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Original Research

Evaluating Multimodel Ensemble Seasonal Climate Forecasts on Rangeland Plant Production in the California Annual Grassland☆

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ABSTRACT

Seasonal precipitation and temperature directly affect total plant production in the California Annual Grassland (CAG). Technological advances have resulted in skillful seasonal climate forecasts (i.e., significant correlations between actual and forecasted climate), which could be input into plant production models to inform stocking and other rangeland management decisions. This study presents a procedure for forecasting plant production in the CAG ecosystem to predict annual plant production for grazing, restoration, or other rangeland management practices using a combination of historical gridMET climate data and seasonal hindcasts (i.e., retrospective forecasts, from the North American Multi-Model Ensemble program). The results of this study first confirmed high forecast skill, throughout the growing season at all sites. We also identified skillful plant production forecasts across most of the growing season at two sites and in three of the seven forecasting months at one study site. Forecasting climate and end-of-year plant production across the growing season at three CAG sites allowed us to identify the places and times in the growing season when forecasting might be most helpful in informing management decisions. Integrating plant production forecasting into rangeland management practices could significantly improve rangeland management outcomes. These procedures provide a user guide for creating plant production forecasts for any given area of interest and may be applicable across a wide range of other agricultural and rangeland management systems.

Introduction

Rangelands in the western United States exhibit high annual and seasonal variability in climatic conditions that control plant phenology and production (George et al. 1989; Rajagopalan and Lall 1999; Khumalo and Holechek 2005; Hardegree et al. 2018). Variable year-to-year plant production forces managers to continually adapt their management and can result in significant financial losses from purchasing livestock at high costs and selling at low prices (Huntsinger et al. 2007; Larson-Praplan 2014; Espeland et al. 2020). Climate variability, however, strongly correlates to yearly plant production across most rangeland ecosystems, including the California Annual Grassland (George et al. 1988a; George et al. 1988b; George et al. 1989; Schantz et al. 2023). Because climate variability is such a strong driver of plant production, skillful climate forecasts could prove useful for informing rangeland management decisions in this and other rangeland ecosystems (An-Vo et al. 2019; Hartman et al. 2020).

Seasonal climate forecasts and historical hindcast data are available through outlets including the North American Multimodel Ensemble (NMME) program and the NOAA's Climate Prediction Center. NMME forecast and hindcast data are provided in the form of monthly precipitation and mean-monthly temperature estimates at a spatial resolution of 1° of latitude and longitude

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(Becker et al. 2014; Kirtman et al. 2014; Klemm and McPherson 2017). Barbero et al. (2017) developed procedures to spatially disaggregate NMME seasonal forecast data into monthly estimates of precipitation and temperature at ~4 km spatial resolution on the same gridded matrix used by the gridMet historical climate-data application (Abatzoglou 2013). In a preliminary study, we assessed individual and aggregated NMME seasonal hindcasts for multiple rangeland sites in the western United States and found management-relevant forecast skill across most rangeland ecoregions, including the CAG.

Forage production in the CAG is largely determined by annual grasses and forbs, which respond strongly to seasonal temperature and precipitation (Ackerly 2009; HilleRisLambers et al. 2010; Becchetti et al. 2016). California also experiences high annual and seasonal variability in precipitation and frequent ecological disturbance from drought and wildfire (Scasta et al. 2016; Chikamoto et al. 2017; Cardil et al. 2021). Producing a skillful plant production forecast model could, consequently, assist managers in making informed decisions about their land management, particularly stocking and destocking decisions, well in advance of peak plant production.

The purpose of this study was to outline and verify a procedure for forecasting plant production in rangeland ecosystems using a combination of historical gridMET climate data and retrospective forecasts (hindcasts) derived from NMME. We developed and verified our procedures at three sites across the CAG ecosystem. Our hypotheses were that 1) there would be skillful climate forecasts (i.e., high correlations between historical gridMET-derived climate variables and climate forecasts across all study sites); 2) skillful models could be constructed to predict peak plant production from both historical and forecasted climate data; and 3) that peak plant production forecast skill would improve over the course of the growing season.

Methods

Study sites

This study was conducted at three long-term field research locations that are all characteristic of the Central CAG and Foothills ecoregions (Omernik and Griffith 2014; Griffith et al. 2016). The University of California (UC) Hopland Research and Extension Center is located in Mendocino County, California at 39.00°N and 123.67°W and has an elevation ranging from 150 to 900 m. The UC Sierra Foothills Research and Extension Center is located in Yuba County at 39.25°N and 121.31°W and has an elevation ranging from 90 to 600 m. The USDA Forest Service, San Joaquin Experimental Range is located in Madera County, at 37.11°N and 119.73°W with an elevation ranging from 300 to 457 m.

Soils across these regions are primarily Mollisols or Alfisols with loamy textures and deep horizons. Common soil orders include Typic Argixerolls, Ultic Argixerolls, Ultic Haploxeralfs, and Thermic Typic Haploxeralfs. CAG plant communities are composed mostly of an oak tree savanna with a herbaceous understory dominated by annual grasses and forbs including *Bromus diandrus* Roth., *B. hordeaceus* L., *Festuca* L. spp., *Erodium* spp., *Croton setigerus* Hook., *Holocarpha virgata* (A. Grey) D.D. Keck, and *Trifolium* L. spp. (Bartolome 1987; Bartolome et al. 2007).

Sites had inherent differences in total plant production and had different sampling strategies for determining peak end-of-season production (Becchetti et al. 2016). Measured plant production was highest at the Sierra Foothills site with a mean of 3 588 ± 1 132 kg-ha^{-1} and an annual production range of 1 200–6 180 kg-ha^{-1}. The Hopland field site also had relatively high production with a mean of 2 767 ± 515 kg-ha^{-1} and range of 1 858–3 868 kg-ha^{-1}. San Joaquin had the lowest plant production with a mean of 2 291 ± 875 kg-ha^{-1} and range of 904 4 450 kg-ha^{-1}. Clipping occurred at six subsampled pasture sites over 39 yr at Hopland. Sampling occurred over 42 yr at San Joaquin and the Sierra Foothills sites, but samples were taken from only a single pasture.

Climate

Climate at these study sites is Mediterranean with hot, dry summers from June to September and mild, rainy winters. Precipitation primarily occurs as rainfall and averages 1 000 mm annually at Hopland, 930 mm at the Sierra Foothills, and 500 mm at San Joaquin. Mean average temperature across the growing season (September–May) at the Hopland site is 11.5°C, with autumn and spring temperatures averaging 13°C and winter temperatures averaging 8°C. At the Sierra Foothills site, growing season temperatures average 12.1°C with autumn temperatures averaging 13°C, winter temperatures averaging 8.4°C, and spring temperatures averaging 14.5°C. At the San Joaquin site, growing season temperatures average 13.7°C with autumn temperatures averaging 12°C, winters averaging 9.9°C, and spring temperatures averaging 18.9°C.

Historical climate data for this study were obtained from the gridMET gridded meteorological database (http://www.climatologylab.org/gridMET.html; Abatzoglou 2013) and included mean daily maximum and minimum temperature and daily precipitation. Daily temperature parameters were averaged, and precipitation estimates accumulated to generate monthly climate metrics.

Plant production forecasting procedure

We used the following six-step procedure to create and verify plant production forecasts across three sites within California Annual Grassland (CAG) ecosystems. We describe this procedure generically because it could be used as a template to conduct similar analyses in other ecosystems.

Step 1 . Select an ecologically significant area that has historical plant production data.

Step 2 . Download the associated historical gridMet climate data from the nearest (preferably adjacent) gridMet node or the nearest node with similar elevation if in an area of complex terrain, from http://www.climatologylab.org/gridMET.html. If there are no nodes with similar elevation, consider averaging climate parameters from two nearby nodes where the mean elevation matches the site.

Step 3 . Develop a plant production model (PPM) (Table 1) that identifies the relationships between plant community peak biomass and monthly and/or seasonal elements of precipitation and temperature for the time period and/or a given area of interest. This model is used to identify the variables input into multiple linear regression models where the dependent variable is total peak plant production and independent variables (T_1) vary by the known gridMET climate and retrospective forecasted climate for each forecasting month of interest (T_0).

The PPM for this study was specifically created for the CAG ecoregion and encompass the climate variables for all input variables (T_1) which in this case were mean monthly precipitation and temperature for the months that contributed to peak plant production. The PPM relies on historical gridMET data for the months before the forecasting month (T_0) and forecasted precipitation and temperature data for the 1–7 mo after T_0 as outlined in Table 1. Forecast precipitation and temperature for the forecasting month (T_0) was determined from the 1-mo lead-time forecast from the previous month. In forecasting months (T_0) where complete 3-mo seasons could be forecast, we used a seasonal forecast (Winter, Spring) instead of a monthly forecast as seasonal forecast skill has been shown to be higher than individual monthly forecast skill (Barbero et al. 2017).

Table 1
Plant production forecasting model: forecasting months (T_0) were the growing season months that contributed to peak plant production (Oct-Apr). Forecasted period (months or seasons; T_1) indicate the climate data inputs of either historical gridMet data (dark gray) or forecasted climate (light gray) used as input into a given plant production models collected throughout the year from June to peak plant production in May. Black cells indicate the forecasting month. For this month we used a 1-mo forecast from the previous month.

		Forecasted Period (Month or Season (T_1))											Clip
		June	July	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
Forecasting Month (T_0)	Oct	X	X	X	X	+	*	*Winter			*Spring		
	Nov	X	X	X	X	X	+	*Winter			*Spring		
	Dec	X	X	X	X	X	X	+	*	*	*Spring		
	Jan	X	X	X	X	X	X	X	+	*	*Spring		
	Feb	X	X	X	X	X	X	X	X	+	*Spring		
	Mar	X	X	X	X	X	X	X	X	X	+	*	*
	Apr	X	X	X	X	X	X	X	X	X	X	+	*

Table 2
Weather models from the North American Multimodel Ensemble used in this study.

Model	Weather model	Source	Citation
1	NCEP-CFSv2	National Center for Environmental Prediction Climate Forecast System Version 2	(Saha et al. 2014)
3	NCAR-CCSM4	National Center for Atmospheric Research Community Climate System Model Version 4	(Gent et al. 2011)
4	CMC2-CanCam4	Canadian Meteorological Center/Canadian Center for Climate Modeling and analysis	(Merryfield et al. 2013)
6	GFDL-NEMO	NOAA Geophysical Fluid Dynamics Laboratory Forecast-Oriented Low Ocean Resolution	(Stewart et al. 2017)

Step 4 . Identify the Climate Forecast Model (CFM) with maximum forecast skill for all monthly and/or seasonal climate parameter components identified in each optimized PPM. This step requires the acquisition of monthly historical forecast (hindcast) data from the current suite of NMME-supported models available through their website at https://www.cpc.ncep.noaa.gov. We suggest using models with the longest hindcast record available because the forecast significance is improved by a greater number of years (Barnston 1992; Neter et al. 1996). In this study, we obtained monthly data for 4 models from the current suite of NMME-supported models that had a hindcast record for the period 1982−2021 (Table 2). Hindcasts were then downscaled to match the 4-km gridMET scale following the procedures described by Barbero et al. (2017).

Previous studies have shown that multimodel aggregate forecasts often exhibit synergistic model skill over that of the individual component models (Becker et al. 2014; Ma et al. 2016). For every combination of site, forecast month (T_0), and forecast length (1−7 mo), we compared historical forecast (hindcast) climate estimates with historical gridMet data for all individual and aggregate NMME climate estimates. Individual or aggregate model formulations with the highest correlation (R) to historical gridMet estimates were determined to be optimal for a given site and temporal scenario (Barnston 1992). We used a significance threshold of $P \leq 0.10$ to identify forecast models with significant skill, following Neter et al. (1996) (Table 3**,** Tables S1 and S3, available online at …).

Step 5 . Validate plant production models for each month in the PPM using historical gridMET climate data (Table 4, Table S2, available online at …). Historical gridMET climate inputs provided monthly and/or seasonal precipitation and temperature for all months, contributing to peak plant production. For each growing season month estimate (T_1), historical gridMET climate data were input into a multiple linear regression model (see Table S2). Because these linear regression models of historical gridMET climate and plant production were created using known climate and plant production values, they always result in a one-to-one equation.

Step 6. Estimate and compare forecasted plant production for each forecasting month (T_0) from the PPM (Table 5). As the ultimate objective of this type of study is to determine if production forecasting skill is sufficient to inform management, we evaluated the PPM's utility in estimating plant production across the growing season in the CAG using a series of multiple linear regression models created from variables identified in the PPM using JMP (SAS Institute Inc. 2023). We recognize, however, that this is just the first step in the development of practical forecasting applications, which would also have to assess model error in the context of economics, and the human dimensions aspects of model uncertainty and willingness to accept risk (Hansen 2002; Hartmann et al. 2002; Fraisse et al. 2006; Garbrecht and Schneider 2007; Marshall et al. 2011; Meredith et al. 2021a).

Results

Climate forecasts

Climate forecasts for this study showed significant skill across much of the growing season at each study site (see Tables 3 and S3; $P \leq 0.10$). Across sites, Hopland had the highest number of significant precipitation climate forecasts where 71% of all forecasted months were significant. At San Joaquin, 43% of precipitation forecasts were skillful, and at Sierra Foothills, 57% of them were skillful. Temperature forecasts were significant in approximately 57% of forecasted months at Hopland and San Joaquin, but in only 36% of forecasted months at Sierra Foothills.

Plant production model validation

Plant production models were validated by correlating peak plant production (May clipping data) to historical gridMET climate and were always significant with correlation (R^2) values ranging from 0.38 to 0.76 for each site (see Table 4; $P < 0.05$). Among sites, R^2 values were highest at the Hopland site, averaging 0.66 across forecasting months, and lowest at the Sierra Foothills site with R^2 values that only averaged 0.44 across forecasting months. Across forecasting months, the correlations between May peak plant production values and historical gridMET climate estimates were always highest in spring, specifically in March at both Hopland and San Joaquin and in April at Sierra Foothills and were lowest in December at both San Joaquin and the Sierra Foothills and in January at Hopland.

Table 3
Climate forecasts: goodness-of-fit correlations between historical and forecast (hindcast) climate across the California Annual Grassland growing season for each forecast month (T_0) and each forecasted period (T_1). Significant interactions ($P < 0.10$) are bolded.

	Site		Hopland			San Joaquin			Sierra Foothills		
Parameter	Forecasting mo (T_0)	Forecasted mo (T_1)	Top model	R^2	P value	Top model	R^2	P value	Top model	R^2	P value
Precipitation	October	November	6	0.009	0.5577	36	0.002	0.7714	6	0.012	0.5099
		Winter	**134**	**0.134**	**0.0221**	346	0.047	0.1905	**34**	**0.088**	**0.0668**
		Spring	**136**	**0.151**	**0.0145**	46	0.015	0.4695	**6**	**0.111**	**0.0381**
	November	Winter	**6**	**0.241**	**0.0015**	**6**	**0.250**	**0.0012**	6	0.039	0.2296
		Spring	**6**	**0.242**	**0.0015**	**36**	**0.156**	**0.0128**	**6**	**0.218**	**0.0027**
	December	January	**1**	**0.160**	**0.0115**	**134**	**0.080**	**0.0817**	**134**	**0.103**	**0.0468**
		February	**34**	**0.151**	**0.0145**	**34**	**0.111**	**0.0383**	**4**	**0.096**	**0.0550**
		Spring	**16**	**0.171**	**0.0088**	**136**	**0.101**	**0.0481**	**36**	**0.132**	**0.0249**
	January	February	6	0.071	0.1007	4	0.059	0.1309	346	0.052	0.1616
		Spring	**14**	**0.169**	**0.0105**	16	0.060	0.1374	**14**	**0.091**	**0.0619**
	February	Spring	**1**	**0.122**	**0.0313**	**1**	**0.080**	**0.0848**	**1**	**0.117**	**0.0333**
	March	April	6	0.035	0.2467	1	0.003	0.7390	6	0.043	0.2062
		May	3	0.061	0.1257	3	0.010	0.5353	3	0.006	0.6303
	April	May	**1**	**0.072**	**0.0951**	13	0.053	0.1544	13	0.023	0.3534
Temperature	October	November	**13**	**0.084**	**0.0741**	13	0.050	0.1703	1	0.035	0.2549
		Winter	146	0.010	0.5522	**346**	**0.118**	**0.0323**	36	0.007	0.6182
		Spring	**134**	**0.101**	**0.0485**	**46**	**0.082**	**0.0767**	146	0.027	0.3217
	November	Winter	4	0.068	0.1081	**46**	**0.211**	**0.0033**	**4**	**0.141**	**0.0183**
		Spring	**16**	**0.136**	**0.0208**	6	0.065	0.1173	6	0.068	0.1088
	December	January	**3**	**0.168**	**0.0094**	**36**	**0.114**	**0.0354**	**3**	**0.181**	**0.0070**
		February	**346**	**0.160**	**0.0116**	**346**	**0.211**	**0.0033**	6	0.055	0.1547
		Spring	**13**	**0.169**	**0.0093**	**36**	**0.112**	**0.0371**	3	0.027	0.3212
	January	February	1	0.060	0.1371	14	0.008	0.5919	146	0.055	0.1547
		Spring	1	0.069	0.1109	6	0.067	0.1115	6	0.027	0.3212
	February	Spring	**16**	**0.103**	**0.0495**	**6**	**0.156**	**0.0129**	**6**	**0.162**	**0.0110**
	March	April	**6**	**0.114**	**0.0356**	**146**	**0.149**	**0.0168**	**16**	**0.110**	**0.0417**
		May	3	0.001	0.8768	16	0.025	0.3407	6	0.006	0.6528
	April	May	36	0.023	0.3610	36	0.060	0.1329	6	0.025	0.3390

Table 4
Peak plant production versus historical gridMET climate at each study site using known historical gridMET climate data as input variables in the Plant Production Model (see Table 1). These regressions should always result in a one-to-one relationship as they are validations of model fit (see supplementary Table 1). Significant models ($P < 0.05$) indicated by asterisk (*).

Site	Mo (T_0)	R2	F ratio	P value	Equation
Hopland	October	0.6494	66.73	< .0001*	Actual Production = –5.30 + 1.00 • Oct GridMET
	November	0.6433	66.73	< .0001*	Actual Production = –5.30 + 1.00 • Nov GridMET
	December	0.6131	58.62	< .0001*	Actual Production = –9.70 + 1.00 • Dec GridMET
	January	0.6131	58.62	< .0001*	Actual Production = –9.70 + 1.00 • Jan GridMET
	February	0.6131	58.62	< .0001*	Actual Production = –9.70 + 1.00 • Feb GridMET
	March	0.7604	117.44	< .0001*	Actual Production = –10.08 + 1.00 • Mar GridMET
	April	0.7604	117.44	< .0001*	Actual Production = –10.08 + 1.00 • Apr GridMET
San Joaquin	October	0.5647	48.00	< .0001*	Actual Production = 0.11 + 1.00 • Oct GridMET
	November	0.5647	48.00	< .0001*	Actual Production = 0.11 + 1.00 • Nov GridMET
	December	0.3866	23.32	< .0001*	Actual Production = 2.82 + 1.00 • Dec GridMET
	January	0.3866	23.32	< .0001*	Actual Production = 2.82 + 1.00 • Jan GridMET
	February	0.3866	23.32	< .0001*	Actual Production = 2.82 + 1.00 • Feb GridMET
	March	0.5178	39.73	< .0001*	Actual Production = 0.43 + 1.00 • Mar GridMET
	April	0.5178	39.73	< .0001*	Actual Production = 0.43 + 1.00 • Apr GridMET
Sierra	October	0.3845	16.94	< .0001*	Actual Production = -33.74 + 1.01 • Oct GridMET
	November	0.3845	16.94	< .0001*	Actual Production = -33.74 + 1.01 • Nov GridMET
	December	0.4205	23.22	< .0001*	Actual Production = -21.56 + 1.01 • Dec GridMET
	January	0.4205	23.22	< .0001*	Actual Production = -21.56 + 1.01 • Jan GridMET
	February	0.4205	23.22	< .0001*	Actual Production = -21.56 + 1.01 • Feb GridMET
	March	0.5140	33.85	< .0001*	Actual Production = 9.04 + 1.00 • Mar GridMET
	April	0.5140	33.85	< .0001*	Actual Production = 9.04 + 1.00 • Apr GridMET

Plant-production forecasts

Plant-production forecast skill showed general improvement as the growing season progressed at all three CAG sites (see Tables 5 and S2; **Fig. 1**; $P < 0.05$). Plant-production forecasts were skillful across all growing season months at Hopland and in six of the seven forecasting months at San Joaquin, but in only three of the seven forecasting months at the Sierra Foothills site. Forecast skill was also highest at Hopland with R^2 averaging 0.38. At San Joaquin, R^2 averaged 0.25 and at the Sierra Foothills site, R^2 only averaged 0.16 across all T_0 forecasting months.

Discussion

Climate forecasting tools are now becoming increasingly available for a broad number of potential applications (Hartman et al. 2020; Lin et al. 2020; Cobon et al. 2021; Liu et al. 2021). Having the ability to verify climate and plant production forecasts has been previously identified as a critical requirement for adoption of this technology by the professional rangeland manager community (Hardegree et al. 2018; Meredith et al. 2021a; Meredith et al. 2021b). The results of this study, along with others, indicate that climate forecast skill across the CAG is reasonable enough to justify taking further steps in application development to include

Table 5
Monthly Plant Production Forecasts: Monthly plant production (kg-ha^{-1}) forecast for each of the growing season forecasting months (T_0). Plant Production Forecasts were built using the PPM model and included both historical gridMet climate and forecasted climate inputs as T_1 independent variables (see Table 1). Significant models ($P < 0.05$) indicated by asterisk (*).

Site	Forecasting mo (T_0)	R^2	P value	Equation
Hopland	October	0.2173	*0.0036**	Actual Production = 824.14 + 0.69 · October Forecast
	November	0.3464	< *.0001**	Actual Production = 418.80 + 0.78*November Forecast
	December	0.3875	< *.0001**	Actual Production = 674.93 + 0.75*December Forecast
	January	0.4743	< *.0001**	Actual Production = 687.76 + 0.76*January Forecast
	February	0.5009	< *.0001**	Actual Production = 600.42 + 0.80*February Forecast
	March	0.3878	< *.0001**	Actual Production = 1 053.93 + 0.57*March Forecast
	April	0.3534	< *.0001**	Actual Production = 1 297.40 + 0.55*April Forecast
San Joaquin	October	0.0953	0.0631	Actual Production = 908.63 + 0.57*October Forecast
	November	0.3091	*0.0003**	Actual Production = 49.30 + 0.93 · November Forecast
	December	0.3940	< *0.0001**	Actual Production = −195.20 + 0.84 · December Forecast
	January	0.2127	*0.0041**	Actual Production = 805.86 + 0.67 · January Forecast
	February	0.2612	*0.0010**	Actual Production = 653.69 + 0.75 · February Forecast
	March	0.2473	*0.0015**	Actual Production = 927.99 + 0.57 · March Forecast
	April	0.2379	*0.0019**	Actual Production = 880.13 + 0.59 · April Forecast
Sierra	October	0.0423	0.2506	Actual Production = 2 008.73 + 0.29 · October Forecast
	November	0.0072	0.6380	Actual Production = 3 136.10 + 0.07 · November Forecast
	December	0.0001	0.9489	Actual Production = 3 463.99 + 0.02 · December Forecast
	January	0.0514	0.2123	Actual Production = 2 098.71 + 0.35 · January Forecast
	February	0.3837	*0.0001**	Actual Production = 53.19 + 0.99 · February Forecast
	March	0.2849	*0.0014**	Actual Production = 1 393.44 + 0.57 · March Forecast
	April	0.3442	*0.0003**	Actual Production = 1 492.36 + 0.64 · April Forecast

stakeholder input, evaluation of human dimensions aspects, and economic analysis of these seasonal production forecasting tools (Hartmann et al. 2002; Schneider and Garbrecht 2003; Fraisse et al. 2006; Klemm and McPherson 2017; Liu et al. 2021; Meredith et al. 2021a).

Consistent with our first hypothesis, historical climate significantly correlated with climate forecasts across all three study sites for most growing-season-forecasting months (see Tables 3, S1, and S3). Temperature and precipitation forecast skill in the CAG is variable throughout the growing season and particularly low for forecast predictions made in the autumn (see Table 3). Higher plant production forecast skill later in the year is likely because of more consistent winter and spring climate conditions (Pendleton et al. 1983; Bartolome 1987; Griffith et al. 2016; Schantz et al. 2023). In this study we found higher climate forecast skill during winter and spring, suggesting that plant production forecasts made following autumn should produce more reliable forage estimates.

In support of our second hypothesis, skillful peak-plant-production forecasts could be created using a combination of historical and forecasted climate data, even when limited to NMME-forecast climate metrics of precipitation and temperature (Schantz et al. 2023). Many previous rangeland-production models developed from historical climate data rely on multiple other measured or derived climate variables such as degree-day accumulation or potential evapotranspiration (Rutherford 1980; Chaplin-Kramer and George 2013; Liu et al. 2021; Copeland et al. 2022). These variables can provide valuable additional environmental information affecting important processes related to transpiration rates and soil water availability but are themselves often estimated from equations that are influenced by precipitation and temperature (Allen et al. 1998; Chen et al. 2019; Blankenau et al. 2020). Given that core seasonal forecast estimates are limited to monthly temperature and precipitation, our production models were also limited to these parameters. Fortunately, we were able to identify skillful production forecasts even with these parameter limitations.

Plant production models across the CAG have historically produced variable spatiotemporal skill (Murphy 1970; Duncan and Woodmansee 1975; Pitt and Heady 1978; George et al. 1988a; Schantz et al. 2023). Consistent with our third hypothesis, however, peak plant production forecast skill for all sites generally improved through the course of the season as more of the model-input data were derived from historical data and less were dependent on forecast climate estimates (see Table 2). We did find, however, the highest forecast skill in February likely because of the combined spring forecasted data as compared with monthly forecasted inputs (see Table 5 and Fig. 1). In this study, Hopland had skillful plant production forecasts for all potential forecasting months, the San Joaquin site had skillful plant production forecasts for 7 of the 8 forecasting mo, but the Sierra Foothills site had skillful forecasts for only the last 3 of the 7 growing season mo (see Table 5). Relatively large site differences in plant production forecasting skill are likely related to the relatively large spatial and temporal heterogeneity within this California ecoregion (Omernik and Griffith 2014; Griffith et al. 2016). In our previous production-modeling manuscript, we found the strongest relationships between climate and plant production at the wettest and driest sites, Hopland and San Joaquin, respectively, which we suggested were because of more consistent climate inputs as compared with the Sierra Foothills (Schantz et al. 2023). Climate pattens tend to be most predictable in regions with less dynamic topography because these regions are less influenced by orographic effects (Stromberg et al. 2007; Liu et al. 2021). While all CAG ecoregions are influenced by topography given that these regions lie within both the Cascade and Sierra Nevada Mountain ranges (Pendleton et al. 1983; Stromberg et al. 2007), areas that are more distinctly windward, such as Hopland, or more distinctly leeward, such as San Joaquin, likely have more predictable climate and therefore better climate and plant production forecasting skill (Stromberg et al. 2007; Liu et al. 2021). We also found that climate conditions in the spring were more strongly correlated with plant production (Schantz et al. 2023), which could be because this season coincides with the most active plant growth and development (Pendleton et al. 1983; Liu et al. 2021). Winter conditions generally have the lowest correlations to plant production in the CAG, which could be because of high interannual variability in winter climate (Luedeling et al. 2009; Rao and Allen 2010; Zhang et al. 2018). While plant growth typically slows following autumn germination (Pendleton et al. 1983; Caldwell et al. 1985) in this ecosystem, winter temperatures above 10°C (~50°F) with available precipitation can reinitiate active plant growth for many of these annual grass species (Pitt and Heady 1978; Cleland et al. 2006; Wainwright et al. 2012). Consequently, while there is significant climate-forecasting skill across

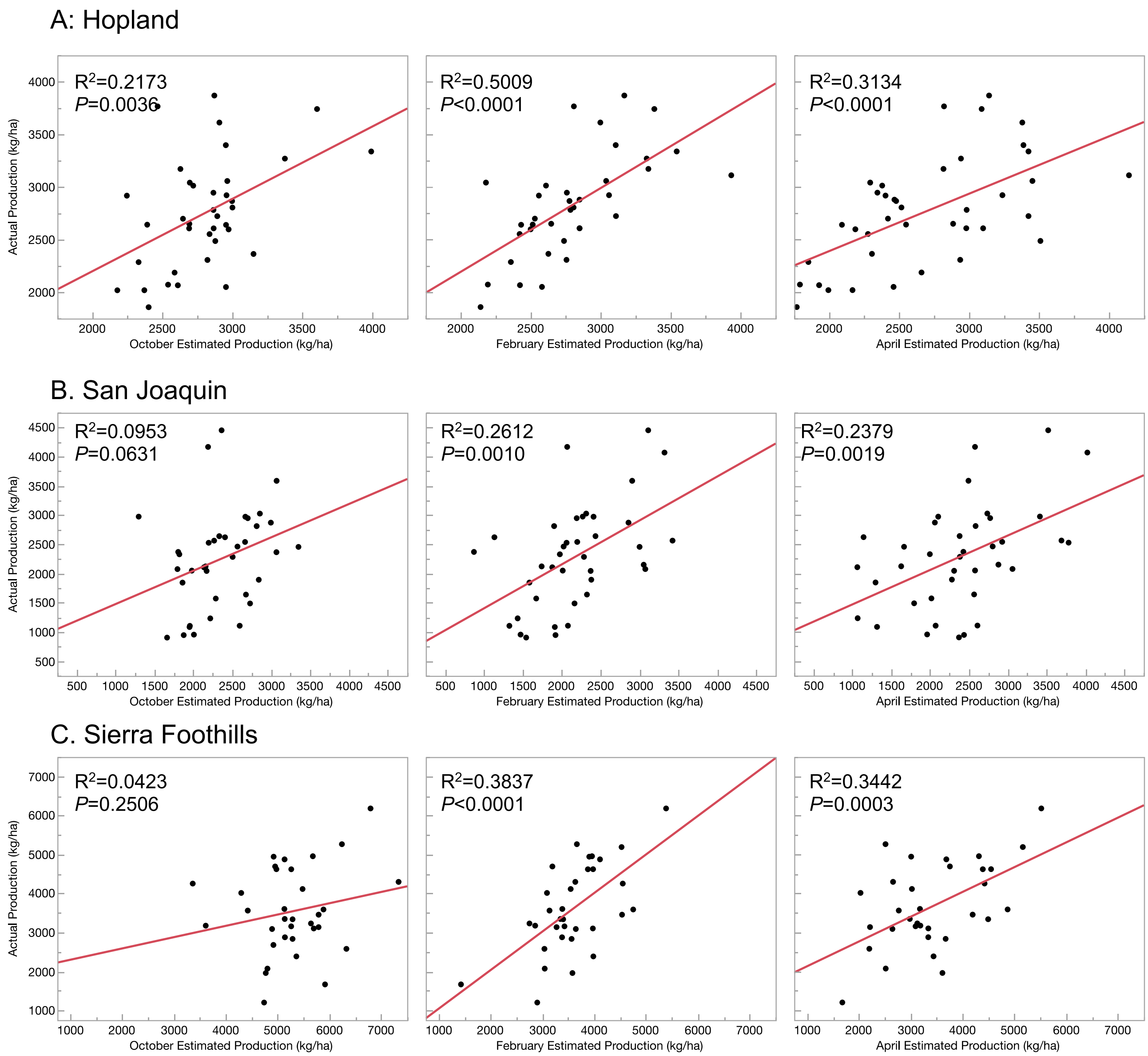

Figure 1. Correlations between actual plant production and forecasted plant production across all study yr (1982–2022) for the months of October, February, and April at all three study sites. **A,** Hopland site. **B,** San Joaquin. **C,** Sierra Foothills. The equation details of these interactions are in Table 5.

all sites, the forecast skill of plant production can be limited by the underlying PPM at a given site. It is useful, therefore, to separately evaluate model-induced variability for the CFM, PPM, and combined plant production estimates for each site and temporal forecasting scenario.

Climate and plant production forecasts are inherently variable, which may be the result of several direct and indirect factors (Allen and Anderson 2018). Variable climate forecast skill could be because of spatiotemporal sampling error associated with the heterogenous topography of these regions since climate varies at small spatial and temporal scales in mountainous regions like the CAG (Lortie et al. 2010; Liu et al. 2021). These effects may also be due to ENSO events, which increase climate variability, primarily during the winter months (Fauvelot et al. 2006; Allen and Anderson 2018; Goddard and Gershunov 2020). During ENSO events, precipitation can increase significantly, up to 10 × average amounts (Holmgren et al. 2001). In this study we did not, however, identify any distinct ENSO effects on plant production, which could have been because much of the precipitation occurs during winter, when plants are not actively growing (Pendleton et al. 1983; Polis et al. 1997). The length of this study may have also negated any ENSO effects on the relationships between climate and plant production since ENSO events are a zero-sum game when viewed over long time periods (Fauvelot et al. 2006; Allen and Anderson 2018; Goddard and Gershunov 2020).

Another main source of potential production-forecast variability may have been the vegetation-sampling strategy as the Hopland site was sampled in multiple pastures each year, but the Sierra Foothills and San Joaquin sites only measured production in a single pasture. Plant production forecast skill at San Joaquin may have also been associated with the relatively higher aridity (< 500 mm of total annual precipitation), which tends to result in greater sensitivity of production to precipitation in many rangeland systems (Huxman et al. 2004; Hsu et al. 2012; Adler et al. 2014). Although these factors may have contributed to site variability in production forecast skill, our step-by-step validation procedure did identify significant forecast skill that could potentially be used to inform management in these systems (Hardegree et al. 2012; Westgate et al. 2013; Hardegree et al. 2019).

Implications for Management

Throughout this study we have demonstrated the utility of climate forecasting in informing plant production estimates. Climate forecasts are useful in contributing to an early-season plant-production forecast but can also be updated throughout the management year to provide additional flexibility for managers of CAG and other rangeland ecosystems (Meredith et al. 2021b). For systems where plant production forecasts can be verified to be skillful, these forecasts could significantly improve decision making for assigning and sustaining stocking rates, estimation of potential wildfire fuel loads, and the anticipated success of restoration management activities. In addition to the ecosystem-specific example of this study, we have also provided a template for production-forecasting that could be used across diverse rangeland and agricultural systems. Although practical implementation of these forecasts in management planning will require additional stakeholder input and consideration of human dimensions and economic aspects; we have demonstrated that underlying forecast skill is available and warrants further investigation as a useful management tool.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.rama.2023.02.013.

References

Abatzoglou, J.T., 2013. Development of gridded surface meteorological data for ecological applications and modelling. International Journal of Climatology 33, 121–131.
Ackerly, D.D., 2009. Evolution, origin and age of lineages in the Californian and Mediterranean floras. Journal of Biogeography 36, 1221–1233.
Adler, P.B., Salguero-Gómez, R., Compagnoni, A., Hsu, J.S., Ray-Mukherjee, J., Mbeau-Ache, C., Franco, M., 2014. Functional traits explain variation in plant life history strategies. Proceedings of the National Academy of Sciences 111, 740–745.
Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. Crop evapotranspiration—guidelines for computing crop water requirements. Irrigation and Drain 56, 1–300.
Allen, R.J., Anderson, R.G, 2018. 21st century California drought risk linked to model fidelity of the El Niño teleconnection. NPJ Climate and Atmospheric Science 1, 1–14.
An-Vo, D.-A., Reardon-Smith, K., Mushtaq, S., Cobon, D., Kodur, S., Stone, R., 2019. Value of seasonal climate forecasts in reducing economic losses for grazing enterprises: Charters Towers case study. The Rangeland Journal 41, 165–175.
Barbero, R., Abatzoglou, J.T., Hegewisch, K.C., 2017. Evaluation of statistical downscaling of North American multimodel ensemble forecasts over the western United States. Weather and Forecasting 32, 327–341.
Bartolome, J.W., 1987. California annual grassland and oak savannah. Journal of Range Management 9, 122–125.
Bartolome, J.W., Barry, W.J., Griggs, T., Hopkinson, P., 2007. Valley grassland. Terrestrial Vegetation of California 3, 367–393.
Becchetti, T., George, M., McDougald, N., Dudley, D., Connor, M., Flavel, D., Vaughn, C., Forero, L., Frost, B., Oneto, S., 2016. Annual range forage production. UCANR Rangeland Management Series 1–12.
Becker, E.v., den Dool, H., Zhang, Q., 2014. Predictability and forecast skill in NMME. Journal of Climate 27, 5891–5906.
Blankenau, P.A., Kilic, A., Allen, R, 2020. An evaluation of gridded weather data sets for the purpose of estimating reference evapotranspiration in the United States. Agricultural Water Management 242, 106376.
Caldwell, R.M., Menke, J.W., Duncan, D.A., 1985. Effects of sulfur fertilization on productivity and botanical composition of California annual grassland. Journal of Range Management 38, 108–113.
Cardil, A., Rodrigues, M., Ramirez, J., de-Miguel, S., Silva, C.A., Mariani, M., Ascoli, D, 2021. Coupled effects of climate teleconnections on drought, Santa Ana winds and wildfires in southern California. Science of the Total Environment 765, 142788.
Chaplin-Kramer, R., George, M.R, 2013. Effects of climate change on range forage production in the San Francisco Bay Area. Plos One 8, e57723.
Chen, M., Parton, W.J., Hartman, M.D., Del Grosso, S.J., Smith, W.K., Knapp, A.K., Lutz, S., Derner, J.D., Tucker, C.J., Ojima, D.S., 2019. Assessing precipitation, evapotranspiration, and NDVI as controls of US Great Plains plant production. Ecosphere 10, e02889.
Chikamoto, Y., Timmermann, A., Widlansky, M.J., Balmaseda, M.A., Stott, L., 2017. Multi-year predictability of climate, drought, and wildfire in southwestern North America. Scientific Reports 7, 1–12.
Cleland, E.E., Chiariello, N.R., Loarie, S.R., Mooney, H.A., Field, C.B., 2006. Diverse responses of phenology to global changes in a grassland ecosystem. Proceedings of the National Academy of Sciences 103, 13740–13744.
Cobon, D., Jarvis, C., Reardon-Smith, K., Guillory, L., Pudmenzky, C., Nguyen-Huy, T., Mushtaq, S., Stone, R., 2021. Northern Australia Climate Program: supporting adaptation in rangeland grazing systems through more targeted climate forecasts, improved drought information and an innovative extension program. The Rangeland Journal 43, 87–100.
Copeland, S.M., Davies, K.W., Hardegree, S.P., Moffet, C.A., Bates, J.D., 2022. Influence of weather and plant association on production dynamics in Wyoming big sagebrush steppe. Rangeland Ecology & Management 85, 48–55.
Duncan, D.A., Woodmansee, R.G., 1975. Forecasting forage yield from precipitation in California's annual rangeland. Journal of Range Management 28, 327–329.
Espeland, E.K., Schreeg, L., Porensky, L.M., 2020. Managing risks related to climate variability in rangeland-based livestock production: What producer driven strategies are shared and prevalent across diverse dryland geographies? Journal of Environmental Management 255, 109889.
Fauvelot, C., Cleary, D.F.R., Menken, S.B.J., 2006. Short-term impact of 1997/1998 ENSO-induced disturbance on abundance and genetic variation in a tropical butterfly. Journal of Heredity 97, 367–380.
Fraisse, C., Breuer, N., Zierden, D., Bellow, J., Paz, J., Cabrera, V.Y, Garcia, A.G., Ingram, K.T., Hatch, U., Hoogenboom, G., Jones, J.W., 2006. AgClimate: a climate forecast information system for agricultural risk management in the southeastern USA. Computers and Electronics in Agriculture 53, 13–27.
George, M., Olson, K., Menke, J., 1988a. Range weather: a comparison at three California range research stations. California Agriculture 42, 30–32.
George, M.R., Raguse, C.A., Clawson, W.J., Wilson, C.B., Willoughby, R.L., McDougald, N.K., Duncan, D.A., Murphy, A.H., 1988b. Correlation of degree-days with annual herbage yields and livestock gains. Journal of Range Management 41, 193–197.
George, M.R., Williams, W.A., McDougald, N.K., Clawson, W.J., Murphy, A.H., 1989. Predicting peak standing crop on annual range using weather variables. Journal of Range Management 508–513.
Goddard, L., Gershunov, A., 2020. Impact of El Niño on weather and climate extremes. El Niño Southern Oscillation in a Changing Climate 361–375.
Griffith, G.E., Omernik, J.M., Smith, D.W., Cook, T.D., Tallyn, E., Moseley, K., Johnson, C.B, 2016. Ecoregions of California. US Geological Survey Open-File Report 1021, 1–45.
Hardegree, S.P., Abatzoglou, J.T., Brunson, M.W., Germino, M.J., Hegewisch, K.C., Moffet, C.A., Pilliod, D.S., Roundy, B.A., Boehm, A.R., Meredith, G.R., 2018. Weather-centric rangeland revegetation planning. Rangeland Ecology & Management 71, 1–11.
Hardegree, S.P., Schneider, J.M., Moffet, C.A., 2012. Weather variability and adaptive management for rangeland restoration. Rangelands 34, 53–56.
Hardegree, S.P., Sheley, R.A., Brunson, M.W., Taylor, M.H., Moffet, C.A., 2019. Iterative-adaptive management and contingency-based restoration planning in variable environment. Rangeland Ecology & Management 72, 217–224.
Hansen, J.W., 2002. Realizing the potential benefits of climate prediction to agriculture: issues, approaches, challenges. Agricultural Systems 74, 309–330.
Hartmann, H.C., Pagano, T.C., Sorooshian, S., Bales, R., 2002. Confidence builders: evaluating seasonal climate forecasts from user perspectives. Bulletin of the American Meteorological Society 83, 683–698.
Hartman, M.D., Parton, W.J., Derner, J.D., Schulte, D.K., Smith, W.K., Peck, D.E., Day, K.A., Del Grosso, S.J., Lutz, S., Fuchs, B.A., 2020. Seasonal grassland productivity forecast for the US Great Plains using Grass-Cast. Ecosphere 11, e03280.
HilleRisLambers, J., Yelenik, S.G., Colman, B.P., Levine, J.M., 2010. California annual grass invaders: the drivers or passengers of change? Journal of Ecology 98, 1147–1156.
Holmgren, M., Scheffer, M., Ezcurra, E., Gutiérrez, J.R., Mohren, G.M., 2001. El Niño effects on the dynamics of terrestrial ecosystems. Trends in Ecology & Evolution 16, 89–94.
Hsu, J.S., Powell, J., Adler, P.B., 2012. Sensitivity of mean annual primary production to precipitation. Global Change Biology 18, 2246–2255.
Huntsinger, L., Bartolome, J.W., D'Antonio, C.M, 2007. Grazing management on California's Mediterranean grasslands. California grasslands 233–253 Dec.
Huxman, T.E., Smith, M.D., Fay, P.A., Knapp, A.K., Shaw, M.R., Loik, M.E., Smith, S.D., Tissue, D.T., Zak, J.C., Weltzin, J.F., Pockman, W.T., Sala, O.E., Haddad, B.M., Harte, J., Koch, G.W., Schwinning, S., Small, E.E., Williams, D.G., 2004. Convergence across biomes to a common rain-use efficiency. Nature 429, 651–654.
Kirtman, B.P., Min, D., Infanti, J.M., Kinter III, J.L., Paolino, D.A., Zhang, Q., Van Den Dool, H., Saha, S., Mendez, M.P., Becker, E, 2014. The North American multimodel ensemble: phase-1 seasonal-to-interannual prediction; phase-2 toward

developing intraseasonal prediction. Bulletin of the American Meteorological Society 95, 585–601.
Khumalo, G., Holechek, J., 2005. Relationships between Chihuahuan desert perennial grass production and precipitation. Rangeland Ecology & Management 58, 239–246.
Klemm, T., McPherson, R.A., 2017. The development of seasonal climate forecasting for agricultural producers. Agricultural and Forest Meteorology 232, 384–399.
Larson-Praplan, S., 2014. History of rangeland management in California. Rangelands 36, 11–17.
Lin, H., Merryfield, W.J., Muncaster, R., Smith, G.C., Markovic, M., Dupont, F., Roy, F., Lemieux, J.-F., Dirkson, A., Kharin, V.V., 2020. The Canadian Seasonal to Interannual Prediction System Version 2 (CanSIPSv2). Weather and Forecasting 35, 1317–1343.
Liu, H., Jin, Y., Roche, L.M., O'Geen, A.T., Dahlgren, R.A., 2021. Understanding spatial variability of forage production in California grasslands: delineating climate, topography and soil controls. Environmental Research Letters 16, 014043.
Lortie, C.J., Munshaw, M., DiTomaso, J., Hierro, J.L., 2010. The small-scale spatiotemporal pattern of the seedbank and vegetation of a highly invasive weed, *Centaurea solstitialis:* strength in numbers. Oikos 119, 428–436.
Luedeling, E., Zhang, M., Girvetz, E.H., 2009. Climatic changes lead to declining winter chill for fruit and nut trees in California during 1950–2099. Plos One 4, e6166.
Marshall, N.A., Gordon, I.J., Ash, A., 2011. The reluctance of resource-users to adopt seasonal climate forecasts to enhance resilience to climate variability on the rangelands. Climatic Change 107 (3), 511–529.
Meredith, G., Bean, A., Brymer, A.B., Friedrichsen, C., Hurst, Z., 2021a. Integrating human dimensions within the LTAR Network to achieve agroecological system transformation. Rangelands 293, 19.
Meredith, G.R., Brunson, M.W., Hardegree, S.P., 2021b. Management innovations for resilient public rangelands: adoption constraints and considerations for interagency diffusion. Rangeland Ecology & Management 75, 152–160.
Murphy, A.H., 1970. Predicted forage yield based on fall precipitation in California annual grasslands. Journal of Range Management 23, 363–365.
Omernik, J.M., Griffith, G.E., 2014. Ecoregions of the conterminous United States: evolution of a hierarchical spatial framework. Environmental Management 54, 1249–1266.
Pendleton, D., Menke, J., Williams, W., Woodmansee, R., 1983. Annual grassland ecosystem model. Hilgardia 51, 1–44.
Pitt, M., Heady, H., 1978. Responses of annual vegetation to temperature and rainfall patterns in northern California. Ecology 59, 336–350.
Polis, G.A., Hurd, S.D., Jackson, C.T., Piñero, F.S., 1997. El Niño effects on the dynamics and control of an island ecosystem in the Gulf of California. Ecology 78, 1884–1897.
Rao, L.E., Allen, E.B, 2010. Combined effects of precipitation and nitrogen deposition on native and invasive winter annual production in California deserts. Oecologia 162, 1035–1046.
Rajagopalan, B., Lall, U., 1999. A k-nearest-neighbor simulator for daily precipitation and other weather variables. Water Resources Research 35, 3089–3101.
Rutherford, M., 1980. Annual plant production-precipitation relations in arid and semi-arid regions. South African Journal of Science 76, 53–57.
Scasta, J.D., Weir, J.R., Stambaugh, M.C., 2016. Droughts and wildfires in western US rangelands. Rangelands 38, 197–203.
Schantz, M.C., Hardegree, S.P., James, J.J., Sheley, R.L., Becchetti, T., 2023. Modeling weather effects on plant production in the California Annual Grassland. Rangeland Ecology & Management 87, 177–184.
Stromberg, M.R., Corbin, J.D., D'Antonio, C.M., 2007. California grasslands: ecology and management. University of California Press, pp. 1–375.
Wainwright, C.E., Wolkovich, E.M., Cleland, E.E, 2012. Seasonal priority effects: implications for invasion and restoration in a semi-arid system. Journal of Applied Ecology 49, 234–241.
Westgate, M.J., Likens, G.E., Lindenmayer, D.B., 2013. Adaptive management of biological systems: a review. Biological Conservation 158, 128–139.
Zhang, T., Hoerling, M.P., Wolter, K., Eischeid, J., Cheng, L., Hoell, A., Perlwitz, J., Quan, X.-W., Barsugli, J., 2018. Predictability and prediction of southern California rains during strong El Niño events: a focus on the failed 2016 winter rains. Journal of Climate 31 555-555.