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Framework for using downscaled climate model projections in ecological experiments to quantify plant and soil responses

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Abstract. Soil and plant responses to climate change can be quantified in controlled settings. However, the complexity of climate projections often leads researchers to evaluate ecosystem response based on general trends, rather than specific climate model outputs. Climate projections capture spatial and temporal climate extremes and variability that are lost when using mean climate trends. In addition, application of climate projections in experimental settings remains limited. Our objective was to develop a framework to incorporate statistically downscaled climate model projections into the design of temperature and precipitation treatments for ecological experiments. To demonstrate the utility of experimental treatments derived from climate projections, we used wetlands in the Great Plains as a model ecosystem for evaluating plant and soil responses. Spatial and temporal projections were selected to capture variability and intensity of projected future conditions for exemplary purposes. To illustrate climate projection application for ecological experiments, we developed temperature and precipitation treatments based on moderate-emissions scenario climate outputs (i.e., RCP4.5–650 ppm CO_2 equivalent). Our temperature treatments captured weekly trends that represented cool, average, and warm temperature predictions, and our daily precipitation treatments mimicked various seasonal precipitation trends and extreme events projected for the late 21st century. Treatments were applied to two short-term controlled experiments evaluating (1) plant germination (temperature treatment applied in growth chamber) and (2) soil nitrogen cycling (precipitation treatment applied in greenhouse) responses to projected future conditions in the Great Plains. Our approach provides flexibility for selecting appropriate and precise climate model outputs to design experimental treatments. Using these techniques, ecologists can better incorporate variation in climate model projections for experimentally evaluating ecosystem responses to future climate conditions, reduce uncertainty in predictive ecological models, and apply predicted outcomes when making management and policy decisions.

Key words: bias correction; climate change; germination study; greenhouse study; mesocosm; statistical downscaling.

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Introduction

Ecosystems face substantial threats due to increased atmospheric greenhouse gas concentrations and, subsequently, global and regional climate change (Hughes 2000, Wuethrich 2000, Walther et al. 2002). Impacts of increasing temperature, shifting precipitation patterns, and increased frequency and severity of extreme precipitation events have been documented in terrestrial, aquatic, natural, and anthropogenic ecosystems, and the consequences of climate change will likely be exacerbated in the 21st century (IPCC 2014, Melillo et al. 2014). Declines in soil moisture and increased temperature have decreased net primary production and biodiversity in terrestrial ecosystems, simultaneously reducing forest and grassland capacity to store carbon in vegetative biomass (Polley et al. 2013, Peñuelas et al. 2017). Aquatic flora and fauna have been impacted directly by atmospheric warming (Covich et al. 1997, Poff et al. 2002) and have experienced climate change effects associated with alterations to surrounding terrestrial ecosystems (Meyer et al. 1999). In addition to altering the physical environment of ecosystems, climate change is likely to have a cascading influence on organisms (humans and wildlife, alike) that rely on ecosystems services such as food resources (Briske et al. 2015, Howard et al. 2018), refugia (Parmesan and Yohe 2003, Root et al. 2003, Haddad et al. 2015) and water supply and quality (Meyer et al. 1999, Gosling and Arnell 2016, Vörösmarty et al. 2016).

Broad landscape-scale changes in natural ecosystems will likely be driven by small-scale changes to vegetation and soil processes, such as plant community composition and function, respiration, gas emissions, and biogeochemical cycling. Plant diversity is expected to decline (Bellard et al. 2012), causing phenotypical changes, shifts in distribution, and possible extinction for some taxa (Thuiller et al. 2005, Kelly and Goulden 2008). However, plant production is expected to increase with elevated atmospheric CO_2 (Parton et al. 1995, Kukal and Irmak 2018). Ecosystem carbon flux, based on the balance between photosynthesis and respiration, is controlled by atmospheric CO_2 levels, temperature, and nutrient availability, and thus, may respond variably to changing climate drivers (Raich and Tufekciogul 2000, Schlesinger and Andrews 2000, Ryan 2008). Nitrogen cycling is also expected to be impacted by climate drivers, but to a lesser extent than carbon cycling (Pastor and Post 1986, Vitousek et al. 1997, Galloway et al. 2004). While trends have been observed over the past 40 yr in a changing climate, it is much more challenging to predict how plant and soil processes may be impacted in the coming decades.

When field observations are not readily accessible, such as under future climate scenarios, plant and soil responses to changing conditions can be predicted using models generated by combining measured responses of natural systems (e.g., plant community composition, soil respiration) under simulated climate drivers such as increased temperature and changing precipitation trends (Cramer et al. 2001, Beaumont et al. 2008, Sofaer et al. 2017). Ecologists widely recognize the importance of capturing climate extremes and spatial and temporal variability when evaluating response of ecological processes to climate change in modeling efforts (Easterling 2000, Easterling et al. 2000, Klein Tank et al. 2009, Bateman et al. 2012, Helmuth et al. 2014); however, approaches incorporating these trends in experimental settings remain limited.

Environmental conditions expected to occur with projected climate change can, to a certain extent, be simulated in controlled settings to better identify soil and plant process responses (Stewart et al. 2013, Medlyn et al. 2015). Controlled experiments allow researchers to hold environmental variables constant and observe the effects of specific climate drivers on a variable of interest (e.g., CH_4 emissions, primary production, organic carbon fractionation, species richness). Experiments of this type are typically conducted in greenhouses, growth chambers, constructed facilities, or in field settings where environmental variables can be manipulated (e.g., rainout shelters for drought studies). Experiments conducted in controlled environments have been used to evaluate impacts of climate change in terrestrial (Fay et al. 2008, Harden et al. 2017) and aquatic settings (Weltzin et al. 2000, Sommer and Lengfellner 2008). However, most studies fail to capture temporal variability associated with future temperature and precipitation scenarios. Instead, studies commonly increase or decrease variables to achieve mean projected values for the duration of an experiment. With increased accessibility to output from atmosphere–ocean global climate models (AOGCMs), it is likely advantageous for experimental scientists to use their simulated projections to design experiments and evaluate impacts of climate change on ecosystems (Barsugli et al. 2013, Harris et al. 2014, Sofaer et al. 2017).

Our objective was to develop a framework for creating empirical data- and projection-derived treatments that can be used in controlled experiments evaluating plant and soil responses to projected climate change. To demonstrate application of this framework, we evaluated plant germination and soil nitrogen cycles in simulated playa wetland mesocosm units. Playa wetlands are ubiquitous throughout the Southern Great Plains, USA, and provide crucial ecosystem services to the region, such as aquifer recharge, wildlife habitat, nutrient filtration from agricultural runoff, and floral and faunal biodiversity (Smith 2003, Smith et al. 2011). Great Plains climate is characterized as highly variable (Melillo et al. 2014) and differs between the northern (Nebraska) and southern (Texas) extent of the playa region. We hypothesized that playa plant and soil processes may readily adapt to extreme conditions of the future. However, even slight perturbations to plant and soil function could have detrimental impacts when combined with other anthropogenic threats to playas (e.g., sedimentation, invasive species encroachment, hydrologic modification; Matthews 2008, Bartuszevige et al. 2012, Johnson et al. 2012, Tsai et al. 2012). While our experimental work is ongoing, here we present a proof of concept with selected results comparing historical climate conditions with three sets of future climate conditions for two locations in the playa region. We selected Nebraska and Texas in order to capture latitudinal differences in playa wetland and climate characteristics within the Great Plains.

Materials and Methods

Future climate projections and historical data: background

Several institutions worldwide archive output from AOGCMs, more commonly referred to as global climate models (GCMs). Climate projections used to inform the IPCC Fourth and Fifth Assessment Reports are known as Coupled Model Intercomparison Project phase 3 (CMIP3) and phase 5 (CMIP5), respectively. Statistically downscaled climate projections from CMIP3 and CMIP5 are available for several future time periods through the end of the 21st century and may be accessed at https://gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html (Reclamation 2013) or https://cida.usgs.gov/gdp/ (Blodgett et al. 2011). The use of these projections by researchers and decision-makers can assist with evaluating impacts of climate change through controlled experiments (Maurer et al. 2007). Emissions scenario terminology differs based on CMIP phase (Table 1), and CMIP3 and CMIP5 output may be obtained in monthly or daily time frames. Spatially, statistically downscaled CMIP3 and CMIP5 datasets are 12 km in resolution; however,

Table 1. Overview of emission and concentration scenarios for Coupled Model Intercomparison Project (CMIP) 3 and 5 (CMIP5) projection datasets, respectively, projected at year 2100 (Meehl et al. 2007, van Vuuren et al. 2011).

Scenario	CO_2 equivalent (ppm)	Description
CMIP3		
B1	550	Low emissions
A1b	700	Moderate emissions
A2	820	High emissions
CMIP5		
RCP2.6	490	Radiative forcing peaks and declines by 2100 (van Vuuren et al. 2006, 2007)
RCP4.5	650	Radiative forcing stabilizes by 2100 at 4.5 W/m^2 (Smith and Wigley 2006, Clarke et al. 2007, Wise et al. 2009)
RCP6.0	850	Radiative forcing stabilizes by 2100 at 6 W/m^2 (Fujino et al. 2006, Hijoka et al. 2008)
RCP8.5	1370	Radiative forcing continues to rise by 2100 (Riahi et al. 2007)

atmospheric scientists often statistically downscale datasets to local scales (<1 km resolution) to capture details that may be lost during spatial averaging of gridded data (Wood and Leung 2004). Temperature attributes vary slightly between CMIP3 (average daily temperature) and CMIP5 (daily minimum and maximum temperatures) datasets, whereas precipitation (mm/d) is reported similarly for CMIP3 and CMIP5 projections. Additional hydrology attributes, such as runoff and humidity, are accessible through Reclamation (2013) and Blodgett et al. (2011), but are not discussed in this study. Here, we discuss techniques for incorporating temperature and precipitation attributes into controlled experiments using CMIP5 downscaled climate outputs. Similar methods for CMIP3 model outputs are discussed in Tabor and Williams (2010).

Statistical downscaling is often used to adjust climate model outputs (e.g., precipitation and temperature) based on bias found between projected and observed values during a period of historical observation at a given spatial location (Gutmann et al. 2014). The spatial and temporal extents of projections dictate the appropriate downscaling method (Teutschbein and Seibert 2012, Kim et al. 2015). Monthly CMIP3 and CMIP5 projections are commonly downscaled using bias-corrected spatial disaggregation (BCSD) methods, and daily data are downscaled using bias correction constructed analogs (BCCA) methods (Maurer and Hidalgo 2008). Daily CMIP5 projections may also be downscaled using localized constructed analogs (LOCA; Pierce et al. 2015). Daily projections produced using CMIP5 BCCA and LOCA produce fairly comparable daily downscaled temperature projections, except in arid regions, whereas LOCA projects spatial precipitation patterns more accurately than BCCA (Maurer and Hidalgo 2008, Pierce et al. 2014). Projections downscaled using BCSD, BCCA, and LOCA techniques, as well as other less common downscaling methods, are available at Reclamation (2013) and Blodgett et al. (2011). For more exhaustive details regarding statistical downscaling methods, see Abatzoglou and Brown (2012), Schoof (2013), and Gutmann et al. (2014).

Climate model projections are widely available for use, but understanding the types of output available and maximizing the appropriateness of projection manipulations is necessary to accurately evaluate ecosystem responses to climate change (Beaumont et al. 2008, Barsugli et al. 2013). When downloading climate projections, it is important to obtain historical and future projections for each AOGCM output to curate an appropriate dataset (Ekström et al. 2015). Complementary historical observation data can be found through the National Centers for Environmental Information (NCEI; https://www.ncdc.noaa.gov/cdo-web/datatools/findstation), formerly the National Climatic Data Center (NCDC). We used a long-term dataset (>30 yr) of historical observations for Hastings, Nebraska (GHCND: USC00253660), and Lubbock, Texas (GHCND: USC00415410), to represent historical climate conditions.

Once historical observations and model projections are obtained, projected future climate model outputs may be corrected for bias before being used to design experimental ecological treatments. Bias correction may not be needed on all downscaled climate projections, especially if downscaled using LOCA techniques. Temperature and precipitation projections are most accurately corrected for local bias separately due to inherent differences in their distributions (Schoof and Pryor 2001). Temperature can typically be corrected to match monthly mean historical and projected temperature values using a delta correction method (Quilbé et al. 2008); however, more complex correction methods are appropriate if delta correction methods reduce variability in temperature projections. Several bias correction methods incorporating parametric or nonparametric transformations can be used to correct precipitation projections (Gudmundsson et al. 2012, Lafon et al. 2013). Parametric bias correction methods may be appropriate for monthly precipitation projections, but due to the gamma distribution of daily precipitation projections (Richardson 1981), nonparametric transformations better capture the error associated with climate model outputs (Gudmundsson et al. 2012). Empirical quantile mapping and gamma-based (rainfall distribution) quantile mapping are two nonparametric bias correction methods commonly used to adjust daily precipitation projections from regional climate model outputs (Lafon et al. 2013). Gamma-based quantile mapping has been reported as less sensitive to differences in climate projection time frame and emissions scenarios, when compared to empirical quantile mapping (Lafon et al. 2013).

Future climate projections and historical data: approach utilized

Great Plains playa wetlands served as a model ecosystem to demonstrate how climate model projections may be used to predict plant and soil response to future climate conditions. The framework we developed to create empirical data-derived treatments for use in controlled experiments is summarized in Fig. 1. For all future climate projections, we aimed to capture variability within a given climate scenario, rather than assess variability associated with low-, moderate-, and high-emissions scenarios. A moderate-emissions scenario, CMIP5 RCP4.5, was selected to assess the impact of future climate conditions on our model ecosystem. Within RCP4.5, we selected models that captured within-scenario variability. For instance, models for temperature studies represented cool, average, and warm projections for RCP4.5 and models selected for precipitation studies represented relatively dry, average, and wet projections for RCP4.5. Within-emissions scenario variability for nineteen AOGCMs which met our selection criteria for two locations in the playa wetlands can be observed in Figs. 2, 3.

Our first experimental study involved evaluating the influence of climate change-induced temperature alterations on playa plant germination. Therefore, we applied our framework for using downscaled climate model projections to develop temperature treatments from local weather station data (historical climate, 1986–2015) and three CMIP5-BCCA AOGCMs for the RCP4.5 emissions scenario (2070–2099) that could be imposed within a temperature-controlled growth chamber.

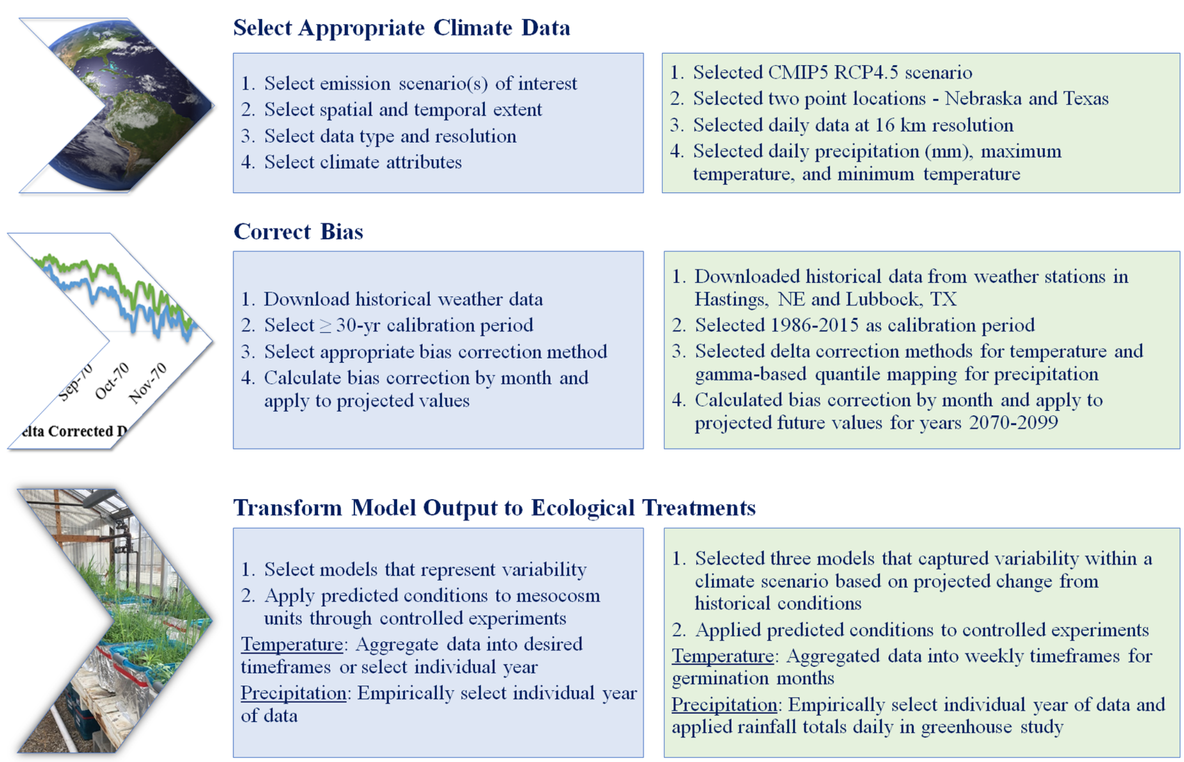

Fig. 1. Suggested flow diagram for using climate model data to create climate treatments for ecological experiments. Because each ecological experiment may have unique research questions and scope, details are intentionally omitted from blue boxes to provide a general framework. Detailed techniques used in this study are described in green boxes, but specific data and methods may not be suitable for all ecological experiments.

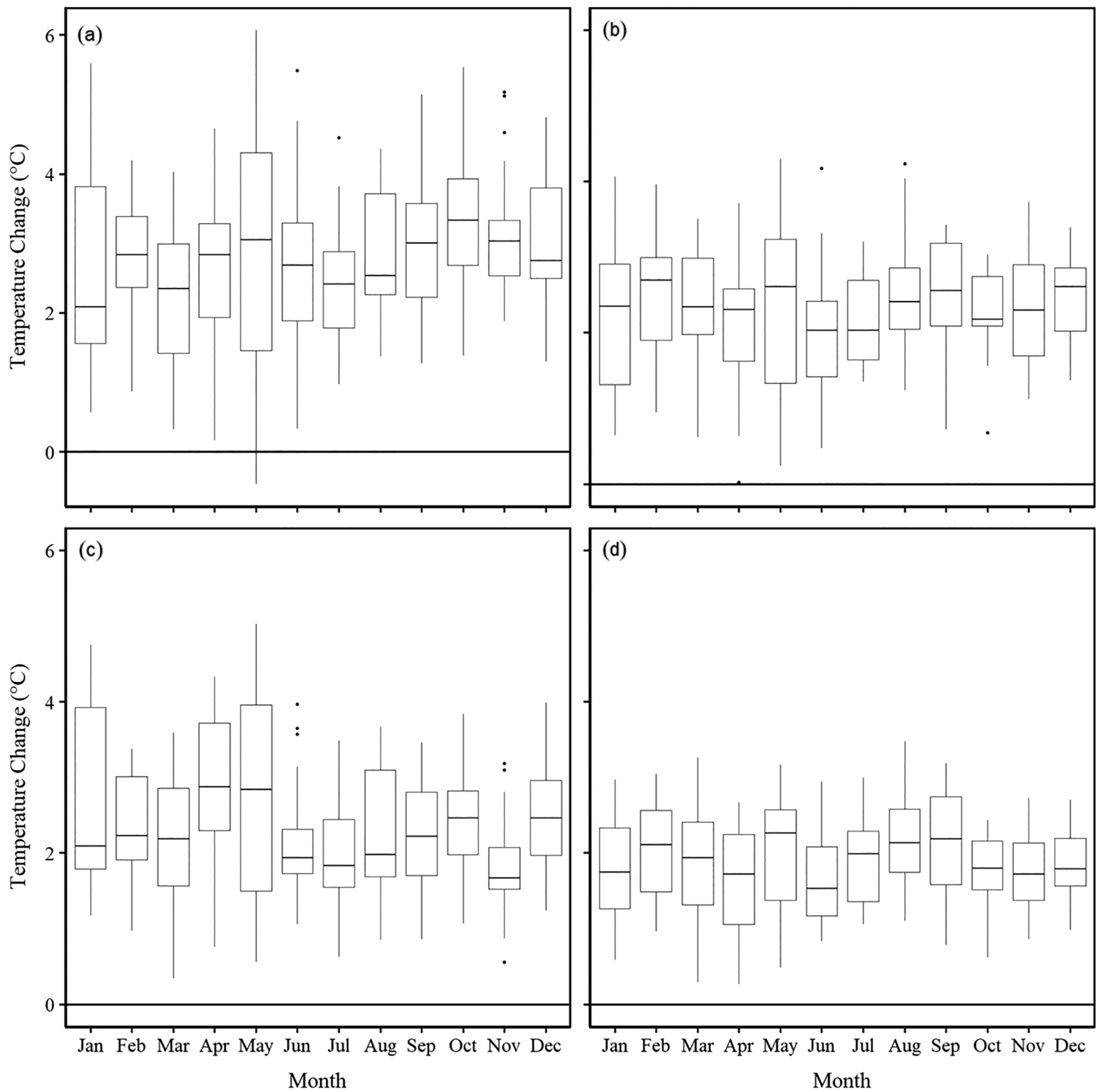

Fig. 2. Overall change between observed (1986–2015) and RCP4.5 projected (2070–2099) maximum daily temperature values for Nebraska (a) and Texas (b) and minimum daily temperature values for Nebraska (c) and Texas (d) for 19 atmosphere–ocean global climate models (see Table 2). Box plots represent the median model (horizontal line), interquartile range of model values (box), range of model values (whiskers), and outliers outside 1.5 interquartile range (dots).

Climate projections were downscaled to a specific location in the playa regions of Nebraska (GHCND:US00253660; 40.608, 98.427) and Texas (GHCND:USC00415410; 33.657, 101.824) using delta correction techniques (Quilbé et al. 2008), which are commonly used to adjust temperature data. We assessed daily temperature maximum (Tmax) and minimum (Tmin) values from nineteen AOGCMs (Table 2) and selected the following three models to capture variability within the RCP4.5 emissions scenario: (1) least temperature change from historical climate (considering

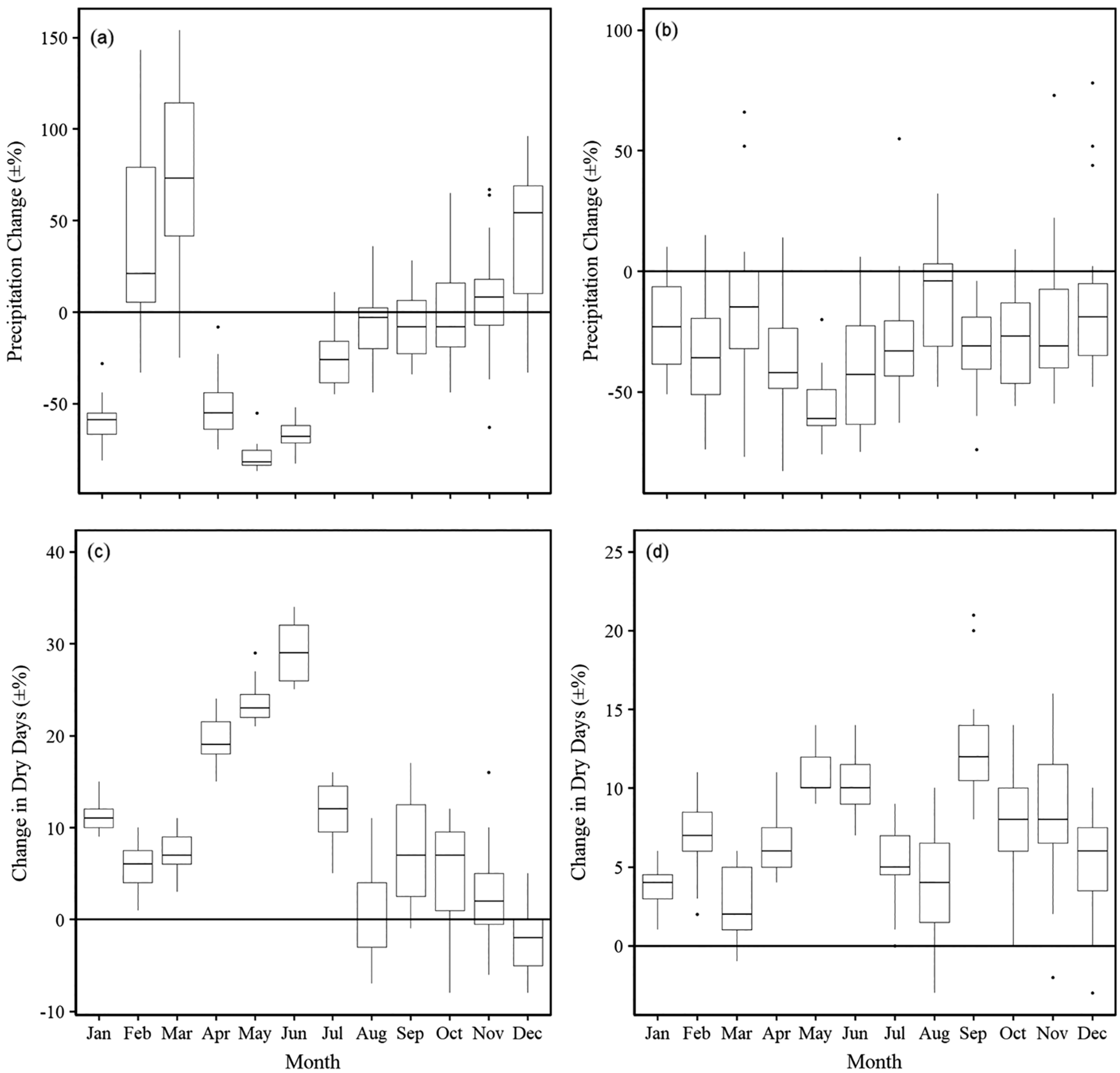

Fig. 3. Monthly percent change from historical (1986–2015) to projected (2070–2099) for precipitation in Nebraska (a) and Texas (b), and number of days without precipitation for Nebraska (c) and Texas (d) point locations for 19 atmosphere–ocean global climate models (Table 2) downscaled using gamma-based quantile mapping. Box plots represent the median model (horizontal line), interquartile range of model values (box), range of model values (whiskers), and outliers outside 1.5 interquartile range (dots).

average monthly maximum and minimum temperature values for Nebraska and Texas); (2) greatest temperature change from historical climate; and (3) a model which represents the average temperature change across the AOGCMs assessed. We used historical and projected 30-yr average daily maximum (T_{max}) and minimum (T_{min}) temperatures reported for each model to develop experimental treatments. We aggregated daily temperature observations and projections into weekly treatments to simulate temporal conditions over the first four weeks of germination (e.g., 30-yr average Tmax values from 1 to 7 March for Texas location were averaged to create Week 1 Tmax treatment conditions; 30-yr average Tmin values from 1 to 7 March for Texas

Table 2. Atmosphere–ocean global climate models for CMIP5-BCCA RCP4.5 downscaled data for years 2070–2099 (Reclamation 2013).

Model no.	Modeling center	Simulations
1	Commonwealth Scientific and Industrial Research Organization (CSIRO) and Bureau of Meteorology (BOM)	ACCESS1-0.1
2	Beijing Climate Center, China Meteorological Administration	BCC-CSM1-1.1
3	Canadian Centre for Climate Modelling and Analysis	CANESM2.1
4	National Center for Atmospheric Research	CCSM4.1
5	Community Earth System Model Contributors	CESM1-BGC.1
6	Centre National de Recherches Meteorologiques/Centre Europeen de Recherche et Formation Avancee en Calcul Scientifique	CNRM-CM5.1
7	CSIRO in collaboration with Queensland Climate Change Centre of Excellence	CSIRO-MK3-6-0.1
8	NOAA Geophysical Fluid Dynamics Laboratory	GFDL-ESM2G.1
9	NOAA Geophysical Fluid Dynamics Laboratory	GFDL-ESM2M.1
10	Institute for Numerical Mathematics	INMCM4.1
11	Institut Pierre-Simon Laplace	IPSL-CM5A-LR.1
12	Institut Pierre-Simon Laplace	IPSL-CM5A-MR.1
13	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute, and National Institute for Environmental Studies	MIROC-ESM.1
14	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute, and National Institute for Environmental Studies	MIROC-ESM-CHEM.1
15	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute, and National Institute for Environmental Studies	MIROC5.1
16	Max Planck Institute for Meteorology	MPI-ESM-LR.1
17	Max Planck Institute for Meteorology	MPI-ESM-MR.1
18	Meteorological Research Institute	MRI-CGCM3.1
19	Norwegian Climate Centre	NORESM1-M.1

Notes: CMIP5, Coupled Model Intercomparison Project phase 5; BCCA, bias correction constructed analogs.

location were averaged to create Week 1 Tmin temperature conditions). Growth chamber settings reflected diurnal temperature cycles for the months of April and March for Nebraska and Texas, respectively (Appendix S1: Table S1). Four climatic temperature treatments (historical, future cool, future average, and future warm) were represented in four-week germination studies, separated by state (Fig. 4). Because playa plant germination is primarily driven by soil moisture (Haukos and Smith 2001) and heat units (Swanton et al. 2000), we did not incorporate daily temperature variability in our experimental design; however, this approach may not be suitable for every ecological experiment.

Our second experiment involved assessing the impact of precipitation changes on soil nitrogen cycling within wetlands of the Great Plains. To develop appropriate precipitation/hydrologic treatments that would simulate future climate projections and could be used in a greenhouse setting, we once again applied our framework for using downscaled climate model outputs to develop appropriate treatments. Treatments were based on historical precipitation patterns (1986–2015) and future precipitation projections (2070–2099) using CMIP5-BCCA AOGCMs for the RCP4.5 emissions scenario for the wetland growing season (April–October).

We corrected precipitation data from nineteen AOGCMs (Table 2) to remove excess drizzle days (<0.25 mm precipitation) and used gamma-based quantile mapping to accurately capture extreme events (Teutschbein and Seibert 2012, Gautam et al. 2018). We selected gamma-based quantile mapping as a bias correction technique as it has been reported as less sensitive to differences in climate projection time frame and emissions scenarios, when compared to empirical quantile mapping (Lafon et al. 2013). Comprehensive bias correction details for precipitation adjustments can be found in Gautam et al. (2018). After adjusting

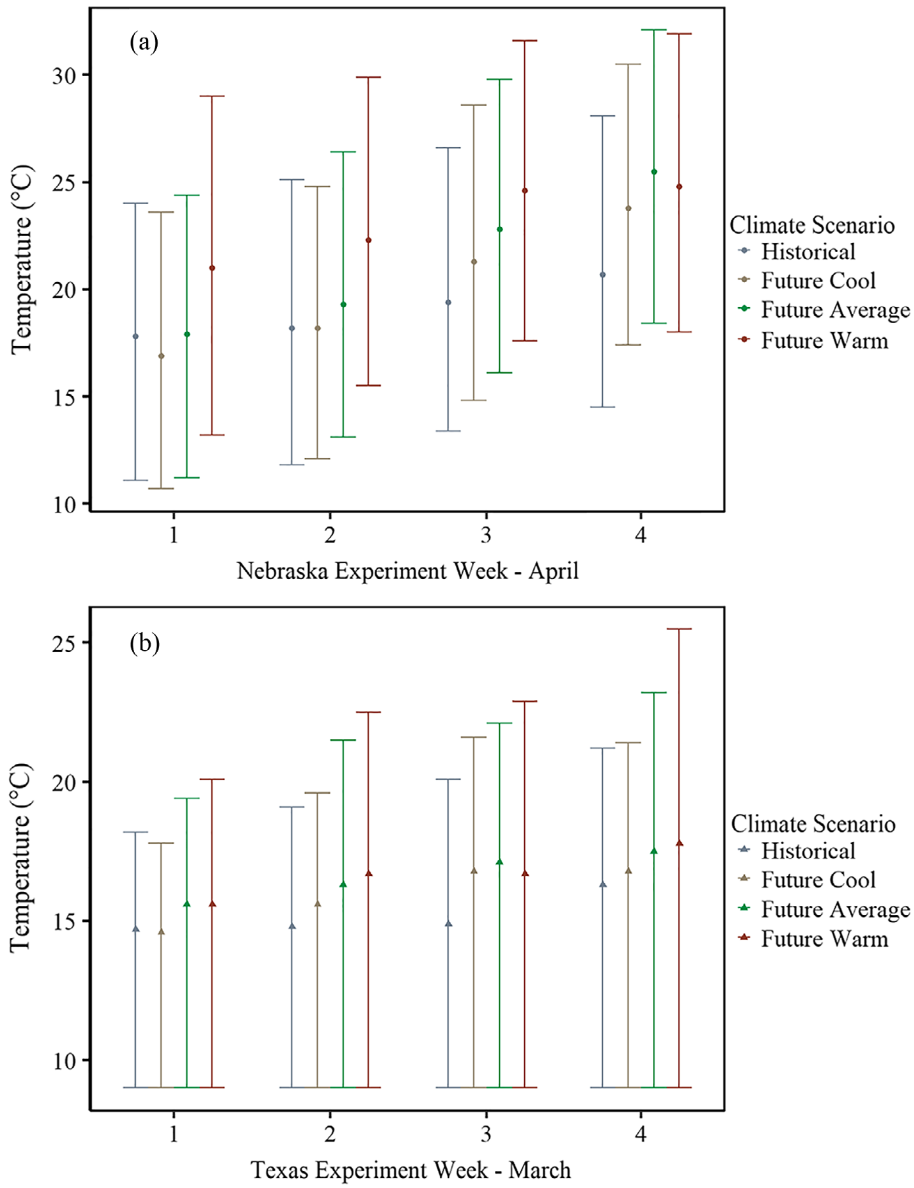

Fig. 4. Temperature treatments for a germination study using soil collected in Nebraska (April, a) and Texas (March, b) for historical data and scenarios based on downscaled CMIP5-BCCA atmosphere–ocean general circulation models for the RCP4.5 emissions scenarios (2070–2099)—future average, warm future, and cool future. Bars represent daily temperature range. CMIP5, Coupled Model Intercomparison Project phase 5; BCCA, bias correction constructed analogs.

projections, we selected three models based on the following criteria for years 2070–2099: (1) an average model, representing the most typical precipitation conditions projected in RCP4.5 scenarios; (2) a model that contained the longest period of no-precipitation days over the course of the growing season (based on 30-yr averages for Nebraska and Texas locations); and (3) a model that contained the greatest number of runoff-inducing precipitation events (Uden et al. 2015) during the growing season (based on 30-yr averages for Nebraska and Texas locations). We then used precipitation projections to determine the timing and amounts of water applied to experimental units as a means to simulate altered hydroperiods during the dominant growing season (1 April–31 October), based on a typical year within historical observations and future projections.

To simulate temporal variability associated with drought events and inherent daily precipitation patterns, we selected a year with the lowest deviation from average model conditions over the wetland growing season (Fig. 5); however, these techniques led to discrepancies in rainfall totals used for this experiment. To obtain a year of precipitation to use for the historical observations and future projections, we selected a year that varied the least from the 30-yr averages on a monthly basis. On a monthly basis, this meant that the precipitation patterns were similar in the selected year compared to the 30-yr average, but the daily patterns and cumulative rainfall amounts did not necessarily align with our stated criteria. For instance, our future average model

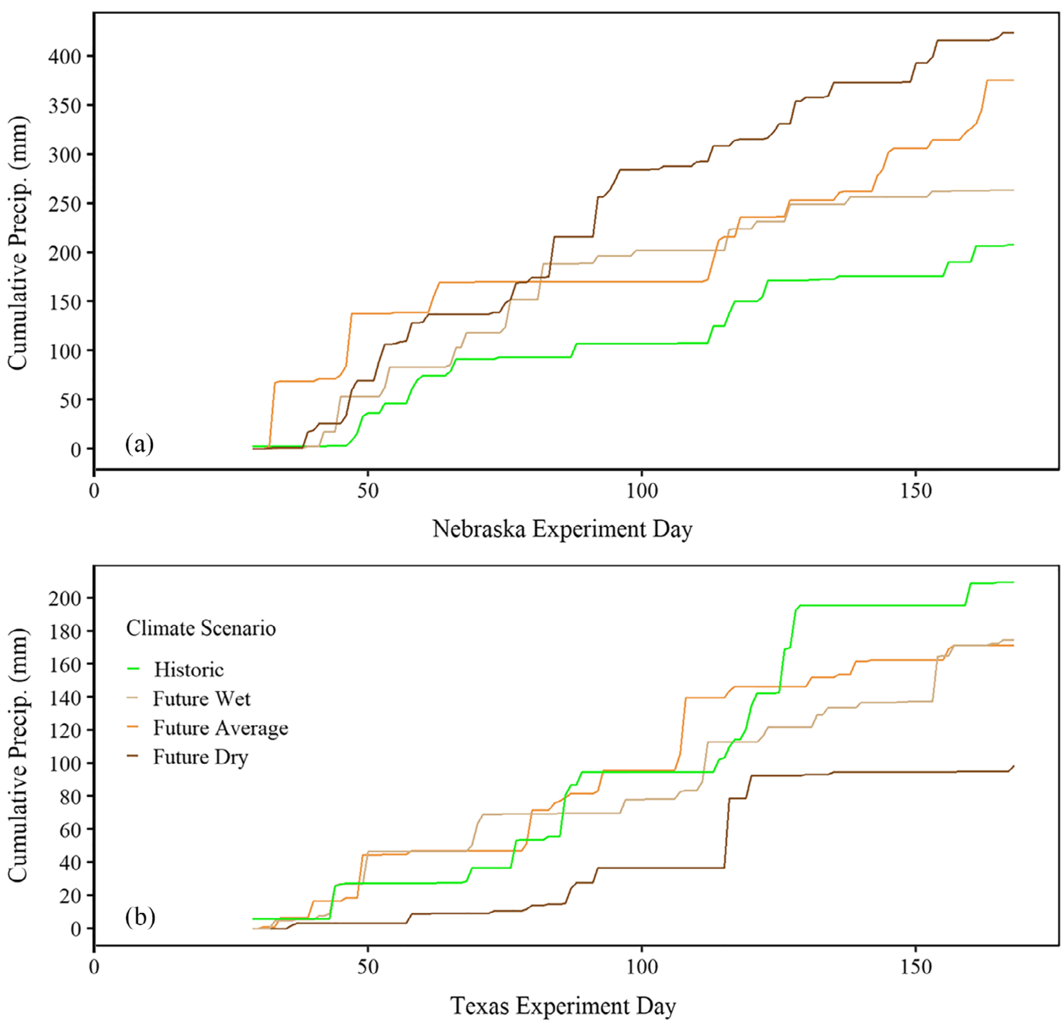

Fig. 5. Precipitation treatments for a greenhouse study for soil collected in Nebraska (a) and Texas (b) for historical data and scenarios based on downscaled CMIP5-BCCA atmosphere–ocean general circulation models for the RCP4.5 emissions scenarios (2070–2099)—future average, wet future, and dry future. Precipitation treatments followed 28 d of constant moisture to allow for uniform germination conditions. CMIP5, Coupled Model Intercomparison Project phase 5; BCCA, bias correction constructed analogs.

produced less cumulative rainfall over the growing season than the future dry model for Nebraska. In our study, "wet," "average," and "dry" refer to the trend from the selected model, rather than the year of observations or projections used in the greenhouse study. These criteria should likely be developed independently for each ecological experiment, and the techniques used in this study may not be best suited for all situations.

Evaluating plant and soil response to climate treatments

*Germination experiment.—*The germination study was conducted to evaluate the response of playa wetland vegetation to changing climate conditions. Temperature treatments consisted of weekly aggregated temperatures for historical, future cool, future average, and future warm temperatures as described previously. Bulk soil was collected from the surface 15 cm in transitional zones (between basin floor and upland) in six playa wetlands, three in Nebraska and three in Texas. Soil was dried at 23°C, ground to pass through 2-mm sieve, and homogenized for each wetland separately. Prior to the germination study, soils were packed into containers at a bulk density representative for each wetland, as determined by core samples collected on site. For each four-week temperature period in the germination study, we held soil moisture constant at 60% water-filled pore space and planted barnyardgrass (*Echinochloa crusgali* L.) seed at a density of 145 kg/ha. We counted germinated plants on the first day of germination and on the last day of each four-week experiment. We used generalized mixed-effects logistic regression models to test the effect of temperature on germination percentage (fitted with a binomial distribution) with random intercept term fit for sampling location. Analyses were conducted in R software package lme4 (Bates et al. 2015), and packages effects and ggplot2 were used to visualize predicted germination percentage with regression model estimates (Fox 2003, Wickham 2016).

*Soil nitrogen cycling experiment.—*To assess how projected climate change will affect playa soil nitrogen cycling, we conducted a greenhouse experiment to mimic the growing season in Nebraska and Texas playas under various hydrologic conditions. Intact soil cores collected from transition zones around the outer rim of ten playas were subjected to four climate treatments (historical, future wet, future average, and future cool) described previously. Precipitation treatments were applied daily to reflect historical and projected future daily rainfall events (mm/d). We were unable to control for temperature or atmospheric CO_2 in greenhouse settings; however, soil and ambient air temperatures were continuously monitored throughout experiment (Appendix S2: Fig. S1). Monthly soil samples were collected to assess shifts in biogeochemical cycling. To demonstrate the utility of assessing biogeochemical response using climate projections, we present inorganic nitrogen results. Nitrate (NO_3^--N) and nitrite (NO_2^--N) were extracted using 1 M potassium chloride solution (Reddy et al. 2013) and quantified using Lachat QuikChem Methods for nitrate determination (Lachat Instruments, Milwaukee, Wisconsin, USA). Statistical analyses were completed using repeated-measures mixed-effects linear models in R software package lme4 (Bates et al. 2015). Packages effects and ggplot2 were used to visualize predicted inorganic nitrogen with regression model estimates (Fox 2003, Wickham 2016).

Results

This framework allowed us to incorporate a range of temperature projections into a controlled growth chamber experiment. In Nebraska and Texas, minimum and maximum temperatures are projected to increase in each month of the year (Fig. 2) based on 19 AOGCMs available at RCP4.5. During the germination months of March for Texas and April for Nebraska, average temperature is expected to increase by a range of 1.0–3.8°C for Texas and 0.1–4.5°C in Nebraska. For our future temperature projection treatments, we selected the INMCM4.1 (#10 Future Cool; Volodin et al. 2010), IPSL-CM5A-LR.1 GCM (#11 Future Average; Dufresne et al. 2013), and MIROC5.1 (#15 Future Warm; Watanabe et al. 2011). These models captured the range of temperatures expected for the Great Plains under the RCP4.5 emissions scenario (Fig. 4). After bias correction, the future cool model (INMCM4.1) projected a mean temperature change of −0.9°C to 3.1°C for Nebraska germination period and

−0.1°C to 1.9°C for Texas germination period. The average future model (IPSL-CM5A-LR.1 GCM) projected a temperature change in Nebraska of 0.1°C–4.8°C and 0.9°C–2.2°C in Texas. The warm future model (MIROC5.1) projected a temperature change of 3.2°C–5.2 °C for Nebraska germination period and 0.9°C–1.9°C for Texas germination period.

Although temperature conditions derived from the climate models used in the germination experiment did not vary significantly between all treatments based on the standard error of 30-year average conditions, germination was impacted by increased temperatures and temporal variability associated with future climate conditions (Fig. 6). In Nebraska, future temperature conditions reduced germination abundance when soil moisture and seed bank density were held constant. In contrast, Texas samples exhibited greater germination percentage under warm future temperatures. We found that germination commenced at air temperatures between 9.0°C and 29.0°C, with peak germination rate at 21.4°C; however, this was likely constrained by our experimental design because peak germination may occur at higher temperatures if experimental conditions allowed (Swanton et al. 2000).

We were also interested in response of playa soil processes to hydroperiod changes associated with altered precipitation regimes in a changing climate. Precipitation is projected to increase during winter months in Nebraska and decrease during spring, summer, and fall months (Fig. 3). Rainfall is projected to decrease throughout the entire year in Texas, but greatest decreases may be seen in early summer. Each of three models selected to capture variability in monthly precipitation and number of dry days reflected decreased precipitation throughout the growing season compared to historical conditions (CESM1-BGC.1, Hurrell et al. 2013; MIROC-ESM-CHEM.1, Watanabe et al. 2011; and MPI-ESM-LR.1, Giorgetta et al. 2013). Based on our selection techniques, the future average treatment had less cumulative precipitation over the growing period for Nebraska than the future dry treatment; however, the temporal conditions of these two treatments mimicked the overall model projections for end-of-century projections and were selected regardless of the discrepancy (Fig. 5).

Application of precipitation treatments derived from climate model outputs within the greenhouse experiment indicated nitrogen cycling response to climate conditions (Fig. 7). For Nebraska samples, inorganic nitrogen concentrations under future average and future wet conditions were significantly greater than historical baseline conditions in experimental months 4 and 5. During these months, very few plants were actively growing in mesocosm units representing future climate conditions, whereas plant communities remained robust for historical mesocosm units. Inorganic nitrogen concentrations were similar in Texas samples; however, future dry conditions only produced significantly greater nitrate and nitrite during experimental month 4 (Fig. 7). There were no differences in nitrate and nitrite concentrations between future and historical conditions for experimental months 1, 2, 3, and 6 for Nebraska samples and experimental months 1, 2, 3, 5, and 6 for Texas samples.

Discussion

Historically, climate change studies have used percentile changes or general temporal and spatial assumptions to develop experimental treatments evaluating ecosystem response to climate change (Weltzin et al. 2000, Sommer et al. 2007, Fay et al. 2008, Harden et al. 2017). However, here we present a method that reduces error by adjusting downscaled projections using historical observations while simultaneously capturing temporal variability and extreme events projected in future climates. We were able to assess variability of each bias-corrected downscaled model output but comparing individual AOGCM outputs with mean outputs from each emissions scenario (RCP4.5 in this case). In doing so, we selected models that captured low, moderate, and high changes in temperature or precipitation conditions within an emissions scenario. When selecting temperature treatments, we were able to utilize a thirty-year average prediction, thus allowing us to assess the standard error of averaging over this time period. For precipitation, we selected an individual year from a thirty-year period to capture daily precipitation trends, but we could assess error by comparing output from the selected year to thirty-year average trends.

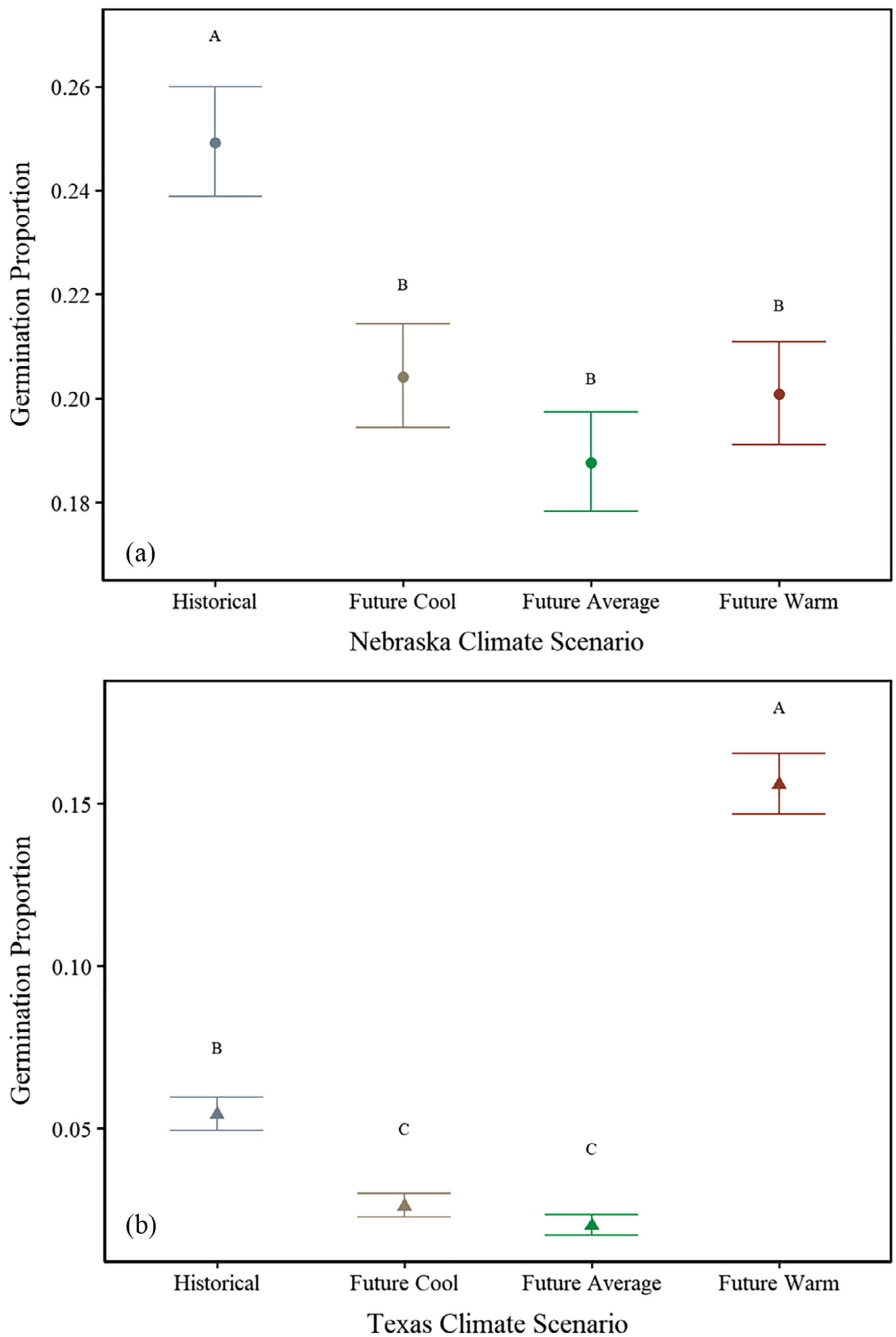

Fig. 6. Model-predicted germination proportion as a function of climate scenario for Nebraska (a) and Texas (b). Error bars represent a 95% confidence interval. Letters designate differences at $P < 0.05$.

While the specific results of our ecological experiments are not the primary outcome of this paper, the germination and greenhouse studies demonstrate how climate projections may be developed for and applied in experimental settings. We predicted that barnyardgrass would be fairly resistant to temperature and soil moisture changes associated with future climate projections

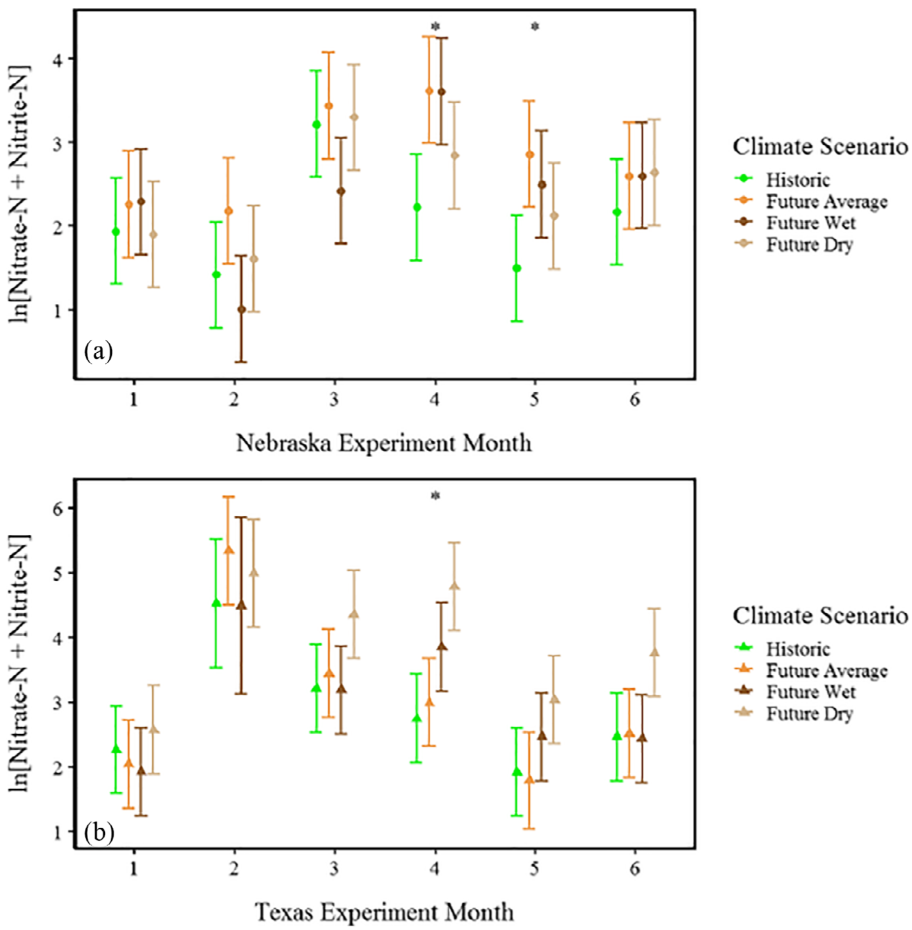

Fig. 7. Model-predicted sum of nitrate-N and nitrite-N concentration ($[NO_3^{-}\text{-N}] + [NO_2^{-}\text{-N}]$) as a function of climate scenario for Nebraska (a) and Texas (b). Error bars represent a 95% confidence interval. Significant differences from historic reference level denoted at $P < 0.05$ (*), $P < 0.01$ (**), and $P < 0.001$ (***) for comparisons within categories separated by dashed lines.

because it has been found to continuously emerge throughout the early growing season in playa wetlands (Haukos and Smith 2001). Based on our study results, overall germination percentage or temporal emergence patterns will likely be impacted by temperature conditions associated with projected climate change. Other playa plants requiring more specific soil moisture and temperature conditions for germination to occur may be more or less competitive in future climate conditions (Haukos and Smith 2001). The framework developed here may be used to further assess these plant community dynamics in controlled ecological experiments.

Similarly, we were able to capture temporal differences in inorganic nitrogen concentrations associated with various hydrologic treatments. Inorganic nitrogen availability is impacted by mineralization and denitrification pathways, which are influenced by soil moisture and precipitation, plant uptake, microbial activity, and substrate availability (Havlin et al. 2005). Using our framework, we were able to identify specific months of the growing season where differences existed between inorganic nitrogen concentrations in historical and future climate conditions. This information can be used to further explore plant, microbial, and other environmental factors that may be causing these differences to exist. In germination and greenhouse studies, controlled environments allowed ample opportunities for additional data collection (not described in this manuscript) to better understand the impacts of changing climate drivers on plant and soil ecosystem response. These data can be used to reduce uncertainty in predictive ecological modeling by improving parameterization of ecosystem response variables (i.e., germination and soil nitrogen cycling) and guide future experiments.

Changing climatic conditions have increased the need for cross-disciplinary partnerships capable of addressing ecosystem threats. Future climate conditions are likely to directly impact ecosystem function and services and may also combine with existing ecosystem threats to exacerbate other anthropogenic pressures (Hughes 2000, Wuethrich 2000, Walther et al. 2002). Through collaborative efforts among ecologists, soil scientists, and climatologists, we were able to develop realistic treatment conditions in an experimental framework that will enhance understanding of ecological alterations caused by climate change. Climate model projections are openly accessible to all scientists and, after correcting for bias associated with downscaling, can be used to simulate future climate conditions in a variety of controlled experiments. With increasing technology used to develop projected future climate model outputs, scientists can use projections to capture emissions scenario variability and better understand how ecosystems and associated processes will respond to climate change.

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Supporting Information

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