232

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Plant production forecasting; current state and opportunities for advancing grazing land management

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Abstract

Forecasting climate and plant production provides an advantageous way to move from reactive to proactive grazing land management. Throughout grazing lands water availability and temperature are primary drivers of annual net primary plant production (ANPP) and total annual precipitation is a fundamental indicator of ANPP in native plant dominated communities that receive less than 500 mm of precipitation. In this paper we review the process by which forecasts are produced and showcase several examples of where climate and plant production forecasts can be useful in diverse US rangeland ecoregions. While forecasting is probabilistic and may not be beneficial in all circumstances, our results suggest that if forecasts are used over time, they can provide higher quality information than just chance alone. Collectively, climate and plant production forecasting could aid in moving grazing land management from a reactive to a proactive discipline by allowing producers to prepare for drought or flooding events, set appropriate stocking rates and avoid inflated hay costs, select the most appropriate crop species for annual conditions, and improve rangeland success by only seeding when weather conditions are suitable for establishment.

Introduction

Water availability and temperature are primary drivers of annual net primary plant production (ANPP) across rangelands (Bradford et al. 2006; Swain et al. 2016). Rangeland plant production is particularly affected by these factors as total annual precipitation is a fundamental indicator of ANPP in native plant dominated communities that receive less than 500 mm of precipitation (Huxman et al. 2004; Hsu et al. 2012; Williams et al. 2023). While climate can be used to produce reliable rangeland plant production forecasts, spatiotemporal climate forecasts first need to be tested for accuracy against historical weather data to ensure quality model output.

Historical climate data

Historical climate data can be acquired in various formats. The highest quality historical climate data are from stationary weather stations (Stawowy et al. 2021; Daly et al. 2008). Weather stations are, however, expensive to acquire and maintain. Across rural grazing land regions, few and sparsely dispersed meteorological tracking has limited quality spatiotemporal climate data to widely distributed point-scale locations (Hardegree et al. 2018). To overcome this limitation, scientists have used gauge data, remote-sensing inputs, and both data interpolation and disaggregation schemes to produce daily historical climate estimates of precipitation, temperature, relative and specific humidity, dew point, radiation and wind velocity, as well as derived estimates of reference evapotranspiration data at 1-4 km gridded spatial resolutions across the contiguous US (Daly et al. 2008; Thornton et al. 2014; Mourtzinis et al. 2017). These gridded databases include PRISM (Daly et al. 2008), DayMET (Thornton et al. 2014), GridMET (Abatzoglou 2013) and others (Mourtzinis et al. 2017). Gridded climate databases like these provide historical data continuity from 1979 until present and can be used across extensive or multi-site field studies where the deployment of weather stations is impractical (Hardegree et al. 2018). While these data have helped overcome data limitations across space, they are still imperfect. The process of statistical data downscaling, for example, can result in significant modelling uncertainty, as averaged and interpolated values cannot reflect complex spatial and temporal variations in climate variables at sub-daily scales. This limitation particularly applies to soil erosion applications that require fine-scale estimates of precipitation timing and intensity (Fullhart et al. 2024).

Stochastic weather generators are another modelling tool that can be used to simulate probabilistic estimates of daily weather time-series that capture additional features of daily and sub-daily climate dynamics (i.e., daily means, variances and covariances, frequencies, extremes, etc.) (Wilks and Wilby 1999). While initially used in association with individual weather stations to simulate probabilistic estimates of historical weather data, Fullhart and his colleagues have expanded the utility of one of these models, i.e., the CLIGEN climate GENerator, for estimating weather time-series across large spatial regions, from hourly to annual temporal scales (Fullhart et al. 2023; Fullhart 2023; Fullhart et al. 2022; Fullhart et al. 2021). Given the spatial and temporal availability of historical weather data and probabilistic scenarios from stochastic weather generators, reliable climate and plant production forecasts, and probabilistic plant-production scenarios can be developed.

Forecasting application and process

Seasonal climate forecasts are being used in a growing number of agricultural and natural resource modeling applications (Mo and Lettenmaier 2014; Klemm and McPherson 2017). These applications have been facilitated by the availability of seasonal forecasts of monthly temperature and precipitation from the North American Multi-Model Ensemble (NMME) program (Kirtman et al. 2014; Becker et al. 2014; Schantz et al. 2024; Roy et al. 2020). To test forecast skill (or reliability as measured via a P-value of $P<0.10$), hindcasts (or retrospective forecasts) are regressed against historical climate data. For this process, hindcasts from models used in the NMME program are acquired, as described by Kirtman et al. (2014) and matched to the spatial resolution of historical climate data at the appropriate grid scale, following a Bias Correction-Spatial Downscaling (BCSD) procedure such as in Barbero et al. (2017). For the studies we showcase here forecast model output from NMME was downscaled to match the 4-km resolution of historical gridMET weather estimates.

Climate forecast skill

In our first study, we evaluated the quality of point-scale forecasts across four US rangeland ecoregions (Fig. 1; Schantz et al. 2024). Key take aways from this study were that 1) forecast skill varies by region with the highest forecast skill in the Desert Southwest and relatively poor forecast skill in the Southern Great Plains; 2) temperature forecasts were found to have higher relative skill than precipitation forecasts; 3) we found no differences in forecast skill as a function of the forecast lead time but forecast skill varied strongly with the season for which the forecast was made; and 4) multi-model aggregate forecasts often had synergistic skill when compared to both individual model forecasts and forecasts based on the ensemble mean of all available models (Schantz et al. 2024).

Plant production forecast skill

Additional region-specific studies have shown that climate forecasts could be used as input into plant-production models to produce reliable estimates of forage yields (Fig. 2,3; (Schantz et al. *In Press-b;* Schantz et al. 2023a). In the California Annual Grassland, for example, forecasts reliably estimated plant production across most of the growing season at two sites and in three of the seven forecasting months at an additional study site (Schantz et al. 2023a). Forecast skill was shown to vary seasonally (Fig. 2) with the best forecasts produced in February following winter precipitation inputs (which is the dominant precipitation time in these regions) and when annual grasses are just beginning growth (Schantz et al. 2023b; Schantz et al. 2023a). This finding has practical application for livestock production systems as most cow-calf operations make stocking decisions in winter (January and February) and having an estimate of potential plant production would aid in the ability to justify alternative stocking decisions. Similarly, in the Great Basin we found that skillful plant-production forecasts were possible, but that forecast skill varied by inherent site conditions, such as, aspect, slope and dominant plant community (Fig. 3: Schantz et al. *In Press a,b*).

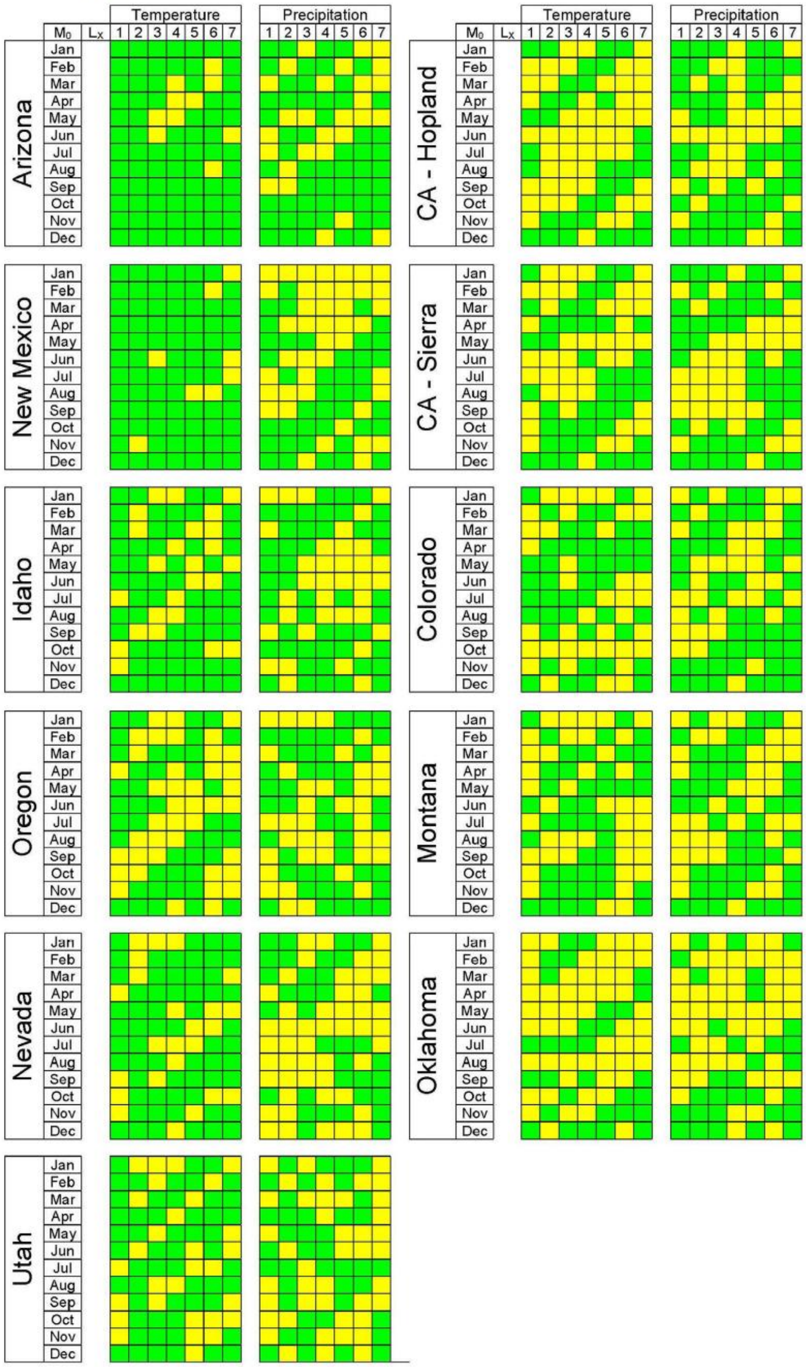

Figure 1. Skill map of 84 temporal scenarios for estimating monthly mean temperature and total precipitation at each point scale rangeland site as a function of the month in which the forecast was made M_0: Jan-Dec) and the forecast lead time L_x 1-7 months. This figure is from Schantz et al. 2024a.

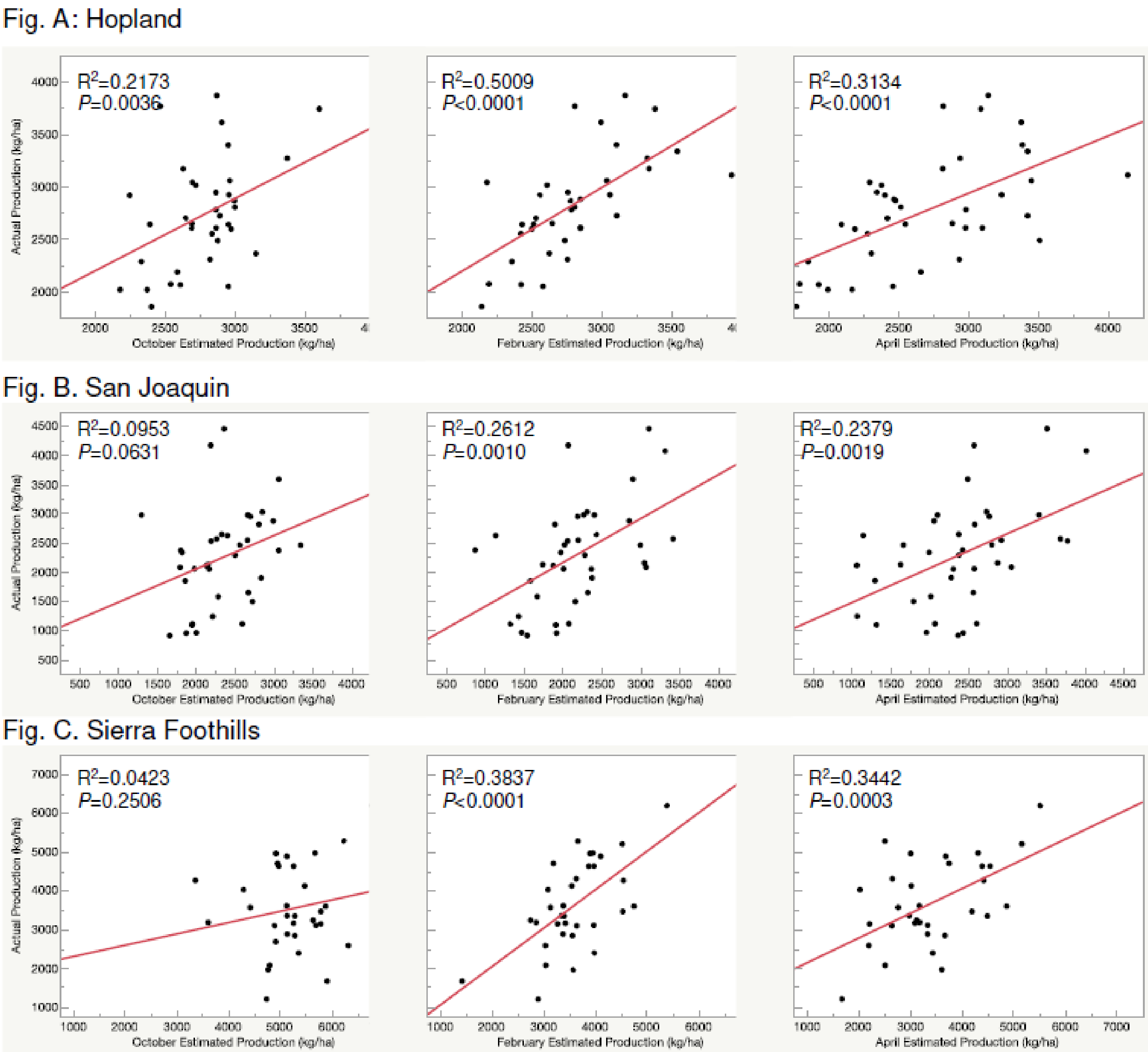

Figure 2. Regressions of actual to forecasted plant production across the study years 1982-2022 for the months of October, February, and April at three California Annual Grassland study sites. Fig. A refers to the Hopland site, B to the San Joaquin site, and C to the Sierra Foothills. This figure is from Schantz et al. 2023b.

The Future of Forecasting

Currently our team is working to provide better forecasting data access and improved tools for using forecasts in diverse agricultural and natural resource modeling applications. Upcoming projects include additional regional assessments of seasonal forecasting skill and evaluations of the utility of climate data type (i.e., stationary weather station, gridded and model-generated climate scenarios) across land use application and ecoregions associated with the Long-Term Agroecosystem Research (LTAR) network.

Conclusions and Implications

Forecasting provides an advantageous way to move from reactive to proactive management. Proactive management would allow producers to better prepare for drought or flooding events, set appropriate stocking rates and avoid inflated hay costs, select the most appropriate crop species for anticipated seasonal conditions, and provide recommendations for rangeland seeding. The process of forecasting begins by accessing high quality climate data. While stationary weather stations provide the highest quality data, they are limited to point-scale locations. Gridded and hybrid gridded stochastic weather generators can help overcome this limitation by providing quality weather information across space. Even with the best historical climate data inputs, forecasting skill will be dependent upon the interaction between region and time of the year. Similarly, the skill of plant production forecasts will depend on the interactions of area of interest, time of year, and plant species phenology. While forecast utility is probabilistic and may not be beneficial in all circumstances, our results suggest that consistent use of climate forecasts could improve the efficiency of agricultural management practices.

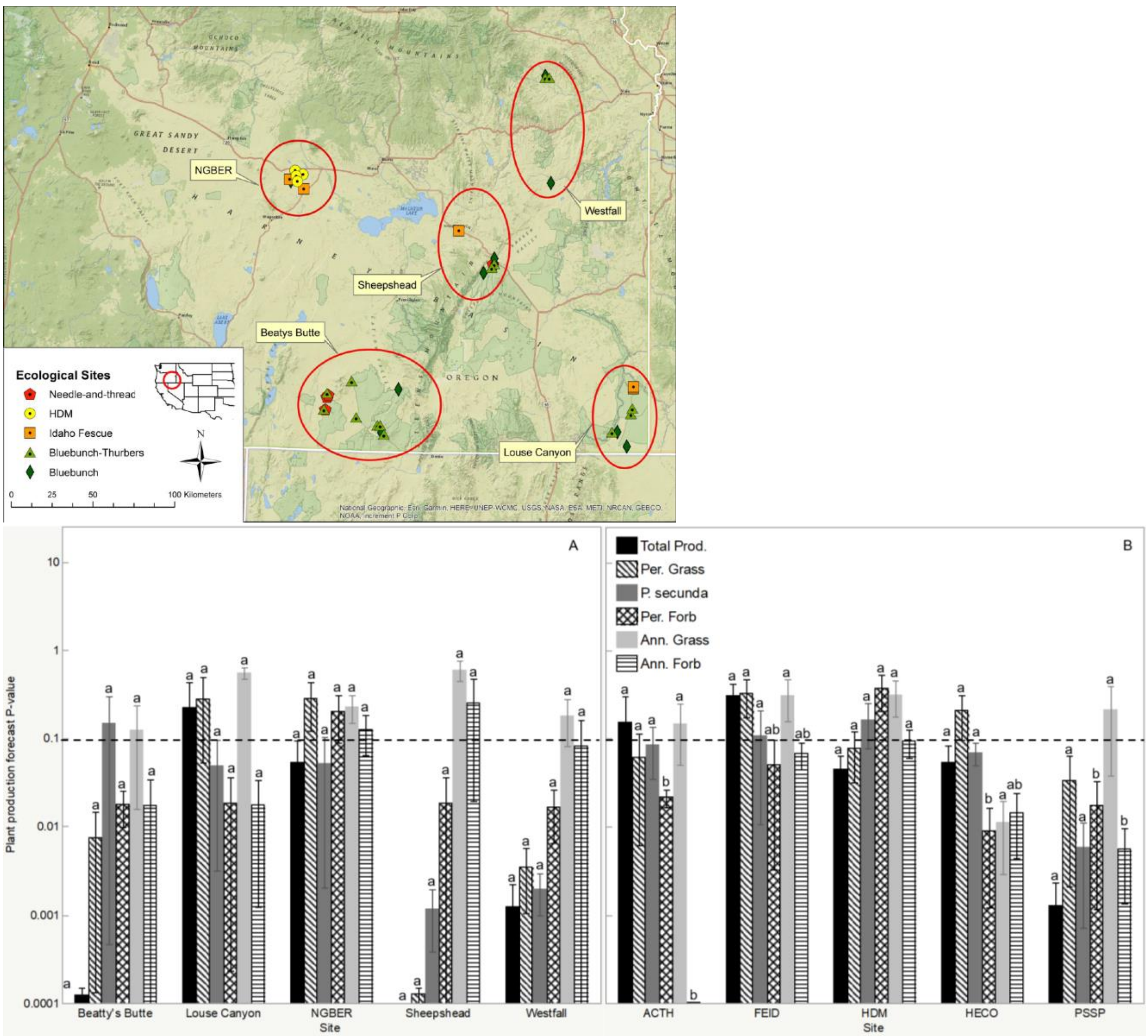

Figure 3. Upper figure refers to the geographical sites and the associated ecological states within those sites.

Lower figure refers to the skill as measured via a *P*-value (*P*<0.10) of forecasts. Figures are from Schantz et al. *In Press*.

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