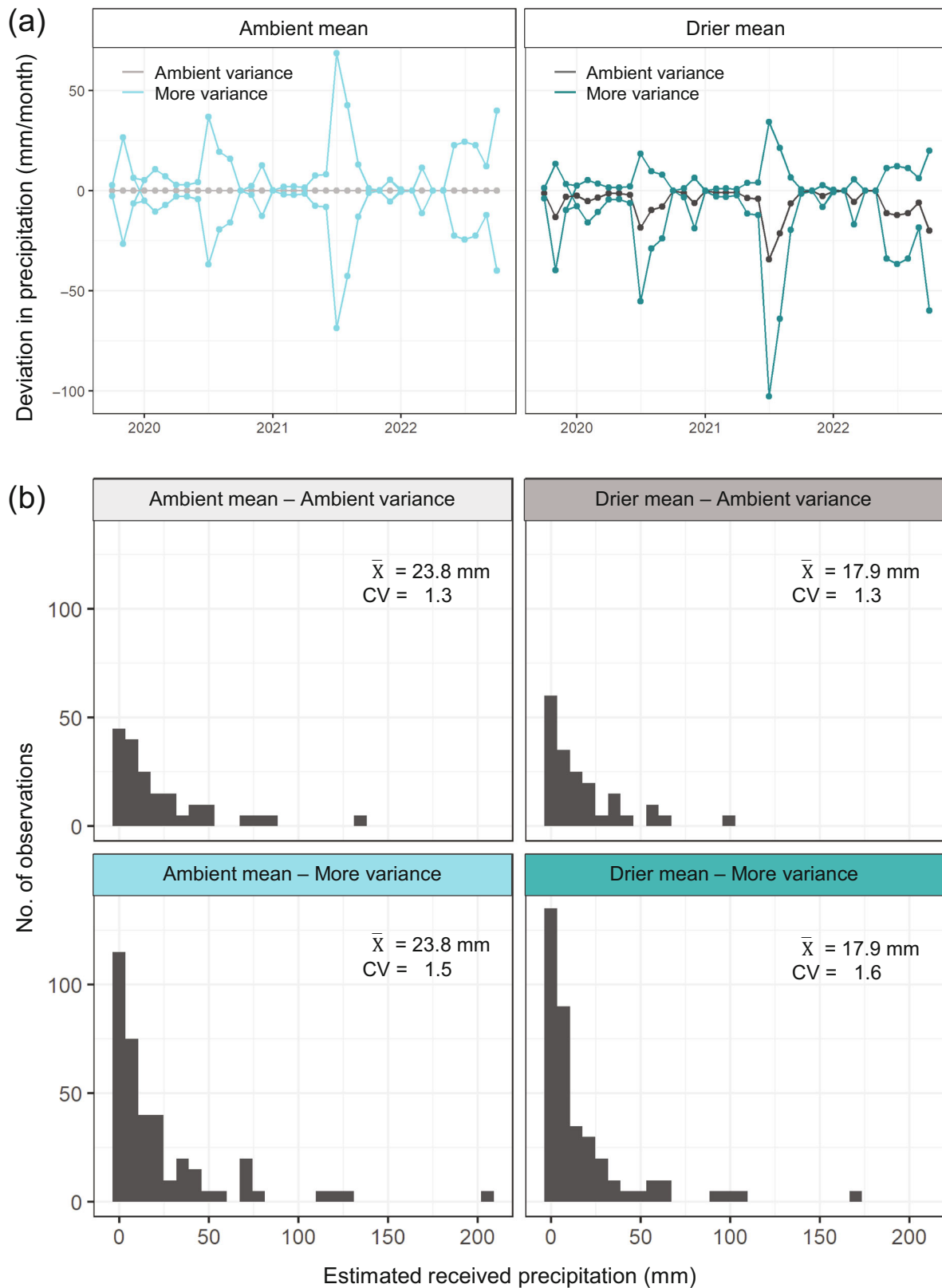


FIGURE 5 (a) Trajectories of estimated monthly precipitation for each treatment combination of the Mean \times Variance Experiment (MVE) in the Plains grassland site at the Sevilleta National Wildlife Refuge, Socorro, NM. Precipitation treatments were established by October 2019 (the beginning of water year 2020), and the deviation in precipitation from the monthly mean for ambient plots was estimated for each month of the time series. Positive deviations are plots receiving supplemental precipitation; negative values are drought plots. (b) Histograms of estimated precipitation for each treatment combination of the MVE, including the mean and CV over the time series.

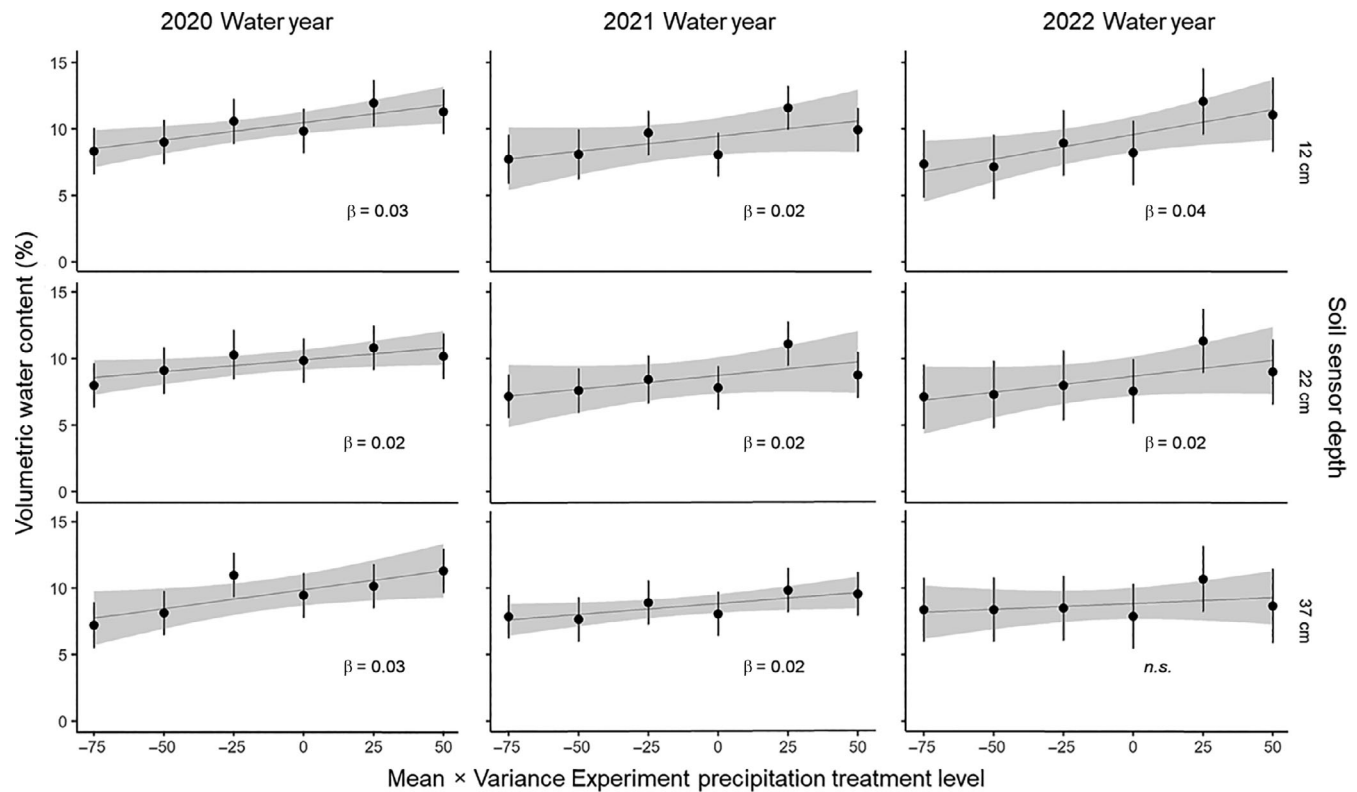


FIGURE 6 Mean volumetric water content (VWC, mean \pm 95% CI) for the precipitation gradient of the Mean \times Variance Experiment for the Plains grassland site at the Sevilleta National Wildlife Refuge, Socorro, NM. Precipitation treatments were established by October 2019 (the beginning of water year 2020), and mean VWC was calculated for each water year. The slope (β) is provided for each soil depth and water year slope and indicates the % change in soil moisture due to % change in precipitation treatment level.

any water year (2020: $\chi^2 = 0.61$, $p = 0.99$; 2021: $\chi^2 = 0.88$, $p = 0.97$; 2022: $\chi^2 = 0.77$, $p = 0.97$). At the daily scale, mean soil temperature varied from a minimum of -0.8°C at 12 cm deep on 31 December 2018 to a maximum of 38.4°C at 12-cm depth on 11 July 2020. Mean daily soil temperature did not vary with soil depth (2020: $\chi^2 = 0.01$, $p = 0.99$; 2021: $\chi^2 = 0.01$, $p = 0.99$; 2022: $\chi^2 = 0.43$, $p = 0.80$). Variability in soil temperature was 81% greater in the More Variance treatment than under ambient variance in precipitation (CV daily temperature, Variance treatment, $\chi^2 = 8.55$, $p = 0.026$), but did not vary with the Drier Mean treatment ($\chi^2 = 0.73$, $p = 0.42$) or with soil depth (depth $\chi^2 = 0.70$, $p = 0.53$; variance treatment \times depth $\chi^2 = 0.75$, $p = 0.51$).

Does microenvironmental spatial variation influence how treatments alter soil moisture profiles?

Microenvironmental spatial variation among plots, caused in part by spatial variation in the amount and depth of clay, influenced the magnitude to which soil moisture responded

to MVE infrastructure (Figure 8, $\chi^2 = 46.25$, $p < 0.0001$). Precipitation treatment effect sizes ranged from a -58% decline in soil moisture relative to pretreatment levels to $+13\%$ increase because the pretreatment soil moisture was, on average, greater than soil moisture during the years of the experiment. During six months of pretreatment observations (November 2018–April 2019), individual plots differed from each other more than two-fold in mean VWC from the driest plot at 8% average VWC to the wettest plot at 19% VWC. Plots with greater soil moisture prior to treatment installation had stronger declines in soil moisture under precipitation reductions (-75 , -50 , or -25) but smaller increases in soil moisture under precipitation additions ($+25\%$, $+50\%$; Figure 8). For example, for a plot that had pretreatment soil moisture that was 10% greater than the average, the precipitation reduction effect size was $\sim 20\%$ stronger and precipitation addition was $\sim 20\%$ weaker than the average effect size (slope of treatment effect size against pretreatment soil VWC: $\beta = -2.0 \pm 0.55$). The magnitude of influence of the pretreatment microenvironment on the responsiveness of soil moisture to MVE infrastructure was consistent across the MVE treatment levels (pretreatment soil moisture \times precipitation

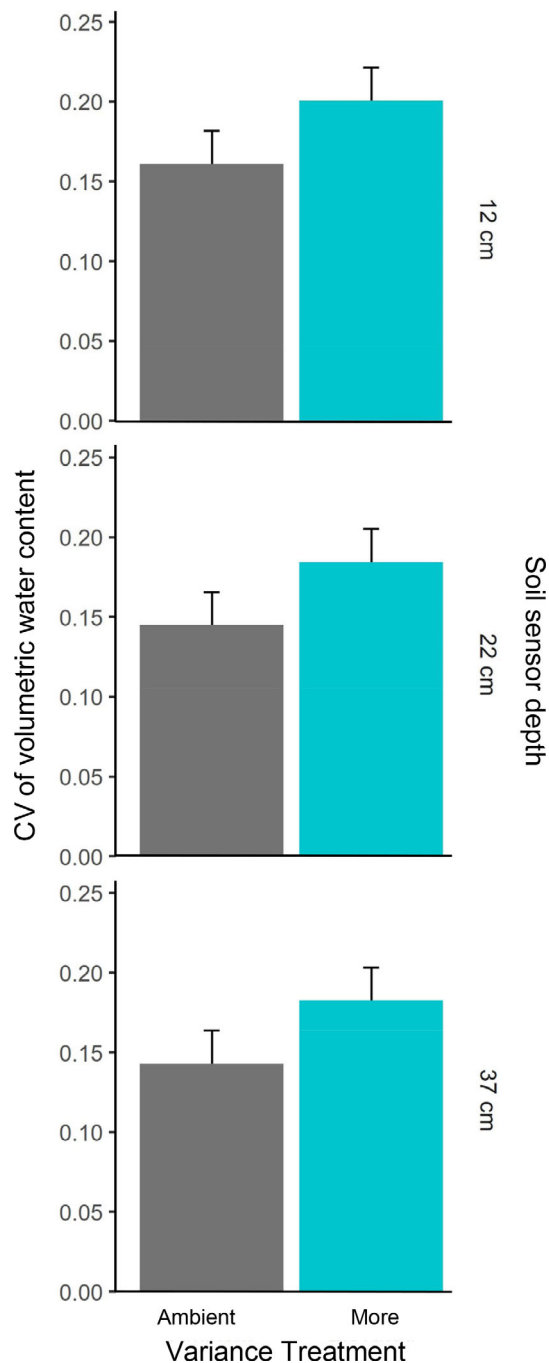


FIGURE 7 The CV in mean volumetric water content (VWC) \pm SE by the Variance treatment and soil sensor depth in the Mean \times Variance Experiment, Plains grassland site in the Sevilleta National Wildlife Refuge, Socorro, NM. Precipitation treatments were established by October 2019 (the beginning of water year 2020), and the CV of VWC was calculated from treatment initiation until 6 November 2022.

gradient, $\chi^2 = 1.59$, $p = 0.90$). However, the influence of microenvironment varied with soil depth ($\chi^2 = 6.65$, $p = 0.036$); it was strongest at intermediate soil depth (22 cm: $\beta = -4.5$) and weakest at the shallowest depth (12 cm: $\beta = -1.9$).

DISCUSSION

A novel experimental design factorially alters the mean and variance of precipitation

To our knowledge, we designed the first field experiment to simultaneously impose climate drying and increase interannual climate variability, which have already changed in tandem in the southwestern United States (Maurer et al., 2020; Rudgers et al., 2018). Our design is important to improving predictions on future population, community, and ecosystem responses to climate change, and in particular, to detecting whether a drying mean climate will alter the ecological consequences of an increasingly more variable climate. Our design will uncover the impacts of climate change across major dryland ecosystem types (Kreyling & Beier, 2013) because we imposed the same treatments in four ecosystem types that represent >60 million ha of the southwestern United States (Anderson-Teixeira et al., 2011).

A key design element is the inclusion of a stochastic (random) component to treatments that increase interannual climate variance. Precipitation often has a substantial stochastic component (Ridolfi et al., 2011). Although there are strong deterministic influences on climate in our region, including the Pacific Decadal Oscillation, El Niño Southern Oscillation, and intra-annual seasonality of the summer monsoon (e.g., ~60% of precipitation in our focal ecosystems occurs during the monsoon season), these can and have been addressed by specific prior climate experiments. An important aspect of the novelty of our experimental design is that our methods are not aimed to replicate any of these nonrandom forcings on climate, but rather to amplify the stochastic (random) component of climate variability.

The precipitation manipulations of MVE successfully altered soil moisture by $\pm 50\%$, measured as VWC with hourly sensors in a subset of the plots. We did not expect to achieve a -75% to $+50\%$ gradient in soil moisture by altering precipitation because of the small event sizes and the low number of days with precipitation events in this semiarid region. The mean daily event size was $3.6 \text{ mm} \pm 0.4$ from 1 October 2018 to 1 October 2022. And, the number of days with precipitation events ranged from only 58 days in 2022 to 96 days in 2020 (water year 2019: 70 days [19% of days], 2020: 96 days [26%], 2021: 66 days [18%], 2022: 58 days [16%]). In drylands, extended periods with no precipitation cause strong down-weighting of average soil moisture and reduce the ability to detect treatment effects because consecutive days of low soil moisture translate to no difference between precipitation treatments. The strength of

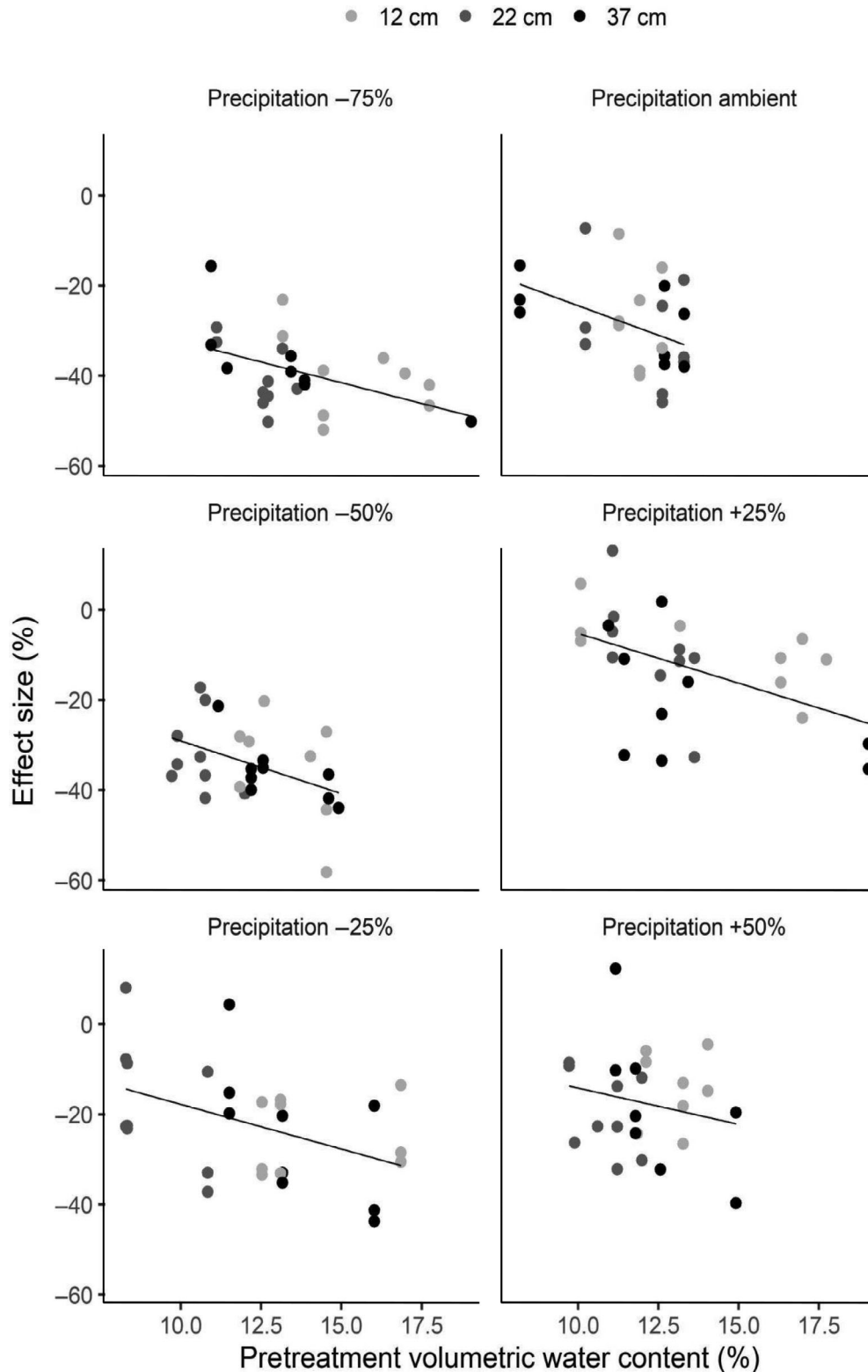


FIGURE 8 Microenvironmental spatial differences among plots in pretreatment soil moisture influenced the magnitude of precipitation manipulations using Mean \times Variance Experiment (MVE) infrastructure at the Plains grassland site in the Sevilleta National Wildlife Refuge, Socorro, NM. Across all treatments, greater pretreatment soil moisture resulted in larger declines in soil moisture with drought treatments (-75% , -50% , or -25%) and weaker increases in soil moisture (less negative effect size) with water addition treatments ($+25\%$, $+50\%$) ($\chi^2 = 46.25$, $p < 0.0001$). The slope of the influence of pretreatment microenvironment on the effect size of the precipitation manipulation (-2.0 ± 0.55 SE) did not vary significantly among MVE treatments ($\chi^2 = 1.59$, $p = 0.90$).

the effect of our precipitation treatments on mean soil moisture declined with soil depth, as we anticipated. Most rain events in our region are small in size, with an average magnitude of 2.1 mm over the long-term record (Petrie et al., 2014), which cannot penetrate into deep soil layers. However, because most plant roots are concentrated in the upper 20–30 cm of soil (Kurc & Small, 2004), treatment effects at shallow soil depths are ecologically relevant. In water year 2022, the soil moisture response to the precipitation gradient was nonsignificant at the deepest sensor depth (Figure 6), consistent with this expectation.

Our design not only altered mean soil moisture over a gradient of six levels, but also successfully increased interannual variation in soil moisture by 25% during just a three-year period (Figure 7). We are now three years into this long-term experiment at our longest running site, and we intend to run it for 20+ years because each year provides only one replicate of interannual variability. Thus far, we have not detected nontarget effects of MVE treatments on soil temperature at any measured depth, and our manipulation of variability in precipitation has remained independent of changes in mean soil moisture, as we intended in our factorial design.

Legacy effects of precipitation manipulation

The effectiveness of rainout and rain-addition infrastructure to alter soil moisture could decline over the planned lifetime of the experiment if strong legacy effects of past year's treatments occur. Here we explore three possible legacy effects. First, a prior experiment that imposed a 66% growing season drought reduced the abundance of cyanobacteria that form biological soil crusts up to 95% (Fernandes et al., 2018). Altered soil microbial communities can influence water infiltration (Kidron et al., 2012), thereby creating a legacy effect of past precipitation on current soil moisture. In our system, the loss of biological soil crusts under drought is predicted to increase water infiltration by reducing soil hydrophobicity caused by cyanobacteria (Chung et al., 2019); however, biological soil crusts of different compositions can have the reverse effect, instead increasing infiltration in some ecosystems (Kidron et al., 2012). Therefore, we have archived soils to monitor microbial legacy effects in the MVE. Second, prior drought experiments in Chihuahuan Desert grasslands caused mass mortality of the dominant grass species (Ladwig et al., 2012; Loydi & Collins, 2021) and also altered its population genetic structure, likely favoring the survival of drought-resistant genotypes

(Griffin-Nolan et al., 2019; Whitney et al., 2019). Therefore, additional legacy effects of prior precipitation could include reduced plant water uptake (and greater soil moisture) due to a combination of reduced plant biomass and changes in how plants that survived drought use water. For example, drought-resistant genotypes can have greater water use efficiencies than drought-sensitive genotypes (Attia et al., 2015; Chaves et al., 2003). Drought can also increase the water use efficiency of subdominant C_3 plant species as evidenced by enriched $\delta^{13}C$ isotopes (Fain, 2022). Third, an extreme drought in our grasslands also altered community-weighted mean plant and seed traits, including height, leaf carbon content (Luo et al., 2021), and seed coat thickness (Luo et al., 2022), and extreme drought increased the collective plant community's drought-escape strategies, rather than drought-resistance strategies (Griffin-Nolan et al., 2019). Such changes in plant species-level and community-level traits could alter water relations, creating legacy effects on soil moisture in subsequent years. For example, a one-year experiment to remove small rain events (<3.8 mm) constrained grassland plant and soil responses to supplemental rain in a subsequent year, slowing grassland recovery (Petrie et al., 2015).

Our new experimental design creates a tractable platform for assessing such legacy effects as they accumulate over time. However, we did not create replicated plots with identical antecedent conditions that would enable us to analyze specific antecedent effect scenarios statistically. This would require a large number of plots and could quickly become cost-prohibitive. The benefit of our design is the increased generalizability gained by randomizing antecedent conditions with our stochastic treatment assignments. Across our design at a single site, there are 10 plots in the More Variance treatment, each with an individual precipitation trajectory. This design enables us to evaluate the general impacts of increased stochastic variance without tying results to a specific future trajectory (e.g., wet–dry–wet–dry cycles).

Experiments to speed climate change in drylands

Our new experimental design is particularly relevant for dryland ecosystems where water is not only the most vital resource (Noy-Meir, 1973) but also has large temporal variability at both local and regional scales (Gutzler & Robbins, 2011; Milne et al., 2003; Notaro et al., 2010). In the northern Chihuahuan Desert, variability in precipitation has increased in recent decades along with an overall drying trend (Maurer et al., 2020; Rudgers et al., 2018), highlighting the relevance of experiments that alter both

mean and variance in precipitation. Although the average number of rain events per day has increased during the summer monsoon, the average size of daily rain events has declined during the past 100 years, resulting in no net change in average precipitation across the region (Petrie et al., 2014). However, models and tree ring data show greater variability and more intense winter El Niño events in recent decades (Grothe et al., 2020; Liu et al., 2017) along with intensification of sub-daily rain events during the summer monsoon (Demaria et al., 2019). Furthermore, tree ring data indicate that the rate of “flipping” between wet and dry years has recently accelerated in the southwestern United States (Oliver et al., 2019). As a consequence, year-to-year variability in precipitation has increased significantly throughout the region alongside aridification (Maurer et al., 2020), reflecting trends that are consistent with model predictions for climate in the future (Gutzler & Robbins, 2011). Meteorological data also show that droughts have already intensified in this region (Zhang et al., 2021), and a suite of climate models all indicate that the frequency, duration, and intensity of drought will increase in the future (Bradford et al., 2020; Cook et al., 2015). Together, observational data and models support a pattern of simultaneous change in the mean and variability of aridity throughout the northern Chihuahuan Desert. The MVE infrastructure will help to understand the ecological impacts of these combined changes for the coming decades, and in particular their potential impacts on the carbon cycle. Of all the land cover classes, arid and semiarid ecosystems contribute most to interannual variability in global carbon flux due to their high year-to-year variability in primary production (Ahlstrom et al., 2015; Fu et al., 2019) and large surface area (~45%), which is rapidly expanding (Huang et al., 2016; Právělie, 2016; Právělie et al., 2019). Experiments, like MVE, that directly manipulate interannual climate variability have the potential to provide new inference on the direct influence of climate variance on carbon fluxes.

Design considerations for other ecosystem types

We successfully established the MVE in four semiarid ecosystem types: two grasslands, one shrubland, and one savanna. In all plots, we included one or more individuals of small-statured shrubs (creosote bush) or trees (one-seeded juniper). However, larger statured plants, including dominant woody species (e.g., pines), would require alternative designs with taller rainout shelters or below-canopy throughfall catchment systems (e.g., Plaut et al., 2013; Sevanto et al., 2014). Our design may additionally require maintenance or repair in situations

of extreme wind. Several of our plots at the Plains grassland site, which experiences upwards of 30 m/s winds, sustained wind damage during initial establishment and required additional stabilization (Figure 3). The orientation of shelters such that one slanted side of the peaked roof faces the prevailing wind direction can help reduce wind stress, and our re-design of the variance infrastructure (see construction documents, <https://zenodo.org/record/7996101>) improved wind resistance. Finally, ecosystems with large overland flow and runoff during rain events or that occur on sloped surfaces may require additional infrastructure beyond trenched flashing (Figure 3) in order to maintain effective water manipulations.

CONCLUSION

In sum, we designed and implemented the first experiment to factorially reduce the precipitation mean while simultaneously increasing the variance of interannual precipitation in a way that captures the stochastic nature of climate variability. We hope that our novel design will inform predictions on future ecological responses to the interactive effects of changes to climate mean and variance.

AUTHOR CONTRIBUTIONS

All authors approve this publication. Anthony Luketich, Brooke E. Wainwright, Jennifer A. Rudgers, Lauren E. Baur, Melissa Bacigalupa, Marcy E. Litvak, Melissa Villatoro-Castañeda, Purbendra Yogi, Tom E. X. Miller, and William T. Pockman designed and/or constructed experimental infrastructure. Anthony Luketich, Melissa Bacigalupa, Jennifer A. Rudgers, Melissa Villatoro-Castañeda, and Purbendra Yogi designed, constructed, and/or maintained irrigation and sensor systems. Brooke E. Wainwright, Melissa Villatoro-Castañeda, and Melissa Bacigalupa collected auxiliary ecological data as well as sensor data. Andrew D. Richardson and Samantha J. Watson designed the PhenoCam systems, curated data streams derived from the camera imagery, wrote the PhenoCam text, and prepared Figure 3. All authors contributed to the writing, including edits and comments on the manuscript draft. All authors agree to be accountable for the aspects of the work that they conducted and ensure that questions related to the accuracy or integrity of any part of their work are appropriately investigated and resolved.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data and scripts (Rudgers, 2023) are available from Zenodo: <https://zenodo.org/record/7996101>.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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