

Can historical data predict population responses to climate change experiments?

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¹ **Summary**

- ² 1. Climate is an important driver of population ecology however there have been few tests of
³ whether observational data correlating population performance with climate variation can be
⁴ used to predict future responses of populations to experimentally imposed climate.
- ⁵ 2. Using longterm historical observational data from a sagebrush steppe plant community, previ-
⁶ ous research has reported a wide variety of climate effects on four dominant plant species. We
⁷ tested whether these climate effects observed in observational data were useful for predicting
⁸ each species response to a drought and irrigation experiment.
- ⁹ 3. We used rainfall shelters and automatic sprinklers to manipulate the soil moisture in sixteen
¹⁰ new plots established at the same field site as the original historical plots. We also re-monitored
¹¹ the original plots as controls. After running the experiment for five years, we analyzed how
¹² the growth, survival and recruitment of each species responded to the experimental drought
¹³ and irrigation treatments.
- ¹⁴ 4. In order to test whether we could predict the observed responses to the experiment we fit two
¹⁵ types of models to the observational data collected prior to the experiment: first we fit a no
¹⁶ climate model that included the effects of plant size and competition on plant performance in
¹⁷ each plot in each year; next we fit a climate model that in addition to size and competition
¹⁸ also included the effects of three seasonal soil moisture variables. Next we used these models
¹⁹ to predict the survival and growth of each individual plant, and the total recruitment in each
²⁰ plot during the course of the experiment. We also used an individual based population model
²¹ parameterized with the vital rate predictions to predict one step ahead changes in population
²² size in the experimental plots. We then compared the predictions made by each of these models
²³ to the observed experimental responses and compared the performance of the no climate model
²⁴ to the climate model.
- ²⁵ 5. Over the course of the experiment, average cover of the perennial grasses, *Hesperostipa comata*
²⁶ and *Pseudoroegneria spicata* declined significantly in the drought treatment. At the level of
²⁷ individual vital rates, experimental drought reduced the survival of *Hesperostipa comata* and
²⁸ *P. spicata* and the growth of the grass *Poa secunda*. In contrast, drought increased the growth
²⁹ of the shrub *A. tripartita*.

30 6. The climate better predicted the response to the experiment than the no climate model in six
31 out of the twelve cases we examined. Across all species and vital rates, there was a strong
32 positive correlation between the observed effects of the experiment and the effects predicted
33 by the climate model fit to the observational data. At the population-level, the climate model
34 made better predictions of the changes in species cover than the no climate model for two
35 species: *P. secunda* and *P. spicata*. Moreover, in the drought treatments the climate model
36 made better predictions for the changes in cover of all four species.

37 7. *Synthesis:* Observational climate data held valuable information for predicting species' re-
38 sponses to a modern climate change experiment in this ecosystem. Treatment responses often
39 matched the direction of predicted responses even when the effects were not significant. We
40 were better able to predict species' responses to the drought treatment than to the control and
41 irrigation treatments. Suggesting that soil moisture is an important factor in predicting the
42 population dynamics of these species but only when water is truly limiting.

43 **Introduction**

44 Climate is one of the most powerful drivers of changes in species abundance across space and time
45 (Post and Forchhammer, 2002; Davis and Shaw, 2001; Walther et al., 2002). The effects of climate
46 on populations and ecosystems are most apparent at the largest scales: climate determines the
47 distribution of ecosystems (Whittaker, 1975), treelines (Kerner, 2012) and the range limits of
48 many species (Parmesan and Yohe, 2003; Davis and Shaw, 2001). Understanding and predicting
49 the effects of climate on populations is an increasingly important goal if we are to anticipate the
50 effects of climate change on earth's ecosystems (Tredennick et al., 2016; Petchey et al., 2015; Ehrlin
51 et al., 2016; Teller et al., 2016).

52 Ecologists often resort to one of two methods for predicting the effects of future climate
53 change on populations and communities: they may use experiments to manipulate aspects of
54 climate directly and observe the response of populations (Elmendorf et al., 2015; Knapp et al., 2016;
55 Compagnoni and Adler, 2014); or they may use longterm observational data on species performance
56 and abundance collected over many years and relate this to ambient annual variation in climate
57 (Koons et al., 2012; Lunn et al., 2016; Dalgleish et al., 2010; Jenouvrier et al., 2009). The strength of
58 the experimental approach is in the stronger inference that comes from manipulating some aspects

59 of climate while controlling for other factors; for instance knowing that loss of snow cover, and not
60 necessarily changes in soil temperature or moisture are the factors causing a species performance to
61 change with warming (Compagnoni and Adler, 2014). It also allows for the creation of conditions
62 that may be more extreme than those observed historically Knapp et al. (2016) but are possible
63 in the future. However, it is often expensive to control climate at even the smallest scales, and
64 larger scale climate manipulation is often impossible. Moreover, experimental manipulation can
65 come with artifacts that may make them less than ideal models for understanding and predicting
66 the effects of future variation in climate (Wolkovich et al., 2012).

67 Using observational data to predict the effects of climate variation on populations has many
68 advantages over using experiments. The primary one being the ever increasing availability of long-
69 term ecological data and ever increasingly detailed climate data. Observational studies may also be
70 the only way to study the effects of climate on large and or migratory species, for which it would
71 be difficult to manipulate climate (Koons et al., 2012; Jenouvrier et al., 2009; Aubry et al., 2013).
72 However, there are many potential drawbacks to using essentially correlative relationships between
73 species performance and climate to predict future species' responses. First, many years of data are
74 needed to reliably detect climate effects, especially when annual variation in demographic rates is
75 high (Teller et al., 2016; Gerber et al., 2015). (Teller et al., 2016) estimate that even cutting edge
76 statistical approaches for fitting relationships between climate and species performance require at
77 least 20-25 years of independent climate observations before they perform well. Moreover, even
78 strong correlations between species performance and the climate covariates we choose to include in
79 our models may not be due to direct causation and may not hold up in future years of observation
80 (Hilborn, 2016).

81 And yet even overcoming this challenge, predicting the effects of climate change would
82 face yet another challenge: in many parts of the world, climate change will lead to mean annual
83 temperatures that will be above the range of historical variation. If species performance responds
84 non-linearly to temperature, we may be unable to predict how species respond to temperatures
85 outside the range of observed variation (Doak and Morris, 2010). In addition, climate change will
86 not just change the average climate, but is also likely to increase the variance in precipitation
87 and lead to extreme events, which will have their own consequences independent of changes in
88 climate averages (Drake, 2005; Jentsch et al., 2007). Any models based on observations drawn

89 from the historical range of variation will therefore be extrapolating beyond both the range of
90 observed averages and variance when used to predict the future (Williams and Jackson, 2007).
91 Demonstrating that models fit to historical data can accurately predict the effects of experimental
92 climate manipulations, especially manipulations that generate extreme conditions, would be strong
93 confirmation that the climate effects they describe are not spurious and will hold even in the novel
94 conditions of the future Adler et al. (2013).

95 There is abundant evidence that plant performance shows high year to year variation, both
96 at the level of individual growth, survival and reproduction and total population abundance. Pre-
97 cipitation is often especially important in driving interannual variation in net primary productivity
98 among terrestrial plants (Knapp and Smith, 2001; Hsu and Adler, 2014). And the growth rates of
99 trees are also often so tightly linked to annual precipitation that growth rings in their stems can
100 serve as accurate records of historical climate variation thousands of years before the present (Yang
101 et al., 2014). Among smaller plants precipitation clearly affects the growth rates of small shrub and
102 sub-shrub species (Srur and Villalba, 2009; Franklin, 2013), and the germination and reproductive
103 output of desert annuals is often tightly linked to annual precipitation (Venable, 2007).

104 Despite the clear signs that climate drives net primary productivity at the ecosystem level
105 and the variation in individual growth rate in many plants, there have been relatively few studies
106 that clearly link observed climate variation to species performance in population models (Ehrln
107 et al., 2016). Fewer still have tested whether the population-level effects of climate variation
108 shown in observational data can actually be used to predict the responses of plant populations to
109 future climate variation. (Adler et al., 2013) showed that population models based on observed
110 correlations between plant population growth rates and precipitation did have some predictive
111 power in describing species response to a short-term climate manipulation in a North American
112 grassland. Three species showed responses to experimentally imposed drought and irrigation that
113 were well predicted by population models fitted to historical observations. However, another three
114 species, showed responses to the experimental conditions that were not well predicted by historical
115 observations. The authors suggested that limited replication in the historical data for two of these
116 species and changing competitive conditions in the community may have led to the poor predictions.

117 The demography of and competitive interactions between three dominant perennial bunch-
118 grasses and a shrub in a sagebrush steppe plant community at the US Sheep Experiment Station

119 near Dubois, Idaho have been described in at least seven different studies since 2010 (Adler et al.,
120 2010, 2012, 2009, 2016; Chu et al., 2016; Chu and Adler, 2015; Dalgleish et al., 2010). And several of
121 these studies report significant effects of climate variation on the vital rates and overall population
122 growth rates of these species (Dalgleish et al., 2010; Adler et al., 2012, 2009; Chu et al., 2016). This
123 well-studied system offers the ideal opportunity to test whether statistical associations between
124 annual climate and plant demography in longterm observational data can be used to predict the
125 responses of plant populations to experimental climate change experiments.

126 In this study, we report how the four dominant plant species at the USSES respond to a
127 five year drought and irrigation experiment and use the results to address two research questions:
128 first, how much do the growth, recruitment and survival of our target species differ between the
129 precipitation manipulation treatments? If our experiment does affect species vital rates we interpret
130 that as strong evidence that changes in precipitation should have an effect on populations in the
131 future. Second, can we predict each species' response to the experimental conditions based on
132 how they respond to natural climate variation in the observational data? If models based on
133 observational data can predict the response of species to this experiment this should give us more
134 confidence in longterm population monitoring data to predict species response to climate change.

135 Methods

136 Study site and data set description

137 The U.S. Sheep Experiment Station (USSES) is located at Dubois, Idaho (44.2°N, 112.1°W), 1500
138 m above sea level. During the period of data collection (1926–2016), mean annual precipitation
139 was 270 mm and mean temperatures ranged from -8°C (January) to 21°C (July). The vegetation
140 is dominated by a shrub, *Artemisia tripartita*, and three perennial C3 grasses: *Pseudoroegneria*
141 *spicata*, *Hesperostipa comata*, and *Poa secunda*. These dominant species account for over 70% of
142 basal cover and 60% of canopy cover at this site.

143 Scientists at the USSES established 26 1-m² quadrats between 1926 and 1932. Eighteen
144 quadrats were distributed among four ungrazed exclosures, and eight were distributed in two pad-
145 docks grazed at medium intensity spring through fall. All quadrats were located on similar topog-
146 raphy and soils. In most years until 1957, all individual plants in each quadrat were mapped using

147 a pantograph (?). The historical data set is public and available online (?). In 2007, we located
148 14 of the original quadrats, all of which are inside permanent livestock exclosures, and resumed
149 annual mapped censusing using the traditional pantograph method. Daily temperature and pre-
150 cipitation has been monitored throughout this period at a climate station located at the USSES
151 headquarters (station id: GHCND:USC00102707) which located within 2 km of the research plots.
152 We downloaded daily and monthly tmin, tmax, and precipitation data from the National Climate
153 Data Centers online database.

154 We extracted data on survival, growth, and recruitment from the mapped quadrats based
155 on plants' spatial locations. Our approach tracks genets representing individual plants. For the
156 shrub, each genet is associated with the basal position of a stem. For the bunchgrasses, each genet
157 represents a spatially distinct polygon in the mapped quadrat. These genets may fragment and/or
158 coalesce over time. Each mapped polygon is classified as a surviving genet or a new recruit based
159 on its spatial location relative to genets present in previous years (Lauenroth and Adler, 2008). We
160 modeled vital rates using data from 21 year-to-year transitions between 1929 and 1957, and four
161 year-to-year transitions from 2007 to 2011.

162 Precipitation experiment

163 In spring 2011, we selected locations for an additional 16 quadrats for the precipitation experiment.
164 We located these in a large exclosure containing six of the historical permanent quadrats. We
165 avoided plots falling on hill slopes, areas with greater than 20% bare rock, or with over 10% cover
166 of the woody shrubs *Purshia tridentata* or *Amelanchier utahensis*. New plots were established
167 in pairs, and one plot per pair was randomly assigned to either the precipitation reduction or
168 the precipitation addition treatment. We mapped the quadrats in June, 2011 and then built the
169 rainfall shelters and set-up the irrigation systems in the fall of 2011. We used a rain-out shelter and
170 automatic irrigation design described in (Gherardi and Sala, 2013). Each rain-out shelter covered
171 an area of 2.5 by 2 m and consisted of transparent acrylic shingles held up 1.5 to 1 m over the plot
172 to channel 50% of incoming rainfall off of the plot and into 75 l reservoirs. The collected water
173 was pumped out of reservoirs and sprayed onto paired irrigation treatment plots. Pumping was
174 initiated automatically with float switches that were triggered when water levels in the reservoirs
175 were approximately 20 l, or equivalently irrigation was triggered once for every 6 mm of rainfall

176 collected. We disconnected the irrigation pumps in late fall each year and re-connected them in
177 April. The drought shelters remained in place throughout the year.

178 We monitored soil moisture and air temperature in four of the precipitation experiment plot
179 pairs using Decagon Devices (Pulman Washington) 5TM and EC-5 soil moisture sensors and 5TE
180 temperature sensors. We installed two soil moisture sensors in each monitored plot at 5 cm and
181 two at 25 cm deep in the soil. Air temperature was measured underneath the roofing of the shelter
182 at 30 cm above ground. For each pair of manipulated plots, we also installed sensors in a nearby
183 area to measure ambient rainfall and temperature. Data were logged automatically every four
184 hours. We augmented automatic monitoring of the climate in these plots with direct measurements
185 of soil moisture with a handheld EC-5 soil moisture sensor at six points around all 16 plots on
186 6/6/2012, 4/29/2015, 5/7/2015, 6/9/2015 and 5/10/2016. We analyzed these spot measurements
187 for significant treatment effects on soil moisture using a linear mixed effects model with the *lmer*
188 package in *R* (?), with plot, plot group, and date as random effects in the model.

189 We conducted a simple statistical to determine the net effect of the experimental treatments
190 on cover in the experiment. First we calculated the log change in cover for each of the four focal
191 species in each quadrat from from the start of the experiment in spring prior to manipulation, to
192 the last year of the experiment. Log change in cover was defined as , $\log(Cover_{2016}/Cover_{2011})$
193 where $Cover_{2016}$ is the cover of each species in 2011 and $Cover_{2015}$ is cover in 2011. We tested for
194 the effect of precipitation treatment on this measure with a linear model in *R*.

195 Soil moisture modeling

196 We expected that our precipitation manipulation experiment would affect plants by altering avail-
197 able soil moisture during the growing season. Because we do not have direct soil moisture measures
198 for each year of observed plant cover in the historical record, we used the SOILWAT soil mois-
199 ture model to estimate daily soil moisture at the USSES from 1925 to the present (?). We used
200 an enhanced version of soilwat that has recently been developed for use in semi-arid shrubland
201 ecosystems (?). SOILWAT uses daily weather data, ecosystem specific vegetation properties and
202 site specific soil properties to estimate water balance processes. SOILWAT specifically estimates
203 rainfall interception by vegetation, evaporation of intercepted water, snow melt and snow redistri-
204 bution, infiltration into the soil, percolation through the soil, bare-soil evaporation, transpiration

205 from each soil layer, and drainage. We parameterized SOILWAT with the generic sagebrush steppe
206 vegetation parameters and site specific soil texture and bulk density data. We used daily weather
207 data collected at the USSES from 1925 until the present as weather forcing data for the SOILWAT
208 predictions.

209 We averaged daily soil moisture predictions from SOILWAT from upper 40 cm of soil and
210 then averaged these seasonally to serve as the covariates in the vital rate regressions for each species.
211 Because we did not monitor soil moisture directly in all control, drought and irrigation plots, we
212 used a model to describe the average treatment effects on soil moisture during the course of the
213 experiment. To do this we first averaged observed soil moisture data by date and plot and then
214 standardized these by the mean and standard deviation of the control soil moisture conditions
215 observed within each plot group. We then found the difference between the soil moisture in the
216 treated plots and the ambient conditions. We then modeled these treatment effects as a function of
217 season and whether a day was rainy or dry. We expected that our drought and irrigation treatments
218 might be more effective during rainy weather than during dry weather. Rainy days were defined as
219 any days when any precipitation was recorded and average temperatures were above 3 degrees C.
220 The day immediately following rainfall was also classified as rainy. We fit this model using the *lmer*
221 package in *R* (?) with random effects for plot group and date. We then used this model to predict
222 the treatment effects on soil moisture for the entire study period from the ambient soil moisture
223 values predicted from the SOILWAT model described above. These adjusted soil moisture values
224 reflected the average season and rainfall dependent effects of the experimental treatments on soil
225 moisture and could be used as covariates for predicting the effects of our manipulation on each
226 species demographic rates.

227 Overview of the analysis

228 Our analysis consists of two separate datasets and three different categories of vital rate models.
229 We refer to the first dataset as the observational data. It consists of all the historical data collected
230 from 1925 to 1957 as well as the modern data collected from the same plots from 2007 to 2010.
231 These data record the response of plants in each plot to the ambient climate variation. We refer
232 to the second dataset as the experimental data. It consists of the data collected from 2011 to 2016

233 from the 16 new experimentally manipulated plots, as well as from 14 of the original historical plots
234 which serve as ambient climate controls.

235 In order describe the effects of the experimental treatments on each vital rate, we fit "treat-
236 ment" models. The treatment models included parameters for the effects of the drought and ir-
237 rigation treatments on each vital rate. We fit these models to both datasets together, all the
238 experimental and all the observational data. We did this because we wanted to focus our predic-
239 tions on the effects of the experimental treatments on the vital rates, rather than any differences
240 between the datasets in the effects of crowding and plant size on the vital rates.

241 Next in order to test how well we could predict the responses in the experimental plots, we fit
242 two classes of models to the observational dataset only. Thus when we used these models to predict
243 the response of each species to the five years of experimental data we are generating predictions
244 for out of sample data. We refer to the first type of model as the "no climate" models. These
245 models include parameters for the effects of competition on each vital rate and the size dependence
246 of survival and growth but they do not include climate or treatment effects. Lastly, we fit the
247 "climate" models which include the effects of annual variation in soil moisture on each vital rate.
248 The no climate model provides us a baseline by which to measure the accuracy of the predictions
249 from the climate model. Because much of the variation in growth, survival and recruitment in this
250 system can be explained by plant size and competition, we expect that these two models will make
251 similar predictions for individual plant performance in the experiment. However, if the climate
252 model makes more accurate predictions than the no climate model, this indicates that the climate
253 parameters it includes contain useful information for prediction.

254 Statistical models of vital rates

255 All three categories of models described above follow the same basic structure and differ only in
256 how they treat climate and treatment effects and (Adler et al., 2010; Chu and Adler, 2015). We
257 model the survival probability of an individual genet as a function of genet size, the neighborhood-
258 scale crowding experienced by the genet from both conspecific and heterospecific genets, temporal
259 variation among years, and permanent spatial variation among groups of quadrats ('group'; here
260 means a set of nearby quadrats located within one pasture or grazing exclosure). In this analysis
261 we only include crowding from the four main focal species.

262 Formally, we modeled the survival probability, S , of genet i in species j , group g , and from
 263 time t to $t + 1$ as

$$\text{logit}(S_{ijg,t}) = \varphi_{jg}^S + \gamma_{j,t}^S + \beta_{j,t}^S u_{ij,t} + \langle \boldsymbol{\omega}_{j,t}^S, \mathbf{W}_{ij,t} \rangle \quad (1)$$

264 where φ is the spatial group dependent intercept, γ is a year-effect, β is year-dependent coefficient
 265 that represents the effect of log genet size, u , on survival in year t . $\boldsymbol{\omega}$ is a vector of interaction
 266 coefficients which determine the impact of crowding, \mathbf{W} , by each species on the focal species. The
 267 vector \mathbf{W} includes crowding from the four dominant species, *A. tripartita*, *P. spicata*, *H. comata*,
 268 and *Poa secunda*. $\langle \mathbf{x}, \mathbf{y} \rangle$ denotes the inner product of vectors \mathbf{x} and \mathbf{y} , calculated as `sum(x*y)` in
 269 R. This model is the no climate model for survival.

270 In the treatment model, a new term is added to the above model, $\mathbf{T}\chi_j^S$ where χ is a vector
 271 of treatment effect coefficients for each experimental treatment level h on the survival rate, and \mathbf{T}
 272 is a design matrix indicating the treatment level of each observation in the data. The design matrix
 273 also includes terms for the interaction between plant size u and the treatment effects which allow
 274 the effect of each treatment to vary with plant size.

275 In the climate model, the above term is replaced with $\mathbf{C}\xi_j^S$, where ξ gives a vector of
 276 coefficients describing the effects of a set of soil moisture covariates \mathbf{C} in treatment h and year t
 277 on the survival rate of species j . \mathbf{C} can include interaction effects between plant size, u , and the
 278 soil moisture covariates allowing the effects of soil moisture to vary with plant size.

279 Our growth model has a similar structure. The change in genet size from time t to $t + 1$,
 280 conditional on survival, is given by:

$$u_{ijg,t+1} = \varphi_{jg}^G + \gamma_{j,t}^G + \chi_{jh}^G + \beta_{j,t}^G u_{ij,t} + \langle \boldsymbol{\omega}_{j,t}^G, \mathbf{W}_{ij,t} \rangle + \varepsilon_{ij,t}^G. \quad (2)$$

281 As in the survival regression above, parameters describing the treatment effects on growth
 282 are added in the treatment model, $\mathbf{T}\chi_j^G$, where χ is a treatment effect describing the effect of
 283 experimental treatment h on growth, including treatment by size interactions.

284 Similarly, in the climate model, the above term is replaced with $\mathbf{C}\xi_j^G$, where ξ is a vector
 285 of coefficients describing the effects of soil moisture covariates in the matrix \mathbf{C} for treatment h and

286 year t on growth of species j . Again this can include interactions between soil moisture and plant
287 size u .

288 Although the main focus of the current analysis the effects of soil moisture, we also modeled
289 the effects of inter- and intra-specific competition in our vital rate models. We model the crowding
290 experienced by a focal genet as a function of the distance to and size of neighbor genets. These
291 effects are well described in previous work (Teller et al., 2016; Adler et al., 2016). Briefly, we model
292 the crowding experienced by genet i of species j from neighbors of species m as the sum of neighbor
293 areas across a set of concentric annuli, k , centered at the plant,

$$w_{ijm,k} = F_{jm}(d_k)A_{i,k} \quad (3)$$

294 where F_{jm} is the competition kernel (described below) for effects of species m on species j , d_k is
295 the average of the inner and outer radii of annulus k , and $A_{im,k}$ is the total area of genets of species
296 m in annulus k around genet i . The total crowding on genet i exerted by species m is

$$W_{ijm} = \sum_k w_{ijm,k}. \quad (4)$$

297 Note that $W_{i,jj}$ gives intraspecific crowding. The W 's are then the components of the \mathbf{W} vectors
298 introduced as covariates in the survival (1) and growth (2) regressions.

299 We assume that competition kernels $F_{jm}(d)$ are non-negative and decreasing, so that distant
300 plants have less effect than close plants. Otherwise, we let the data dictate the shape of the kernel
301 by fitting a spline model using the methods of Teller et al. (2016). We used data from all historical
302 plots and contemporary control-treatment plots to estimate the competition kernels and these are
303 described in more detail in (Adler et al., 2016).

304 Once we had estimated the competitions kernels, we used them to calculate the values of \mathbf{W}
305 for each individual, and fit the full survival and growth regressions, which include the interspecific
306 interaction coefficients, $\boldsymbol{\omega}$. All genets in a quadrat were included in calculating W , but plants
307 located within 5 cm of quadrat edges were not used in fitting.

308 We model recruitment at the quadrat level rather than at the individual genet level because
309 the mapped data do not allow us to determine which recruits were produced by which potential

³¹⁰ parent plants. We assume that the number of individuals, y , of species j recruiting at time $t + 1$ in
³¹¹ the location q follows a negative binomial distribution:

$$y_{jq,t+1} = NegBin(\lambda_{jq,t+1}, \theta) \quad (5)$$

³¹² where λ is the mean intensity and θ is the size parameter. In turn, λ depends on the composition
³¹³ of the quadrat in the previous year:

$$\lambda_{jq,t+1} = C'_{jq,t} \exp \left(\varphi_{jg}^R + \gamma_{j,t}^R + \langle \boldsymbol{\omega}^R, \sqrt{\mathbf{C}'_{q,t}} \rangle \right) \quad (6)$$

³¹⁴ where the superscript R refers to Recruitment, $C'_{jq,t}$ is the ‘effective cover’ (cm^2) of species j in
³¹⁵ quadrat q at time t , φ is a group dependent intercept, γ is a random year effect, $\boldsymbol{\omega}$ is a vector of
³¹⁶ coefficients that determine the strength of intra- and interspecific density-dependence, and \mathbf{C}' is
³¹⁷ the vector of “effective” cover of each species in the community. Following previous work (Adler
³¹⁸ et al., 2010), we treated year as a random factor allowing intercepts to vary among years.

³¹⁹ Because plants outside the mapped quadrat could contribute recruits to the focal quadrat or
³²⁰ interact with plants in the focal quadrat, we estimated effective cover as a mixture of the observed
³²¹ cover, C , in the focal quadrat, q , and the mean cover, \bar{C} , across the spatial location, g , in which
³²² the quadrat is located: $C'_{jq,t} = p_j C_{jq,t} + (1 - p_j) \bar{C}_{jg,t}$, where p is a mixing fraction between 0 and
³²³ 1 that was estimated as part of fitting the model.

³²⁴ In the treatment model for recruitment, a new term is added to the exponential term in
³²⁵ the equation above, $\mathbf{T}\boldsymbol{\chi}_j^R$ where χ describes the effect of each treatment level on recruitment.

³²⁶ Likewise in the climate model this term is replaced by $\mathbf{C}\boldsymbol{\xi}_j^R$ where the $\boldsymbol{\xi}$ gives a set of
³²⁷ coefficients for the year, and treatment specific soil moisture covariates in \mathbf{C} .

³²⁸ We fit all vital rate models using Hamiltonian-Markov Chain Monte Carlo (HMC)C
³²⁹ simulations in the programs STAN 10.1 and rStan ((?) and (?)). The priors and model code
³³⁰ are described more completely in appendix A. Each model was run for 2,000 iterations and four
³³¹ independent chains with different initial values for parameters. We discarded the initial 1,000
³³² samples. Convergence was observed graphically for all parameters, and confirmed by assessing the
³³³ split \hat{R} statistic which at convergence is equal to one (?).

We fit the treatment models for species survival and growth with and without the size by treatment interactions in the treatment effect term χ . We then judged whether including the interaction terms improved model fit by comparing the Watanabe-Aikake Information Criteria (WAIC) scores of each version of the model and retained the version with the lower WAIC score (?). WAIC are similar to AIC scores and allow for comparison of Bayesian models. Lower WAIC scores indicate a more parsimonious model. When a treatment model for survival or growth of a species included a size by treatment effect in χ , we also included a size by soil moisture effect in the ξ term in the climate model for that species and vital rate. This allowed us to more directly compare the predictions from the climate model to the effects in the treatment model.

Selecting soil moisture covariates

After generating a time series of predicted daily soil moisture from SOILWAT, we averaged daily soil moisture across spring, summer and fall seasons in each year. We considered each of the three seasonal soil moisture variables at three different time periods relative to the demographic transition from year t to year $t + 1$. Soil moisture in the year between t and $t + 1$ is indicated with a "1" subscript. Soil moisture in the year before t is indicated with a "0" subscript. And soil moisture preceding this year is indicated with a "lag" subscript. For example, for the year 2010, $spring_1$ indicates soil moisture in the spring of 2010, $spring_0$ indicates soil moisture during spring of 2009 and $spring_{lag}$ indicate soil moisture during spring 2008.

We wanted to avoid fitting nine soil moisture covariates (three seasons and three lags each) for each species and vital rate, so we used only three soil moisture covariates per species and vital rate. We selected these three by calculating the correlations of each soil moisture variable with the random year effects from the no climate model fit and then selecting the three soil moisture variables with the strongest correlations with these year effects. This screening technique has been used in previous demographic studies at this site (Dalgleish et al., 2010) and is often used in dendrochronology to screen for potential climate influence on tree-ring growth (Wang et al., 2003). We felt this approach was justified because we did not make inference on these fitted parameters until after we validated their ability to predict the out of sample data in the experimental plots.

361 **Predicting cover from individual-based models**

362 The vital rate regressions allow us to evaluate whether soil moisture and the experimental treat-
363 ments had an effect on species performance. But the population response ultimately depends on
364 the integrated effects of treatment or soil moisture on all three vital rates. To evaluate whether the
365 climate models could predict the responses of these species in the drought and irrigation experiment
366 at the overall population level we used an individual-based model (IBM) to compare observed and
367 predicted changes in population size from one year to the next.

368 To simulate changes in cover in each quadrat from year t to year $t + 1$, we initialized the
369 IBM with the observed genet sizes and locations of the four focal species observed in year t in each
370 quadrat. For every individual genet in a quadrat, we projected its size and survival probability in
371 the next year using the growth and survival models and the appropriate crowding and soil moisture
372 or treatment covariates for that year and quadrat. Likewise we projected the number of new recruits
373 in the quadrat in the next year using the recruitment model. We calculated the expected cover in
374 year $t + 1$ as the total area of new recruits, plus the sum of the predicted area of each existing plant
375 at time $t + 1$ multiplied by each plant's expected survival probability from time t to $t + 1$.

376 We generated predictions using 1000 samples from the posterior distributions of each model
377 parameter which allowed us to carry forward all of the uncertainty of the fitted vital rate models into
378 our cover predictions. Because we were interested in comparing model predictions to observations,
379 and were not interested in the effects of demographic stochasticity, we used a deterministic version
380 of the models (e.g., recruitment is the λ of (6), rather than a random draw from a negative binomial
381 distribution with a mean of λ).

382 After generating predictions for each year from the climate and no climate models, we found
383 the predicted quadrat-level changes in cover as $\log(Cover_{t+1}/Cover_t)$.

384 **Quantifying predictive accuracy**

385 We assessed the predictive performance of the climate and no climate by calculating the mean
386 square error (MSE) between the predicted and observed responses in the experimental data as,

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - E(y_i|\theta))^2, \quad (7)$$

387 where y_i is the outcome of observation i and $E(y_i|\theta)$ gives the expected outcome given the pa-
 388 rameters in the model θ . The MSE is easy to interpret, but is not always appropriate for models
 389 fit with non-normal error structures (Gelman et al., 2014). A more general statistic for assessing
 390 model predictions is the log pointwise predictive density (lppd) (Gelman et al., 2014). The lppd
 391 for a given model is defined as,

$$lppd = \sum_{i=1}^n \log \int p(y_i|\theta)p_{post}(\theta)d\theta, \quad (8)$$

392 where the integral on the right side gives the probability of observing the outcome y at each data
 393 point i given the full posterior distribution of the parameters in the model $p_{post}(\theta)$. In practice we
 394 computed the lppd from the posterior simulations generated by STAN as,

$$\widehat{lppd} = \sum_{i=1}^n \log \left(\frac{1}{S} \sum_{s=1}^S p(y_i|\theta^S) \right), \quad (9)$$

395 where the summation of $p(y_i|\theta^S)$ gives the total probability of observing the the actual response y_i
 396 given the simulated posterior distribution θ^S across the full set of model simulations S . The log of
 397 this sum is then averaged across the set of all observations i . Higher lppd scores indicate that the
 398 model better predicts the observations.

399 In addition, we evaluated whether the climate model predicted treatment effects of similar
 400 direction and magnitude to those observed in the experiment. We did this by extracting the soil
 401 moisture coefficients contained in ξ for each of the vital rates and then multiplying those by the
 402 appropriate soil moisture covariates for each year and treatment level in the experiment. We then
 403 averaged these across all five years in the experiment to find the average treatment effect predicted
 404 by the climate model. We compared these to the posteriors of the treatment parameters, chi , from
 405 the treatment model. As a measure of agreement between our predictions and observed response
 406 we calculated the correlation between the predicted and observed treatment effects.

407 We considered the effect of climate covariates or treatment effects to be significant when
 408 the 95% Bayesian credible intervals on the posterior estimates did not overlap zero.

409 All data and R code necessary to reproduce our analysis will be deposited in the Dryad
 410 Digital Repository once the manuscript is accepted. The current version of the computer code

⁴¹¹ is available at <https://github.com/pbadler/ExperimentTests/tree/master/precip> and the data are
⁴¹² available at <https://bitbucket.org/ellner/driversdata>.

⁴¹³ Results

⁴¹⁴ Effects on soil moisture

⁴¹⁵ Our treatments successfully changed the soil moisture in the experimental plots in the directions
⁴¹⁶ expected (fig. 1). Spring spot measurements of soil moisture from all the plots showed that on
⁴¹⁷ average the drought plots were roughly 50% drier, while irrigated plots were roughly 40% wetter
⁴¹⁸ than ambient conditions (table 1).

⁴¹⁹ The continuously recorded soil moisture data also showed treatment effects on soil moisture,
⁴²⁰ but these effects were weaker on average than the spot measurements and depended on season and
⁴²¹ recent rainfall (table 2; fig 2). We saw weaker effects during the spring than during the fall and
⁴²² summer: the drought plots were about 20-30% drier in the fall and summer but only 7 to 14% drier
⁴²³ during the spring, while the irrigated plots were 30% wetter during the fall and summer but only
⁴²⁴ 20-25% wetter during the spring. Treatment differences were slightly larger during rainy periods,
⁴²⁵ especially in the spring. We did not find evidence that the drought shelters and the irrigation
⁴²⁶ treatments consistently affected air temperature at 30 cm above the plots.

⁴²⁷ The SOILWAT soil moisture model predicted average monthly soil volumetric water content
⁴²⁸ of between 10 ml/ml and 15 ml/ml each month, with the month of April being the wettest and the
⁴²⁹ month of July, August and September being the driest on average. Annual variation in seasonal
⁴³⁰ soil moisture for each year was positively correlated with seasonal precipitation and negatively
⁴³¹ correlated with seasonal temperature. During the course of the experiment, SOILWAT reproduced
⁴³² much of the daily variation observed in soil moisture recorded by our automatic data loggers, but
⁴³³ the average soil moisture predicted by SOILWAT was about 5 ml/ml wetter than the soil moisture
⁴³⁴ content recorded by the data loggers.

⁴³⁵ After adjusting the SOILWAT seasonal soil moisture predictions by the treatment effects,
⁴³⁶ we found that the soil moisture predicted in the drought plots during the course of the experiment
⁴³⁷ was well below the historical seasonal averages: the summer of 2012 and 2013, the fall of 2013, and
⁴³⁸ the spring and winter of 2014 fell below the 5th percentile limit for drought in the historical period

⁴³⁹ 3. Soil moisture in our irrigation plots was generally above the historical average soil moisture but
⁴⁴⁰ conditions never exceeded the 90th percentile for soil moisture in the historical period.

⁴⁴¹ **Effects on cover and vital rates**

⁴⁴² The cover of *H. comata* and *P. spicata* fell significantly in the drought plots from 2011 to 2016
⁴⁴³ (tables 4, 6, fig 4). The cover of *P. secunda* showed a slight decrease in the drought plots and an
⁴⁴⁴ increase in the irrigated plots but these changes were not significant (table 5). In contrast to the
⁴⁴⁵ grasses, the cover of *A. tripartita* increased slightly in all three treatments (fig 4).

⁴⁴⁶ Our treatment models fit to the experimental and observational data indicated a variety of
⁴⁴⁷ treatment effects on the vital rates of each species. After comparing WAIC scores for the growth
⁴⁴⁸ models with and without the size by treatment effects, we retained size by treatment interaction
⁴⁴⁹ effects in the growth models for *A. tripartita* and *P. secunda*, and the survival model for *P. secunda*.
⁴⁵⁰ For *A. tripartita* we found significant size by treatment effects of drought: drought had positive
⁴⁵¹ effects on plants of average size and smaller 5, but plants larger than the mean size by more than 1.5
⁴⁵² standard deviations grew slightly less in the drought treatment than in the controls. *A. tripartita*
⁴⁵³ showed the opposite response in the irrigated plots, (although the irrigation parameters were not
⁴⁵⁴ technically significant at the 95% confidence level): irrigation reduced growth for small plants while
⁴⁵⁵ irrigation increased growth of plants more than 1.5 standard deviations greater than the mean size.
⁴⁵⁶ Drought led to a strong (but not significant) decrease in *H. comata* growth, while irrigation had
⁴⁵⁷ no effect on growth. Like *A. tripartita*, we saw size by treatment effects on *P. secunda* growth,
⁴⁵⁸ with the negative effects of drought becoming greater for larger plants. *P. secunda* showed the
⁴⁵⁹ opposite response in the irrigation plots with larger plants showing the largest increase in growth
⁴⁶⁰ in response to irrigation (although these effects were technically not significant). *P. spicata* growth
⁴⁶¹ was relatively unaffected by the drought and irrigation treatments.

⁴⁶² Drought decreased the survival of all three grass species (fig 6). And *P. secunda* showed a
⁴⁶³ negative size by drought interaction effect, indicating that the survival of larger plants was more
⁴⁶⁴ negatively affected by drought than that of the smaller plants, with the smallest plants (plants one
⁴⁶⁵ standard deviation smaller than the mean) actually seeing a slightly positive effect of drought. *A.*
⁴⁶⁶ *tripartita* survival was relatively unaffected by the drought and irrigation treatments.

467 Recruitment in our irrigation plots was significantly less than in control plots for two grass
468 species *P. secunda* and *P. spicata* (fig 7). However, recruitment was also lower in the drought plots
469 than in the the control plots (although not significantly so), indicating that the decrease in the
470 irrigated plots may have not been entirely due to the irrigation itself. The recruitment data for *A.*
471 *tripartita* were relatively limited, with only 32 new recruits in total observed in all 30 plots over
472 the course of the five year experiment.

473 As expected from previous research most of our demographic models estimated strong
474 negative intra-specific crowding effects and weaker negative inter-specific crowding effects on the
475 focal species (appendix) (Adler et al., 2010; Chu et al., 2016; Chu and Adler, 2015).

476 Effects of soil moisture on vital rates

477 We choose three seasonal soil moisture variables for each species' climate model based on their
478 correlation with the random year effects in the no climate model fit to the observational data
479 (table 7). We included size by soil moisture variables for *A. tripartita* and *P. secunda* based on
480 the treatment response we observed in the experiment. All three time lags and all three seasons
481 show up in the choosen variables. After fitting the vital rate models with the selected soil moisture
482 variable we observed a trend towards positive soil moisture effects on growth of all three grasses
483 8. For *H.comata* the soil moisture of the most recent summer had a significantly positive effect
484 while the soil moisture of the previous summer and the fall before that were also positive but not
485 significant. For *A. tripartita* the summer and fall soil moisture of the previous year had strong
486 negative effects on growth. There were also strong positive size by climate interaction effects for
487 these variables: soil moisture had a stronger negative effect on small plants and a positive effect
488 only on the largest plants.

489 Soil moisture had significant effects on the survival of all four species 9. As for growth the
490 grasses showed mainly positive effects while *A. tripartita* showed a significant negative effect of soil
491 moisture in the summer of the previous year and a strong negative effect of spring soil moisture of
492 the previous year. *H. comata* showed a significant positive effect of spring lag soil moisture and a
493 strong positive effect of spring soil moisture in the previous year. *P. secunda* showed a significant
494 positive effect of the previous spring's soil moisture and there was a significant interaction between

495 this effect and plant size: as plant size increased this effect became more strongly positive. Finally
496 for *P. spicata* there was a significant positive effect of lag spring soil moisture on survival.

497 There were only two significant effects of soil moisture on recruitment: lag fall soil moisture
498 had a positive effect on *P. secunda*, and lag summer soil moisture had a negative effect on *P. spicata*
499 recruitment. Soil moisture of the previous year's summer had also had a strong negative effect on
500 *P. spicata* recruitment.

501 The intra- and interspecific crowding effects estimated in the climate model were similar to
502 those estimated in the treatment model (appendix) (Adler et al., 2010; Chu et al., 2016; Chu and
503 Adler, 2015).

504 Evaluating the predictions

505 For most models adding climate covariates did not improve our ability to predict species responses
506 in the experiment 8. However, the climate models did improve overall prediction MSE for growth of
507 *A. tripartita* and growth and survival of *P. secunda* (table 8). In terms of lppd, the climate model
508 outperformed the no climate model for *A. tripartita* growth, *H. comata* recruitment, *P. secunda*
509 growth and survival and *P. spicata* recruitment. .

510 When we look at the predictions for each treatment separately we see that climate covariates
511 improved model predictions more often in the drought treatments than in the control or irrigation
512 treatments SI-1. For all four species, the climate model outperformed the no climate model for
513 predicting the response of growth to drought in terms of lppd SI-1. The climate model outperformed
514 the no climate model for predicting irrigation effects on growth for all species except *H. comata*.

515 Overall our climate models often predicted the correct direction of the drought and irriga-
516 tion treatments 11. In four cases we both observed and predicted treatment effects significantly
517 different from zero based on the 95% Bayesian credible interval around the parameters: the drought
518 response of *H. comata* survival (fig SI-6), the drought response of *P. secunda* growth (fig SI-3),
519 the irrigation response of *P. spicata* recruitment (fig ??) and the irrigation response of *P. secunda*
520 recruitment (fig ??). In only one of these cases, for *P. secunda* recruitment, was the predicted effect
521 in the opposite direction from the observed treatment effect 11. The overall correlation between
522 the predicted and observed treatment effects for all treatments, species and vital rates was $r =$
523 0.54, whereas the correlation for the drought treatment effects ($r = 0.77$) was better than for the

524 irrigation effects ($r = 0.46$). Also for the three models in which we included size by treatment or
525 size by climate interactions the correlation of these size dependent effects were much stronger than
526 the intercept parameter estimates 11.

527 Using the vital rate models for each species we generated one step ahead cover predictions
528 for each quadrat in each year of the experiment. Average cover predicted by the climate model
529 tended to be lower than the observed cover each year for *A. tripartita* and *P. secunda* (fig 12).
530 Comparing the overall population growth rates predicted to those observed in the experiment,
531 we see that the MSE of the climate model was lower than the MSE of the no climate model for
532 *P. secunda* and *P. spicata* (table 9). The predictions produced by the climate model for these
533 species were also slightly more correlated with the observations than the predictions produced by
534 the no climate model (table 9). Considering each treatment and species separately we see that the
535 predicted population growth rates for *A. tripartita*, *P. secunda* and *P. spicata* were all consistently
536 lower than the observed population growth rates (figs ??, 15, 16). The climate model showed lower
537 MSE for *A. tripartita*, *P. secunda* and *P. spicata* in the irrigation treatment, *P. spicata* in the
538 control treatment and *H. comata* in the drought treatment (figs 14). However, the correlations
539 between the predicted and observed log changes in cover did not always show the same pattern as
540 MSE: the climate model made more strongly correlated predictions with the observations than the
541 no climate model only for *P. spicata* and *P. secunda* in the control treatment and *P. secunda* and
542 *H. comata* in the drought treatment.

543 Discussion

544 Our experiment showed that observational data on the response of plant populations to interannual
545 climate variation can indeed help us predict the direction of species response to experimental climate
546 manipulations 11. This was true even though adding climate parameters to the demographic models
547 only improved vital rate predictions for half of the models 8. This should give us some hope that
548 even when climate effects in demographic models to observational data are weak, they may contain
549 useful qualitative information on the direction of climate effects in the future.

550 * discuss biggest successes—astreces in fig 11 * discuss biggest mistake, *P. secunda* recruit-
551 ment went in wrong direction.

552 Scaling up to the population level, the climate models only produced better one step a head
553 predictions of the overall response of the species to the experiment for two species: *P. spicata* and
554 *P. secunda* (table 9). However adding climate effects produced better population-level predictions
555 in the drought treatments for *P. secunda* and *H. comata*. Both the survival and the growth of these
556 species were positively affected by increased soil moisture (fig 8, 9), and so it makes intuitive sense
557 that we would observe declines in these species cover in the drought treatment (fig 4).

558 *Among our species, we had the most success predicting the response of the three grass
559 species and less success predicting the response of the shrub species *A. tripartita*. Why might
560 ARTR be different?

561 *We also had more success predicting species response to the drought treatment than to the
562 irrigation treatment. We also tended to see species respond more strongly to the drought treatment
563 than they did to the irrigation treatment. This tells us that in some cases, demographic models
564 based on observational data may be of more use for prediction in extreme conditions than when
565 conditions are close to average. Our drought treatment likely created extremely low soil moisture
566 compared to the historical average 3. We hypothesize that this made water the most limiting
567 resource for plants in these plots. In contrast, in the control and irrigated plots soil moisture may
568 not have always been limiting during the course of the experiment. It may make sense then that
569 our climate models did not make more accurate predictions in these conditions than the no climate
570 model.

571 *Mixed success at predicting species responses to high and low moisture availability has
572 interesting implications. On the one hand it is re-assuring that observational data is sometimes
573 useful. On the other hand, for predictions to be truly useful we would also like more information
574 to help us sort out why our predictions for some species were good and for others no better than
575 a no climate model. In other words, we have little ability to predict when our predictions are
576 likely to be accurate. Among plants detailed physiological ecology may give us a guide to which
577 factors and climate conditions are likely to affect which species. In our system, for instance, it may
578 make sense that the grasses showed a stronger response to the drought treatment than the a woody
579 shrub. Although these grasses are adapted to the arid conditions that characterize the sagebrush
580 steppe, they thrive during the brief window in spring and early summer when the soil moisture
581 and temperatures are warmer. *A. tripartita* on the other hand grows throughout the summer and

582 generally has deeper roots than the grasses. These traits may help it tolerate the water stress
583 induced by drought.

584 *Will our predictions be useful for the longer term? Because these species compete, one
585 could argue that our predictions for any one species in this community will only be as good as the
586 predictions we make for their competitors. For instance, while we observed little effect of drought
587 on *A. tripartita* in our experiment, it is possible that it will eventually respond positively to the
588 drought treatment as cover of the grass species it competes with declines (fig 4). We know that
589 grass species compete strongly with *A. tripartita*. However, we also know from previous work in
590 this community that each species is more limited by intra-specific competition than by inter-specific
591 crowding. This fact ensures that the direct effects of climate change will generally be greater than
592 the competition mediated indirect effects of climate change Chu et al. (2016); ?.

593 *Our results give us more confidence that historical observational data can in theory be
594 used to detect and predict the demographic effects of climate change. This should encourage more
595 researchers to try and use observational data to predict the future in both experimental and natural
596 settings. Nevertheless, our success at predicting the short-term response of two species to a small-
597 scale climate manipulation is not likely to be very reassuring to applied ecologists and resource
598 managers wishing to make accurate medium to long-term quantitative predictions about the effects
599 of climate change on the species they manage. Clearly more work is needed to distinguish which
600 predictions are worth having confidence in and which predictions we should have less confidence in.
601 Towards that goal, perhaps the best way to build confidence in ecological predictions is conduct
602 more tests like this one.

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Tables

Table 1: Treatment effects on spring soil moisture

	Model 1	
(Intercept)	8.81*	[5.78; 11.83]
TreatmentDrought	-3.97*	[-4.84; -3.09]
TreatmentIrrigation	3.26*	[2.39; 4.14]
AIC	3191.87	
BIC	3222.92	
Log Likelihood	-1588.93	
Num. obs.	624	
Num. groups: plot	24	
Num. groups: PrecipGroup	8	
Num. groups: date	5	
Var: plot (Intercept)	0.45	
Var: PrecipGroup (Intercept)	0.23	
Var: date (Intercept)	11.24	
Var: Residual	8.90	

* 0 outside the confidence interval

Table 2: Model of treatment effects on soil moisture

	Model 1	
(Intercept)	-0.57*	[-0.89; -0.26]
TreatmentIrrigation	1.23*	[1.18; 1.29]
rainfallrainy	-0.05	[-0.12; 0.01]
seasonspring	0.27*	[0.23; 0.32]
seasonsummer	0.15*	[0.10; 0.19]
seasonwinter	0.25*	[0.21; 0.29]
TreatmentIrrigation:rainfallrainy	0.18*	[0.13; 0.24]
TreatmentIrrigation:seasonspring	-0.23*	[-0.29; -0.16]
TreatmentIrrigation:seasonsummer	-0.26*	[-0.33; -0.20]
TreatmentIrrigation:seasonwinter	-0.33*	[-0.40; -0.27]
rainfallrainy:seasonspring	-0.23*	[-0.31; -0.16]
rainfallrainy:seasonsummer	-0.07	[-0.14; 0.01]
rainfallrainy:seasonwinter	-0.07	[-0.20; 0.07]
AIC	14581.58	
BIC	14695.49	
Log Likelihood	-7274.79	
Num. obs.	9133	
Num. groups: date	1596	
Num. groups: PrecipGroup	8	
Var: date (Intercept)	0.00	
Var: PrecipGroup (Intercept)	0.19	
Var: Residual	2.50	

* 0 outside the confidence interval

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.2835	0.4627	-0.61	0.5487
TreatmentDrought	0.9378	0.7743	1.21	0.2434
TreatmentIrrigation	0.8882	0.7743	1.15	0.2682

Table 3: Treatment effects on log cover change for *A. tripartita* from 2011 to 2016. Intercept gives control effects.

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.3982	0.2587	1.54	0.1548
TreatmentDrought	-2.9951	0.5784	-5.18	0.0004
TreatmentIrrigation	-0.1219	0.4953	-0.25	0.8105

Table 4: Treatment effects on log cover change for *H. comata* from 2011 to 2016. Intercept gives control effects.

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.7247	0.4613	-1.57	0.1298
TreatmentDrought	0.0273	0.8208	0.03	0.9737
TreatmentIrrigation	1.1459	0.7797	1.47	0.1552

Table 5: Treatment effects on log cover change for *P. secunda* from 2011 to 2016. Intercept gives control effects.

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.0188	0.2124	0.09	0.9303
TreatmentDrought	-0.8851	0.3780	-2.34	0.0287
TreatmentIrrigation	0.1453	0.3780	0.38	0.7044

Table 6: Treatment effects on log cover change for *P. spicata* from 2011 to 2016. Intercept gives control effects.

vital_rate	species	climate variable	Int. cor.	p val.	Size cor.	Size p. val.
growth	ARTR	su.0	-0.49	0.02	0.26	0.26
growth	ARTR	f.0	-0.28	0.23	0.40	0.08
growth	ARTR	sp.1	0.17	0.45	-0.33	0.14
growth	HECO	su.1	0.69	0.00		
growth	HECO	su.0	0.50	0.02		
growth	HECO	f.lag	0.37	0.10		
growth	POSE	f.lag	0.31	0.17	-0.11	0.64
growth	POSE	su.lag	0.29	0.20	-0.20	0.38
growth	POSE	sp.1	0.26	0.25	-0.20	0.38
growth	PSSP	f.lag	0.34	0.13		
growth	PSSP	su.lag	0.25	0.27		
growth	PSSP	f.0	-0.22	0.34		
recruitment	ARTR	su.lag	-0.32	0.16		
recruitment	ARTR	su.0	-0.26	0.25		
recruitment	ARTR	sp.1	0.22	0.34		
recruitment	HECO	su.lag	-0.31	0.18		
recruitment	HECO	su.0	-0.30	0.18		
recruitment	HECO	f.lag	0.19	0.40		
recruitment	POSE	sp.1	0.49	0.02		
recruitment	POSE	f.lag	0.34	0.13		
recruitment	POSE	f.1	0.32	0.16		
recruitment	PSSP	su.lag	-0.52	0.02		
recruitment	PSSP	su.0	-0.48	0.03		
recruitment	PSSP	sp.0	0.30	0.19		
survival	ARTR	su.0	-0.60	0.00		
survival	ARTR	sp.0	-0.41	0.06		
survival	ARTR	su.1	-0.40	0.07		
survival	HECO	sp.0	0.44	0.04		
survival	HECO	sp.lag	0.43	0.05		
survival	HECO	f.1	0.33	0.14		
survival	POSE	sp.0	0.44	0.04	0.22	0.34
survival	POSE	sp.1	0.27	0.23	-0.46	0.04
survival	POSE	f.lag	-0.00	0.99	0.30	0.19
survival	PSSP	sp.0	0.36	0.11		
survival	PSSP	sp.lag	0.34	0.13		
survival	PSSP	su.1	0.26	0.26		

Table 7: Selected climate variables for each vital rate model for each species. Correlations and p-values between the chosen variables and the intercept of the no climate model are shown. For ARTR growth and POSE growth and survival, the correlations between the year effects on size and the soil moisture variables are also given. "f" = fall, "su" = summer, "sp" = spring. ARTR = *A. tripartita*, HECO = *H. comata*, POSE = *P. secunda*, PSSP = *P. spicata*.

species	vital_rate	score	climate model	no climate model	diff	improved
ARTR	growth	lppd	-186.08	-189.17	3.09	***
ARTR	growth	MSE	0.55	0.55	-0.00	***
ARTR	recruitment	lppd	-79.05	-77.81	-1.24	
ARTR	recruitment	MSE	169.86	9.47	160.39	
ARTR	survival	lppd	-37.55	-36.42	-1.13	
ARTR	survival	MSE	0.06	0.06	0.00	
HECO	growth	lppd	-475.54	-454.36	-21.18	
HECO	growth	MSE	1.26	1.18	0.09	
HECO	recruitment	lppd	-149.43	-151.60	2.17	***
HECO	recruitment	MSE	288.16	235.57	52.59	
HECO	survival	lppd	-158.99	-147.06	-11.93	
HECO	survival	MSE	0.12	0.11	0.01	
POSE	growth	lppd	-1823.71	-1831.56	7.85	***
POSE	growth	MSE	1.72	1.73	-0.01	***
POSE	recruitment	lppd	-260.05	-257.46	-2.59	
POSE	recruitment	MSE	45.40	37.32	8.08	
POSE	survival	lppd	-698.06	-718.60	20.54	***
POSE	survival	MSE	0.14	0.14	-0.00	***
PSSP	growth	lppd	-1232.93	-1237.92	4.99	***
PSSP	growth	MSE	1.51	1.51	0.00	
PSSP	recruitment	lppd	-271.34	-273.94	2.60	***
PSSP	recruitment	MSE	79.09	42.68	36.41	
PSSP	survival	lppd	-332.47	-307.26	-25.21	
PSSP	survival	MSE	0.11	0.10	0.01	

Table 8: Comparison of model predictions from climate model and no climate model for each species and vital rate. Two prediction scores are reported, MSE and lppd. Lower MSE indicates improved predictions whereas higher lppd indicates improved predictions. Instances where the climate model outperformed the random no climate model are marked with "****" in the last column. ARTR = *A. tripartita*, HECO = *H. comata*, POSE = *P. secunda*, PSSP = *P. spicata*.

	species	stat	no climate model	climate model	diff	improved
1	ARTR	cor	0.48	0.19	-0.29	
2	ARTR	MSE	0.30	0.30	0.00	
3	HECO	cor	0.29	0.22	-0.07	
4	HECO	MSE	0.49	0.57	0.07	
5	POSE	cor	0.45	0.53	0.07	***
6	POSE	MSE	0.42	0.41	-0.01	***
7	PSSP	cor	0.36	0.38	0.03	***
8	PSSP	MSE	0.39	0.39	-0.01	***

Table 9: MSE of predicted log cover changes and correlations between log cover changes predicted and observed. Predictions for the cover changes in the experimental plots were generated either from the no climate or the climate models. Instances where the climate model made better predictions than the no climate model are indicated with the "****". ARTR = *A. tripartita*, HECO = *H. comata*, POSE = *P. secunda*, PSSP = *P. spicata*.

Figures

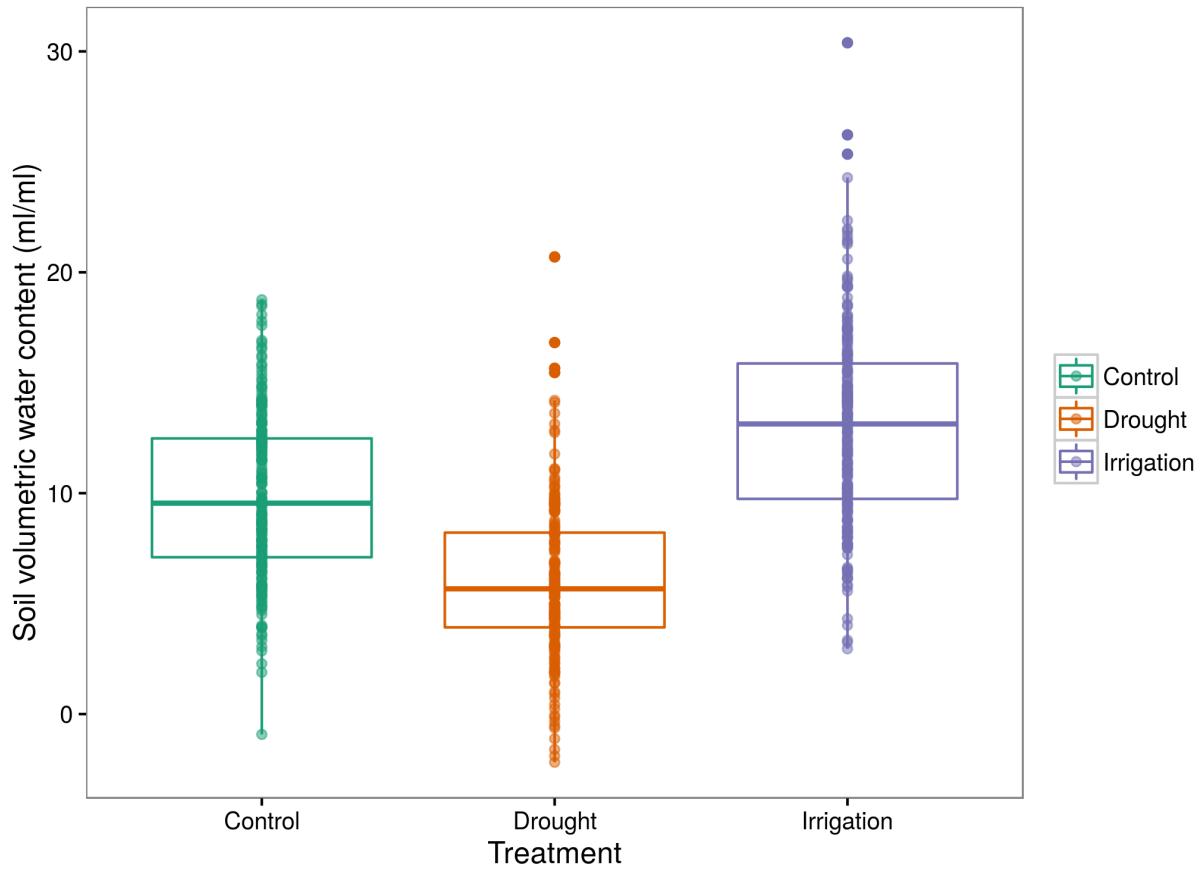


Figure 1: Soil moisture in the upper 5 cm of drought and irrigated plots compared to ambient controls. Soil moisture was measured at six locations around each plot at five different dates during the spring. Control plots were nearby areas of experiencing ambient soil moisture. Box plots show the median soil moisture and the interquartile range. Dots show individual soil moisture measurements. Readings of volumetric soil moisture less than zero were occasionally obtained in very dry soil.

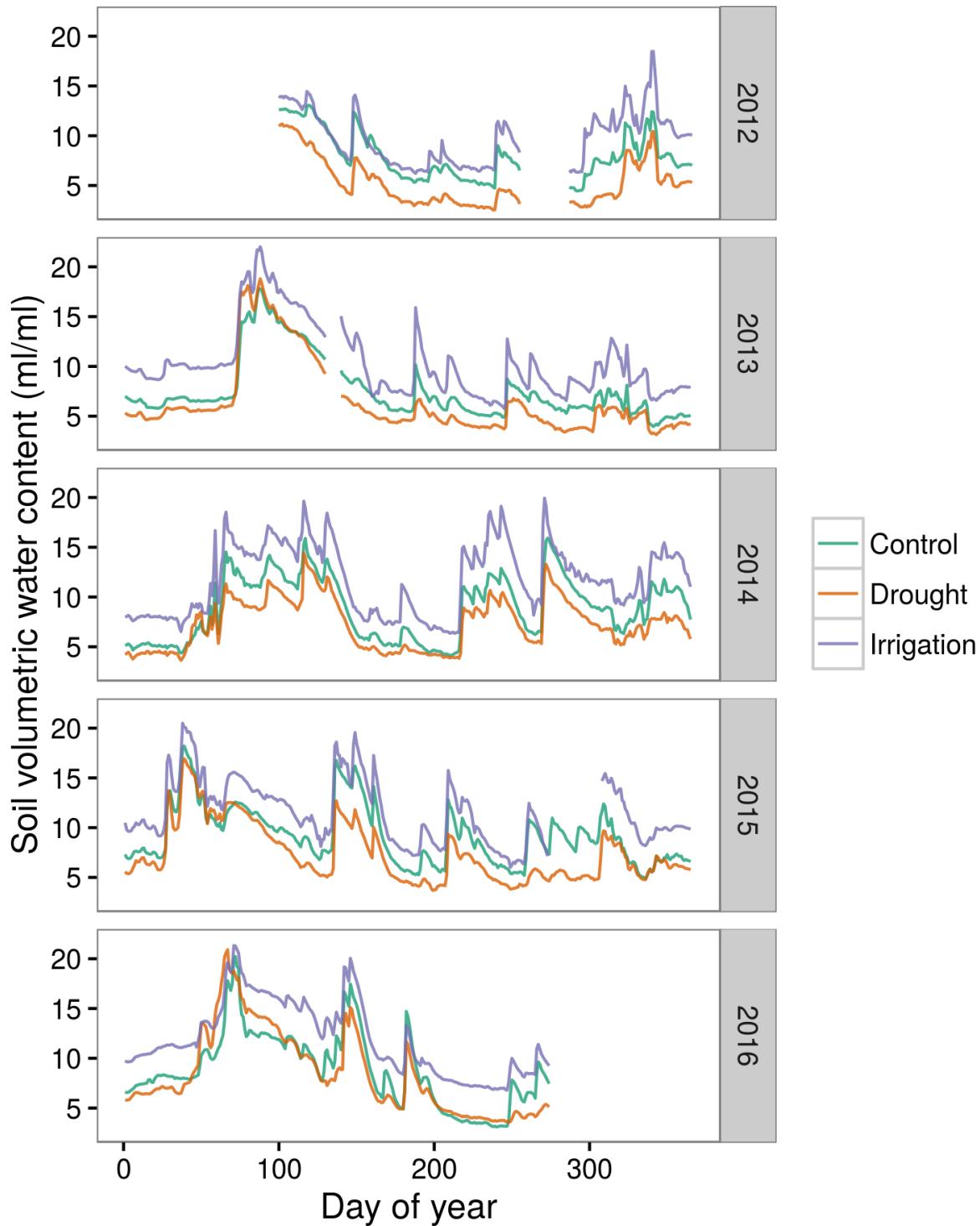


Figure 2: Average soil moisture in the control, drought, and irrigation treatments during each year of the experiment. Soil moisture was monitored in four drought plots, four irrigated plots and four ambient control plots. Two sensors were installed at 5 cm depth at each plot and two at 25 cm and data was logged every 2 hours.

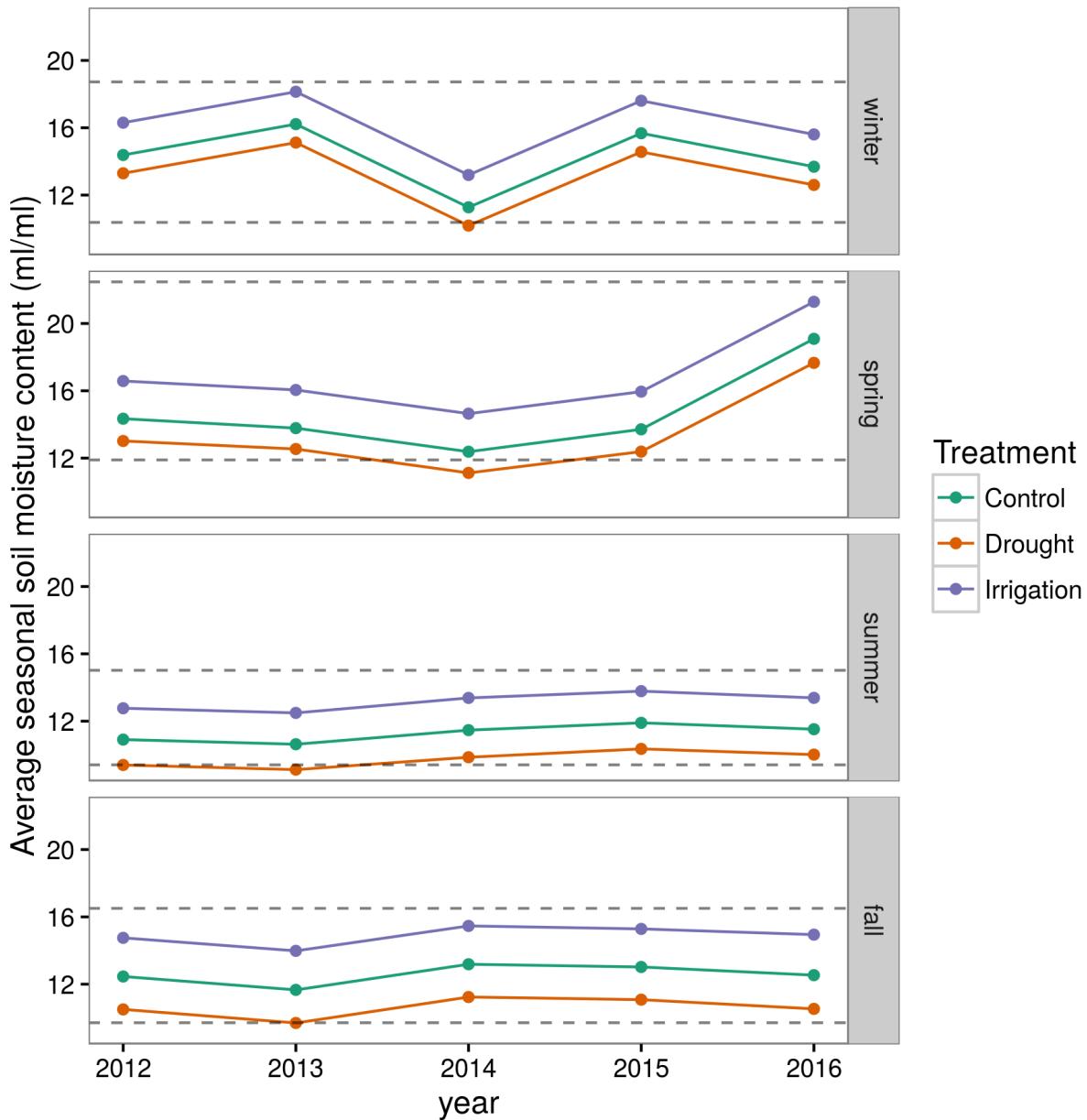


Figure 3: Average seasonal soil moisture in the control, drought, and irrigation treatments during each year of the experiment. The dashed gray lines give the 5th percentile and 95th percentile limits for seasonal soil moisture in the historical record (1929 to 2010).

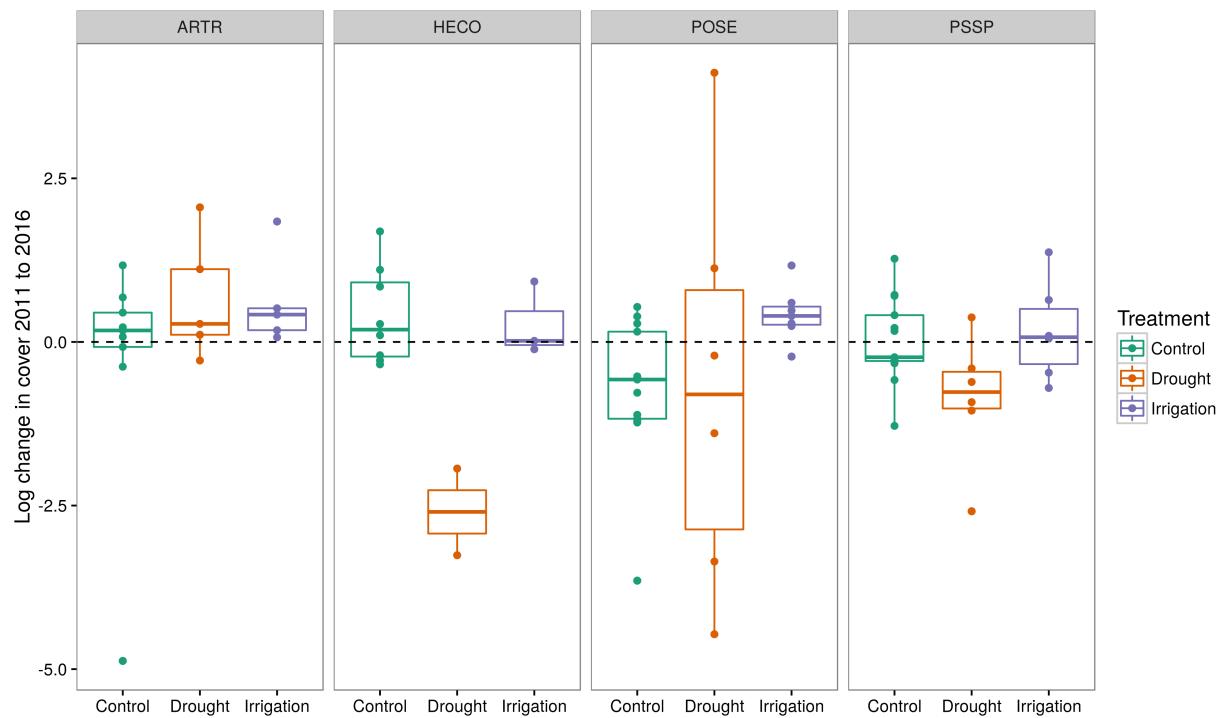


Figure 4: Log change in cover in each of the experimental plots from the pre-treatment monitoring in 2011 to the last year of the experiment in 2016. Box plots show the median cover change and the interquartile range. ARTR = *A. tripartita*, HECO = *H. comata*, POSE = *P. secunda*, PSSP = *P. spicata*.

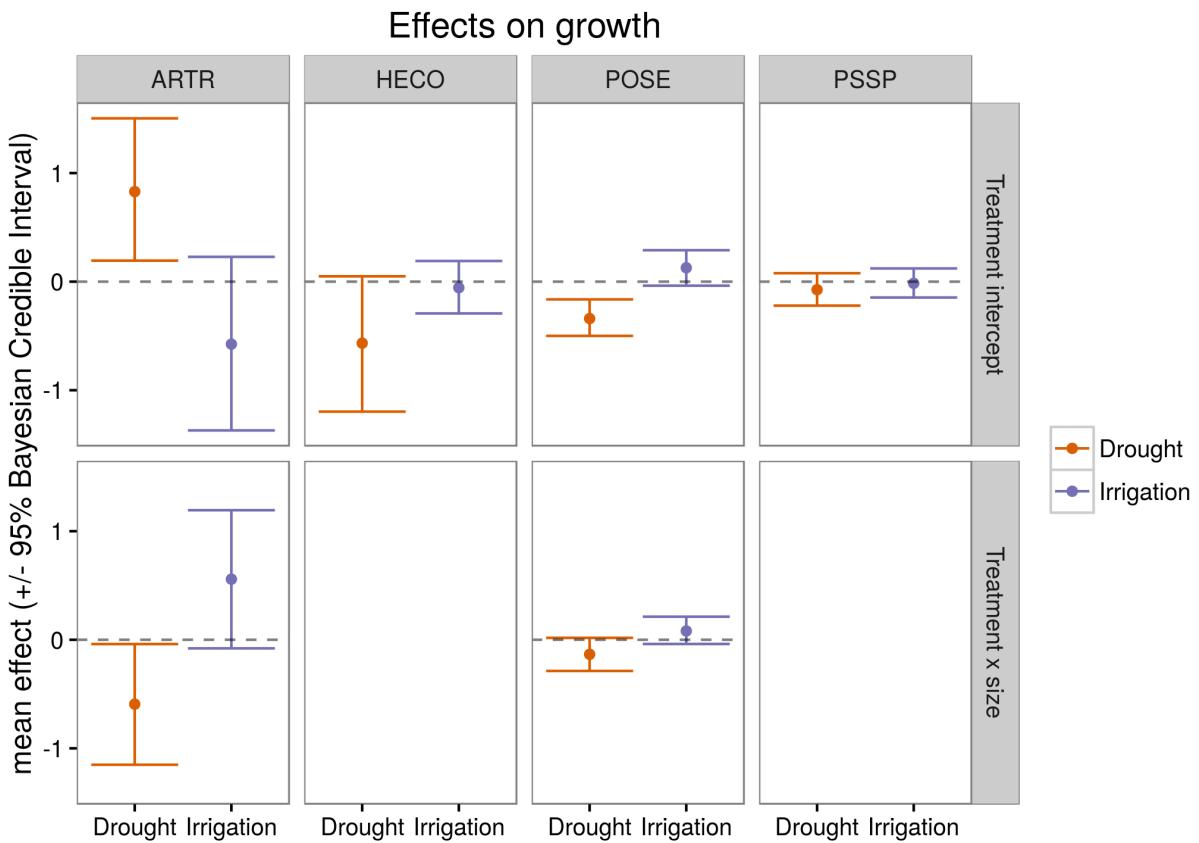


Figure 5: Parameter estimates for the effects of treatment on growth of all four species. We assessed a parameter as significant when the 95% Bayesian credible intervals did not overlap zero. Size by treatment interactions were only fit for ARTR, and POSE. Plant size was centered on mean size and scaled by its standard deviation. ARTR = *A. tripartita*, HECO = *H. comata*, POSE = *P. secunda*, PSSP = *P. spicata*.

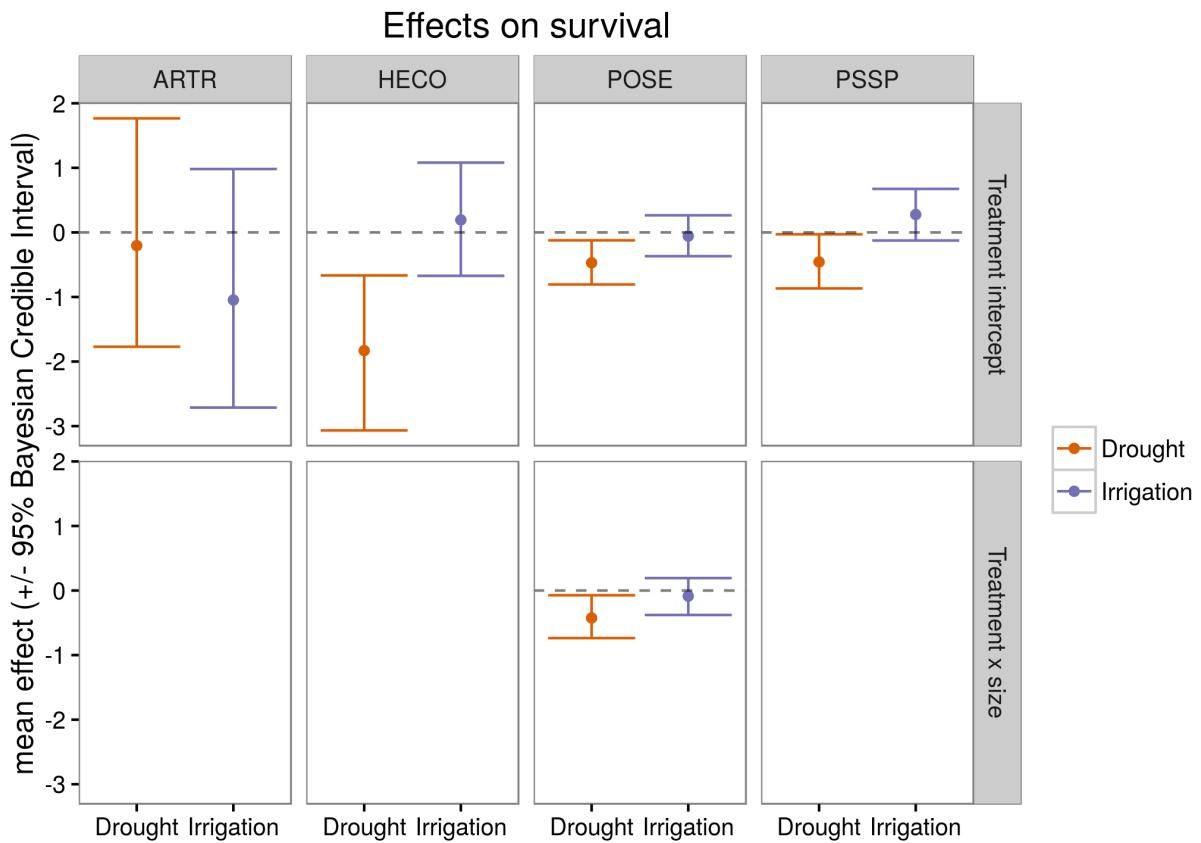


Figure 6: Parameter estimates for the effects of treatment on survival of all four species. We assessed a parameter as significant when the 95% Bayesian credible intervals did not overlap zero. Size by treatment interactions were only fit for POSE. Plant size was centered on mean size and scaled by its standard deviation. ARTR = *A. tripartita*, HECO = *H. comata*, POSE = *P. secunda*, PSSP = *P. spicata*.

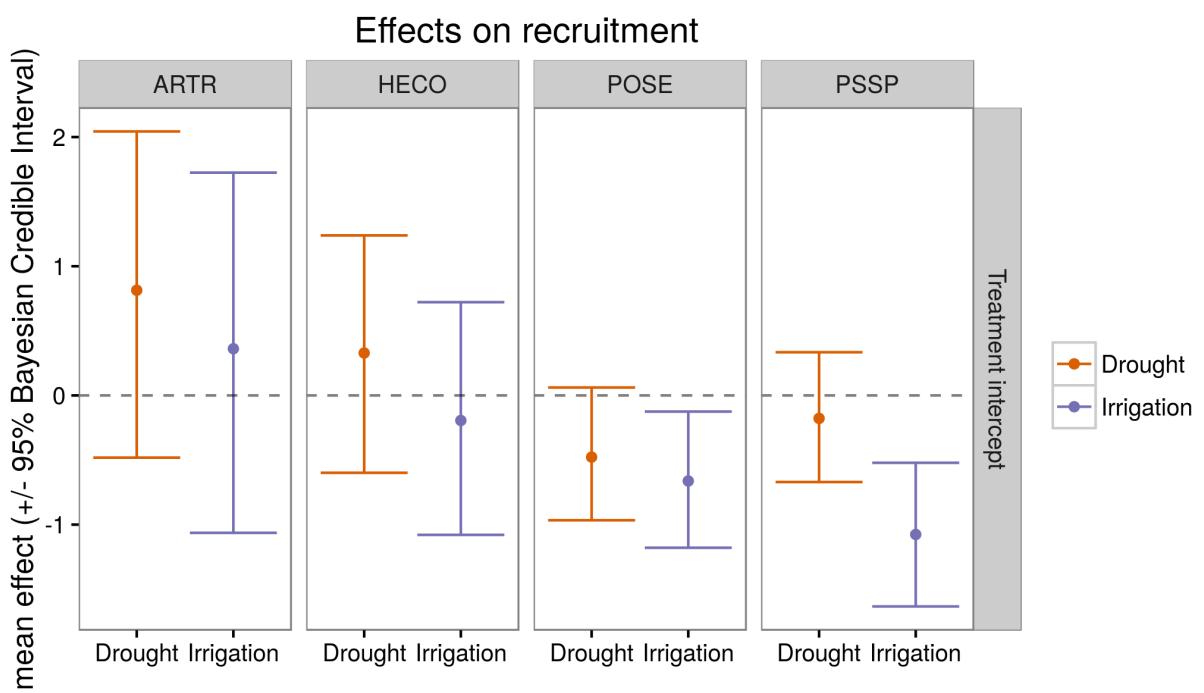


Figure 7: Parameter estimates for the effects of treatment on recruitment of all four species. We assessed a parameter as significant when the 95% Bayesian credible intervals did not overlap zero. ARTR = *A. tripartita*, HECO = *H. comata*, POSE = *P. secunda*, PSSP = *P. spicata*.

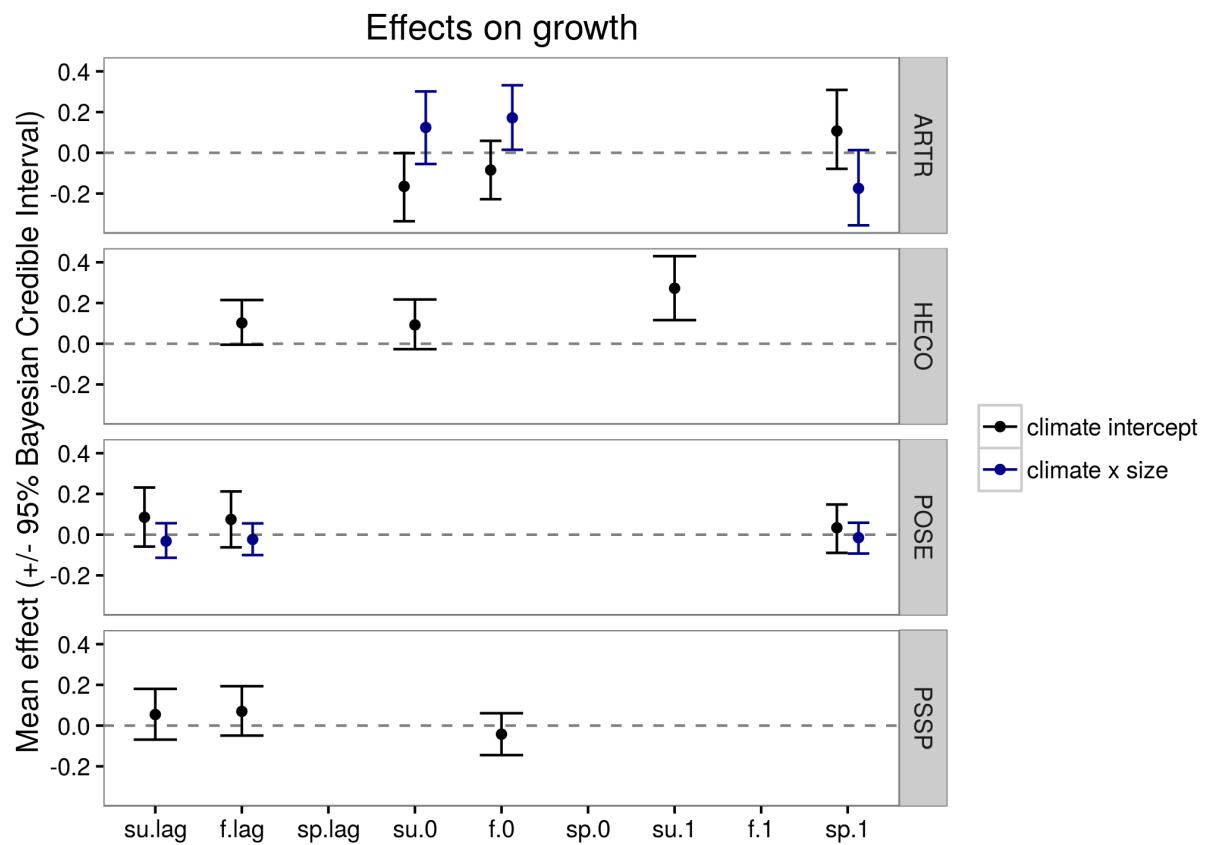


Figure 8: Parameter estimates for the selected seasonal soil moisture covariates on the growth of all four species. Parameters are ordered chronologically from most recent to the current growing season on the right to most distant on the left. Dark blue parameters show size x climate interaction effects. We assessed a parameter as significant when the 95% Bayesian credible intervals did not overlap zero. ARTR = *A. tripartita*, HECO = *H. comata*, POSE = *P. secunda*, PSSP = *P. spicata*.

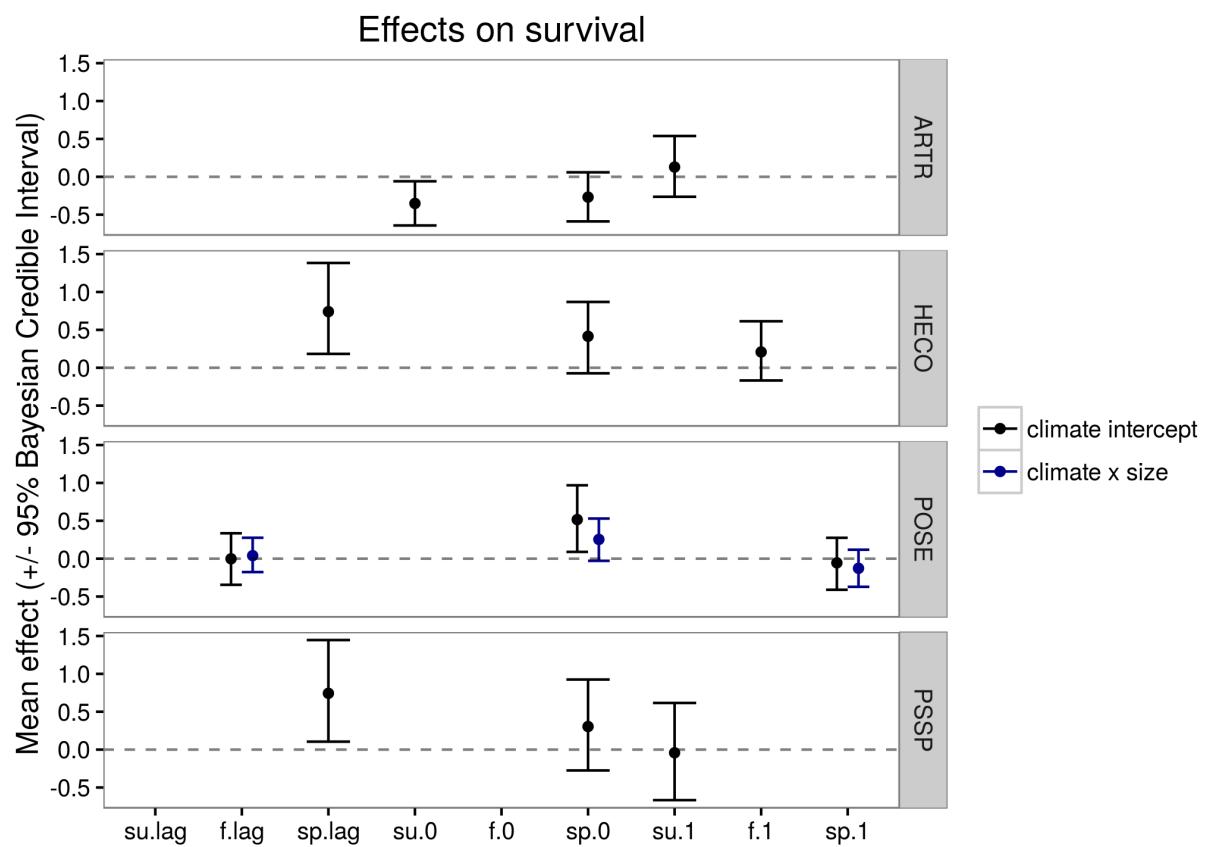


Figure 9: Parameter estimates for the selected seasonal soil moisture covariates on the survival of all four species. Parameters are ordered chronologically from most recent to the current growing season on the right to most distant on the left. Dark blue parameters show size x climate interaction effects. We assessed a parameter as significant when the 95% Bayesian credible intervals did not overlap zero. ARTR = *A. tripartita*, HECO = *H. comata*, POSE = *P. secunda*, PSSP = *P. spicata*.

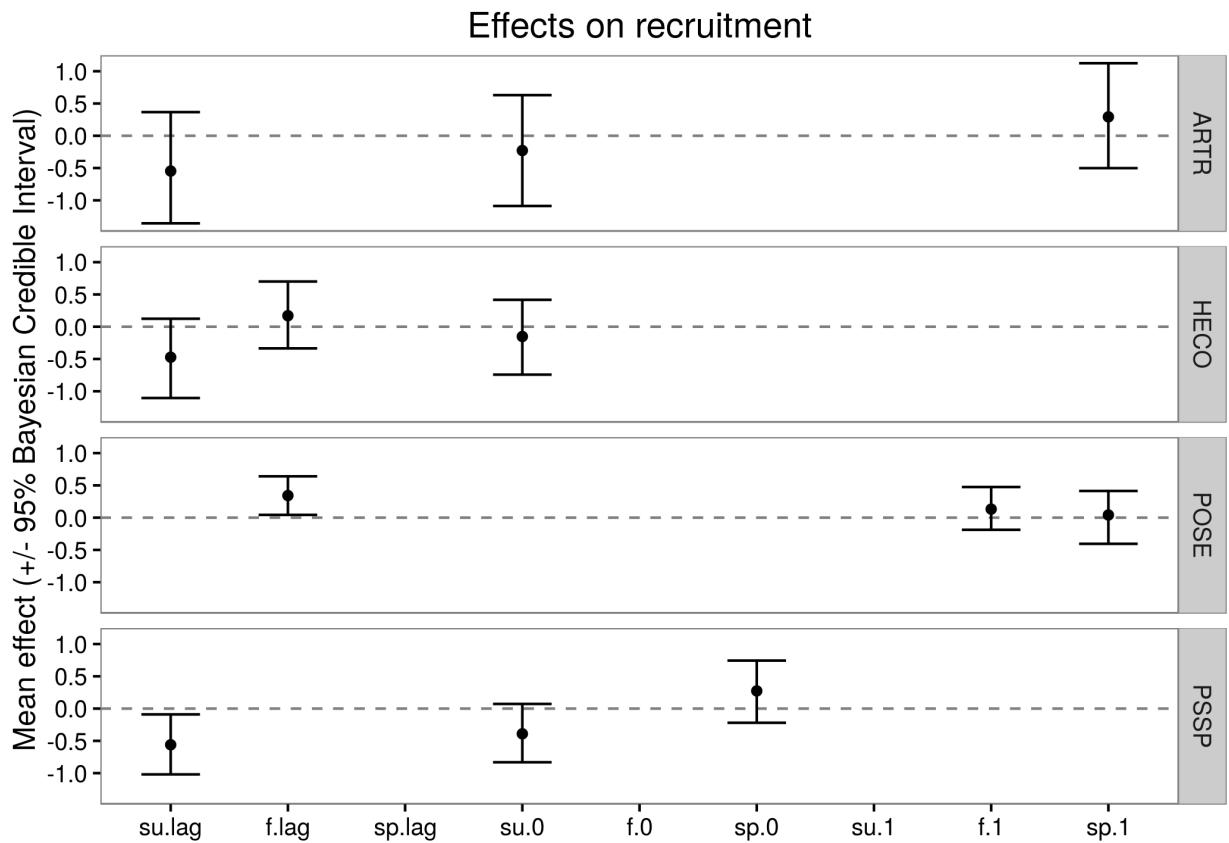


Figure 10: Parameter estimates for the selected seasonal soil moisture covariates on the survival of all four species. Parameters are ordered chronologically from most recent to the current growing season on the right to most distant on the left. Dark blue parameters show size x climate interaction effects. We assessed a parameter as significant when the 95% Bayesian credible intervals did not overlap zero. ARTR = *A. tripartita*, HECO = *H. comata*, POSE = *P. secunda*, PSSP = *P. spicata*.

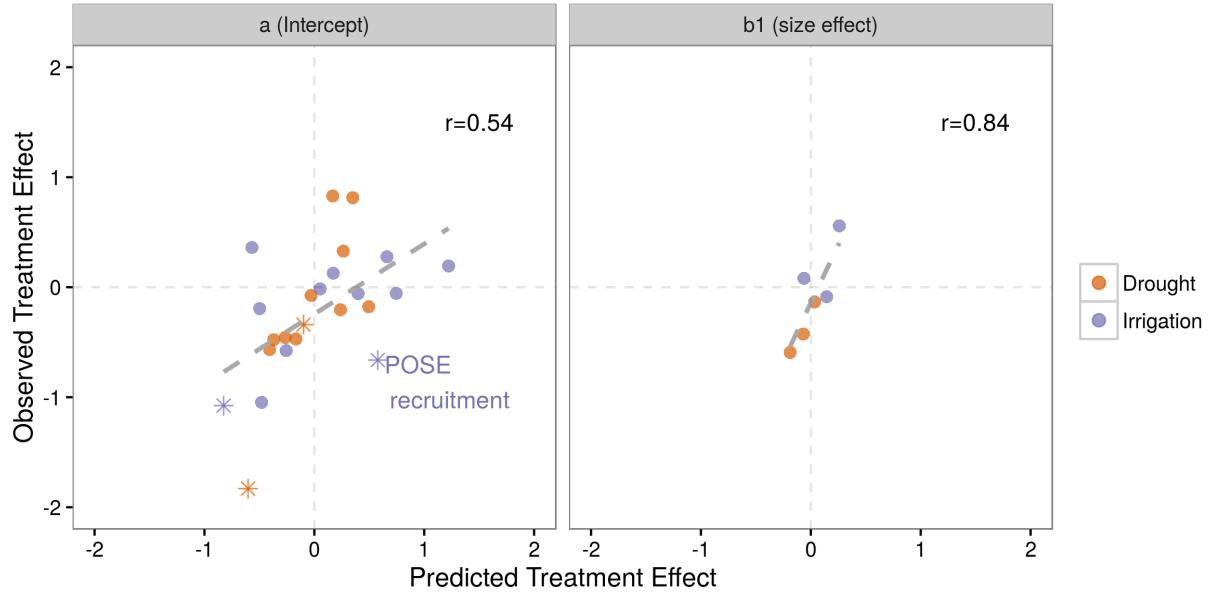


Figure 11: The treatment effects predicted by the climate model compared to the treatment effects observed for the intercept parameters (left side) and size by climate/treatment effects (right side). The observed treatment effects come from the treatment model fitted to all the data including the five years of the experiment. The predicted parameters come from the climate model fitted to all years of observational data but do not include the five years of the experiment (2011 to 2016). Treatment parameters that were both observed and predicted to be significantly different from zero are shown with the “*” symbol. The correlation between predicted and observed parameters is given on each panel. *P. secunda* recruitment was predicted to be positively affected by the irrigation treatment but was in fact negatively affected. The other significant effects were in the correct direction. We assessed a parameter as significant when the 95% Bayesian credible intervals did not overlap zero.

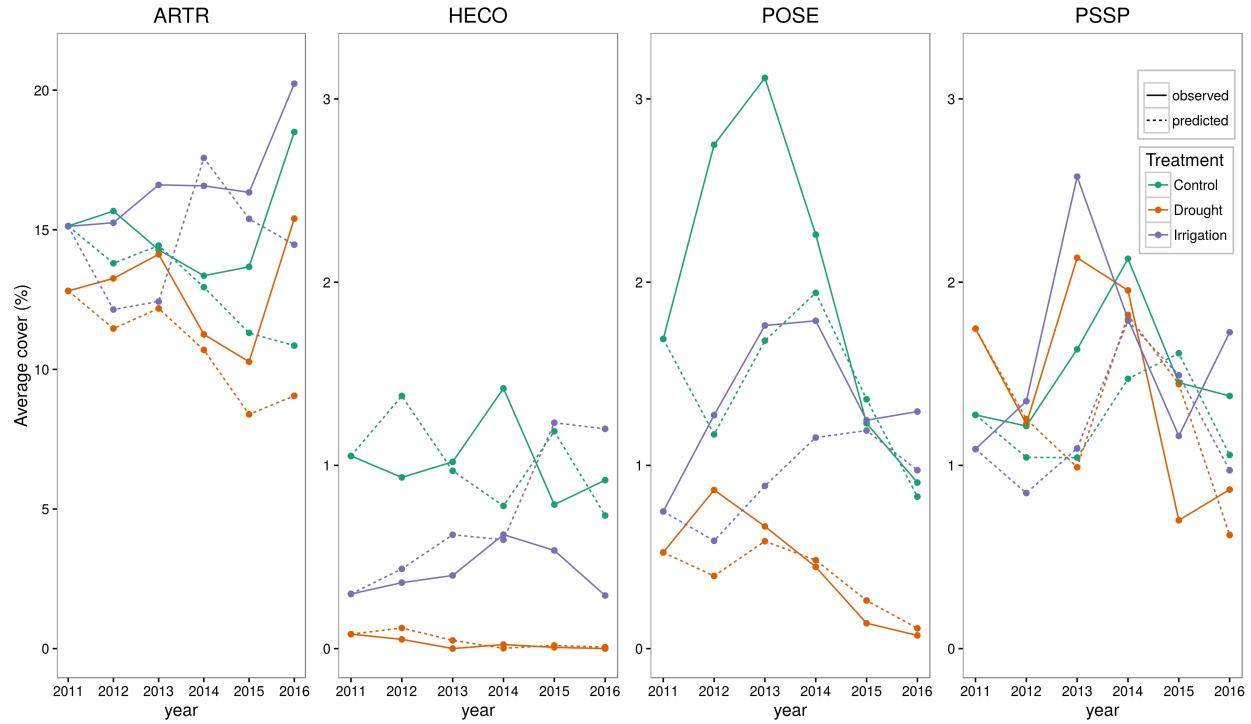


Figure 12: Observed average cover per quadrat in the experimental and control plots and one step ahead cover predictions from the climate model. Cover predictions for each year are generated from the IBM based on the observed distribution of plants in each quadrat in the current year. Quadrat cover was not predicted for the first year of the experiment in 2011. Note the different cover scales for ARTR and the three grass species. ARTR = *A. tripartita*, HECO = *H. comata*, POSE = *P. secunda*, PSSP = *P. spicata*.

A. tripartita

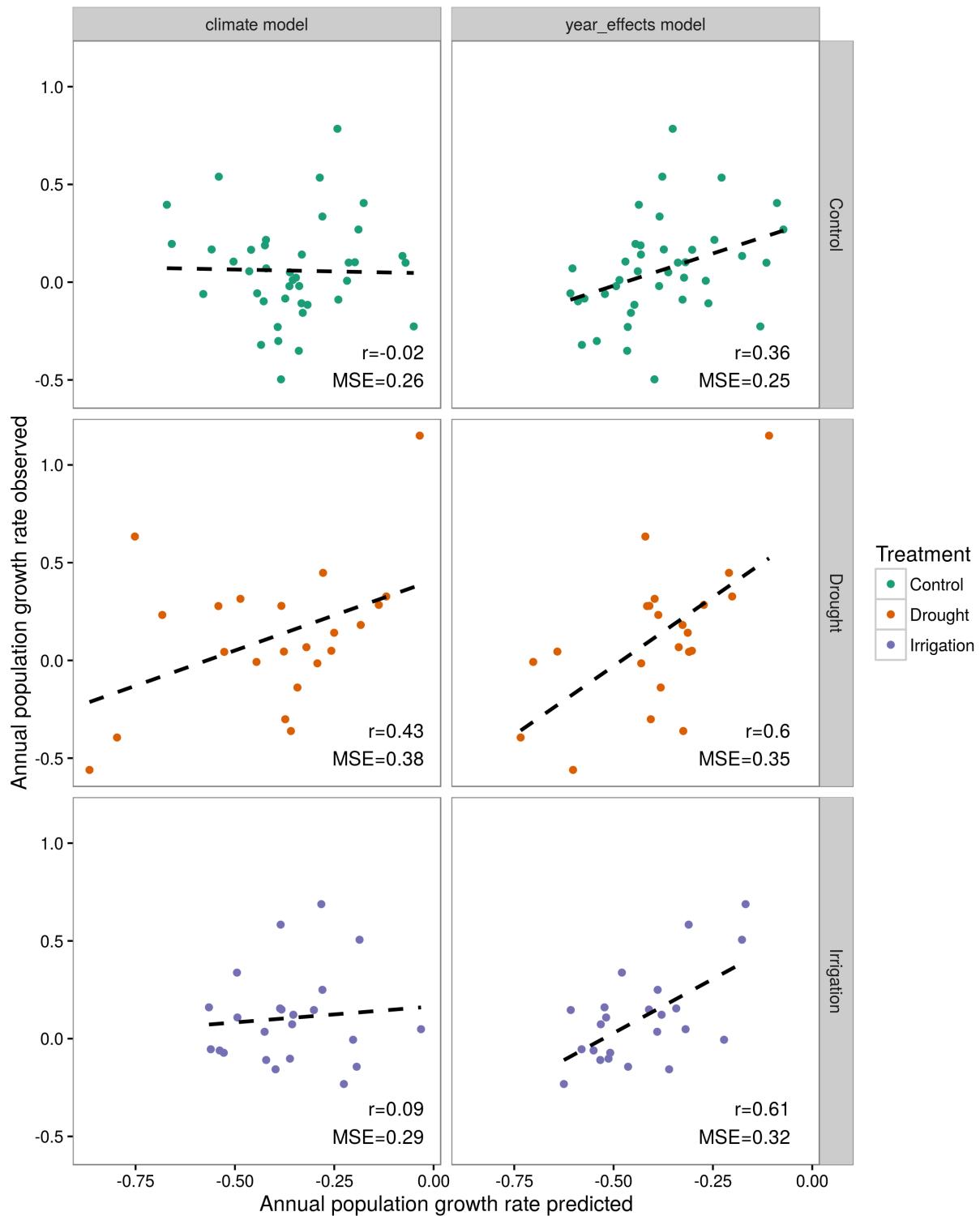


Figure 13: Observed and predicted one step ahead log change in *A. tripartita* cover in the experiment. Changes in cover predicted by the climate model are shown on the left and those predicted by the no climate model are shown on the right. Correlations coefficients between predictions and observations and MSE are shown for each treatment and model.

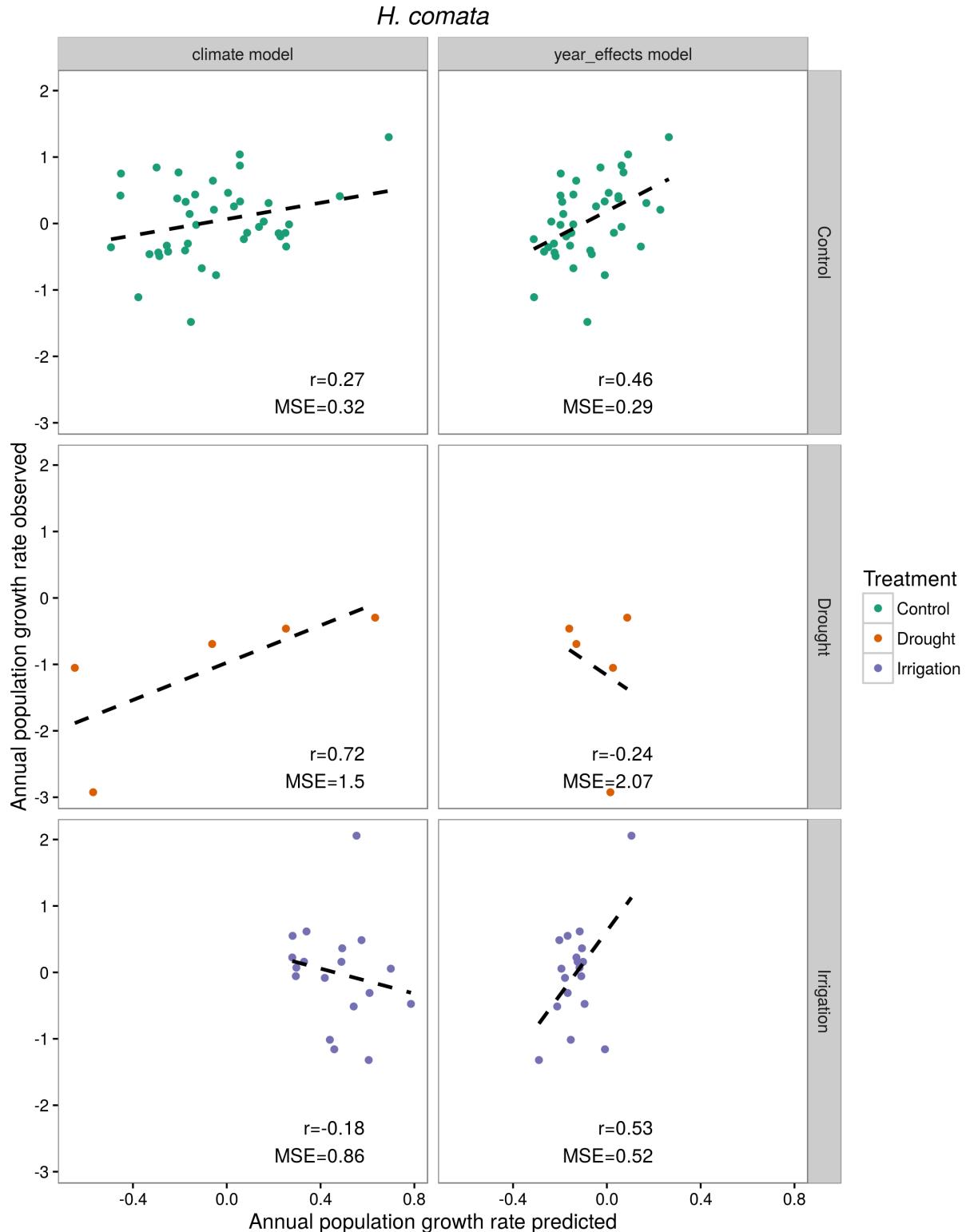


Figure 14: Observed and predicted one step ahead log change in *H. comata* cover in the experiment. Changes in cover predicted by the climate model are shown on the left and those predicted by the no climate model are shown on the right. Correlations coefficients between predictions and observations and MSE are shown for each treatment and model.

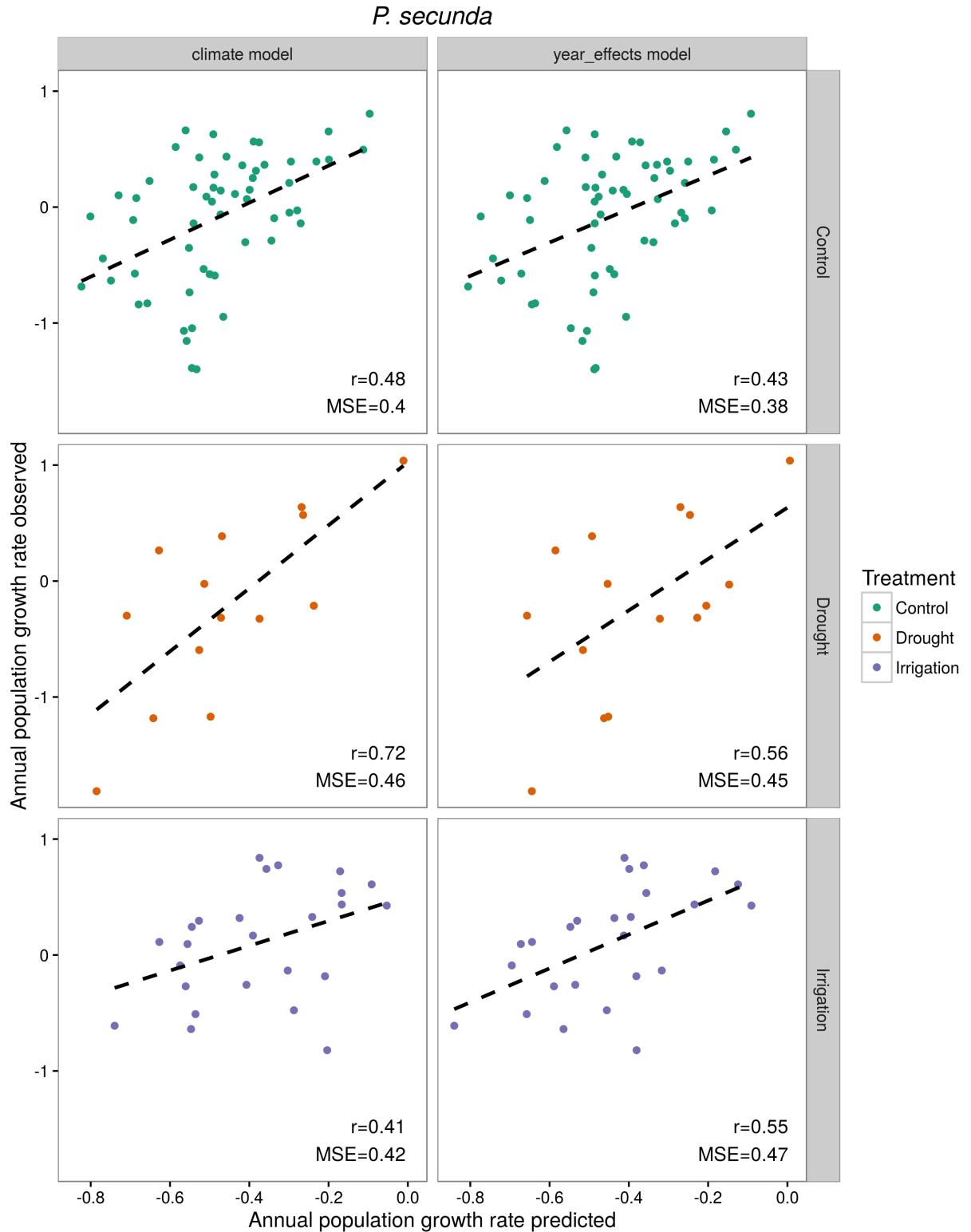


Figure 15: Observed and predicted one step ahead log change in *P. secunda* cover in the experiment. Changes in cover predicted by the climate model are shown on the left and those predicted by the no climate model are shown on the right. Correlations coefficients between predictions and observations and MSE are shown for each treatment and model.

P. spicata

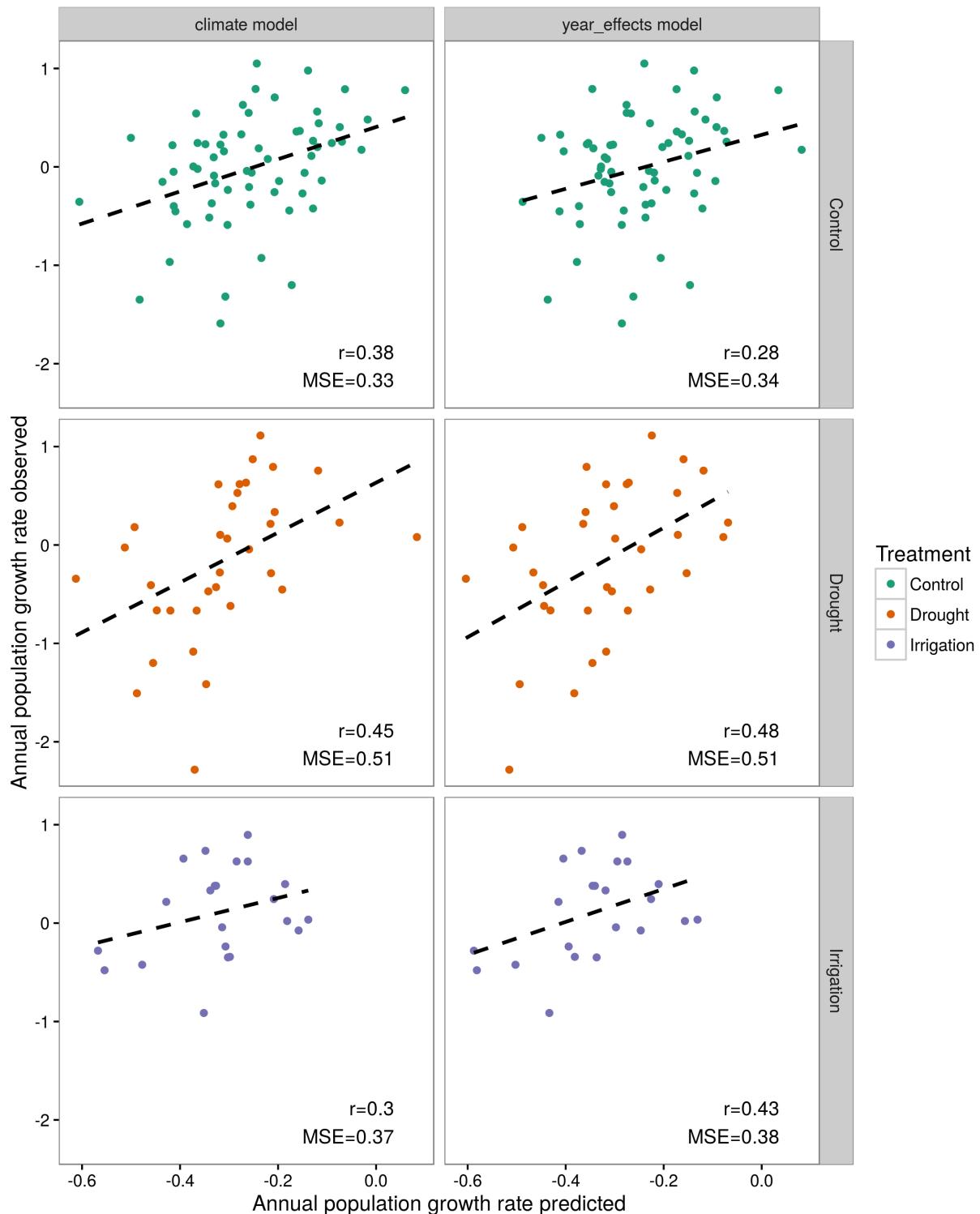


Figure 16: Observed and predicted one step ahead log change in *P. spicata* cover in the experiment. Changes in cover predicted by the climate model are shown on the left and those predicted by the no climate model are shown on the right. Correlations coefficients between predictions and observations and MSE are shown for each treatment and model.

Supporting Information

Adler et al., “Weak interspecific interactions”

Supplementary Methods

Interspecific covariance in local crowding

We explored interspecific covariance in local crowding experienced by individual plants, by regressing the W values exerted by one neighbor species, the response variable, against the W values of all other species, the independent variables. Because some $W = 0$, we conducted two separate regressions. First, using all W ’s, we fitted a generalized linear model with a logit link function to evaluate whether the probability that the focal species’ $W = 0$ is influenced by the value of other species’ W ’s. In this model, the dependent variable is a Bernoulli variate coding for the zero or non-zero value of the focal species’ crowding, and the independent variables are the W ’s for all other species. Second, for the set of records in which the focal species has $W > 0$, we performed a linear regression, where the focal species’ W is the dependent variable, and the other species’ W ’s are the independent variables. We repeated these regressions for each focal species. Due to large samples size, interspecific W values were often statistically significant predictors of intraspecific. However, they explained very little variance. The maximum reduction in deviance for the generalized linear regressions and R^2 for the linear regressions were both less than 8%. The R code for this analysis is included as ..\Wdistrib\exploreSurvivalWs.r.

Mean field approximation of local crowding for the IPM

Adler et al. (2010) developed a mean field approximation for local crowding when the competition kernels are all Gaussian functions, $F_{jm}(d) = e^{-\alpha_{jm}d^2}$. The approximation is explained in the online SI to Adler et al. (2010) and in section 5.3 of ?. Here we explain how that approximation was modified for the IPMs in this paper, which used fitted nonparametric competition kernels.

For $j \neq m$ (between-species competition), overlap between individuals is allowed. The mean field approximation is that from the perspective of any focal plant in species j , individuals of species m are distributed at random in space, independent of each other and of their size.

Consider the region between the circles of radius x and $x + dx$ centered on a focal genet of species j . The area of this annulus is $2\pi x \, dx$ to leading order for $dx \approx 0$. A species m genet in the annulus puts competitive pressure $F_{jm}(x)$ times its area on the focal genet. The expected total competitive pressure from all such genets is therefore is $F_{jm}(x)2\pi x \, dx$ times the expected fractional cover of species m in the annulus (fractional cover is the total area of species m genets, as a fraction of the total area). The excepted fractional cover C_m of species m in the annulus equals its fractional cover in the habitat as a whole, because of the assumption of random distribution spatial distributions. We therefore have $C_m = \int e^u n_m(u, t) du / A$ where A is the total area of the

habitat. The total expected competitive pressure on a species- j genet due to species m is then

$$W_{jm} = \int_0^\infty C_m F_{jm}(x) 2\pi x \, dx = C_m \left[2\pi \int_0^\infty x F(x) \, dx \right]. \quad (\text{SI.1})$$

The quantity in square brackets is a constant (that is, it only depends on what the kernel function is) so it can be computed once and for all for each kernel used in the IPM. The integral is finite because all fitted kernels fall to zero at a finite distance from the focal plant.

Our kernel fitting method only uses competition kernel values at the “mid-ring” distances halfway between the inner and outer radii of a series of annuli around each focal plant, scaled so that the value at the innermost mid-ring distance equals 1. In the IPM we defined the kernel at other distances by linear interpolation between values at mid-ring distances, except that for the innermost ring a kernel value of 1 was specified at the outer radius of the ring and at distance $x = 0$.

Now consider within-species competition. We assume that conspecifics cannot overlap. Genet shapes are irregular, but we nonetheless implement the no-overlap rule by assuming that a genet of log area u_i is a circle of radius r_i where $\pi r_i^2 = e^{u_i}$. The no-overlap rule is then that the centroids of two conspecific individuals must be separated by at least the sum of their radii.

For any one focal genet, the no-overlap restriction on its neighbors’ locations affects only a negligibly small part of the habitat. The expected cover of individuals in the places where they can occur (relative to one focal plant) is thus assumed to equal their expected locations in the habitat as a whole.

Let $C_m(u)$ be the total cover of species m genets of radius r or smaller,

$$C_m(r) = \int_L^{\log(\pi r^2)} e^z n_m(z, t) \, dz. \quad (\text{SI.2})$$

A focal genet of radius r cannot have any conspecific neighbors centered at distances less than r . It can have a neighbor centered at distance $x > r$ if that neighbor’s radius is no more than $x - r$. Adding up the expected cover of all such possible neighbors for a focal genet of radius r ,

$$W_{mm}(r) = 2\pi \int_r^\infty F_{mm}(x) x C_m(x - r) \, dx \quad (\text{SI.3})$$

This integral is again finite and computable because the kernels F fall to 0 at finite x .

Additional Tables

	species	vital_rate	Treatment	score	climate model	no climate model	diff	improved
1	ARTR	growth	Control	lppd	-107.53	-108.40	0.87	***
2	ARTR	growth	Control	MSE	0.57	0.56	0.01	
3	ARTR	growth	Drought	lppd	-39.71	-40.01	0.30	***
4	ARTR	growth	Drought	MSE	0.53	0.49	0.03	
5	ARTR	growth	Irrigation	lppd	-38.85	-40.75	1.91	***
6	ARTR	growth	Irrigation	MSE	0.50	0.57	-0.07	***
7	ARTR	recruitment	Control	lppd	-32.61	-31.05	-1.56	
8	ARTR	recruitment	Control	MSE	61.88	10.59	51.29	
9	ARTR	recruitment	Drought	lppd	-28.93	-26.52	-2.41	
10	ARTR	recruitment	Drought	MSE	523.95	11.62	512.33	
11	ARTR	recruitment	Irrigation	lppd	-17.51	-20.24	2.73	***
12	ARTR	recruitment	Irrigation	MSE	4.72	5.34	-0.62	***
13	ARTR	survival	Control	lppd	-24.19	-23.06	-1.13	
14	ARTR	survival	Control	MSE	0.07	0.07	0.00	
15	ARTR	survival	Drought	lppd	-5.48	-5.34	-0.13	
16	ARTR	survival	Drought	MSE	0.04	0.04	-0.00	***
17	ARTR	survival	Irrigation	lppd	-7.88	-8.01	0.13	***
18	ARTR	survival	Irrigation	MSE	0.06	0.06	-0.00	***
19	HECO	growth	Control	lppd	-377.77	-369.46	-8.31	
20	HECO	growth	Control	MSE	1.11	1.09	0.02	
21	HECO	growth	Drought	lppd	-8.74	-10.97	2.23	***
22	HECO	growth	Drought	MSE	3.12	4.35	-1.23	***
23	HECO	growth	Irrigation	lppd	-89.03	-73.93	-15.10	
24	HECO	growth	Irrigation	MSE	2.02	1.47	0.55	
25	HECO	recruitment	Control	lppd	-93.35	-93.47	0.12	***
26	HECO	recruitment	Control	MSE	613.41	499.11	114.29	
27	HECO	recruitment	Drought	lppd	-25.39	-27.56	2.17	***
28	HECO	recruitment	Drought	MSE	1.94	2.33	-0.38	***
29	HECO	recruitment	Irrigation	lppd	-30.69	-30.56	-0.12	
30	HECO	recruitment	Irrigation	MSE	5.21	7.62	-2.41	***
31	HECO	survival	Control	lppd	-124.59	-112.70	-11.90	
32	HECO	survival	Control	MSE	0.12	0.11	0.01	
33	HECO	survival	Drought	lppd	-17.89	-20.82	2.93	***
34	HECO	survival	Drought	MSE	0.22	0.26	-0.05	***

Continued on next page

	species	vital_rate	Treatment	score	climate model	no climate model	diff	improved
35	HECO	survival	Irrigation	lppd	-16.51	-13.54	-2.97	
36	HECO	survival	Irrigation	MSE	0.09	0.07	0.02	
37	POSE	growth	Control	lppd	-1117.20	-1117.29	0.08	***
38	POSE	growth	Control	MSE	1.50	1.51	-0.00	***
39	POSE	growth	Drought	lppd	-254.17	-257.32	3.16	***
40	POSE	growth	Drought	MSE	2.66	2.69	-0.03	***
41	POSE	growth	Irrigation	lppd	-452.34	-456.95	4.61	***
42	POSE	growth	Irrigation	MSE	1.87	1.90	-0.03	***
43	POSE	recruitment	Control	lppd	-127.64	-128.73	1.09	***
44	POSE	recruitment	Control	MSE	35.20	44.82	-9.61	***
45	POSE	recruitment	Drought	lppd	-60.34	-63.15	2.80	***
46	POSE	recruitment	Drought	MSE	23.60	33.88	-10.28	***
47	POSE	recruitment	Irrigation	lppd	-72.06	-65.58	-6.48	
48	POSE	recruitment	Irrigation	MSE	85.04	27.63	57.41	
49	POSE	survival	Control	lppd	-366.49	-380.49	14.00	***
50	POSE	survival	Control	MSE	0.12	0.12	-0.00	***
51	POSE	survival	Drought	lppd	-175.29	-187.88	12.59	***
52	POSE	survival	Drought	MSE	0.21	0.22	-0.01	***
53	POSE	survival	Irrigation	lppd	-156.28	-150.23	-6.05	
54	POSE	survival	Irrigation	MSE	0.13	0.13	0.00	
55	PSSP	growth	Control	lppd	-627.07	-625.63	-1.44	
56	PSSP	growth	Control	MSE	1.38	1.36	0.02	
57	PSSP	growth	Drought	lppd	-292.90	-297.61	4.71	***
58	PSSP	growth	Drought	MSE	1.82	1.85	-0.03	***
59	PSSP	growth	Irrigation	lppd	-312.96	-314.67	1.71	***
60	PSSP	growth	Irrigation	MSE	1.51	1.51	-0.00	***
61	PSSP	recruitment	Control	lppd	-123.81	-125.23	1.42	***
62	PSSP	recruitment	Control	MSE	30.59	34.79	-4.20	***
63	PSSP	recruitment	Drought	lppd	-87.34	-86.58	-0.77	
64	PSSP	recruitment	Drought	MSE	222.16	54.58	167.58	
65	PSSP	recruitment	Irrigation	lppd	-60.18	-62.12	1.94	***
66	PSSP	recruitment	Irrigation	MSE	20.90	44.57	-23.67	***
67	PSSP	survival	Control	lppd	-148.69	-140.15	-8.54	
68	PSSP	survival	Control	MSE	0.10	0.09	0.01	
69	PSSP	survival	Drought	lppd	-83.26	-78.09	-5.17	
70	PSSP	survival	Drought	MSE	0.11	0.11	0.01	

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	species	vital.rate	Treatment	score	climate model	no climate model	diff	improved
71	PSSP	survival	Irrigation	lppd	-100.52	-89.02	-11.50	
72	PSSP	survival	Irrigation	MSE	0.13	0.11	0.01	

Table SI-1: Comparison of model predictions from climate model and no climate model for each species and vital rate and treatment. Two prediction scores are reported, MSE and lppd. Lower MSE indicates improved predictions whereas higher lppd indicates improved predictions. Instances where the climate model outperformed the no climate model are marked with “***” in the last column. ARTR = *A. tripartita*, HECO = *H. comata*, POSE = *P. secunda*, PSSP = *P. spicata*.

Additional Figures

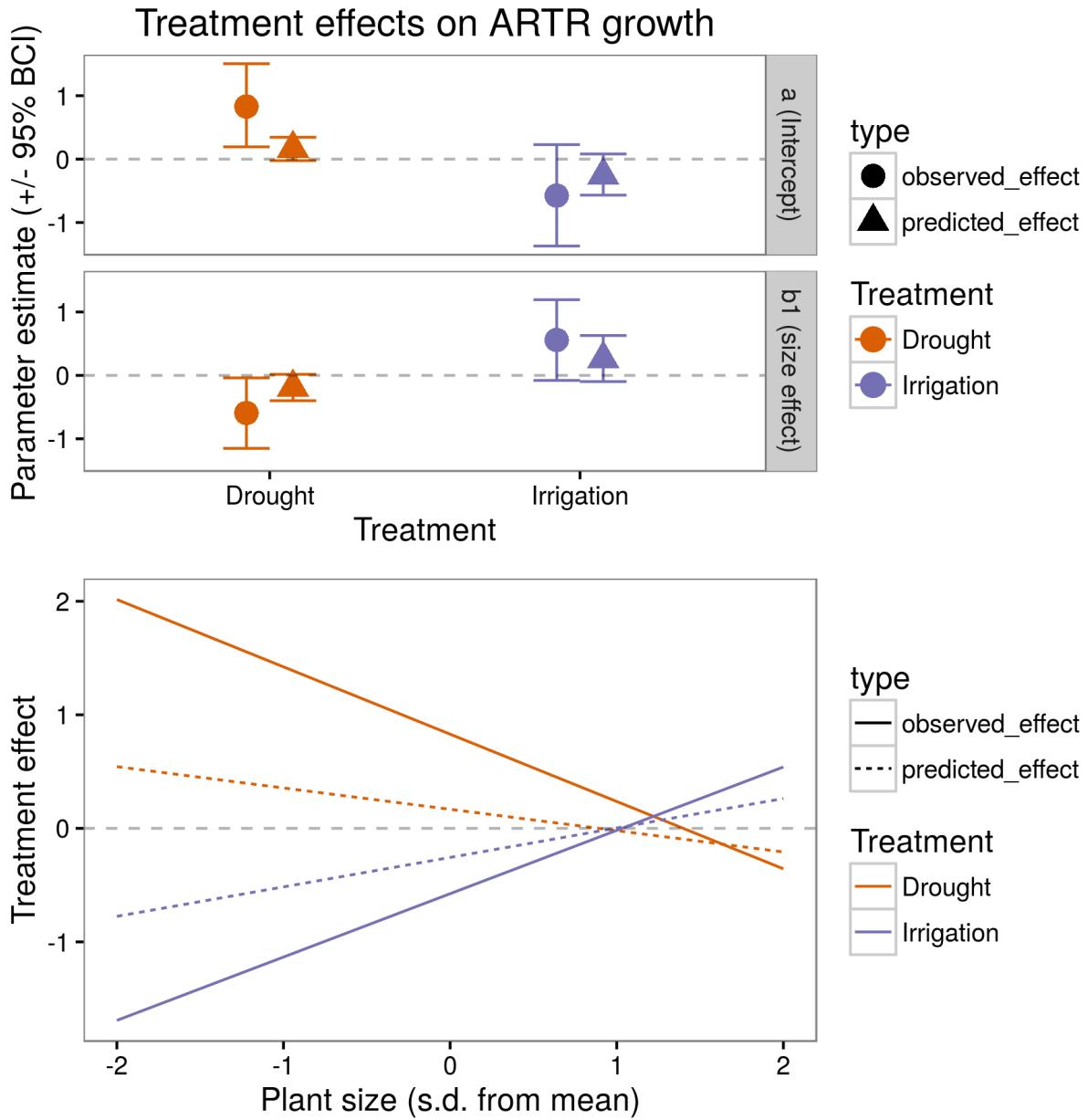


Figure SI-1: Comparison of treatment effects predicted and observed for *A. tripartita* growth. Upper figure shows each parameter estimate separately while the lower figure shows the effect of treatment as a function of plant size. The observed treatment effects come from the treatment model fitted to all the data including the five years of the experiment. The predicted parameters come from the climate model fitted to all years of observational data but do not include the five years of the experiment (2011 to 2016). We assessed a parameter as significant when the 95% Bayesian credible intervals did not overlap zero.

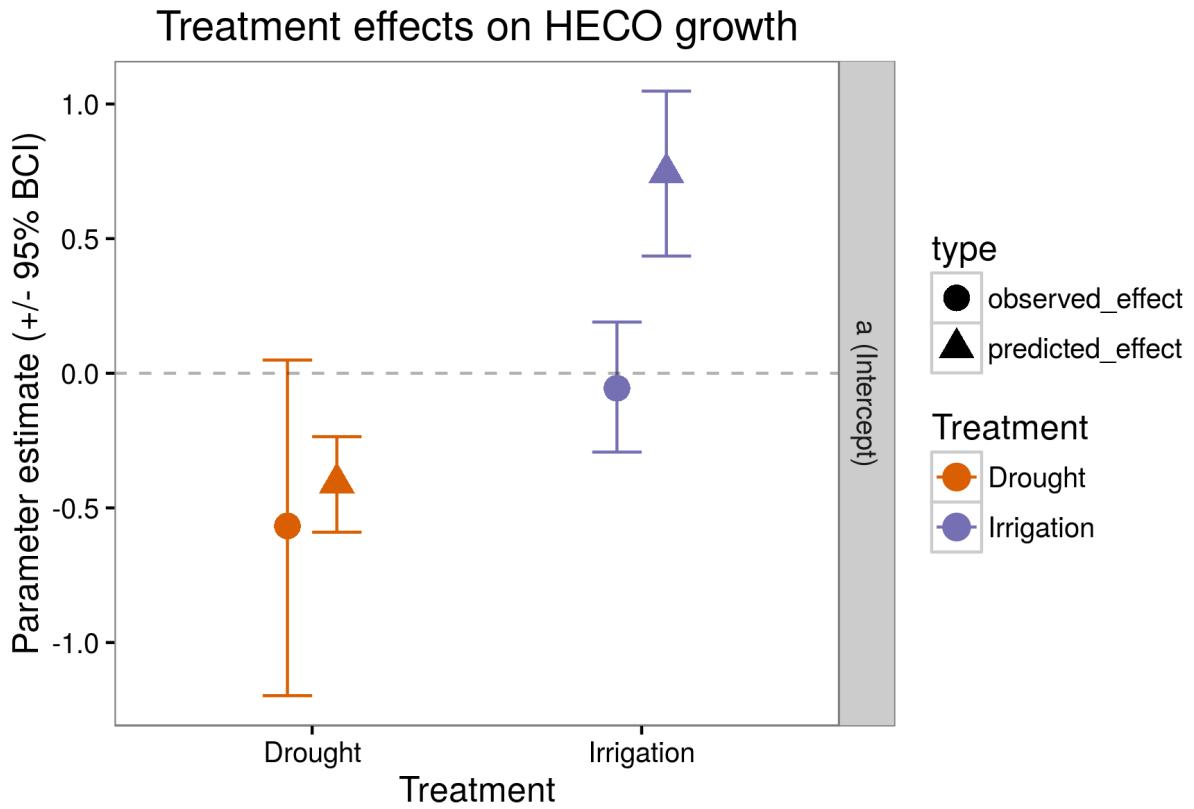


Figure SI-2: Comparison of treatment effects predicted and observed for *H. comata* growth. The observed treatment effects come from the treatment model fitted to all the data including the five years of the experiment. The predicted parameters come from the climate model fitted to all years of observational data but do not include the five years of the experiment (2011 to 2016). We assessed a parameter as significant when the 95% Bayesian credible intervals did not overlap zero.

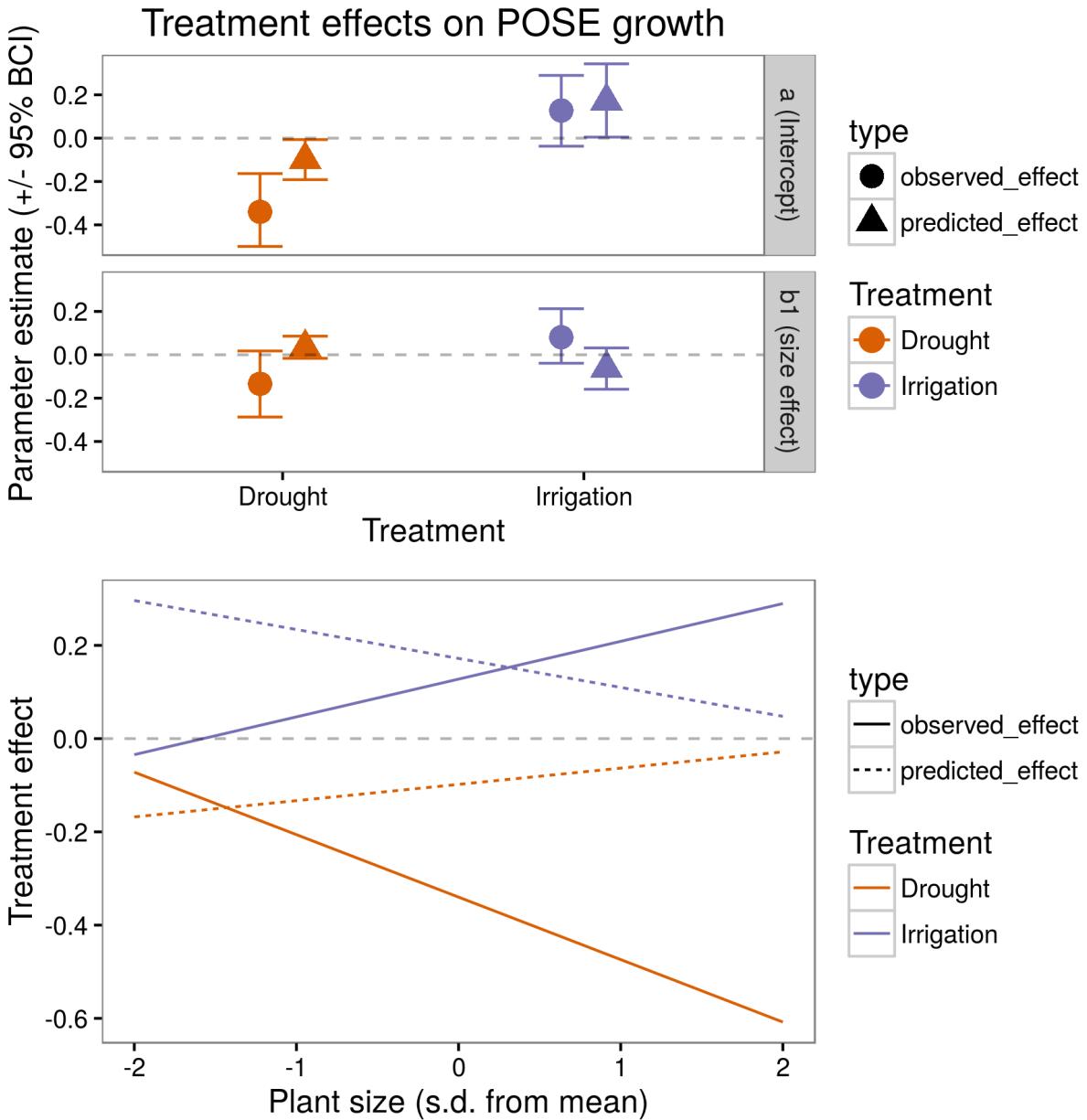


Figure SI-3: Comparison of treatment effects predicted and observed for *P. secunda* growth. Upper figure shows each parameter estimate separately while the lower figure shows the effect of treatment as a function of plant size. The observed treatment effects come from the treatment model fitted to all the data including the five years of the experiment. The predicted parameters come from the climate model fitted to all years of observational data but do not include the five years of the experiment (2011 to 2016). We assessed a parameter as significant when the 95% Bayesian credible intervals did not overlap zero.

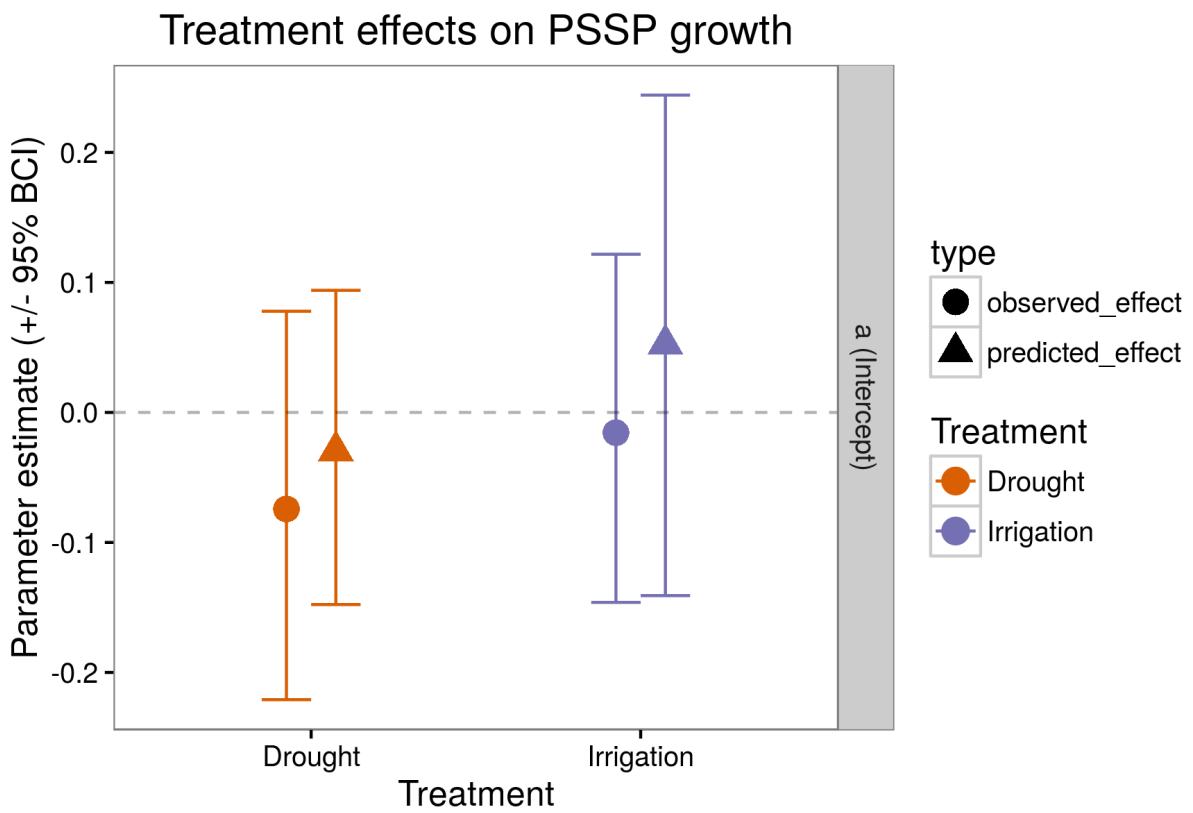


Figure SI-4: Comparison of treatment effects predicted and observed for *P. spicata* growth. The observed treatment effects come from the treatment model fitted to all the data including the five years of the experiment. The predicted parameters come from the climate model fitted to all years of observational data but do not include the five years of the experiment (2011 to 2016). We assessed a parameter as significant when the 95% Bayesian credible intervals did not overlap zero.

Treatment effects on ARTR survival

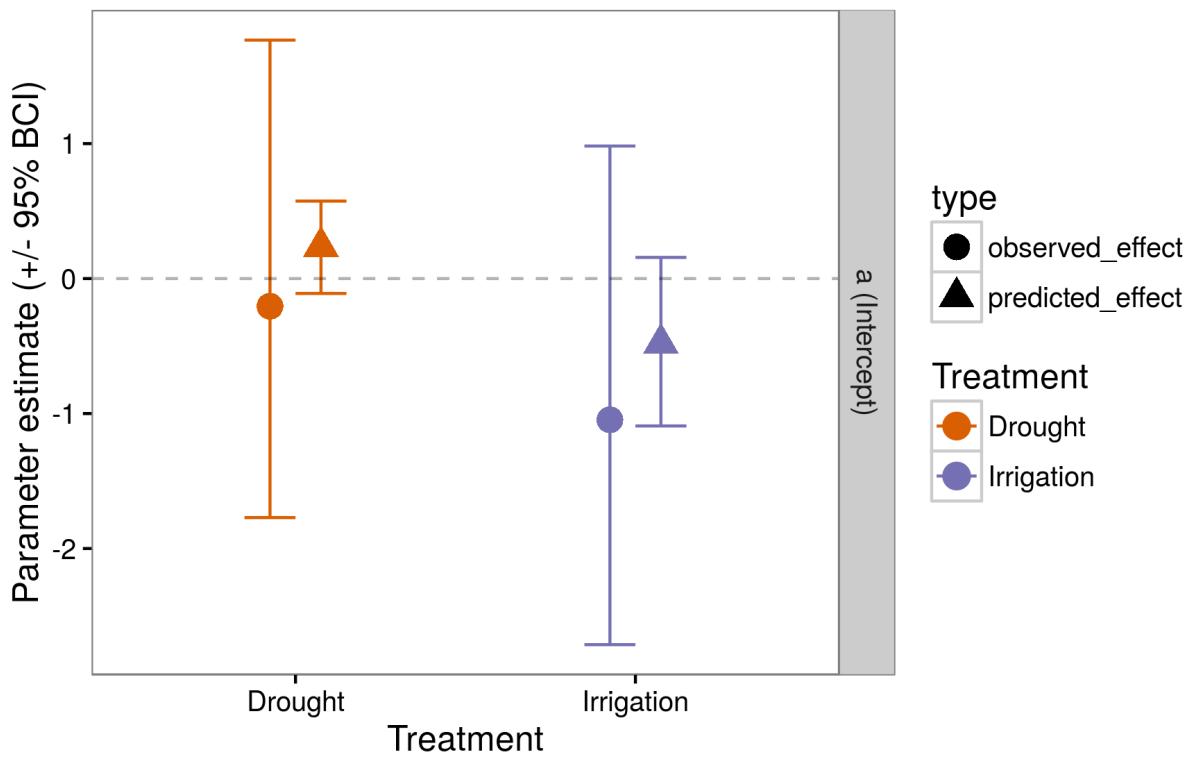


Figure SI-5: Comparison of treatment effects predicted and observed for *A. survival* survival. The observed treatment effects come from the treatment model fitted to all the data including the five years of the experiment. The predicted parameters come from the climate model fitted to all years of observational data but do not include the five years of the experiment (2011 to 2016). We assessed a parameter as significant when the 95% Bayesian credible intervals did not overlap zero.

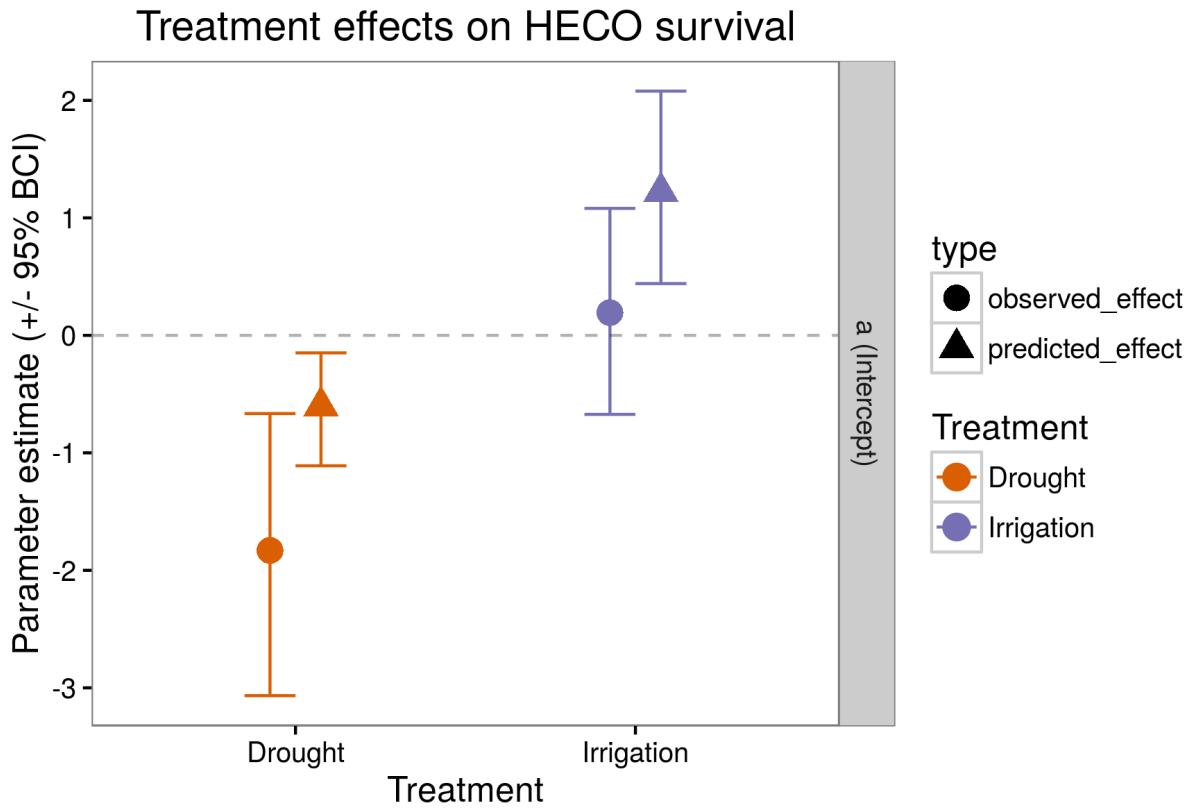


Figure SI-6: Comparison of treatment effects predicted and observed for *H. comata* survival. The observed treatment effects come from the treatment model fitted to all the data including the five years of the experiment. The predicted parameters come from the climate model fitted to all years of observational data but do not include the five years of the experiment (2011 to 2016). We assessed a parameter as significant when the 95% Bayesian credible intervals did not overlap zero.

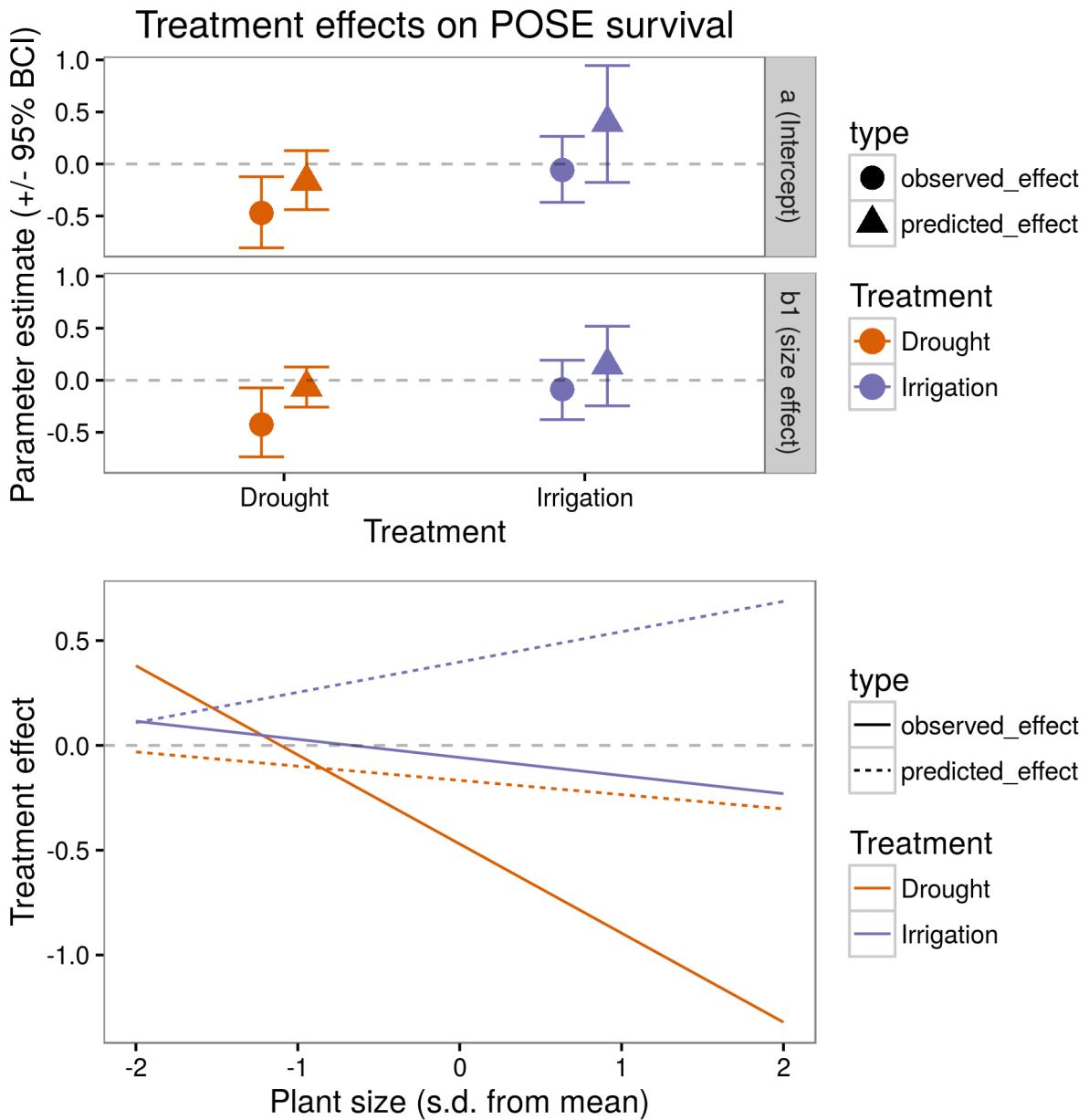


Figure SI-7: Comparison of treatment effects predicted and observed for *P. secunda* survival. Upper figure shows each parameter estimate separately while the lower figure shows the effect of treatment as a function of plant size. The observed treatment effects come from the treatment model fitted to all the data including the five years of the experiment. The predicted parameters come from the climate model fitted to all years of observational data but do not include the five years of the experiment (2011 to 2016). We assessed a parameter as significant when the 95% Bayesian credible intervals did not overlap zero.

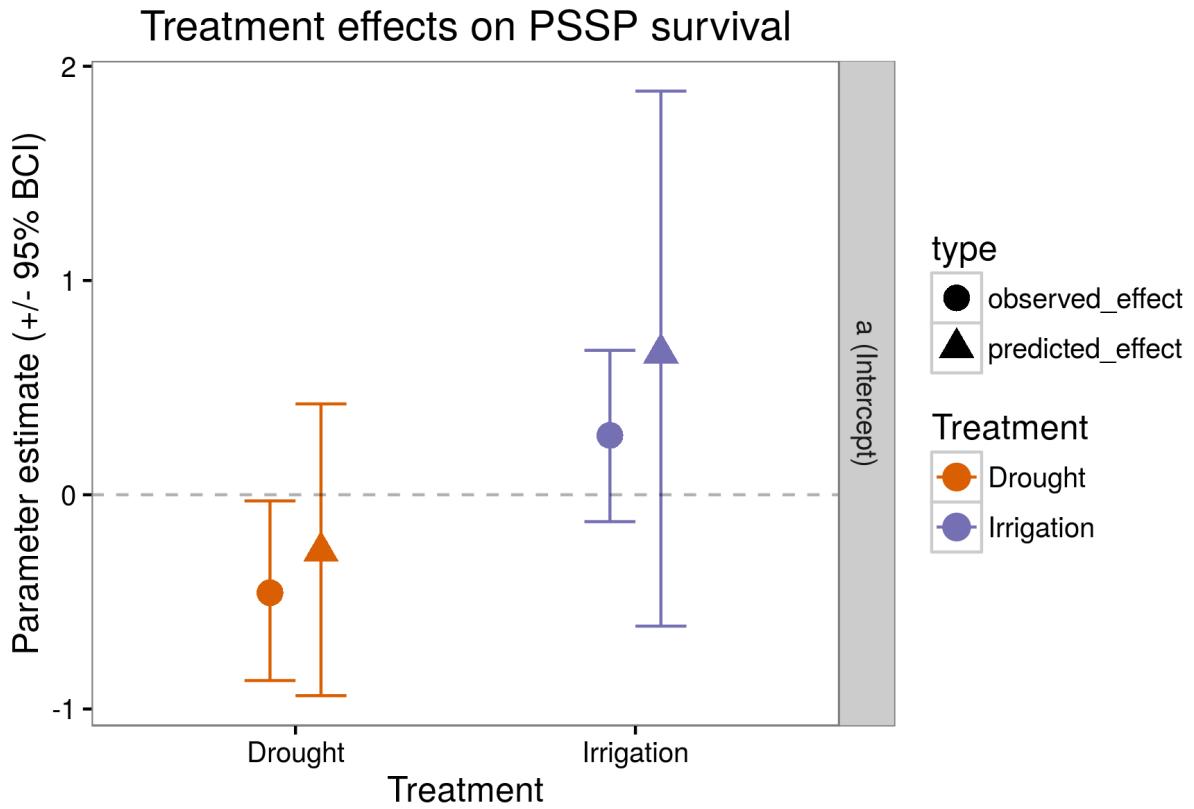


Figure SI-8: Comparison of treatment effects predicted and observed for *P. spicata* survival. The observed treatment effects come from the treatment model fitted to all the data including the five years of the experiment. The predicted parameters come from the climate model fitted to all years of observational data but do not include the five years of the experiment (2011 to 2016). We assessed a parameter as significant when the 95% Bayesian credible intervals did not overlap zero.