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Satellite Assessment of Early-Season Forecasts for Vegetation Conditions of Grazing Allotments in Nevada, United States☆

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ABSTRACT

The extent and heterogeneity of rangelands in the state of Nevada (United States) pose a challenging situation for land managers when determining stocking levels for livestock grazing. Overutilization can cause lasting environmental damage, while underutilization can create unnecessary economic hardship for livestock operators. An improved ability to forecast vegetation stress later in the growing season would allow resource managers to better manage the tradeoffs between ecological and economic concerns. This research maps how well growing season conditions for vegetation within grazing allotments of Nevada can be predicted at different times of the year by analyzing 15 yr of enhanced vegetation index (EVI) data from the Moderate Resolution Imaging Spectroradiometer sensor, cumulative monthly precipitation, and the Palmer drought severity index. Land cover classes within the grazing allotments that are not relevant to grazing were removed from the analysis, as well as areas that showed > 50% change in EVI since these likely represented transitions or disturbances that were not related to interannual climate variability. The datasets were gridded at spatial resolutions from 4 to 72 km, and the correspondence between image and meteorological datasets was found to improve as measurements were averaged over larger areas. A 16-km sampling grid was judged to provide the best balance between predictive ability and spatial precision. The average R^2 of regressions between the vegetation index and meteorological variables within each of the 16-km grid cells was 0.69. For most of Nevada, the ability to predict vegetation conditions for the entire growing season (February–September) generally peaks by the end of May. However, results vary by region, with the northeast particularly benefiting from late-season data. Regressions were performed with and without very wet years, and the ability to make early predictions is better when including wet years than in dry to typical conditions.

Introduction

Publicly owned rangelands that are managed by the US Bureau of Land Management (BLM) cover approximately 18 million ha, and livestock grazing is one of the most commonly permitted activities on public lands in Nevada. Rangelands managed by the BLM-Nevada office cover over 2 million hectares and are divided into 745 grazing allotments of widely varying sizes and characteristics. Permits issued by the BLM define stocking levels and the timing of grazing activities within these allotments for approximately 550 operators, with the goal of maintaining soil and site stability, hydrologic function, and biotic integrity. One point of contention between ranchers and range management agencies arises from the assignment of stocking levels well before the end of the rainy season. In some cases, anomalous late-season precipitation leads to underutilization of grazing resources and unnecessary economic losses for ranchers. Disputes regarding stocking levels or management responses to drought and wildfire can lead to a lack of trust in the land management agency (van Kooten et al., 2006).

Although the BLM's mission is to sustain the health, diversity, and productivity of America's public lands for the use and enjoyment of present and future generations, variations in weather and climate can make this task difficult. Adjustments to existing public land use authorizations can occur during drought conditions in order to reduce stress on rangeland ecosystems and maintain the long-term productivity of public lands. Such adjustments to grazing activities include reducing

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livestock numbers, shortening the season of use, altering pasture move dates, changing pasture rotations, authorizing water hauling, closing allotments to grazing, or allowing grazing in vacant allotments. From 2014 through 2016 the Farm Service Agency (FSA) declared much of Nevada a drought disaster area, making livestock producers who own or lease grazing or pasture lands eligible for federal compensation via the Livestock Forage Disaster Program (LFP). Drought disaster declarations are based on U.S. Drought Monitor map (USDM) (Svoboda et al., 2002), and lengths of LFP payments are based on drought categories of severe to exception drought, equating to one to five monthly payments, respectively (FSA, 2016). Improved early season forecasts for vegetation conditions on rangelands could help to improve the timeliness of such drought response and mitigation actions.

It is a challenge to respond in an adaptive manner to changing conditions on these rangelands due to their large spatial extent, rough terrain, and highly variable biological and physical attributes (Weltz et al., 1994; Tueller, 2001; Marsett et al., 2006; Bradley and O'Sullivan, 2011). Long-term observations from satellite remote sensing systems can support adaptive management strategies by ameliorating many of the challenges of field monitoring, such as deployment logistics, cost, training, limited sample sizes, observer bias, and undefined reference conditions (Beever et al., 2005; Miller, 2008; Herrick et al., 2010). Satellite-based remote sensing systems can quantify plant cover, leaf area, and forage availability (Qi et al., 2000; Hunt et al., 2003; Marsett et al., 2006; Röder et al., 2008). Many satellite-based vegetation studies use spectral indices that respond to the amount and vigor of green vegetation. A prominent example is the normalized difference vegetation index (NDVI, Rouse et al., 1974), a ratio of reflected light from the red and near infrared (NIR) wavelengths in the form: (NIR – red)/(NIR + red). Sellers (1987) demonstrated a meaningful linear relationship between NDVI and photosynthetic capacity, though the index may be negatively affected by soil background color (Huete and Tucker, 1991) and requires proper atmospheric correction (Crippen, 1988). Since the development of NDVI, a number of other spectral vegetation indices have been developed with the goal of minimizing the confounding effects of soil background and atmosphere. These indices include the soil-adjusted vegetation index (SAVI, Huete, 1988), modified soil-adjusted vegetation index (MSAVI, Qi et al., 1994), transformed soil-adjusted vegetation index (TSAVI, Baret et al., 1989), and enhanced vegetation index (EVI, Huete et al., 2002). In rangelands, senesced plant material is also important for grazing, so Marsett et al. (2006) developed the soil-adjusted total vegetation index (SATVI) that responds to green and nonphotosynthetic biomass. Such satellite-based vegetation indices have been effective in monitoring shrub-steppe environments like the Great Basin (Ramsey et al., 2004) and are responsive to interannual changes in production of rangeland vegetation that is associated with precipitation (Browning et al., 2010).

Here we quantify the effectiveness of early-season forecasts of vegetation conditions within grazing allotments based on statistical relationships between cumulative precipitation, soil moisture status, and satellite-derived measures of vegetation vigor.

Methods

Study Area

The state of Nevada is located predominantly within the Great Basin region, the largest contiguous area of endorheic basins in North America. The southernmost portion of the state is in the Mojave Desert. Nevada's terrain is largely associated with the Basin and Range physiographic region, a vast area of horst and graben faulting that created parallel ranges of north-south — oriented mountain ranges separated by arid valleys (Fig. 1A). Prevailing winds are intercepted by the Sierra Nevada mountains to the west, creating a rain shadow that makes Nevada the driest state in the country. Annual precipitation ranges from 106 mm at Las Vegas in the south to 249 mm at Elko in the northeast (Fig. 1B). Greater precipitation occurs at higher altitudes in the many mountain ranges. The majority of lowland precipitation in the western and south-central portions of the state falls in the winter, the central and northeastern portions receive more in the spring, and some areas of the east receive the most from thunderstorms in late summer.

Across most of the Great Basin, the majority of precipitation occurs during colder months, November through April. Evaporative demands are minimal during this time period, allowing for a significant portion of the precipitation to be stored as soil moisture. Moisture that is stored during the winter months provides the majority of water for plant growth in the spring and summer. Tang et al. (2015) show that winter and spring precipitation plays a much larger role than air temperature in driving the interannual variability of vegetation greenness in the Great Basin, as measured by satellite-based NDVI. Summer precipitation is erratic and spatially discontinuous as thunderstorms skip across large areas of the state, saturating some grazing allotments while missing other allotments. Plant communities across the Great Basin have developed ecohydrologic survival mechanisms to take advantage of the seasonal nature of available precipitation and soil moisture.

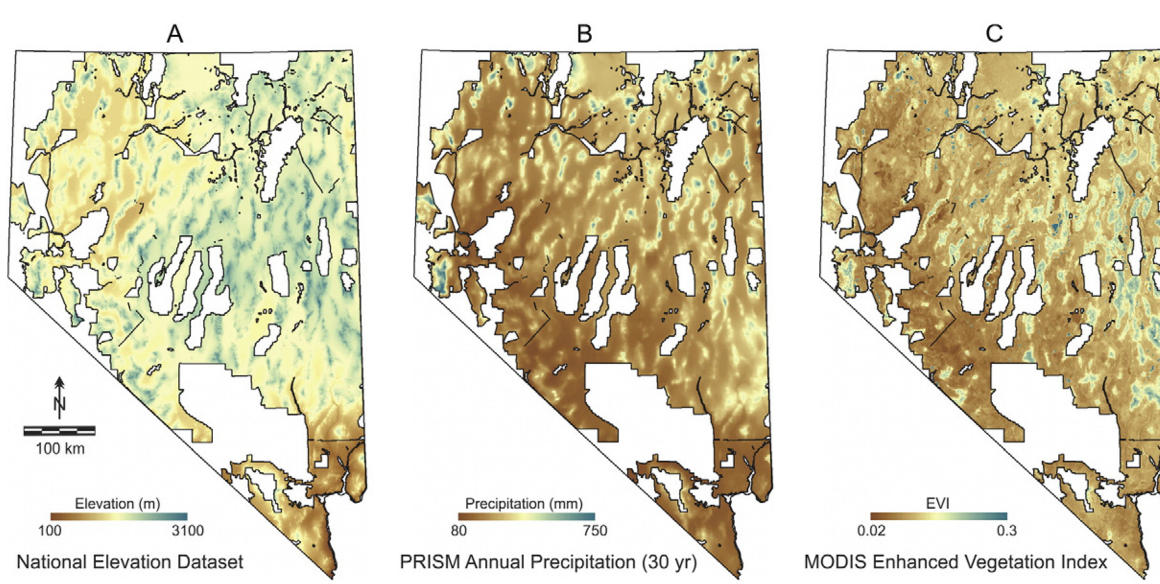

Figure 1. Elevation (**A**), precipitation (**B**), and enhanced vegetation index (**C**) within grazing allotments of Nevada.

In this study monthly measures of cumulative precipitation and the Palmer drought severity index (PDSI; Palmer, 1965) are compared with EVI data (Fig. 1C) from the space-borne Moderate Resolution Imaging Spectroradiometer (MODIS) to infer how well early-season meteorologic data can predict rangeland conditions over the entire growing season.

Measurements

The vegetation of Nevada's grazing allotments was measured using the 16-day EVI products (MOD13A1 and MYD13A1) that are produced from MODIS sensors aboard the Terra and Aqua satellite systems. This EVI product uses land surface reflectance measurements that are measured at a 500-m spatial resolution and are corrected for atmospheric absorption and scattering and for directional illumination effects. The formulation of EVI is:

$$\mathrm{EVI} = 2.5\ \frac{(\rho_{nir} - \rho_{red})}{(L + \rho_{nir} + C_{red}\ \rho_{red} + C_{blue}\ \rho_{blue})} \tag{1}$$

where ρ_{red} = red surface reflectance, ρ_{nir} = NIR surface reflectance, ρ_{blue} = blue surface reflectance, L = a canopy background adjustment (L = 1), C_{red} = weight for aerosol correction using the red waveband (6.0), and C_{blue} = weight for aerosol correction using the blue waveband (7.5).

The EVI products are composited using the maximum EVI value within a 16-d window to create complete coverage of the area that is free of transient atmospheric effects (clouds, smoke, haze) and data drop-outs. EVI data were obtained for growing seasons from 2001 through 2015. For each growing season, all EVI images from the beginning of February to the end of September were averaged to indicate the vigor of vegetation throughout the growing season. This date range captured the range of vegetation phenologies from early green-up in the Mojave Desert to late-summer monsoon responses in the eastern part of the state.

In rangelands of the western United States, temporal variability in seasonal precipitation can mask patterns of annual net primary productivity that are estimated using remote sensing (Wessels et al., 2007), particularly for higher-resolution datasets with infrequent and cloud-affected coverage. Also, senescent plant material is an important component of forage in rangelands that is not captured in a single EVI image. Here the use of an averaged value of EVI for the entire growing season that in turn is based on maximum value compositing of daily observations within 16-d sampling intervals should ameliorate these issues. Such frequently sampled EVI does catch the photosynthetic production that created the leaf area that would later senesce. While many studies have documented linear or near-linear relationships of satellite-derived vegetation indices to photosynthesis, plant cover, and leaf area (Sellers, 1987; McGwire et al., 1999; Xiao and Moody, 2005), this study does not convert EVI to a specific field-measured characterization of the quantity or quality of the vegetation in grazing allotments. Instead, EVI is used directly as an indicator of the relative vigor or stress of vegetation over the 15-yr period.

Average monthly precipitation was taken from GRIDMET (Abatzoglou, 2013), a gridded weather dataset with a 4-km spatial resolution that is computed from the Parameter Regression on Independent Slopes Model (Daly et al., 1994) and the North American Land Data Assimilation System (Mitchell et al., 2004). Studies in the western United States are often based on the water year that runs from October 1 through September 30 due to its logical correspondence to the seasonality of precipitation and temperature. This study uses the cumulative water equivalent of precipitation from October 1 through the end of successive months from February through July. July is the last month considered, since management decisions for the current growing season would be effectively irrelevant if one were to wait until the end of August.

The effect of soil moisture on MODIS EVI is also tested using a PDSI dataset with 4-km spatial resolution from Abatzoglou et al. (2014). PDSI has been used extensively in studies of drought, climate effects, grazing impacts, and restoration in rangelands of the western United States (Mouat et al., 1997; Washington-Allen et al., 2010; Coppock, 2011). PDSI is computed using gridded estimates of precipitation, evaporative demand derived from the Standardized Penman-Montieth equation (ASCE-EWRI, 2005), and soil water capacity from the STATSGO soils database. With these inputs the PDSI algorithm estimates water balance components that drive a two-stage "bucket" model of soil moisture. PDSI values of ≤ −4 correspond to extreme drought, and values of ≥ 4 represent extremely wet conditions. Average values of PDSI are tested for individual months from February through July. PDSI has a temporal scale of approximately 9−12 mo (Vicente-Serrano et al., 2010), so a February PDSI value would predominantly reflect climatic conditions from the previous calendar year.

Data Preparation and Analysis

Grazing allotments are administrative units that may contain land covers irrelevant to grazing, so the LANDFIRE vegetation map (USGS, 2013) was used to eliminate all areas that had the lifeform attribute (EVT_LF) of developed, agriculture, water, and bare or a National Vegetation Classification System physiognomic order attribute (EVT_Order) of tree-dominated. In addition, the data were visually checked and manually edited to ensure that changes in agricultural areas over time and high-altitude ridgelines were eliminated from the study. Changes in green leaf cover associated with interannual variability in precipitation may be obscured in satellite imagery when the landscape is undergoing other long-term stresses or a systematic shift in composition of the vegetation community. For example, changes in depth to groundwater may cause detectable shifts in NDVI for phreatophytic communities (Pritchett and Manning, 2012; Huntington et al., 2016). Likewise, areas that experience a wholesale shift in vegetation communities due to grazing, fire, or encroachment of invasive plants or neighboring vegetation communities (Norman and Taylor, 2005; Weisberg et al., 2007; Sankey and Germino, 2008) could obscure or even invert the statistical relationship of NDVI to annual precipitation. To remove such confounding effects, the maximum of the average growing season EVI value for every image pixel in the 15-yr-long time series was divided by the minimum for that pixel. Areas where EVI displayed a change > 50% over the 15-yr series were removed from the analysis.

The relationship between interannual variability in precipitation and the vigor of vegetation is examined at both an aggregated level for all grazing areas in the state and disaggregated to localized subareas. In disaggregating the precipitation/EVI relationship, it is important to select a spatial scale that best relates to the physical phenomena and is appropriate to the datasets. As an example, a finer spatial scale is required to isolate orographic effects on precipitation than is required to characterize latitudinal gradients. The 4-km GRIDMET data set may be appropriate for the former, but it is actually a modeled interpolation from a much sparser set of meteorological stations that were developed to characterize the latter. Between these extremes there may be an optimal resolution for smoothing out the local anomalies within a legitimate overall relationship, such as the unknown variation in precipitation within individual 4-km GRIDMET grid cells or localized land uses and disturbances that could decouple EVI from the interannual variability of precipitation.

Individual BLM grazing allotments in Nevada vary from 2 ha to more than half a million ha. This extraordinary range of spatial scales precludes the use of allotments as the spatial sampling unit for correlating variables due to the modifiable aerial unit problem (Openshaw, 1983). Therefore environmental data within the area covered by Nevada's grazing allotments were averaged by grids of varying spatial resolution, from 4 km to 72 km. The appropriate grid size for subsequent analyses was determined by comparing the coefficient of determination (R^2)

values of regressions between precipitation and growing season EVI for each grid scale. The dependence of regression results on the scale of the grid was supplemented with a variogram analysis of the EVI dataset that is portrayed in Figure 1C. Variograms characterize the distances over which a measurement is correlated with neighboring measurements. This indicates the relative smoothness of changes over short distances (called nugget variance), how far one would typically need to go to find samples that are independent of each other (range), and the degree of variability in independent samples at those long distances (sill).

The relationship of meteorological variables to EVI was determined for each grid cell using monthly PDSI values from end of February through the end of July along with cumulative precipitation from the beginning of the water year (October 1) through the end of these same months. The predictive ability of meteorological variables was assessed by using the adjusted R^2 for linear regressions against the EVI data. R^2 values indicate the proportion of year-to-year variance in vegetation vigor that is explained, so locations with a higher R^2 have more predictable relationships to the meteorological variables. The adjusted R^2 compensates for the number of predictor variables, allowing valid comparisons when using one or both of the meteorological variables. Separate regression analyses were performed using all years from 2001 to 2015 versus when the wettest years (2005, 2011) were excluded and conditions were dry or typical. Maps were generated to show how the date that best predicts the greenness of vegetation for the entire growing season varied across the state. The ability to make earlier inferences about the vigor of vegetation during the growing season was then explored by mapping the earliest time periods whose R^2s fell within 90%, 75%, and 50% of the best date. If an early month has an $R^2 > 90\%$ of the R^2 for the best month that comes later, then a decision in that early month may be seen as missing < 10% of the information required for the best possible decision.

Results

Figure 2 presents how the timing of precipitation data can be more important than the duration of measurement when predicting vegetation response in Nevada. Figure 2A plots average growing season EVI versus cumulative water year precipitation through May over the entire area of grazing allotments. At this coarse level, variability around the regression line may reflect differences in the timing of rainfall or air temperature of a given year. Figure 2B shows how the relationship between precipitation and average growing season EVI actually weakens when including precipitation that falls after the end of May, with the R^2 dropping from 0.93 to 0.77. In Figure 2B, the relative proportion of summer precipitation was high for 2009, 2012, 2013, and 2014, shifting those points away from the regression line. Conversely, 2010 was particularly dry in the summer, so as the regression line moved to fit higher precipitation values, 2010 was left behind. Residual error around the regression in Figure 2B is not correlated with available information on the acreage burned by wildfire ($R = -0.09$), and the 2 yr with the greatest acreage burned (2005, 2006) fall near the regression lines.

Vegetation in the Great Basin is adapted to the seasonality of temperature and precipitation, and the timing of precipitation is important in determining whether the moisture can be utilized effectively by vegetation. While some species in the Great Basin are able to make use of heavy thunderstorms in August and September (West and Gastro, 1978), the majority of plants in the Great Basin and Mojave Desert adapt to the hot, dry summers by slowing or halting leaf and shoot growth (Comstock and Ehleringer, 1992). Therefore, late-season precipitation introduces irrelevant variability to a statewide regression (Fig. 2B).

The regressions in Figure 2 appear to be dominated by the wet years of 2005 and 2011. However, if 2005 and 2011 are removed, the regression equation in Figure 2A changes little (0.0012x + 0.0918). Surprisingly, the additional removal of 2006 has practically no further effect on the regression line (0.0012x + 0.0916). Thus, while the wetter years were infrequent and comparatively extreme, the relationship between precipitation and the vigor of rangeland vegetation in drier years is on a linear trend with that of wetter years.

A more precise, spatially variable understanding of rangeland vegetation has much greater utility than the gross statewide patterns of Figure 2. Figure 3A shows the effect of grid size on the spatially disaggregated analysis of October – May precipitation versus growing-season EVI. Points in Figure 3A are the average of R^2 values for all the cells of each sampling grid, ranging from 4 to 72 km. As data values are averaged to coarser resolutions, interannual variability in precipition explains an increasing proportion of the interannual variability in the vigor of vegetation. For the purpose of choosing a balance between explanatory power and the spatial precision of the analysis, the remainder of this paper will be based on a 16-km grid. Going to coarser resolutions would provide incremental improvements to the variance explained by regressions until we reach the point of maximum predictability and minimum spatial precision when the entire state is averaged into one grid cell, as represented in Figure 2A.

Figure 3B shows the distances over which MODIS EVI data (see Fig. 1C) are spatially autocorrelated. Vegetation can change abruptly over short distances, resulting in a relatively high nugget variance for EVI (distance = 0). The north-south orientation of mountain ranges in

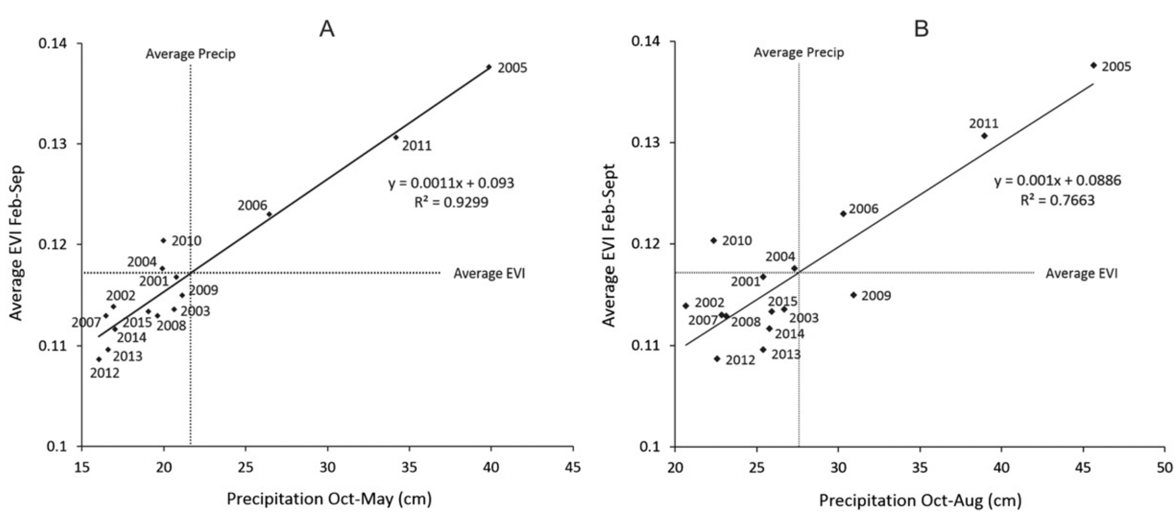

Figure 2. Predictive relationship is dependent on timing. Average growing season enhanced vegetation index versus precipitation from October through May (**A**) and October through August (**B**).

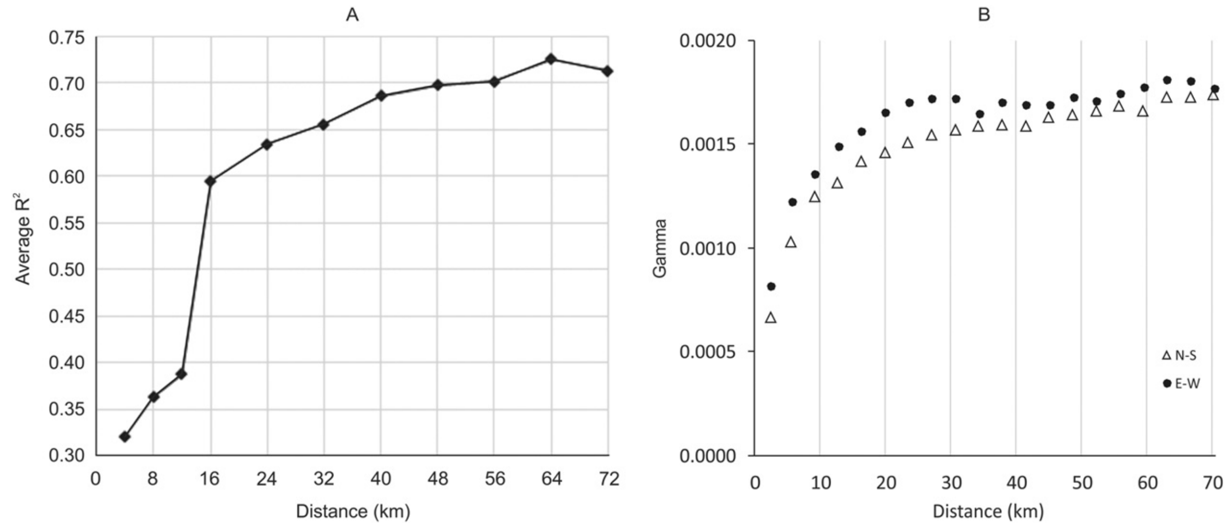

Figure 3. Effects of spatial aggregation: (**A**) average R^2 of regressions between average growing season greenness and precipitation from October through May. (**B**) Variogram of linearly detrended enhanced vegetation index across grazing allotments of Nevada.

the Basin and Range province is expressed as longer spatial autocorrelation lengths in the north-south direction than the east-west direction. East-west differences between elevation values or between precipition values become random at a separation of approximately 16 km but approximately 27 km when comparing north-south. The upward trend in north-south variance (gamma) at long distances arises from EVI's response to regional changes in elevation and precipitation.

Regressions of EVI versus precipitation and PDSI were calculated for each 16-km grid cell, first for all years, and then excluding 2005 and 2011, during which precipitation was more than one standard deviation above average. The ability of meteorological variables to predict growing season greenness on a given date was assessed by calculating the average of R^2 values from all grid cells. Figure 4A shows that when including the wettest years, the combination of PDSI and cumulative precipitation performed better together than individually through the end of May. After May, PDSI by itself was the best predictor of growing season EVI. For dry-typical years (Fig. 4B), PDSI had greater predictive value than cumulative precipitation. The combination of both variables provided only marginal improvement early in the growing season, and on average the best date for predicting growing season EVI shifted toward earlier dates. It is likely that the lower R^2s for dry-typical years are due to the truncation of the range of input variables rather than an inherently lower level of predictability.

On the basis of Figure 4, 5A maps the R^2 within each 16-km grid cell when using the best date of cumulative precipitation and PDSI (February–May) or just PDSI (June–July) to predict EVI across all years (2001 − 2015). The choice of meteorological variables was kept the same for all grid cells because 15 yr of observations were not enough to protect against overfitting the data if there were a larger number of permutations. This map shows how the ability to infer interannual changes in growing season conditions based on precipitation varies across grazing allotments in the state. The average R^2 value in Figure 5A is 0.69, indicating that a generally high amount of interannual variability in greenness across the growing season is captured by the meteorological variables. R^2 values are generally lower in the northern to eastern portion of the state and in Esmeralda County near the southwestern border. Figure 5B presents the average EVI value for each grid cell across all years (2001 − 2015). The area with low R^2s in Esmeralda County corresponds to the lowest EVI values in the state, but otherwise there is little correspondence between R^2s and the average satellite measured greenness.

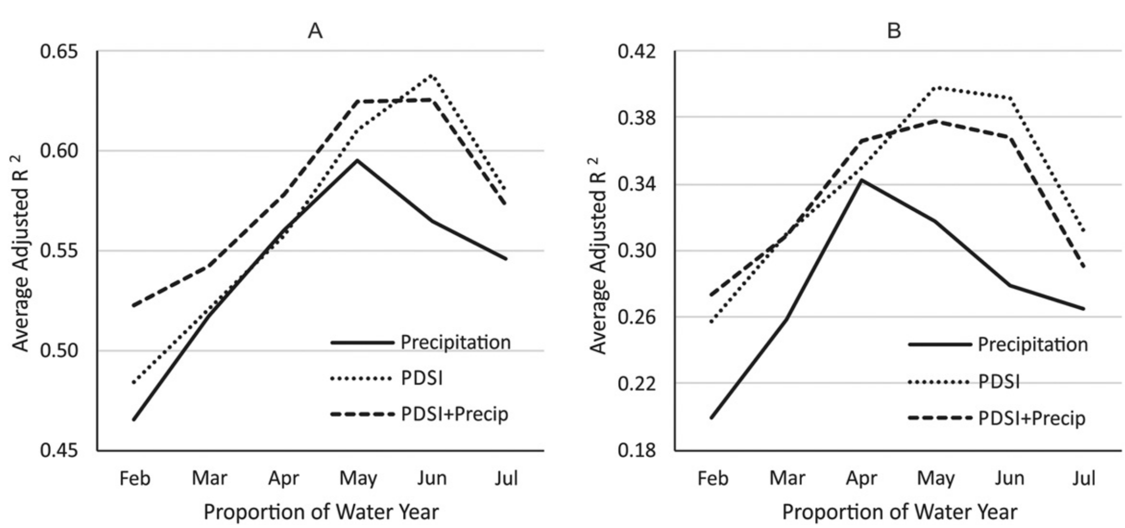

Figure 4. Average adjusted R^2 of growing season enhanced vegetation index with precipitation and Palmer drought severity index from October through the end of May for all 16-km grid cells including wet years (**A**) and just dry-typical years (**B**).

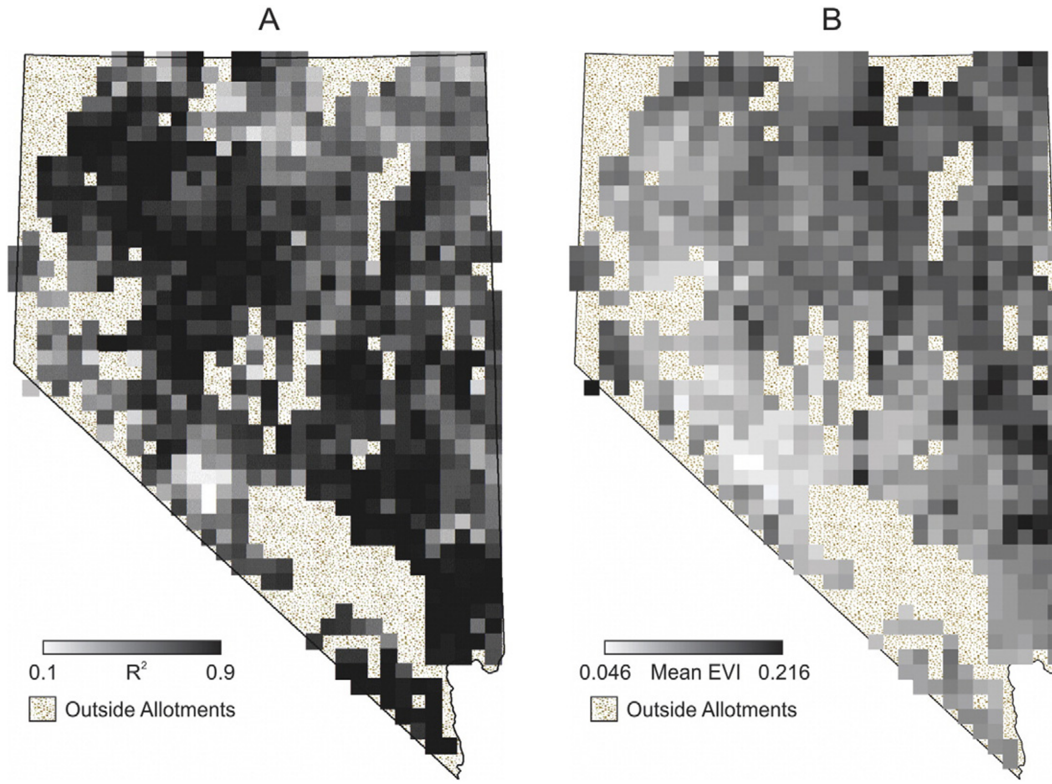

Figure 5. Maximium R^2 of any date, including wet years (***A***) and mean enhanced vegetation index across all years (***B***).

The leftmost maps in Figure 6 show the date that has the best correspondence between EVI and the meteorological variables suggested in Figure 4 for wet years (top row Fig. 6) and dry to typical years (bottom row Fig. 6). Maps to the right in Figure 6 show the end of the earliest month ("early call") that would be within 90%, 75%, and 50% of the maximum R^2 value.

The maps in Figure 6 that include wet years (top row) reflect the expected regional precipitation regimes, with earlier months generally appearing in the Mojave Desert and later months in the monsoon-affected areas in the northeast. However, some earlier and later months are scattered across the state. The "early call" maps that include wet years show that for much of the state, a prediction at the end of February would explain 75% of the typical interannual variability in satellite-measured greenness. However, late-season conditions remain important for areas along the northern and western boundaries, particularly in the northeast. When removing the wettest years from the regressions, the best month for predicting EVI throughout the growing season (bottom left Fig. 6) is similar to results that include wet years (top left Fig. 6). However, in these dry to typical years the ability to make an early call without losing predictive strength is much more limited.

Discussion

At the coarsest of scales, there is an extremely strong relationship between precipitation and interannual changes in the vigor of rangeland vegetation in Nevada. However, timing is important, and even if the amount of total rainfall in a year is normal, differences in the timing of precipitation can have an effect on plant growth due to soil moisture availability (Fay et al., 2002; Knapp et al., 2002). Using rainout shelters at sites on the Colorado Plateau, Schwinning et al. (2005a,b) found a strong effect of summer drought on plant water status, but that winter drought was more important in determining plant growth, and they suggest this may be an evolved adaptation to the uncertainty of summer rainfall. Likewise, Evans et al. (2013) found that summer irrigation did not offset the effects of winter/spring precipitation on vegetation productivity at Owens Lake in another part of the Great Basin. These prior observations are mirrored here in the dramatic reduction in R^2 from 0.93 to 0.77 when including precipitation data from later in the growing season (see Fig. 2), as well as the declines for July that are observed in Figure 4.

In moving to a more localized consideration of vegetation responses to moisture availability, there was a benefit in going from the 4-km resolution of the original meteorological datasets to at least a 16-km grid. This may be attributed in part to reconciling the actual variability measured by 500-m MODIS data to the smoother interpolated values of climate data. However, the variogram in Figure 3B suggests that part of that benefit derives from smoothing out localized deviations from the overall relationship (McGwire et al., 1993). Within the unmasked area of the grazing allotments, the datasets have a high level of spatial autocorrelation over short distances. For example, points that are close together are more likely to have the same topographic aspect, have the same vegetation, or be under a particular type of land management. Each such set of coincidental relationships may influence the specific relationship to the amount and timing of rainfall, resulting in a noisy relationship. By aggregating over larger distances that average over many aspects, vegetation types, and management actions, the relationship to monthly meteorological data becomes more consistent.

When including wet years in the analysis, the combination of PDSI with cumulative precipitation is most useful in February, but precipitation becomes progressively less influential through the months until June when its added information content does not overcome the downweighting of two variables by the adjusted R^2 and PDSI alone is sufficient (see Fig. 4). In contrast, for dry to typical years the cumulative precipitation does not provide much additional benefit to PDSI for early estimates of EVI throughout the growing season. Soil moisture "memory" built into the PDSI is likely contributing to stronger relationships and better predictability of EVI compared with precipitation alone. Recall that PDSI includes precipitation and indicates climatic conditions from approximately the previous 9 — 12 mo. Root zone soil moisture is slow to change relative to rapidly changing weather and precipitation patterns,

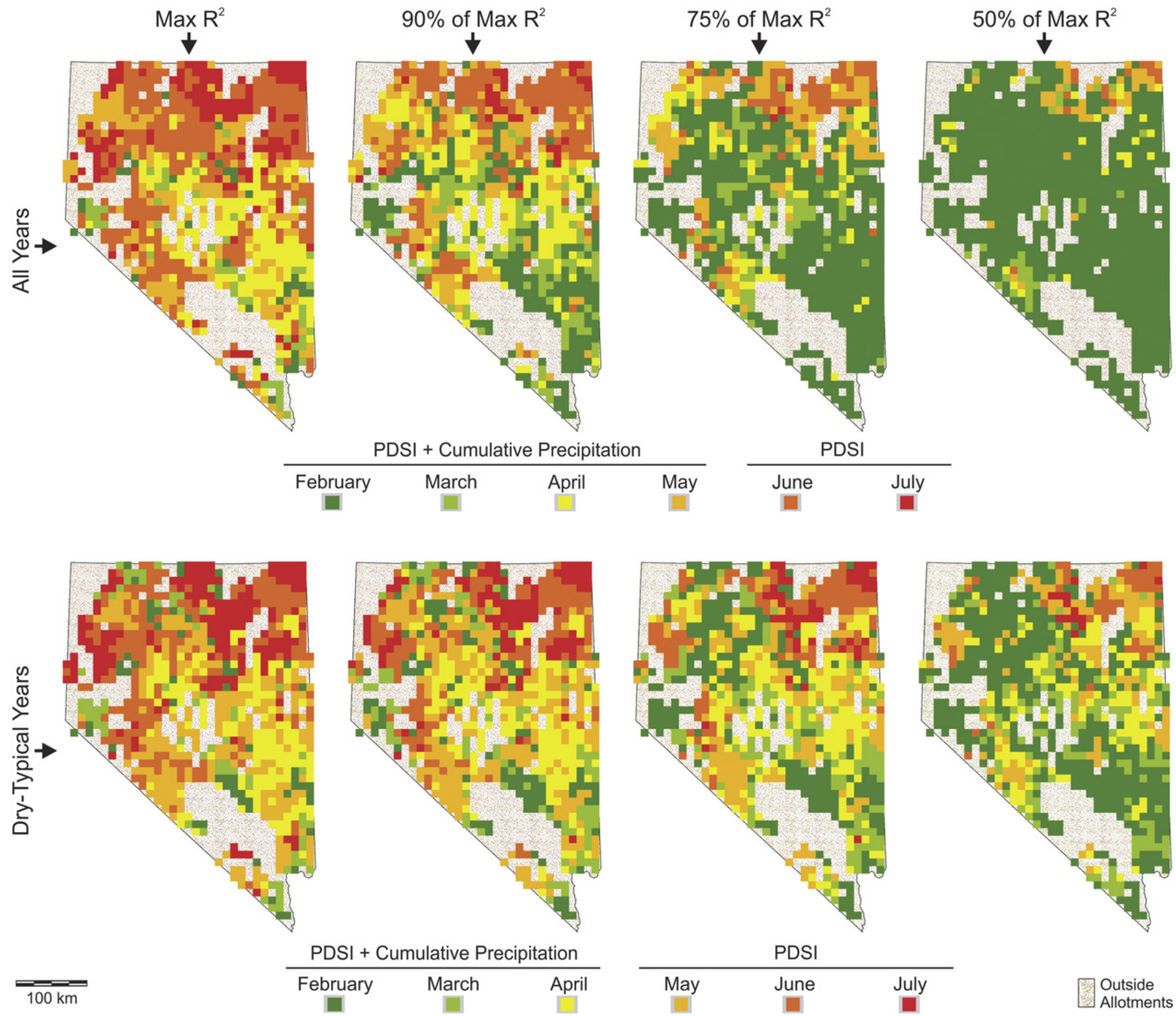

Figure 6. Date of best prediction for growing season enhanced vegetation index and tradeoffs for an "early call." Variable selection is based on the charts in Figure 4.

and summer precipitation patterns in Nevada are largely driven by convective monsoonal surges that tend to be spatially nonuniform.

Figure 5A shows that there are regional differences in the dependence of growing season EVI on PDSI and precipitation using the maximum R^2 of any month. The areas that are most predictable do not necessarily correspond to the areas that are most productive or important from a management perspective. Even though Figure 4 shows a strong drop in average adjusted R^2 from June to July on a statewide basis, there are still grid cells in Figure 6 whose best prediction is in July. These grid cells are generally less predictable, and their prediction benefits from the longest period of observation. Results that included wet years in Figure 6 (top row) show that for much of the state, an early call for the season can be made with a relatively high degree of confidence.

Uncertainty in making an early call for the entire growing season is dependent on the typical climate regime and the associated types of vegetation. Figure 6 shows that the northeast corner of Nevada cannot be predicted early with much certainty, and Figure 5A shows that even when waiting until the end of July this area is not as predictable as some other parts of the state. Monthly precipitation for Contact, Nevada (Fig. 7) shows that the wettest months for this northest corner are in May and June. This ensures that soil moisture is typically high through the early summer, so there may be less selective pressure for species to limit summertime production. While northern regions are generally cooler, the average monthly minimum temperature for Contact rises above freezing in May like many other weather stations in central and eastern Nevada (www.wrcc.dri.edu/summary/Climsmnv.html), so differences in the start of the growing season would not seem to be a large factor in explaining the great difference in timing for the northeast corner that is so apparent in the top right map of Figure 6.

A second correspondence between Figures 6 and 7 relates to the dropoff in precipitation during late spring relative to winter months, as seen at Boulder City and Minden. These two locations in Figure 6 generally have their peak R^2 before April regardless of whether wet years are included. The reduced influence of summer precipitation in these regions also appears to lead to greater predictability for growing season conditions (see Fig. 5A). If higher uncertainty (lower R^2) is acceptable, the area over which an early call can be made expands from these two zones. Previous research in the western Great Basin and northern Mojave found that summer irrigation of greasewood (*Sarcobatus vermiculatus*), rubber rabbitbrush (*Ericameria nauseosa*), and saltbush (*Atriplex confertfolia* and *A. parryi*) improved plant physiological performance, but in eight of nine cases it did not result in increased canopy growth (Snyder et al., 2004). Waiting until later in the growing season will not improve predictive power if additional summer water does not result in growth. The failure of plants to use additional summer water for growth is consistent with the idea that plants have evolved adaptations in areas with low predictabilty of summer rainfall

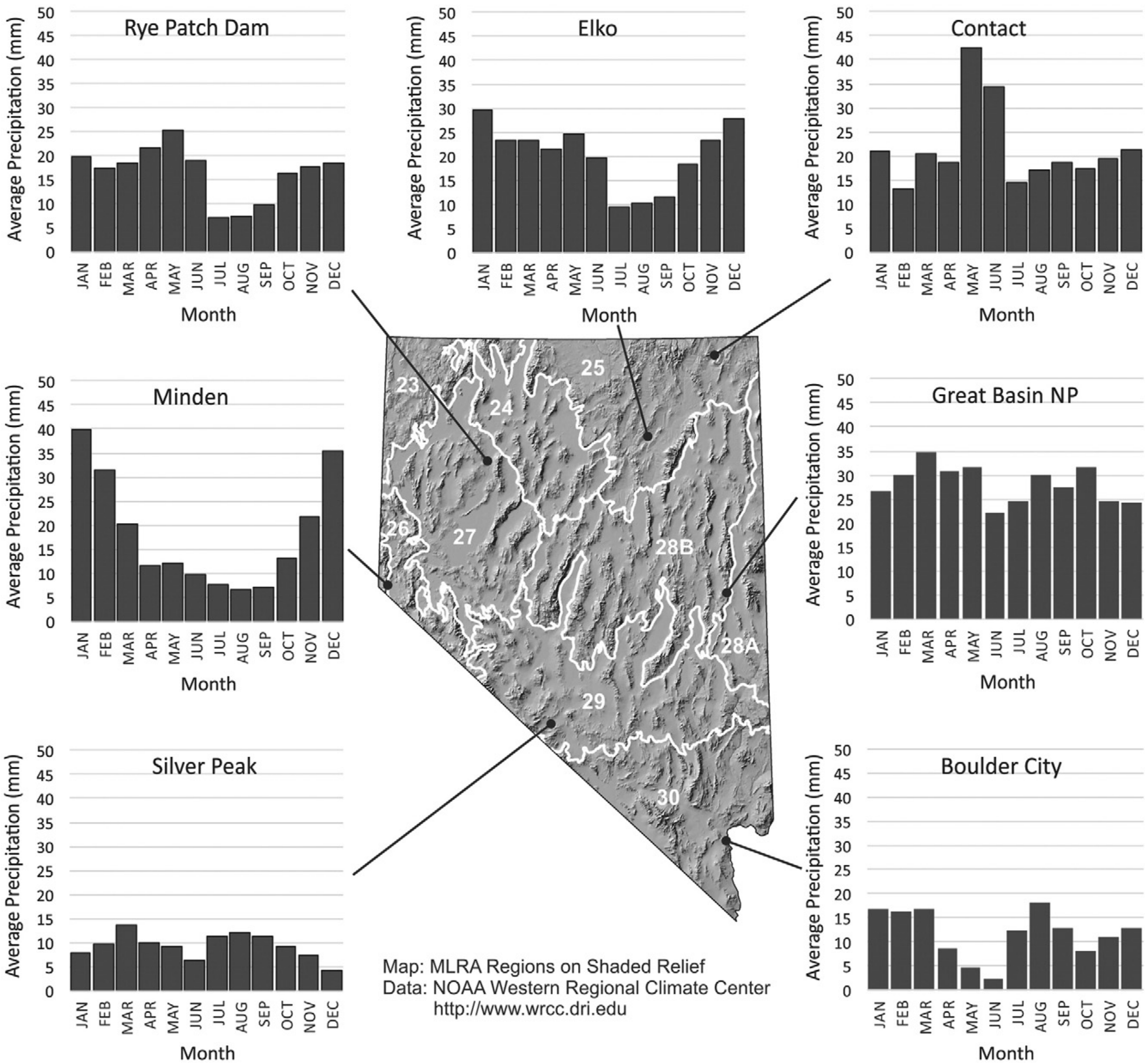

Figure 7. Seasonality of precipitation around Nevada.

(Schwinning and Sala, 2004). Alternatively, it might indicate that plant growth is colimited by other nutrients; species may be phenologically canalized to only acquire nutrients during the spring (James and Richards, 2005); soil temperatures may limit shallow root activty (Williams and Ehleringer, 2000); or summer rainfall may just be substituted for deeper soil water, resulting in no net gain (Schwinning et al., 2002). An additional factor may be the quality of shallow soil water associated with summer rainfall. The salinity of soils in the hydrologically closed basins that are associated with salt desert scrub can be problematic for nonhalophytic plants, such as rubber rabbitbrush, which survives in these environments by relying on groundwater from below saline soils (Kray et al., 2012).

Plots for Rye Patch Dam and Elko (see Fig. 7) show that precipitation tends to persist into June across northwestern Nevada and then rapidly drop off by July. This is seen in Figure 6, where the highest R^2 values occur later in the season. The relationship between growing season EVI and meteorological variables in this northern region is more predictable than many other parts of the state (see Fig. 5A). An early call with somewhat lower certainty can be made as early as February for some grid cells (see Fig. 6), particularly with wet years. This ability to make early calls is likely due to the small proportion of summer precipition relative to winter months. In these northern regions soil moisture may also be buffered by snowpack, which on average leads to a more predictable infiltration of snowmelt to deeper soil moisture storage (Schlaepfer et al., 2012) and, hence, lower late-season variability.

Finally, monthly precipitation at Silver Peak and Great Basin National Park (GBNP) (see Fig. 7) correspond to areas in Figure 6 that are not suited to very early forecasts during dry-typical precipitation. In these areas, the summer minimum for precipitation in June is still a large fraction of that observed in winter months, and the amount of late summer precipitation is similar to wintertime. The predictability of these areas is generally not as high as in the northwestern or southern parts of the state (see Fig. 5A). Predictability is particularly low, and early-season calls are less useful near the Silver Peak. EVI values around the Silver Peak station are very low (see Fig. 5B), and it is likely that the sparse vegetation supported by such low precipitation is at the detection limits of EVI. If so, there may be an interannual response to precipitation that is strong relative to the amount of vegetation present, though very small in an absolute sense. In the east, near GBNP, early-season predictions are more robust for wet years than for dry/normal years (see Fig. 6).

In this area of more predictable summer precipitation, it appears that plants might not limit summer growth to the degree that is seen near Minden or Boulder City (see Fig. 7). In wet years, sufficient soil moisture might be stored early in the season to allow the vegetation to reach some maximum potential of growth, while for dry/normal years the ability to reach that potential may depend on precipitation that falls much later in the growing season.

The National Resource Conservation Survey (NRCS) has developed Major Land Resource Areas (MLRAs), which are geographically defined management units for regional agricultural planning. MLRAs identify regions with similar physiography, geology, soils, and biological resources (see Fig. 7). MLRAs in the northern part of Nevada have some degree of rough correspondence to the patterns seen in Figure 6. However, in the south there is a notable shift in the relationship between satellite-measured greenness and precipitation/PDSI between the eastern and western portions of MLRA 29, with the eastern region being more predictable at an earlier date. A similar east/west trend occurs in MLRA 30, though it is less pronounced and disappears at 75% of the maximum R^2 or lower when wet years are included.

West (1983) identifies a distinction between sagebrush steppe and sagebrush semidesert (Fig. 8) that also corresponds to the patterns seen in Figure 6. The boundary between the semidesert and steppe sagebrush communities subdivides MLRA 25 in a way that corresponds well to the northwest region that is particularly resistant to early forecasts, most clearly seen in the two top right maps of Figure 6. Much of the semidesert sagebrush area is well predicted in April/May, while the best predictions in the steppe are in June/July. Forbs are common in both sagebrush communities, but while forbs in the semidesert are almost entirely annuals, many forbs in the steppe are perennial (Schultz and McAdoo, 2002). The ability of perennial forbs to utilize summer precipitation could help explain the reduced ability to make early predictions of growing season conditions in the northwest. A study by Dalgleish et al. (2011) found that the demography of needle-and-thread grass *(Hesperostipa comata),* which is more common in the semidesert than the steppe, was reduced in response to increased summer temperature and decreased precipitation during the prior year. If other species in the semidesert sagebrush community have a similar response to drought in the prior year, this might combine with the long lag time built into PDSI to explain the pattern of better early predictions in central and eastern Nevada.

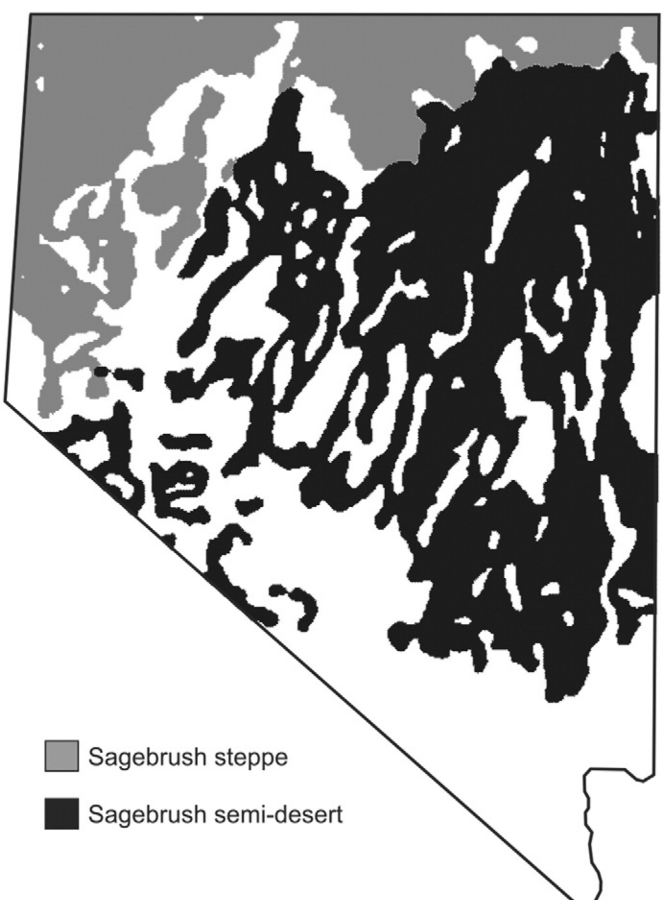

Figure 8. Sagebrush semidesert versus steppe in Nevada (adapted from West, 1983 and Schultz and McAdoo, 2002).

Implications

Satellite remote sensing and weather data can provide guidance to improve the timing of management decisions for grazing allotment permits, and basing such decisions on publicly available datasets might increase the confidence of stakeholder communities in management decisions. Even though the best date for understanding the year's vegetation conditions might be later in the season, this analysis indicates the relative level of uncertainty in trying to make an early decision in different parts of the state. Notably, the flexibility in making an early decision is much lower when wet years are removed from the analysis.

In this study there was no effort to directly relate EVI to forage production within grazing allotments, but there is a wealth of literature indicating a relationship to the amount and vigor of vegetation. In addition, consideration of a particular grazing allotment must factor in smaller-scale features, such as springs, wetlands, and management practices, that may not be well represented at this scale of analysis. However, decision-making tools have been developed for imagery from the Landsat satellite system to make site-specific adjustments in stocking rates (Dunn et al., 2013), and this study presents an additional quantitative framework for informing such decisions.

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