

Ecosystem and community resistance to five years of drought and deluge in a sagebrush steppe

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Abstract

Precipitation is predicted to become more variable in the western U.S., meaning years of above and below average precipitation will become more common. Such periods of drought and deluge could become major drivers of plant community dynamics and ecosystem functioning. Here we report the results of a five-year experiment where we used drought and irrigation treatments (50% decrease/increase) to see how a sagebrush steppe plant community in Idaho will respond to future climate changes. The ecosystem was surprisingly resistant to both drought and irrigation. Aboveground net primary productivity (ANPP) responded positively to ambient growing season precipitation, but the response did not vary across treatments. There was also no evidence that treatment effects grew over time. The similarity of ecosystem functioning was not due to shifts at the plant community level, where species composition among treatments was similar and remarkably stable over the five years. At least in the short-term, ecosystem functioning and community composition in this sagebrush steppe system is resistant to increases and decreases in growing season precipitation.

Key words: drought, aboveground net primary productivity, ecosystem resistance, climate change, species composition, sagebrush steppe

1 Introduction

2 Chronic alterations to resource availability should cause community composition to shift over
3 time. Species' relative abundances are expected to re-order and, eventually, some species will be
4 lost from the local community and new species will be gained (Smith et al. 2009, Avolio et al.
5 2015). Ecosystem functioning, such as productivity and stability, may remain relatively constant
6 (CITATION) or shift to a new mean state (CITATION) depending on the trait-space of the new
7 community.

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Different ecosystems are sensitive to different global changes. For example, Flombaum et al. (2017) found aboveground net primary productivity (ANPP) in a Patagonian steppe was less sensitive to drought than a North American tallgrass prairie, relative to other global changes. Taken together with other results, Flombaum et al. (2017) conclude that ecosystem sensitivity to a resource alteration is inversely related to the natural variation of the resource. In the above example, precipitation is much more variable in the Patagonian steppe than the North American tallgrass prairie.

This leaves us with the following qualitative understanding. Chronic resource alteration should induce shifts in community composition and, maybe, ecosystem functioning, but only if the focal ecosystem is predisposed to be sensitive to the particular resource that is altered. While a crude understanding, this does allow us to make testable predictions when confronted with an ecosystem–resource pairing.

In many areas of the western United States, precipitation is likely to become more variable. This will result in swings back-and-forth between multiyear periods of above and above average precipitation. An obvious question is, how will semiarid ecosystems respond to periods of drought and deluge? A naive expectation is that alterations in precipitation, and subsequently available soil moisture, should cause changes in plant community composition and increase or decrease ANPP depending on the direction of precipitation change. But our emerging qualitative understanding suggests an alternative expectation: altering soil moisture may have little to no effect on plant community composition and ecosystem functioning. This expectation stems from the fact that precipitation is already a variable resource in semiarid systems, meaning the plant community is not sensitive to realistic increases/decreases in precipitation.

Here we test our qualitative understanding of how altering precipitation will impact a sagebrush steppe ecosystem by imposing drought and irrigation for five years. In particular, we test the following competing predictions:

- P1.** Altering precipitation will favor certain species over others, resulting in a shift in the plant community composition. ANPP will increase (irrigation) or decrease (drought), and the treatment effects will get stronger over time (a treatment \times year interaction).
- P2.** Altering precipitation will not favor certain species and plant community composition will not change. ANPP will increase (irrigation) or decrease (drought), and the treatment effects will get stronger over time.

Note that both predictions assume ANPP will respond to precipitation alteration. Under **P1**, ANPP response stems directly from plant community shifts to species able to take advantage of the new precipitation regime. Under **P2**, ANPP response stems from all species responding similarly to changes in precipitation.

Materials and Methods

Study Area

We conducted our precipitation manipulation experiment at the United States Sheep Experimental Station (USSES) near Dubois, Idaho (44.2° N, 112.1° W), 1500 m above sea level. The vegetation is typical of high elevation sagebrush steppe. The plant community is dominated by the shrub *Artemesia tripartita* and three perennial bunchgrasses, *Pseudoroegneria spicata*, *Poa secunda*, and *Hesperostipa comata*. During the period of our experiment, average mean annual precipitation was xxx mm and mean monthly temperature ranged from -x°C in January to x°C in July.

Precipitation Experiment

Between 1926 and 1932, range scientists at the USSES established 26 permanent 1 m² quadrats to track vegetation change over time. In 2007, we (well, one of us [P. Adler]) relocated 14 of the original quadrats, six of which were inside a large, permanent livestock enclosure. We use these six plots as control plots that have recieved no treatment, just ambient precipitation. In spring 2011, we (well, two of us [A. Kleinhesselink and P. Adler]) established 16 new 1 m² plots. We avoided areas on steep hill slopes, areas with greater than 20% cover of bare rock, and areas with greater than 10% cover of the shrubs *Purshia tridentata* and/or *Amelanchier utahensis*. We established the new plots in pairs and randomly assigned each plot in a pair to receive a “drought” or “irrigation” treatment.

Drought and irrigation treatments were designed to decrease and increase the amount of ambient precipitation by 50%, respectively. To achieve this, we used a system of rain-out shelters and automatic irrigation (Gherardi and Sala 2013). The rain-out shelters consisted of transparent acrylic shingles 1-1.5 m above the ground that covered an area of 2.5 × 2 m. The shingles intercepted approximately 50% of incoming rainfall, which was channeled into 75 liter containers. Captured rainfall was then pumped out of the containers and sprayed on to the adjacent irrigation plot via two suspended sprinklers. Pumping was triggered by float switches once water levels reached about 20 liters. We disconnected the irrigation pumps each fall and reconnected them, often with difficulty, each spring. The rain-out shelters remained in place throughout the year.

To make sure the treatments were having the desired effects, we monitored soil moisture in four of the drought-irrigation pairs using Decagon Devices (Pulman, Washington) 5TM and EC-5 soil moisture sensors. We installed four sensors in each plot, two at 5 cm soil depth and two at 25 cm soil depth. We also installed four sensors in areas nearby the four selected plot pairs to measure ambient soil moisture at the same depths. Soil moisture measurements were automatically logged

every four hours. We coupled this temporally intensive soil moisture sampling with spatially extensive readings taken at six points within all 16 plots and associated ambient measurement areas. These snapshot data were collected on 06/06/2012, 04/29/2015, 05/07/2015, 06/09/2015, and 05/10/2016 using a handheld EC-5 sensor.

[ANDY: paragraph here on SOILWAT. Is this the right thing to show/do? See Fig. 1C.]

Data Collection

We estimated aboveground net primary productivity (ANPP) using a radiometer to relate ground reflectance to plant biomass (see Byrne et al. 2011 for a review). We recorded ground reflectance at four wavelengths, two associated with red reflectance (xxx and xxx) and two associated with near-infrared reflectance (xxx and xxx). At each plot in each year, we took four readings of ground reflectances at the above wavelengths. We also took readings in ten calibration plots adjacent to the experimental site, in which we harvested all aboveground biomass, dried it to a constant weight at 60°C, and weighed it to estimate ANPP.

For each plot and year, we averaged the four readings for each wavelength and then calculated NDVI using the MODIS and AVHRR algorithms. To convert NDVI to ANPP we regressed NDVI against the dry biomass weight from the ten calibration plots. We fit regressions to MODIS-based NDVI and AVHRR-based NDVI for each year and retained the regression with the better fit. Using the best regression equation for each year, we predicted ANPP (Appendix 1).

Species composition data came from annual census maps for each plot made using a pantograph (Hill 1920). The maps record the spatial location and size of each individual plant. Using those annual maps, we aggregated over individuals to calculate total basal cover for each species in each plot.

Data Analysis

We fit generalized linear mixed-effects models (GLMMs) with precipitation, treatment, year, and treatment×year main effects and a random effect for plot. To account for temporal dependency in the data (i.e., ANPP in 2012 is likely more correlated with ANPP in 2013 than in 2016), we also include an autoregressive error structure [AR(1)]. Thus, our GLMMs account for the fact that each plot is sampled repeatedly over time, and that those yearly samples are not independent. Our models take the form:

$$\mu_{i,t} = \mathbf{x}_{i,t}\beta + \gamma_i \quad (1)$$

$$\mathbf{y}_i \sim \text{MVN}(\mu_i, \Sigma_i) \quad (2)$$

$$\Sigma_i = \begin{bmatrix} 1 & \rho_i & \rho_i^2 & \rho_i^3 & \rho_i^4 \\ & 1 & \rho_i & \rho_i^2 & \rho_i^3 \\ & & 1 & \rho_i & \rho_i^2 \\ & & & 1 & \rho_i \\ & & & & 1 \end{bmatrix} \sigma_i^2 \quad (3)$$

where $\mu_{i,t}$ is the predicted value of $\log(\text{ANPP})$ in plot i and year t , $\mathbf{x}_{i,t}$ is the vector of covariates (including the intercept) associated with plot and year, β is the vector of fixed effects associated with each term in $\mathbf{x}_{i,t}$, and γ_i is the random effect for plot. We sample the vector of yearly observed $\log(\text{ANPP})$ values in each plot (\mathbf{y}_i) from a multivariate normal likelihood with the means from the regression equation (e.g., μ_i) and a variance-covariance matrix (Σ_i) with an AR(1) structure that is unique for each plot. Our model assumes the variance term (σ^2) is unique for each plot, but consistent across years in a plot. The correlation term (ρ) in the covariance matrix determines the correlation of measurements across years. The superscripts (e.g., ρ^2) correspond to the lag time between two measurements, and ensure that the correlation decays as the lag increases.

We fit the above model for the drought and irrigation treatments independently because we are only interested in comparing each treatment to the control, not to each other. We fit the model using a Bayesian approach, obtaining posterior estimates of all unknowns via the No-U-Turn Hamiltonian Monte Carlo sampler in Stan (Stan Development Team 2016a). We used the R package ‘rstan’ (Stan Development Team 2016b) to link R (R Core Team 2016) to Stan.

To see if community composition differed among treatments through time, we used non-dimensional multivariate scaling (NMDS) based on Bray-Curtis distances. For each year of the experiment, we first calculated Bray-Curtis distances among all plots, and then extracted those distances for use in the NMDS. We plotted the first two axes of NMDS scores to see if community composition overlapped, or not, among treatments in each year. We used functions in the R package ‘vegan’ (Oksanen 2016) to calculate Bray-Curtis distances and then to run the NMDS analysis. Lastly, we examined rank clocks of species’ abundances through time to assess the stability of community composition over the course of the experiment (Collins et al. 2008). Rank clocks were made using ‘ggplot2’ (Wickham 2009) and R code from Hallett et al. (2016).

All R code and data necessary to reproduce our analysis has been archived on Figshare ([link here after acceptance](#)) and released on GitHub (https://github.com/atredennick/usses_water/releases/v0.1). We also include annotated Stan code in our model description in Appendix 1.

Results

Three of our five treatment years fell in years of below average rainfall (Fig. 1A). Thus, those three years represent a lower magnitude of absolute change in precipitation experienced by the treatments. Averaged across treatments, ANPP varied from a minimum of xxx g m^{-2} in 2014 to a maximum of xxx g m^{-2} in 2016 (Fig. 1B). ANPP was slightly higher in irrigation plots and slightly lower in drought plots (Fig. 1B), corresponding to estimated soil volumetric water content (VWC) differences among treatments (Fig. 1C). Such differences in soil VWC indicate our treatment infrastructure was successful.

Growing season precipitation had a positive effect on ANPP (Fig. 2 and Table 1), but ANPP over the entirety of the experiment was not different from control plots for either drought ($\text{Pr}(\text{Drought} < \text{Control}) \leq 0.95$) or irrigation ($\text{Pr}(\text{Irrigation} > \text{Control}) \leq 0.95$) treatments (Fig. 2 and Table 1). There was also no evidence that the treatment effects became more important over time ($\text{Pr}(\text{Treatment} \times \text{Year}) \leq 0.95$; Fig. 2B and Table 1).

Community composition was similar among treatments, whether looking at basal cover or density (Fig. 3). Likewise, community composition was remarkably stable over time, with no evidence of divergence among treatments (Fig. 3). Species' abundances and ranks showed no deviation over the five-year experiment, regardless of treatment (Fig. 4).

Discussion

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Table 1: Probability that each log(ANPP) coefficient is greater or less than zero for each of the precipitation treatments. Probabilities denote $\max(\Pr(\text{coefficient}) > 0, \Pr(\text{coefficient}) < 0)$, where the sign of the coefficient was ignored. Thus, probabilities represent the probability of the coefficient being important in the model. Bold coefficients denote $\Pr(\text{coefficient}) \geq 0.95$.

log(ANPP) Coefficient	Drought	Irrigation
Precipitation	1.00	1.00
Treatment	0.57	0.96
Year	1.00	1.00
Treatment x Year	0.89	0.78

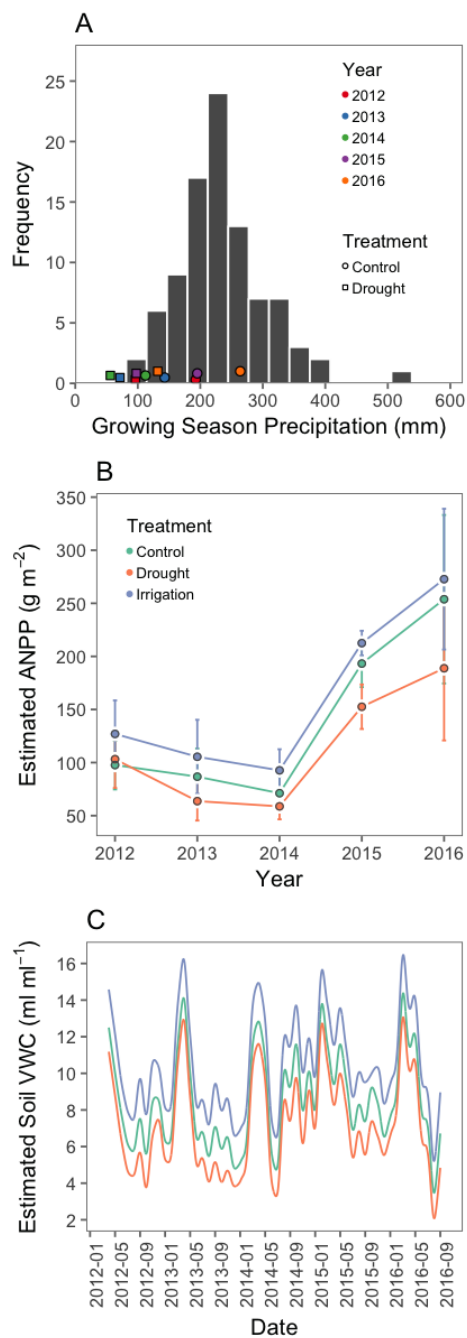


Figure 1: (A) Histogram of historical precipitation from 1926-2016, with the years of the experiment overlaid as colored points. “Drought” treatments (squares) are shown as a 50% reduction from the observed precipitation. “Irrigation” treatment precipitation levels are not shown. (B) Mean (points) ANPP and its standard deviation (error bars) for each year of the experiment. (C) Monthly average estimated soil volumetric water content (VWC) from SOILWAT model fit using soil moisture data from experimental plots.

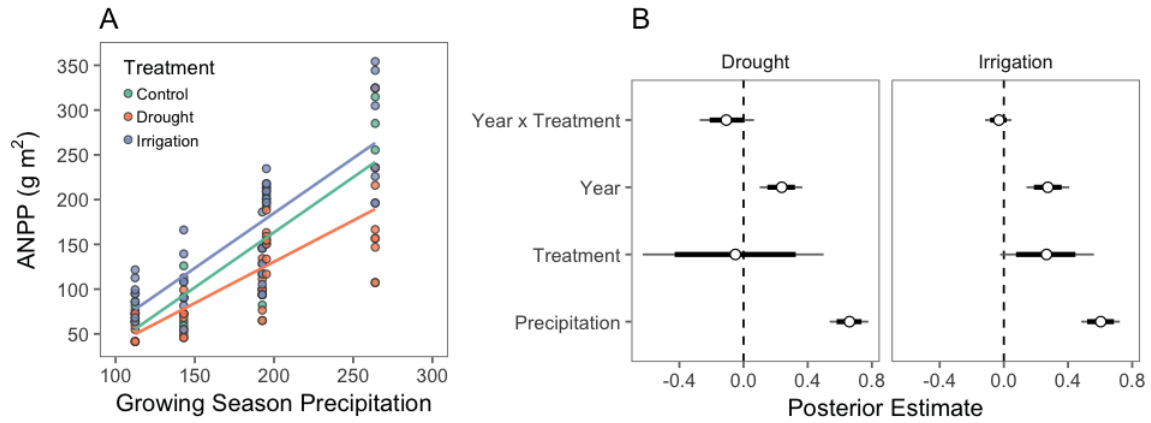


Figure 2: (A) Relationship between ANPP and growing season precipitation over the course of the experiment. Regression lines are independent linear fits for each treatment for visual clarity of the mean trends. (B) Posterior medians (points), 80% BCIs (heavy lines), and 95% BCIs (light lines) of effects from the fitted repeated measures generalized linear mixed-effects model for each treatment-control comparison. BCI refers to 'Bayesian Credible Interval', which is the upper and lower quantiles of the posterior distribution at the specified level.

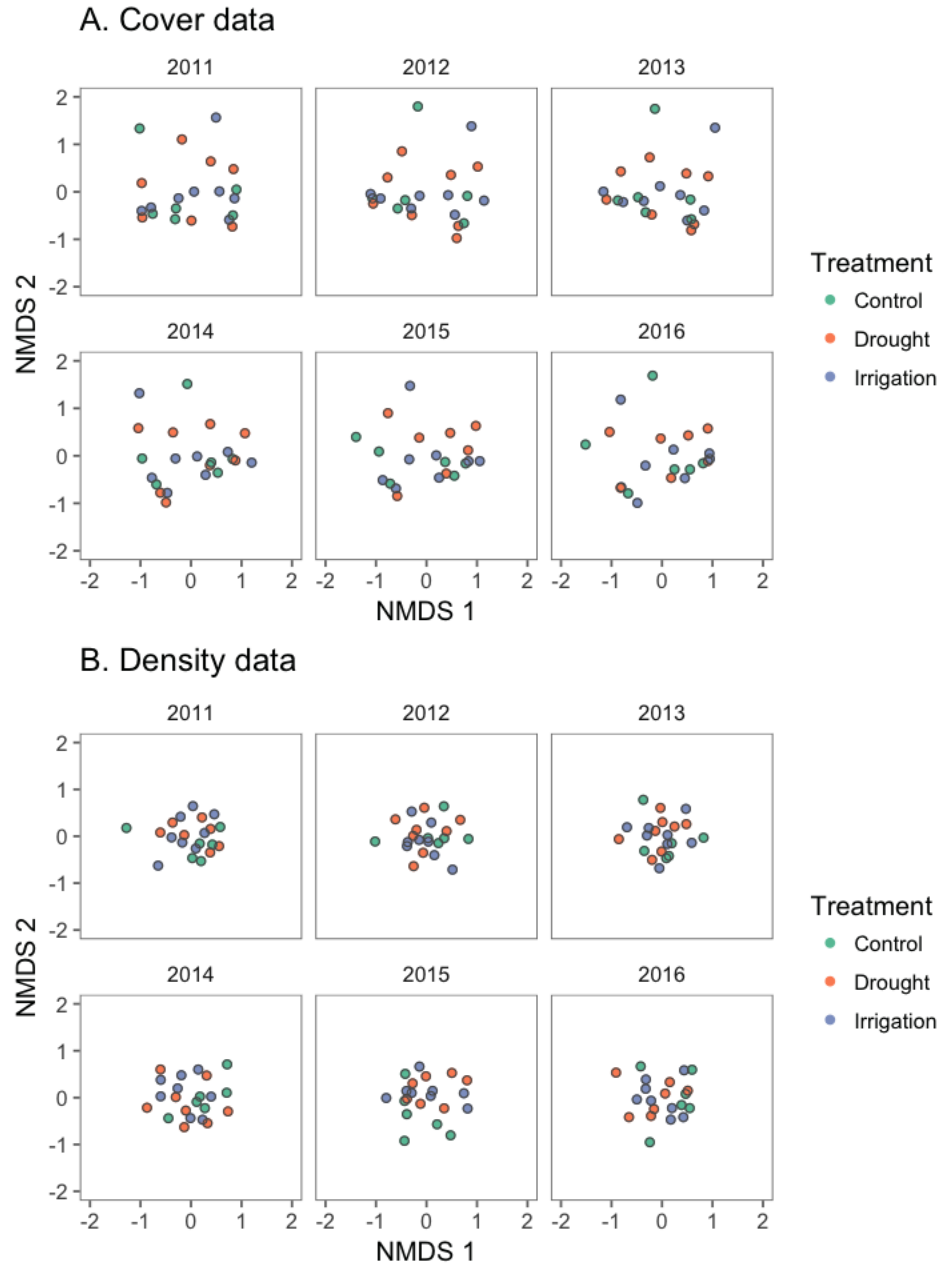
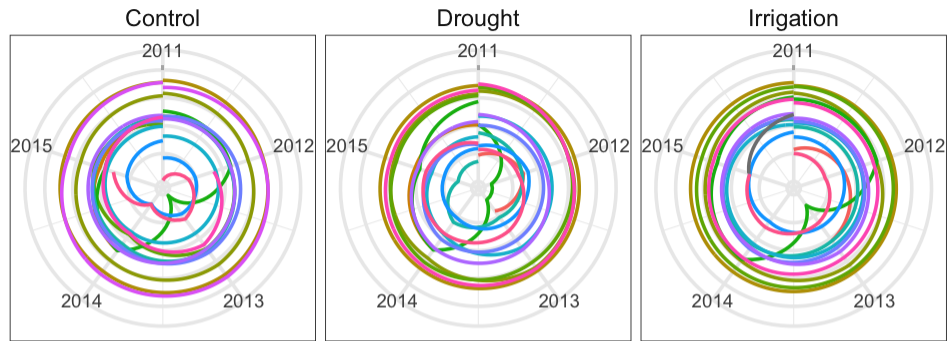


Figure 3: Nonmetric multidimensional scaling scores representing plant communities in each plot, colored by treatment. (A) NMDS results using basal cover data; (B) NMDS results using individual density data. 2011 is a pre-treatment year.

A. All species



B. Dominant species

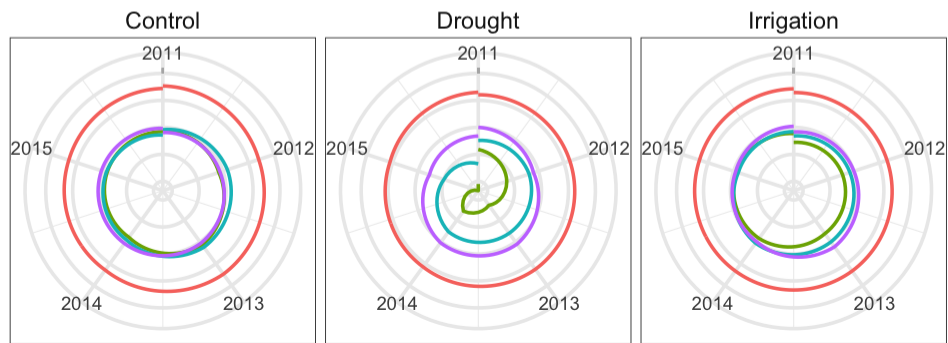


Figure 4: Rank clocks of average species' basal cover by treatment. (A) All species. (B) Dominant species. Cover is log-transformed to improve visualization of species with low cover.

References

- Avolio, M. L., K. J. L. Pierre, G. R. Houseman, S. E. Koerner, E. Grman, F. Isbell, D. S. Johnson, and K. R. Wilcox. 2015. A framework for quantifying the magnitude and variability of community responses to global change drivers. *Ecosphere* 6:1–14.
- Byrne, K. M., W. K. Lauenroth, P. B. Adler, and C. M. Byrne. 2011. Estimating Aboveground Net Primary Production in Grasslands: A Comparison of Nondestructive Methods. *Rangeland Ecology & Management* 64:498–505.
- Collins, S. L., K. N. Suding, E. E. Cleland, M. Batty, S. C. Pennings, K. L. Gross, J. B. Grace, L. Gough, J. E. Fargione, and C. M. Clark. 2008. Rank clocks and plant community dynamics. *Ecology* 89:3534–3541.
- Flombaum, P., L. Yahdjian, and O. E. Sala. 2017. Global-change drivers of ecosystem functioning modulated by natural variability and saturating responses. *Global Change Biology* 23:503–511.
- Gherardi, L. A., and O. E. Sala. 2013. Automated rainfall manipulation system: a reliable and inexpensive tool for ecologists. *Ecosphere* 4:1–10.
- Hallett, L. M., S. K. Jones, A. A. M. MacDonald, M. B. Jones, D. F. B. Flynn, J. Ripplinger, P. Slaughter, C. Gries, and S. L. Collins. 2016. codyn: An r package of community dynamics metrics. *Methods in Ecology and Evolution* 7:1146–1151.
- Hill, R. R. 1920. Charting Quadrats with a Pantograph. *Ecology* 1:270–273.
- Oksanen, J. 2016. *Vegan: ecological diversity*.
- R Core Team. 2016. *R: A Language and Environment for Statistical Computing*. Vienna, Austria.
- Smith, M. D., A. K. Knapp, and S. L. Collins. 2009. A framework for assessing ecosystem dynamics in response to chronic resource alterations induced by global change. *Ecology* 90:3279–3289.
- Stan Development Team. 2016a. *Stan: A C++ Library for Probability and Sampling, Version 2.14.1*.
- Stan Development Team. 2016b. *Rstan: the R interface to Stan, Version 2.14.1*.
- Wickham, H. 2009. *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag, New York.