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Landscape Phenology, Vegetation Condition, and Relations with Climate at Colorado National Monument, 2000–2019

Natural Resource Report NPS/NCPN/NRR—2022/2384



ON THE COVER

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Natural Resource Report NPS/NCPN/NRR—2022/2384

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Executive Summary

Quantitatively linking satellite observations of vegetation condition and climate data over time provides insight to climate influences on primary production, phenology (timing of growth), and sensitivity of vegetation to weather and longer-term patterns of weather referred to as climate. This in turn provides a basis for understanding potential climate impacts to vegetation—and the potential to anticipate cascading ecological effects, such as impacts to forage, habitat, fire potential, and erosion, as climate changes in the future.

This report provides baseline information about vegetation production and condition over time at Colorado National Monument (NM), as derived from satellite remote sensing. Its objective is to demonstrate methods of analysis, share findings, and document historic climate exposure and sensitivity of vegetation to weather and climate as a driver of vegetation change. This report represents a quantitative foundation of vegetation–climate relationships on an annual timestep. The methods can be modified to finer temporal resolution and other spatial scales if further analyses are needed to inform park planning and management.

For this analysis, vegetation alliance groups were derived from vegetation-map polygons by lumping vegetation types expected to respond similarly to climate. Relationships between vegetation production and phenology were evaluated for each alliance map unit larger than a satellite pixel (~300 × 300 m). We used a water-balance model to characterize the climate experienced by plants. Water balance translates temperature and precipitation into more biophysically relevant climate metrics, such as soil moisture and drought stress, that are often more strongly correlated with vegetation condition than temperature or precipitation are. By accounting for the interactions between temperature, precipitation, and site characteristics, water balance helps make regional climate assessments relevant to local scales.

During the study period (2000–2019), there were dry years, as well as dry periods extending for several years, that resulted in substantial declines in vegetation cover. At the end of the study period, vegetation condition at Colorado NM was close to the long-term average after rebounding from a three-year drought.

Key findings:

- The patterns of pivot points and responses can serve as a guide to anticipate what, where, when, and why vegetation change may occur.
- Multiple indicators suggest production has increased in all vegetation alliance groups at Colorado National Monument since 2000.
- Non-native grasslands declined in production, but none of the native alliance groups decreased in production.
- Increases in production occurred everywhere in the park, except in non-native grasslands.
- Annual precipitation and annual production were generally among the most strongly correlated variables, suggesting that increases in annual precipitation may have caused the increase in production over the study period.
- Perennial and annual exotic grasslands and dry shrublands were more drought-tolerant than juniper or pinyon-juniper woodlands.
- Mixed montane shrublands were the least drought-tolerant alliance group.
- Annual exotic grasslands were most sensitive to interannual variation in precipitation.

- Two-to-three years of annual average soil moisture was the best indicator of annual production at the park scale. This was also generally true at the alliance-group scale.
- By the end of the study period, the growing season was starting earlier for all alliance groups except annual exotic grasslands and wet shrublands.
- By the end of the study period, the growing season was ending earlier for some alliance groups (perennial exotic grasslands and dry shrublands) but later for others (annual exotic grasslands).
- By the end of the study period, the timing of peak growth was occurring later in the calendar year.
- Date of complete snowmelt, actual evapotranspiration, and temperature were the most important determinants of start of growing season.

This report provides a foundation for interpreting weather and climate as a driver of changes in primary production over a 20-year period at the polygon and alliance-group scale. Additionally, it demonstrates how vegetation type and site characteristics, such as soil properties, slope, and aspect, interact with climate at local scales to determine trends in vegetation condition. It quantitatively defines critical water needs of vegetation and identifies which alliance types, in which locations, may be most susceptible to climate-change impacts in the future. This knowledge can inform vulnerability assessments for Climate Smart Conservation planning by park managers. Finally, this report explains how findings can be used in the Climate Smart Conservation framework, with scenario planning, to help manage park resources through transitions imposed by climate change.

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1 Introduction

This report provides baseline information about vegetation production and condition over time as derived from satellite remote sensing at the scale of vegetation alliances and alliance groups. The objective is to demonstrate the methods of analysis, share standardized findings, and document historic climate exposure and sensitivity to weather and climate as a driver of vegetation change at Colorado National Monument. This study quantitatively defines critical water needs of vegetation and demonstrates how vegetation type and site characteristics interact with climate at local scales to determine trends in vegetation condition. It provides a foundation for interpreting weather and climate as a driver of changes in primary production over a 20-year period at local scales. It can be used to quantitatively determine which alliance types, in which locations, may be most susceptible to climate-change impacts in the future, providing a basis for vulnerability assessments in Climate Smart Conservation planning (see Section 3.8).

1.1 The importance of primary production

Photosynthesis is the process in plants that converts sunlight, CO_2, water, and minerals into chemical forms of energy (carbohydrates, and sugars) essential to life. All terrestrial life depends on photosynthesis, also called "primary production" because it is the foundation of food webs. As the first step in creating food and habitat for wildlife, vegetation production is an important indicator, or "vital sign" of ecosystem health that can be tracked over time to assess conditions that support higher life forms in parks. The complex temporal and spatial patterns of primary production are influenced by many factors, including disturbances, such as wildfire and drought; differences in precipitation across space or over time; vegetation assemblages that differ in response to change; topography and soil properties; land use; and invasive species (Kariyeva and van Leeuwen 2011).

Sunlight provides the energy used to synthesize organic compounds from CO_2 and water. In semi-arid environments like the Colorado Plateau, sunlight and CO_2 are abundant and rarely limit production. But primary production is controlled by different environmental variables in different places. In tropical forests, primary production may be controlled by availability of sunlight (due to cloud cover and dense canopy) or soil nutrients. In deserts, primary production is mostly controlled by water availability. At the highest elevations on the Colorado Plateau, it may be controlled by cold temperatures and a short growing season. Changes in primary production may indicate changes in ecological structure (e.g., change in vegetation assemblage) or ecological function (e.g., loss of vegetation cover, resulting in erosion and loss of soil nutrients).

1.2 Satellite monitoring of primary production

Assessing the rate of photosynthesis and the condition of vegetation at broad landscape scales provides insight to the cycles of energy, nutrients, and water that sustain life in parks. Sunlight reflected from vegetation provides information about photosynthetic rates, leaf area, and biomass accumulation, as well as conditions of habitat and forage for animals. High-frequency satellite remote sensing of vegetation condition provides a broad-scale view of spatial patterns in vegetation condition, production, and change in response to climate, disturbance, and management actions over time.

The Northern Colorado Plateau Network (NCPN) monitors landscape-scale vegetation condition and trends using satellite imagery collected more frequently than ground-based data (which are also collected). The high frequency of observations and complete spatial coverage of satellite images is ideal for assessing seasonal as well as annual conditions and trends. The imagery also provides insight on the response of vegetation to climate patterns and disturbance (e.g., fire and forest disease, often mediated by climate) that cannot be obtained at broad scales in any other cost-effective way.

Quantitatively linking satellite observations of vegetation condition and climate data

over time provides insight to climate influences on primary production, phenology (timing of growth), and sensitivity of vegetation to weather and long-term weather patterns referred to as climate. This in turn provides a basis for understanding potential climate impacts to vegetation and the potential to anticipate cascading ecological effects, such as impacts to forage, habitat, fire potential, and erosion, as climate changes in the future.

Primary production assessed via satellite remote sensing does not indicate which species are present, or which species are performing well or poorly. It is also not a "good" or "bad" judgement (i.e., increased or decreased production is not inherently good or bad). Monitoring primary production is analogous to monitoring river flow. Flow monitoring measures the timing and abundance of water that provides habitat for animals and other essential ecological functions. It does not indicate which organisms are present, or how different species are faring.

1.3 Vegetation condition and vulnerability

Vegetation condition and trend are monitored as changes in vegetation production, or the cumulative green biomass of leaves that grow via photosynthesis. Green biomass is strongly correlated with near-infrared and red wavelengths of solar energy reflecting off vegetation measured by satellites (Thoma et al. 2002). The satellite imagery reveals repeating seasonal fluctuations in growth and senescence, as well as annual trends or abrupt changes due to disturbances.

Climate is a strong driver of vegetation distributions (Stephenson 1998). Variation in weather strongly affects vegetation condition through stress (e.g., drought) and disturbance (e.g., wildfire). Linking changes in vegetation production to climate provides important information about resistance to disturbance (resilient or susceptible) and recovery from disturbance (fast or slow). Vegetation that is susceptible to disturbance and slow to recover is considered the most vulnerable to change (Kariyeva and van Leeuwen 2011). This kind of information can be used to assess vulnerability of vegetation assemblages to climate change.

1.4 Pivot points and responses

In semi-arid environments, vegetation persists when there is a positive balance between growth and resistance to drought (Noy-Meir 1973). Vegetation traits, such as rooting depth, xylem diameter, and stomatal density and resistance interact with climate and site conditions to determine how vegetation responds to climate. Understanding these interactions provides insight to potential changes in vegetation condition and composition as the climate changes. When coupled with climate data, two important ecological characteristics, pivot points and responses, can be derived from measuring change in vegetation condition over time (Munson 2013).

A pivot point is the value of a climate variable at which annual vegetation production teeters between above- or below-average condition. For water variables, pivot points determine whether vegetation increases or decreases given the water available for growth. They are analogous to the recommended eight glasses of water per day for adults: Except in extreme cases, more water is generally not bad—but less can have detrimental effects, even when unmet needs are slight. Semi-arid plants generally respond more positively than humans to water that exceeds minimum needs. But as with people, receiving less than the minimum can cause deterioration in condition. As such, the pivot point can be considered a critical water need as well as an indicator of drought tolerance. A species's basic water needs, and the rate of change when those needs are unmet or exceeded, are important ecological variables that determine how plants respond to weather and climate.

Plant traits determine how much water vegetation needs to maintain production. How much water is available depends on climate, weather, soil, and site properties. These interactions can cause variation in the magnitude of pivot points for the same climate variable across vegetation types. Some types may be more or less tolerant of drought conditions than others.

Vegetation response is the sensitivity of vegetation to a climate variable or, more specifically, the amount of change in vegetation production per unit change in a climate variable. This rate of change is a quantitative measure of vegetation sensitivity to climate. Cumulative annual vegetation production and phenology are indicators of vegetation response to a suite of environmental conditions. Some conditions are spatially variable but stable over time, such as slope, aspect, and soil properties. Others, such as climate, vary both temporally and spatially. The vegetation growing at any location reflects adaptations suited to the environment where it persists. If conditions change, either abruptly or gradually, plants respond. The change can be spatial, due to differences in soil type or elevation. It can also be temporal, as weather and climate change over time.

Differences in vegetation response rates, or sensitivity, to water availability reflect survival strategies for persisting through drought or responding rapidly when water is available, making species more competitive as long as water needs are met. The survival strategies are a consequence of vegetation traits, including rooting depth, stomatal density, leaf area, and perennial versus annual growth forms that confer competitive advantage under different climate conditions. Generally, plant traits that favor one strategy preclude the other (Noy-Meir 1973; Thoma et al. 2019).

Individual plant responses to environmental conditions cumulatively scale up, resulting in spatial and temporal landscape patterns that can be detected in satellite imagery (Thoma et al. 2019). Because vegetation production and phenological responses are interrelated, it is useful to measure and report the two simultaneously. It is not always possible to know what caused a change noted in satellite imagery, but communication with park staff and ground-based monitoring can help interpret findings in this report.

1.5 Phenology

The annual cycle of vegetation growth and senescence, and reoccurring biological phenomena, such as seasonal migrations, are collectively known as phenology. Commonly known measures of vegetation phenology include timing of bud burst, first leaf, and spring bloom, all observed from the ground (Beurs and Henebry 2010). The high-frequency observations from satellites make it possible to track vegetation phenology (Dunn and de Beurs 2011) at broad spatial scales that include an assemblage of different vegetation species, referred to as "land-surface phenology." Land-surface phenology is an indicator of ecosystem health because it regulates dependent ecological functions, such as pollination and onset of forage production (Dunn and de Beurs 2011). On the Colorado Plateau, springtime vegetation growth is preceded by warming temperatures and snowmelt. In drier regions, onset of springtime growth may be limited if there was insufficient accumulation of fall and winter soil moisture. (Workie and Debella 2018).

Changes in land-surface phenology can provide an early indication of cascading climate-change impacts that may result in changing species assemblages and shifting range boundaries (Workie and Debella 2018). These may affect pollinators, as well as bird and mammal migrations. Determining the drivers of phenology, and changes in phenology over time, provides insights to cascading effects on pollinators and migrating animals that depend on growth initiation, forage production, and the length of growing season.

2 Methods

2.1 Overview

At the March 2003 scoping meeting for vegetation mapping at Colorado National Monument (NM), park staff and cooperators identified a project area of 12,685 hectares (31,345 ac). Of this area, 8,257 hectares (20,404 ac) occurred within the park boundary and 4,428 hectares (10,942 ac) in the surrounding area. The surroundings were included to support management of the wildland–urban interface and coordinate management on adjacent public lands. They consisted of private lands (largely in housing developments) and lands managed by the Bureau of Land Management.

This report was compiled by comparing climate data with variation in land-surface greenness over time, as measured in satellite imagery of the vegetation-mapping project area. A large archive of (460) remotely sensed satellite images was downloaded and processed in the statistical analysis software "R." A large amount of gridded climate data for the same area was downloaded and processed in Excel to estimate water-balance variables, such as soil moisture, evapotranspiration, and water deficit from temperature and precipitation (see Section 2.6). The imagery and water-balance/climate data were merged in R separately for each vegetation alliance polygon (see Section 2.2) and analyzed statistically for spatial patterns across park landscapes and over time for trends.

2.2 Remote-sensing targets

Two scales of analysis are presented in this report: vegetation-alliance polygon and vegetation-alliance group. Vegetation-alliance polygons were derived from vegetation-map polygons by lumping together vegetation types expected to respond similarly to ecological disturbances, such as climate change (Jennings et al. 2009). The polygon scale features finer spatial resolution—but with higher resolution comes more complexity in interpretation. The group scale lumps similar alliances together for broader-scale interpretations, but is not always as accurate as the polygon scale, because lumping even slightly dissimilar objects introduces variation.

It is important to note that satellite-based proxies for primary production reflect production from all vegetation within a sampling unit, regardless of the alliance name (which identifies the dominant or diagnostic vegetation types). For example, a woodland alliance type may include shrub or graminoid understory that influences the satellite signal. Untangling the proportional influence of the named alliance components from background components is beyond the scope of this report.

2.2.1 Alliance polygons

The National Vegetation Classification Standard (NVCS) identifies eight hierarchical levels of classification, ranging from Formation Class (Level 1, the broadest scale) to Association (Level 8, the finest scale). The finest scale used in this report was the vegetation Alliance (Level 7). The NVCS defines a vegetation alliance as "A characteristic range of species composition, habitat conditions, physiognomy, and diagnostic species, typically at least one of which is found in the uppermost or dominant stratum of the vegetation layer, and reflecting regional to subregional climate, substrates, hydrology, moisture/nutrient factors and disturbance regimes" (FGDC 2008).

Vegetation alliances are useful targets for tracking production and phenology because they are spatially repeating, relatively homogenous in type composition, and share similar affinities and responses to environmental conditions, such as climate. They are also mapped consistently across park units, making them an ideal classification level for cross-park analysis. Polygon boundaries for the alliances were obtained from park vegetation maps (Von Loh et al. 2007).

Analysis at the alliance, rather than association level, resulted in larger and fewer polygon targets that contained a larger number of satellite pixels. This helped ensure that satellite-image pixels fell mostly within target polygons and improved the

signal-to-noise ratio necessary for tracking change in response to climate. Improving the signal-to-noise ratio in remote sensing of sparsely vegetated environments is achieved by spatially averaging pixels within relatively homogenous areas (see Figure 4 in Thoma et al. 2017). For this reason, the analysis in this report relies primarily on aggregated pixel means across the spatial extent of each target polygon, rather than per-pixel analysis. More detail on pixel screening to exclude low-quality observations and outliers can be found in Sections 2.3 and 2.5, below.

2.2.2 NCPN alliance groups

For purposes of this study, alliances that respond similarly to climate based on structure and life-history traits were further grouped by NCPN ecologist Dana Witwicki (personal comm.) to simplify interpretations and reporting.[1] We created our own grouping system to simplify the alliance naming conventions and reduce the large number of alliances, which were too numerous for meaningful reporting.

Beginning with 98 different National Vegetation Classification alliances mapped consistently across NCPN park units, we created 32 alliance groups based on floristics, canopy structure, and local environmental conditions. Of those, 11 occurred in Colorado National Monument (Table 2-1, Figure 2-1). The alliance group names are shortened representations of the dominant alliance(s) in each group. Hereafter, we refer to the grouped alliance categories as "NCPN alliance groups" or "alliance groups," but it should be noted that these groups are similar to, but different than, Level 6 of the NVCS. A key that links each NCPN alliance group to vegetation mapping units familiar to NCPN managers can be found in Table S-1 of Thoma (2022).

The image-analysis targets were the ungrouped alliance polygons, so while results

[1]Although there is an NVCS Group level (6), the "NCPN alliance groups" discussed in this report were developed independently from the NVCS for purposes of this study.

Table 2-1. NCPN alliance groups and corresponding National Vegetation Classification alliances, Colorado National Monument.

NCPN alliance group	National Vegetation Classification alliance(s)[1]
Disturbed	Non-natural
Geology	Geology, Barren Land, Dry Washes
Annual Exotic Grassland	Cheatgrass - Medusahead Ruderal Annual Grassland Alliance
Perennial Exotic Grassland	Crested wheatgrass - Smooth brome - Kentucky bluegrass Ruderal Grassland Alliance
Juniper Woodland	Utah juniper / Shrub Understory Woodland Alliance
Pinyon-Juniper Woodland	Two-needle pinyon - Utah juniper / Shrub Understory Colorado Plateau Woodland & Scrub Alliance
Riparian Woodland	Rio Grande cottonwood - Plains cottonwood - Peachleaf willow Riparian Woodland Alliance
Dry Sagebrush Shrubland	Sagebrush species - Mixed Shrub Ruderal Understory Shrubland Alliance Wyoming big sagebrush Dry Steppe & Shrubland Alliance Black sagebrush Steppe & Shrubland Alliance
Dry Shrubland	Shrubland Vegetation - environs Fourwing saltbush Scrub Alliance
Mixed Montane Shrubland	Utah serviceberry - Alderleaf mountain-mahogany - Littleleaf mountain-mahogany Shrubland Alliance
Wet Shrubland	Greasewood Intermountain Wet Shrubland Alliance

[1]The alliance names shown in this table do not match those found in Von Loh and others (2007) because alliance names and codes in that report were subsequently updated to USNVC Version 2.01, released March 30, 2017. The names from 2007 were cross-walked to the current names displayed here. For information on nomenclature, see FGDC (2008).

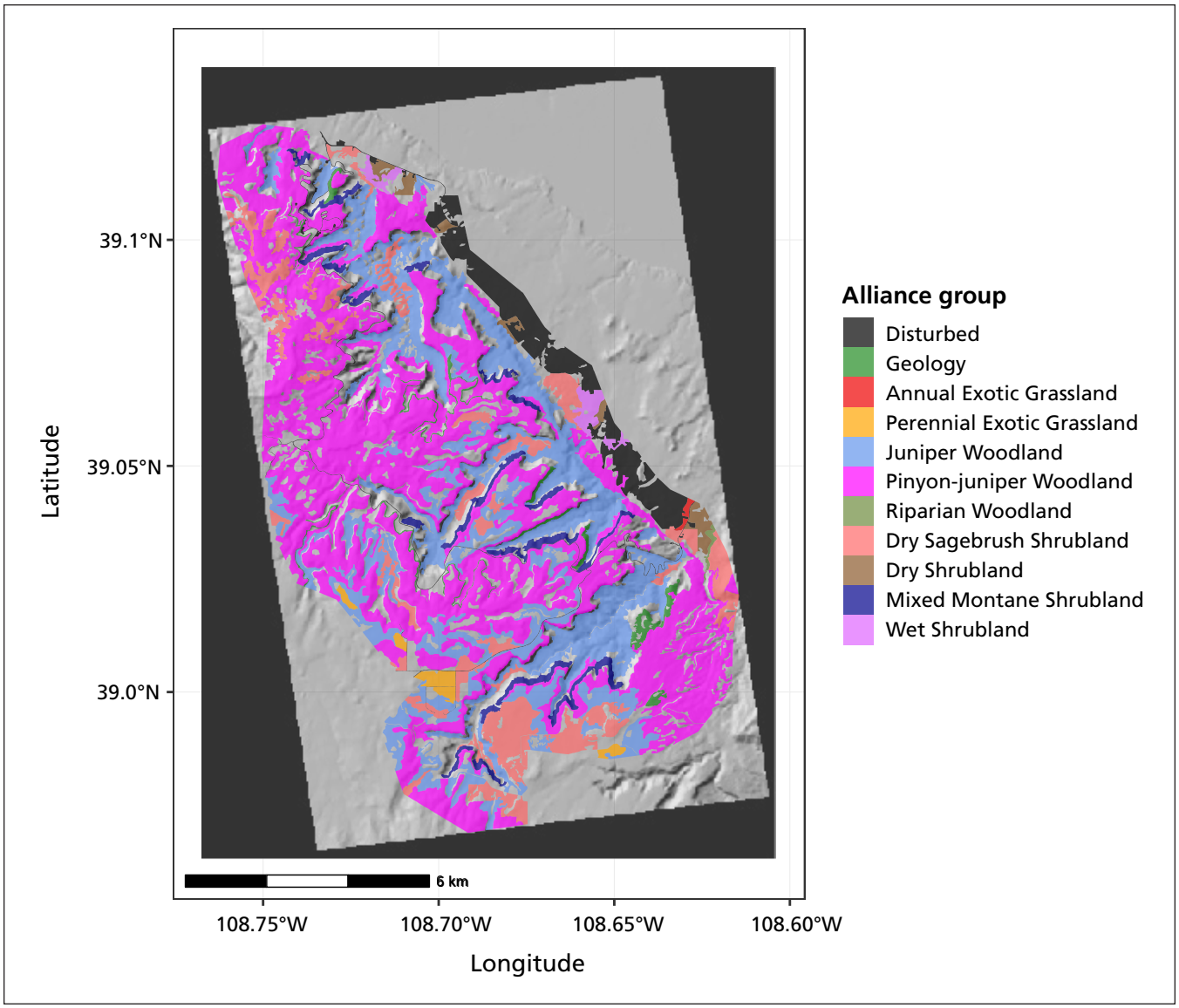


Figure 2-1. NCPN alliance groups analyzed for trends in production, phenology, and climate relations at Colorado National Monument. Areas not colored within the study boundary are alliance polygons smaller than the minimum target area of 8.3 hectares.

reported in the body of this report are for NCPN alliance groups, results are also available by polygon for un-grouped alliances in Appendix A.

2.3 Satellite imagery

Since early 2000, the moderate resolution imaging sensor (MODIS) on the Terra satellite, operated by NASA, has collected daily imagery of Earth at a spatial resolution of 250 meters (820 ft). Because cloud cover, cloud shadows, aerosols, smoke, and water vapor can interfere with clear views of Earth's surfaces, daily images are composited into a single image for 16-day windows of time (product MOD13Q1). The 16-day composite images are created from values obtained from the clearest view during the 16-day window. They are generally the best-quality observations for every pixel during the 16-day window.

Even so, during extended periods of poor atmospheric viewing conditions, some pixel values are unreliable. For this reason, each pixel in the composite image is tagged with a quality rating that can be used to screen out unreliable values influenced by poor viewing conditions. Sophisticated algorithms are used to assess the quality of every pixel value based on measurements of atmospheric

conditions made by the satellite during image acquisition (Didan et al. 2010).

There are 23 fixed, 16-day window periods in a year (with a few overlapping days at year's end to account for leap years). Thus, there were theoretically 457 viewing opportunities and 23 observations per year for every pixel in the NCPN during the period of record covered in this report. Observation completeness was calculated on an annual and seasonal basis (March–November) for the 20-year study period as the percentage of pixels in each polygon that were observed under high-quality viewing conditions. In semi-arid environments, there are typically many high-quality observations during the growing season, but fewer in winter due to clouds and snow cover.

2.4 Soil Adjusted Vegetation Index

The Soil Adjusted Vegetation Index (SAVI) is a measure of primary production (Bunting et al. 2019; Qi et al. 1994) obtained from reflectance in red and near-infrared wavelengths, adjusted for soil backgrounds in semi-arid environments (Huete 1988). It is calculated as

$$SAVI = \frac{(1 + L)(NIR - Red)}{(NIR + Red + L)}$$

where L is the soil background adjustment factor (L=1), NIR is reflectance in the near-infrared wavelengths, and Red is reflectance in red wavelengths.

These wavelengths were selected specifically because they are sensitive to the abundance of green vegetation and optimized for detecting spatial and temporal changes in vegetation. We use SAVI in this report, rather than the normalized difference vegetation index (NDVI), because of the thin vegetation cover and soil background reflectance in most NCPN parks. This combination of factors results in unfavorable signal-to-noise ratios that can make remote sensing of spatial and temporal change difficult in semi-arid environments. However, in addition to working with a vegetation index specifically designed to reduce the background noise caused by soil variability (SAVI), there are many steps in the processing workflow that help further alleviate these issues.

2.5 Pixel timeseries extraction and smoothing

Despite precautions taken by the imagery providers to minimize noise and provide an analysis-ready product from the MODIS sensor, there were lingering issues that required attention prior to analysis (Thoma et al. 2017). Each polygon larger than 8.3 hectares (the area of a MODIS pixel at NCPN latitude) was analyzed independently for trends in production and phenology and its relationship with multiple climate variables. Pixels extracted from target polygons above the 90th percentile or below the 10th percentile of average greenness were removed from analysis. This step served several purposes. First, it removed pixels that fell on alliance-group boundaries if the reflectance was very different across the boundary, such as riparian ribbons adjacent to dry uplands. Second, it eliminated areas that may have been classified incorrectly in the vegetation maps if the result of misclassification included an area of substantially different reflectance. It also eliminated inclusions of contrasting reflectance (if any occurred).

After outliers were removed, each pixel was weighted according to its proportional area that fell within the target (see Section 2.2). This step further minimized the effect of any remaining pixels that overlapped target boundaries. After computing an area-averaged value at each timestep for the pixels within a polygon target, missing polygon-average values that were a consequence of quality screening in earlier steps of the timeseries were gap-filled. Finally, a smoothing filter was used to remove high-frequency noise from the timeseries of each polygon.[2] After smoothing across large gaps in winter, prominent dips in timeseries (artificially low values that were an artifact of the smoothing) were truncated to a minimum winter

[2]High-frequency noise is inherent in most satellite imagery in semi-arid areas. It is related to relatively weak greenness signals, background reflectance from soil, and limits of sensor sensitivity. Smoothing high-frequency noise helps accentuate signals in noisy data, which improves the signal-to-noise ratio.

value based on pixel values that were likely reflectance from bare soil or senesced vegetation (Wang et al. 2018).

2.6 Water-balance model

Vegetation responds to seasonal and interannual variations in temperature and water availability depending on adaptations and site conditions (Munson et al. 2015; Thoma et al. 2019). To understand climate drivers of vegetation condition and potential impacts across large environmental gradients (hot/dry to cold/wet), we used a water-balance model to determine how different aspects of climate and site characteristics affected vegetation production and phenology. The water-balance model quantitatively accounts for temperature, precipitation, and their interactions with local site conditions (such as soil water-holding capacity, slope, and aspect) that affect soil moisture, evapotranspiration, and drought stress (Thoma et al. 2020). To calculate the water-balance variables in the model, we used 1-kilometer, gridded, Daymet temperature and precipitation data (Thornton et al. 2018).

The model partitions precipitation (P, mm) into rain (RAIN, mm) or snow (SNOW, mm of water), which accumulates until warming temperature (T, °C) causes it to melt. Soil moisture (SOIL, mm) is stored in the top meter of soil, which was treated in the model as a single layer with a maximum storage defined by its water-holding capacity. Water-holding capacity was obtained from soil surveys where data were available (NRCS 2015), but was fixed at 100 millimeters otherwise. This fixed value accommodated analyses where soil surveys have not yet been conducted, and also accounted for some water storage in geologic structures (cracks or porous, rocky material) that may be mapped as having no water-holding capacity, but support sparse vegetation detected by the satellite sensor. Water input that exceeds the storage capacity becomes runoff.

Potential evapotranspiration (PET, mm), calculated via the Oudin method, is the amount of water that could be evapotranspired from a short grass with available energy if water was unlimited. The Oudin method calculates PET using daily mean temperature, daylength, and solar radiation (Oudin et al. 2005). Actual evapotranspiration (AET, mm) is the loss of water from soil via evapotranspiration, limited by soil-water availability. Climatic water deficit (D, mm) is the unmet water need of vegetation, and is a measure of drought stress calculated as the difference between PET and AET (Stephenson 1998).

Water-availability variables include P, RAIN, SNOW, and SOIL. Variables that estimate water use include AET and PET; however, AET is limited by dry soil. Two aspects of heat that influence vegetation growth are average annual temperature (T) and growing degree days (GDD) (McMaster and Wilhem 1997).

This study also evaluated two variables that could influence vegetation production and phenology: vapor-pressure deficit (Pa) and solar radiation (W m^{-2}), available from Daymet. Vapor-pressure deficit is the difference between the amount of water vapor air can hold and the amount of vapor in the air. Solar radiation is the energy plants receive from the sun that can be used for photosynthesis (Grossiord et al. 2020; Seager et al. 2015; Stephenson 1990).

In the following sections, state variables, representing condition at a point in time (e.g., soil moisture, temperature, pressure), are averaged (Table 2-2). Variables representing fluxes of water (water passing through the environment) are summed annually or seasonally—except for SOIL, which is presented as an average value because soil water-holding capacity has an upper limit that summation could exceed, which is physically impossible.

The effects of summing or averaging have important implications for interpreting results. Whereas additional precipitation can substantially change the cumulative magnitude of annual precipitation, it takes a large amount of water input to change an annual average soil-moisture value even a small amount. For example, 10 millimeters of additional precipitation falling on dry soil on one day in one year would increase annual precipitation by 10 millimeters, but increase average annual soil moisture by just

Table 2-2. Climate and water-balance variables used to identify correlations with vegetation production and phenology.

Variable	Abbreviation	Units	Type[1]	Temporal summary[2]
Precipitation	P	mm	flux	sum
Rain	RAIN	mm	flux	sum
Snow	SNOW	mm	flux	sum
Snow Pack Water Equivalent	PACK	mm	flux	sum
Date of Complete Snowmelt	Meltd	day-of-year	state	day
Actual Evapotranspiration	AET	mm	flux	sum
Potential Evapotranspiration	PET	mm	flux	sum
Climatic Water Deficit	D	mm	flux	sum
Solar Radiation	SRAD	W m^{-2}	state	mean
Temperature	T	°C	state	mean
Temperature Maximum	Tmax	°C	state	maximum
Temperature Minimum	Tmin	°C	state	minimum
Soil Moisture	SOIL	mm	state	mean
Vapor Pressure	VP	Pa	state	mean
Vapor-pressure Deficit	VPD	Pa	state	mean
Growing Degree Days	GDD	°C	state	sum

[1]State variables describe the instantaneous condition of the environment that varies spatially and temporally. Flux variables refer to those that move through the environment as heat or water.
[2]The statistic and period vary depending on the variable and analysis interval. Flux variables are summed, whereas state variables are averaged over time or space. GDD is a state variable that is summed to create an index of heat accumulated on a daily basis from the state variables, Tmin and Tmax. Periodicity includes water year (Oct 1–Sept 30 of the following year) for annual and growing season timesteps for iSAVI, and variable period lengths for phenology analysis that begins on January 1 and ends on the start-of-season date.

0.027 millimeters (10/365). Temperature and pressure variables are also summarized as means in this analysis. Units of measure are millimeters for water terms, degrees Celsius for temperature, and pascals for pressure.

Snowmelt (Meltd) date used in the phenology analysis was determined from the water-balance model variable, PACK. This term is the daily snow water equivalent (mm) stored in the snowpack that accumulated over winter. In spring, PACK declines rapidly with warming temperature. Determining the day of complete melt is somewhat subjective due to flashy spring snow events that may linger for one to a few days, even in late spring after the initiation of vegetation growth. The algorithm used to identify day of melt begins by searching backward from May 1 (user-specified date) for PACK values greater than 4 millimeters (user-specified depth) for a span of three days (also user-specified). In the water-balance model, the combination of depth and span are the minimum degree-days necessary to yield the user-specified depth of snowmelt water. Visual inspection of snowmelt date plotted on timeseries of daily PACK values confirmed this was a reasonable approach to differentiating between periods that were predominantly snow-covered and snow-free.

2.7 Measures of vegetation production

Because net primary production is generated through photosynthesis and spectral indexes are responsive to abundance of photosynthetically active vegetation, vegetation indexes are good proxies for primary production (Paruelo et al. 2000). Characteristics of the annual repeating cycle of SAVI curves were used as proxies for production and phenology (Figure 2-2). We determined trends in three variables derived from the SAVI timeseries for each polygon: mean annual SAVI, maximum annual SAVI (maximum value regardless of month in which it occurred), and

iSAVI (or sum of daily interpolated SAVI), the area under the curve during the growing season (February through October). Daily interpolation was made via linear regression with a maximum gap size of 16 days. Mean annual SAVI (sum of 16-day observations / 23 periods per year) is a measure of average productivity across the calendar year. Maximum annual SAVI is an indication of peak instantaneous rate of vegetation production, or rate of maximum biomass accumulation. It is strongly correlated with both green cover and leaf-area index. Sum of SAVI (iSAVI) is a proxy for vegetation production during the growing season. It is most strongly correlated with biomass production and cumulative productivity (Garroutte et al. 2016; Johnson et al. 2018; Thoma et al. 2002).

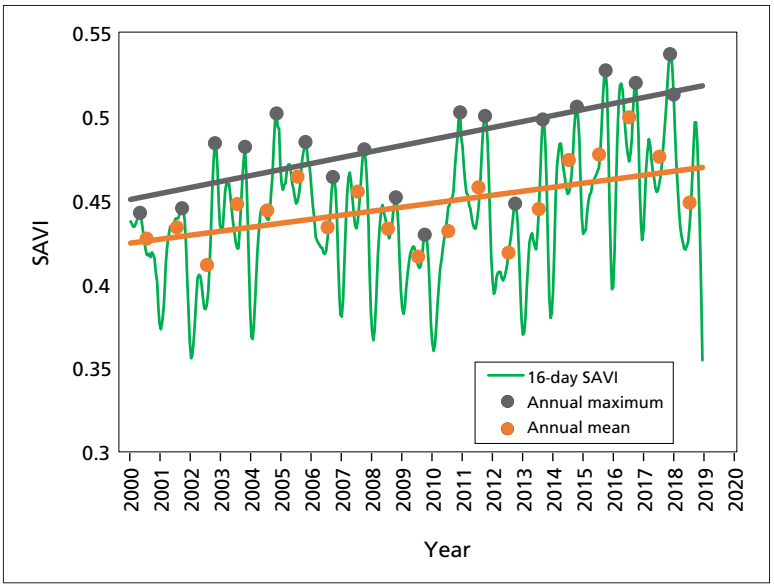


Figure 2-2. Measures of annual production from a timeseries of 16-day soil adjusted vegetation index (SAVI) derived from MODIS imagery. Linear trends against time for annual maximum and annual mean values are shown as straight lines.

2.8 Calculating the measures

Trends in production were assessed by tracking changes in maximum and mean annual SAVI for 2000–2019 using the annual aggregated timeseries method (AAT) and Mann-Kendall trend test (Forkel et al. 2013) (Figure 2-2). The rate of change (regression slope) was estimated via linear regression. Significance of change was estimated by the Mann-Kendall trend test (Forkel et al. 2013). Trends in annual maximum values were more reliable than changes in mean annual values due to use of the full annual curves that include screened and gap-filled winter values. Trends in growing-season greenness were considered in the annual pivot-points analyses below.

Representing the sum of daily interpolated SAVI values during the growing season, iSAVI is an holistic measure of the cumulative production of actively photosynthesizing vegetation (Mendez-Barroso et al. 2009; Reed et al. 1994). This proxy for above-ground net primary production results from the intentional construction of spectral indexes, such as SAVI, that are strongly responsive to absorbed, photosynthetically active radiation used by plant canopies to capture and store carbon and energy during growth.

Trends in iSAVI timeseries were noted in some polygons, which confounds relationships with climate unless the trend in iSAVI is removed before analysis. For this reason, we used the first difference in iSAVI, which represents the change in growing-season production from one year to the next, as an indicator of response to weather on an annual basis. This helps guard against overfitting when a trend exists in a timeseries. The annual change in iSAVI was calculated as

$$\Delta iSAVI = \frac{iSAVIt_2 - iSAVIt_1}{t_2 - t_1}$$

where $iSAVIt_1$ is sum of growing-season SAVI for year t_1, and $iSAVIt_2$ is sum of growing-season SAVI for year t_2. Positive values indicate increasing growth from one year to the next. Negative values indicate decreasing growth. This framing of the response variable makes increase or decrease in growth contingent on conditions in the previous year, allowing change to be linked to variation in weather from one year to the next. This is essentially equivalent ($r^2 \sim 0.99$) to the specific-growth concept used in plot-based studies of vegetation response to climate over long periods of time (Munson 2013).

2.9 Climate correlates with annual production

Two types of analysis were used to explore climate relations with annual production (iSAVI).

2.9.1 Single-variable analysis

First, simple linear-regression models compared a single climate variable to the annual increase or decrease in production relative to the prior year. The adjusted r^2 measured the strength of relationships between the climate variable and vegetation production in a range between 0 and 1, with stronger relationships closer to one. This revealed the proportion of variation in ΔiSAVI explained by variation in climate.

Simple linear regression was used to determine pivot points and production responses (Figure 2-3; see Section 1.4). Every polygon was tested against every climate and water-balance variable. After screening out relationships that were not significant (p-value >0.05), the adjusted r^2 terms were averaged across polygons from the same alliance group to see if any one climate variable outperformed the others as a predictor of vegetation production.

2.9.2 Multiple-variable analysis

Second, multiple-regression models compared multiple climate variables simultaneously with production. These included lagged climate effects characterizing climate condition 1–2 years prior to an observation. This modeling framework helps account for legacy effects, or conditions in prior years that set limits on production in a current year (Sala et al. 2012). By accounting for legacy effects, the longer-term cumulative effects of drought or good growing conditions in prior years can be considered.

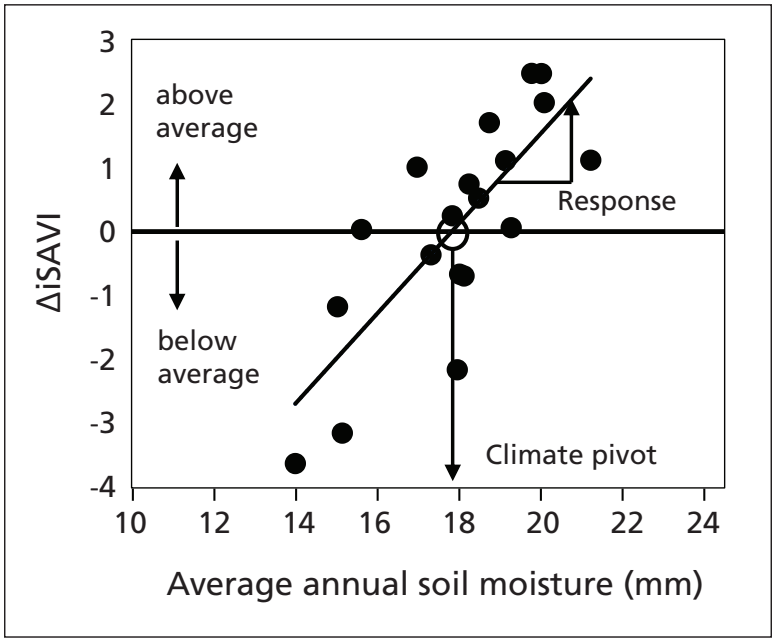


Figure 2-3. Conceptual diagram of soil-moisture pivot point and response of a single vegetation-alliance map unit to variation in annual average soil moisture. Vegetation production transitions from below- to above-average condition at the soil moisture pivot point. The response is the rate of change in iSAVI per millimeter of change in average soil moisture. Pivot-point figures like this can be constructed for other climate variables.

Additionally, this approach can help determine if climate variables interact in important ways to influence production. Whereas the linear-regression framework used to determine pivot points only considers the influence of a single variable, such as AET, on production, multiple regression can determine interactions of AET and Deficit, or other interactions and lags that include effects from prior years.

To account for multiple interacting factors that collectively influence vegetation production on an annual basis, we established a suite of a priori candidate models (Table 2-3) based on expected vegetation responses to climate variables and lags from our earlier experience working in semi-arid landscapes. In those studies (Thoma et al. 2019; Witwicki et al. 2016), we found water-balance variables to be better predictors of vegetation response than temperature and precipitation. In addition, lag effects were apparent as much as two years prior to a given satellite observation.

We then competed the models against each other using generalized linear mixed-effects models and model selection based on delta AICc values of <4 to determine the best combination of climate variables acting over one or more years to influence growing-season vegetation production. Models that did not compete well (AICc >4) were excluded. Several models could be competitive in any given polygon because every a priori model was evaluated for every polygon. We first looked for a global best model of primary production at the park level by aggregating results from all polygons in the park. Then, we tabulated how frequently the top model occurred by NCPN alliance group to determine the best climate correlates and lags or cumulative duration of effect on production at the alliance-group level.

Table 2-3. A priori models of climate influence on vegetation production competed via generalized linear mixed-effects modeling to identify best correlates with production.

Model	Climate variables[1]											
	AET	AET (lag1)	AET (lag2)	D	D (lag1)	D (lag2)	SOIL	SOIL (lag1)	SOIL (lag2)	P	P (lag1)	P (lag2)
AET1	X	–	–	–	–	–	–	–	–	–	–	–
AET12	X	X	–	–	–	–	–	–	–	–	–	–
AET123	X	X	X	–	–	–	–	–	–	–	–	–
AET123_D1	X	X	X	X	–	–	–	–	–	–	–	–
AET123_D12	X	X	X	X	X	–	–	–	–	–	–	–
AET123_D123	X	X	X	X	X	X	–	–	–	–	–	–
SOIL1	–	–	–	–	–	–	X	–	–	–	–	–
SOIL12	–	–	–	–	–	–	X	X	–	–	–	–
SOIL123	–	–	–	–	–	–	X	X	X	–	–	–
AET1_D1	X	–	–	X	–	–	–	–	–	–	–	–
AET12_D12	X	X	–	X	X	–	–	–	–	–	–	–
D1_SOIL1	–	–	–	X	–	–	X	–	–	–	–	–
D1_SOIL2	–	–	–	X	–	–	–	X	–	–	–	–
D1_SOIL12	–	–	–	X	–	–	X	X	–	–	–	–
P1	–	–	–	–	–	–	–	–	–	X	–	–
P12	–	–	–	–	–	–	–	–	–	X	X	–
P123	–	–	–	–	–	–	–	–	–	X	X	X

[1]X = variable used in model, – = variable not used in model. AET = annual sum of actual evapotranspiration (mm), D = annual sum of climatic water deficit (mm), SOIL = annual average soil moisture (mm), P = annual sum of precipitation (mm). Lags refer to models that include the water balance term for the preceding one (lag1) or two (lag2) years.

2.10 Conceptual basis of climate pivot points and responses

Using the pivot-point framework, annual change (ΔiSAVI) was regressed (linear regression) with climate data to determine the degree to which annual variation in weather affected production (Munson 2013). In this analysis, a pivot point is the critical magnitude of a climate or water-balance variable where vegetation "teeters" between above- or below-average condition. Generally, water pivot points are important in water-limited environments. Temperature pivot points are important at higher elevations, where cold temperature limits growth (Thoma et al. 2020).

Vegetation response, or sensitivity to climate or water balance, is the rate of change in condition per unit change in water or temperature. In this analysis, vegetation response is the slope of the regression line when interannual change in iSAVI is related to the corresponding change in climate or water balance for the same period (see Figure 2-3).

Pivot points and responses are depicted graphically (see Figure 2-3) as the x-axis value where each linear-regression line crosses the horizontal line, indicating no change from one year to the next. Production values plotting above the x-axis indicate that vegetation increased in production from the previous year. Points below the line indicate vegetation production decreased from the previous year. If a deficit pivot point was exceeded during the growing season, vegetation production was likely below average, because vegetation has an inverse or negative relationship with water deficit, a measure of drought stress. If an AET pivot point was exceeded during the growing season, vegetation production was likely above average, because production is positively

related to AET. Thus, the interpretation of exceeding a pivot point depends on the influence the climate variable has on vegetation (negative for water deficit, positive for water-availability variables).

Polygons that cross the horizontal line further to the left, where the x-axis variable is a water-availability metric, are considered more drought-tolerant. That is, their performance is above average at lower water availability than a polygon that crosses the horizontal line further to the right. For example, a vegetation assemblage with a precipitation pivot point of 250 millimeters is more drought-tolerant than a vegetation assemblage with a pivot point of 300 millimeters. The opposite is true if the x-axis is deficit. In that case, polygons that cross the horizontal line further to the left are less drought-tolerant; that is, their production declines to below-average condition when drought stress is relatively low.

The slope of the regression line quantifies the expected change in iSAVI per millimeter of water or degree of temperature. Polygons with steeper regression slopes are more sensitive to a change in water availability. For each unit change in a climate or water-balance variable, a more sensitive vegetation type will have a larger change in growing-season iSAVI.

Together, pivot points and responses determined from historical observations of vegetation condition and weather are two important ecological indicators of critical water amounts (in arid environments) or heat (in alpine environments) needed for growth, and how growth changes per unit change in the climate variable. For this reason, pivot points and responses are indicators of expected change in vegetation production as the climate changes in the future (Munson et al. 2011). When linked with projections of future climate, these two important ecological variables can be used in quantitative vulnerability assessments as part of the Climate Smart planning framework (Stein et al. 2014), which helps managers set long-range goals achieved by near-term tactical actions (see Section 3.8).

2.10.1 Operational use of pivot points for "now-casts"

This report provides information for estimating vegetation condition using climate data. By tracking the climate variable with the strongest relationship to production in real time relative to its corresponding pivot point, we can determine if weather conditions are below, near, or above predetermined pivot points, and by what amount. In this way, we can use climate data to provide real-time "now-casts" indicating when weather conditions suggest production is likely to be above or below that of the previous year.

The interpretation of climate conditions against a pivot-point value requires consideration of pivot-point precision determined by the standard error around the regression line where it crosses the horizontal axis. The range is larger in polygons where the relationship between climate and vegetation growth is more variable. At the alliance-group level, pivot-point range is caused by variability in plant assemblages in different polygons of the same alliance, as well as variations in soil and site properties. Additional variation is caused by noise in the MODIS sensor near its sensitivity limits in sparsely vegetated environments, errors in the gridded climate data, and vegetation-legacy effects that cause plants to respond differently to the same weather, depending on what happened in the recent past.

All these factors contribute to the observed standard error of a pivot point that brackets weather conditions determining if vegetation is likely performing above or below average.[3] Vegetation performance when weather conditions are within the standard error of the pivot point is best described as "near average." When weather conditions exceed the standard error of the pivot point (above or below the pivot point), there is higher confidence that vegetation production is above or below average.

[3]Although not shown graphically, the standard error of pivot points is available for every polygon (Table S-2 in Thoma 2022).

2.10.2 Lapse-rate adjustment of station data for operational use with pivot points

Operationally, vegetation condition can be reported in real time using weather-station data to calculate daily water balance (see ClimateAnalyzer.org). These data can be compared to a pivot point. The relationships between climate and vegetation in this report used Daymet (a gridded climate dataset). For this reason, before operational reporting commences using weather-station data, a relationship needs to be established between the Daymet climate dataset at a location of interest and the weather station, typically located at park headquarters. Specifically, station temperature and precipitation data should be lapse-rate adjusted for the location of interest if there is more than 500 meters' difference in elevation between the weather station and the site of interest. This is because temperature and precipitation change with elevation.

These considerations have been made in a demonstration project at Capitol Reef National Park, where daily water-balance calculations made from the headquarters weather station were used to determine how conditions at grazing allotments evolve in real-time with respect to the pivot point during the growing season. Weekly updates are sent via an auto-generated e-mail to park staff.

2.11 Phenology metrics and climate drivers

Phenology metrics were determined using the derivative method in the greenbrown R package (Forkel 2015) after smoothing and interpolation to daily values. The derivative method identifies growing-season phenology by recognizing inflections in the annual curves where growth rate accelerates (start), peaks (maximum) and decelerates (end) (Figure 2-4). Length of growing season is the span of time between start and end. Phenology metrics were determined for every alliance polygon but summarized across alliance groups.

Climate drivers of phenology were identified by focusing on start-of-season, because plant growth in spring is most sensitive to climate (Fu et al. 2014). A suite of climate variables was reduced by dropping variables highly correlated with day-of-year (r^2 >0.7) and determining pairwise correlations between remaining explanatory variables. In the case of correlated variable pairs, the more integrative variable was retained. For example, vapor-pressure deficit, solar radiation, and day length were strongly correlated with day-of-year and excluded, but because actual evapotranspiration integrates the effects of solar radiation and day length and was not as strongly correlated with day-of-year, it was retained.

The timing of green-up, peak greenness and its magnitude, senescence, and growing-season length were derived from the full annual curves for each polygon with winter-period minimums truncated to 60% of the winter maximum during the period of record. The cutoff value of 60% was determined via trial and error that both minimized lengths of winter gaps and included growing-season SAVI in every year. This prevented long periods of snow or winter cloud cover from having undue influence on the timing of phenology. The truncation of winter minimum values described above was a simplified version of published methods (Wang et al. 2018).

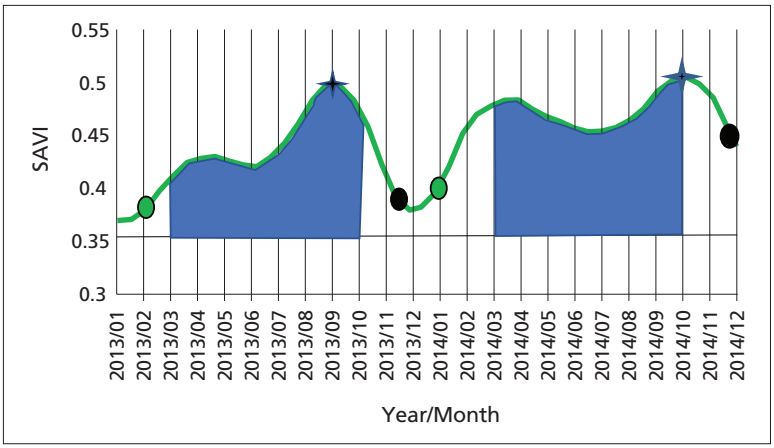


Figure 2-4. Area under the growing-season curve (shaded area) for one polygon over two calendar years. The months used to calculate growing-season production are fixed and include March through October. Phenology metrics are derived using a process that determines inflection points on the annual curves determined by the derivative (rate of change in growth rate) method. In some years, phenology cannot be determined in semi-arid environments due to weak or noisy signals. The fixed growing-season duration used for calculating iSAVI and the start and end of growing season determined from phenology analysis may not always agree. Start of growing season (green point), peak (star), and end of growing season (black point) indicate important annual milestones in vegetation growth over two consecutive years.

Some vegetation types (primarily conifer and shrublands) in the western US exhibit a peak satellite-observed greenness (measured using the normalized difference vegetation index, or NDVI) in winter months that is an artifact of shadows when the angle between reflected sunlight and the satellite is large (Norris and Walker 2020). It is unknown how this issue affects SAVI. The bands used to calculate SAVI are the same as those used to calculate NDVI, but a soil-correction factor is applied in SAVI to account for variable background reflectance. There is currently no known solution for resolving this shadowing effect. Thus, polygons-year combinations that exhibit winter peaks cannot be used in phenology analysis. These polygon-years are screened by determining if their annual peak of greenness occurs during winter months, defined as the period between November 1 and April 1. If any winter peaks in SAVI occurred during any year of the study period, the polygon-year was flagged and removed from analysis for that year. This allowed us to retain polygon-year combinations that did not result in spurious satellite observations, rather than removing a polygon from analysis if only a few years failed the screening rules.

Two statistical methods were used to identify climate drivers of start-of-season, or green-up. This helped identify multiple lines of evidence for drivers if both methods yielded similar results. The first method relied on preconceived notions of phenology drivers. The second method, a machine-learning approach, let the data tell the story. In the first method, a priori models thought to be important in western rangelands were identified (Table 2-4) (St. Peter 2015). These models were competed against one another to determine top models of green-up.

Second, the random-forests machine-learning technique was used to determine important drivers of phenology and provide predictive models of the start of the growing season (Breiman 2001). Random forests is a learning method for regression that constructs a multitude of decision trees until the optimum combination of factors describing a result is obtained. In this case, a priori candidate models were not specified beforehand. Rather, the random-forests algorithm used climate and water-balance variables to identify a top model using a subset consisting of 70% of the data, which was randomly selected. The random-forests algorithm generated 2,000 decision trees with a maximum of four variables randomly chosen per split, which is the recommended number for a model testing the utility of 12 predictors. Sampling was done with replacement, which is the default setting.

The top model was validated against a hold-out dataset consisting of the remaining 30% of observations. Variable importance plots were used to identify which variables had the most predictive power. They consisted of percent increase in mean square error (%IncMSE), which is a measure of model improvement when adding each variable to the model, and increase in node purity (IncNodePurity), which is the difference in residual sum-of-squares in regression with or without each variable.

After model fitting with the training data, predictions for the start of the growing season were made using the validation dataset, where start-of-season predictions could be compared against observations in the validation dataset. The accuracy of predictions for start-of-season were characterized by the mean absolute error (MAE), which is the mean value of differences between predictions and observations with units of days. The MAE is the average magnitude of error in days without specifying direction of error, thus specifying the average plus or minus error rate of predictions.

Table 2-4. A priori models of climate influence on timing of green-up (start of the growing season).

Model[1]	Climate variable[2]											
	AET	GDD	P	RAIN	D	VPD	Srad	Tmax	Tmin	VP	SOIL	Packmelt
AET	X	–	–	–	–	–	–	–	–	–	–	–
GDD	–	X	–	–	–	–	–	–	–	–	–	–
P	–	–	X	–	–	–	–	–	–	–	–	–
RAIN	–	–	–	X	–	–	–	–	–	–	–	–
D	–	–	–	–	X	–	–	–	–	–	–	–
VPD	–	–	–	–	–	X	–	–	–	–	–	–
Srad	–	–	–	–	–	–	X	–	–	–	–	–
Tmax	–	–	–	–	–	–	–	X	–	–	–	–
Tmin	–	–	–	–	–	–	–	–	X	–	–	–
VP	–	–	–	–	–	–	–	–	–	X	–	–
GDD_P	–	X	X	–	–	–	–	–	–	–	–	–
GDD_RAIN	–	X	–	X	–	–	–	–	–	–	–	–
GDD_SOIL	–	X	–	–	–	–	–	–	–	–	X	–
GDD_AET	X	X	–	–	–	–	–	–	–	–	–	–
Srad_AET	X	–	–	–	–	–	X	–	–	–	–	–
Srad_P	–	–	X	–	–	–	X	–	–	–	–	–
Meltd	–	–	–	–	–	–	–	–	–	–	–	X
Meltd_Srad	–	–	–	–	–	–	X	–	–	–	–	X
Meltd_P	–	–	X	–	–	–	–	–	–	–	–	X

[1]Models were competed via generalized linear mixed-effects modeling to identify best correlates with green-up. All climate variables were summed or averaged from January 1 to the day of year when green-up began. AET = cumulative actual evapotranspiration (mm); GDD= cumulative growing degree days (Deg. C), P = cumulative precipitation (mm), RAIN = cumulative precipitation as rain (mm), D = cumulative deficit (mm), VPD = sum vapor-pressure deficit (Pa), Srad = average solar radiation (W m^2), Tmax = average daily maximum temperature, Tmin = average daily minimum temperature, VP = average vapor pressure (Pa), SOIL = average soil moisture (mm), Meltd = day of year when snowpack melt-out was complete.

[2]X = variable used in model, – = variable not used in model.

3 Results and Discussion

3.1 Completeness of satellite observations

Completeness of growing-season observations was near 100% across all targets for the 20-year period of analysis. Clouds, aerosols, and snow cover reduced the average completeness of high-quality observations to 80–90% of potential observations on an annual basis across all polygon targets. The average completeness for annual and seasonal observations was 84.9% and 98.3%, respectively. The minimum completeness for any single polygon on an annual or seasonal basis was 60.6% and 73.2%, respectively.

Before analyzing satellite observations with climate and water balance, gaps were linearly interpolated prior to smoothing, which removed high-frequency noise in the timeseries that could not be removed via quality screening. There were no missing climate or water-balance data.

3.2 Timeseries

At Colorado NM, SAVI observations reflected differences in vegetation response to climate that were apparent when observations were organized by NCPN alliance group (Figure 3-1). Some polygons were generally greener than others (indicating higher productivity and biomass accumulation), but within alliance groups there was considerable variation. That variation can be due to species assemblages within the alliance and site properties that modify the local effects of climate. Some outlier polygons within alliance groups might need to be considered separately in future analyses if interest is in the central tendency of an alliance group.

Gap-filled and smoothed timeseries of 16-day SAVI illustrated a broadly similar upward trend in all alliance groups during the study period (Figure 3-1). However, the alliance groups showed a high degree of variability in amplitude and timing of peak values. It was typical for some polygons in an alliance group to exhibit "outlying character," indicating they were not a good fit with other polygons in the group. This issue was most notable in the Disturbed and Mixed Montane Shrubland alliance groups. This could happen for several reasons, including grouping vegetation types into alliance groups, which forces some dissimilarity among group members; misclassification in the vegetation-mapping process; or, less commonly, disturbance since mapping was completed that resulted in a different vegetation response signal than what is characteristic of other polygons in the alliance group.

It is important to evaluate "outlier" polygons carefully, with consideration given to potential effects of land use or disturbance. For instance, timeseries in the Geology alliance group were surprising because based on the alliance-group name, little if any vegetation should have been present. Strong seasonality and relatively high-amplitude SAVI suggested that (1) there was some vegetation growing in areas mapped as geology, or (2) there was some pixel overlap of polygon boundaries picking up vegetation signals that could not be removed despite the rigorous screening criteria. Without further investigation, it is not possible to know which of these issues, or a combination, was in play.

3.3 Trends in production

Significant upward trends ($p < 0.05$) in maximum annual SAVI were found in 99.5% of polygons analyzed. Only 0.5% of polygons decreased in maximum annual SAVI. The greatest area of mean annual and maximum annual iSAVI increase occurred in the Pinyon-Juniper and Juniper woodlands, representing 76% of the area analyzed in and near Colorado NM. The only decrease in production was a downward trend in annual maximum iSAVI that occurred in Perennial Exotic Grassland (Table 3-1, Appendix A, Figure A-1). This alliance group represented one half of one percent of the area analyzed in and near the park. The downward trend in production may be due to management interventions that can be verified by park staff.

Significant upward trends in mean annual SAVI occurred in 100% of polygons analyzed (Table S-3 in Thoma 2022). Significant upward trends in growing-season iSAVI,

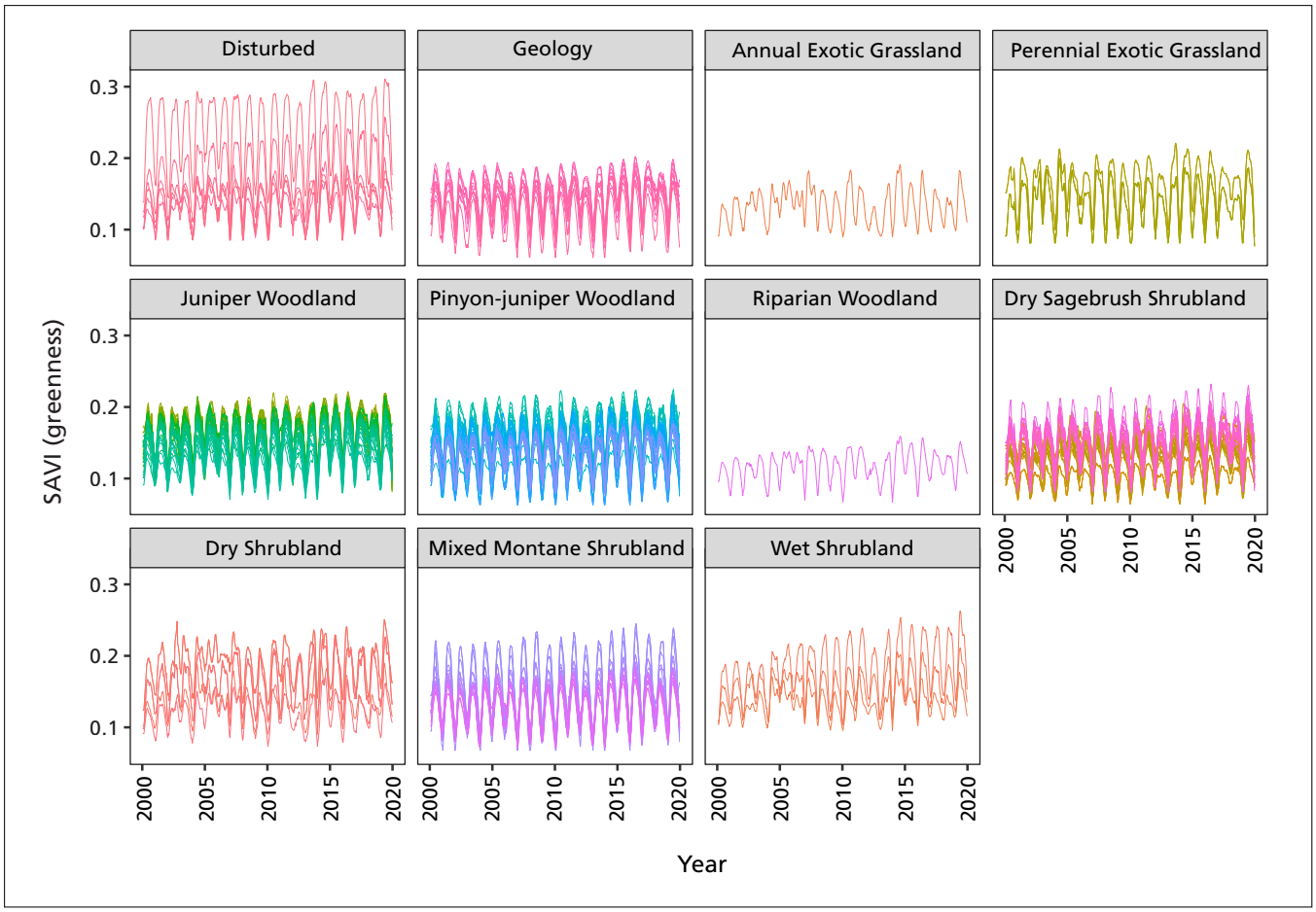


Figure 3-1. Soil-adjusted vegetation index timeseries by alliance group for 183 polygons analyzed for 2000–2019. Colors help differentiate individual polygon timeseries traces. Each polygon timeseries was filtered to include only high-quality pixel values, with minimum values truncated to winter minimum, gap-filled, and then smoothed with a Savitsky-Golay moving-window filter to remove high-frequency noise. Analysis was limited to polygons of >8.3 hectares. A single-line trace indicates either all polygon units have similar seasonality and interannual variation, or only one polygon of the alliance group was sampled.

Table 3-1. Amount of park area with increasing (pos) or decreasing (neg) trends in mean annual or maximum annual SAVI by alliance group.

Alliance group	Annual trend[1]		Hectares	# of polygons	% of park area[2]
	Mean	Maximum			
Pinyon-Juniper Woodland	pos	pos	4,949.8	45	48.3
Juniper Woodland	pos	pos	2,821.7	46	27.6
Dry Sagebrush Shrubland	pos	pos	1,065.6	40	10.4
Disturbed	pos	pos	636.5	6	6.2
Mixed Montane Shrubland	pos	pos	307.8	19	3
Geology	pos	pos	165.3	11	1.6
Dry Shrubland	pos	pos	102.2	6	1
Wet Shrubland	pos	pos	89	3	0.9
Perennial Exotic Grassland[3]	pos	neg	53.1	3	0.5
Perennial Exotic Grassland[3]	pos	pos	28.3	2	0.3
Annual Exotic Grassland	pos	pos	10.1	1	0.1
Riparian Woodland	pos	pos	11.4	1	0.1

[1]Production estimated as linear trend in annual or maximum annual SAVI. [2]Percent area was calculated as the ratio of total park area analyzed to area of polygons where trends were significant ($p<0.05$). [3]Some areas of Perennial Exotic Grassland increased in both mean and max SAVI, whereas others increased in mean, but decreased in maximum SAVI.

determined via simple linear regression, were also found for most alliance groups—with the exception of both annual and perennial exotic grasslands, which trended upward but were not statistically significant (p value = <0.05) (Figure 3-2).

As a subset of the annual period, the growing-season iSAVI focused on March through October, revealing climate-driven temporal patterns in all alliance groups. Decreases in growth were most extreme in 2003, 2009–2010, and 2012, corresponding with dry periods, followed by recovery that peaked in 2005, 2011, and 2014–2016, corresponding with wet periods. A pronounced downward trend occurred in 2016–2018, during a drought, with recovery in 2019 to above-average levels of production (Figure 3-2), demonstrating the resilience of Colorado NM vegetation production to drought stress of this magnitude.[1]

Evaluation of simple linear-regression slopes indicated that Wet Shrubland increased in greenness at nearly twice the rate of any other alliance group over the 20-year period of observations. There was an upward trend

[1]This finding does not imply vegetation composition was not affected or did not change. Composition change cannot be determined from this analysis.

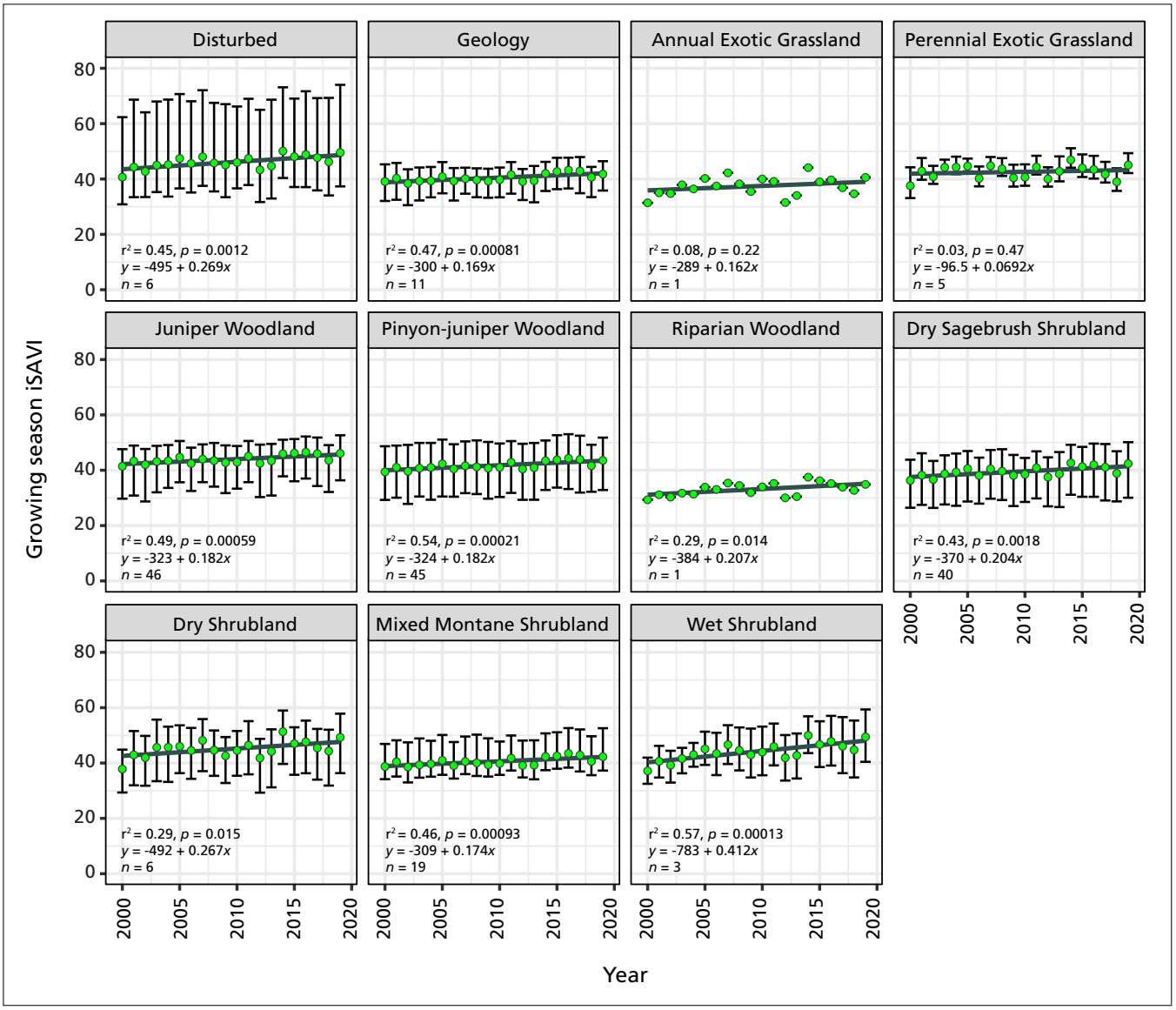


Figure 3-2. Trends in mean growing-season iSAVI by alliance group, determined via simple linear regression. Bars are standard error among polygons within each alliance group. n = number of polygons analyzed in each alliance group, r^2= coefficient of determination, p = p-value, y = growing season iSAVI, x = year.

in growing-season production over those 20 years, with areas in the southern and central portions of the park showing the strongest upward trend (Figure 3-3; see Figure 3-2 for slopes).

The mostly upward production trends for the woody-plant alliance groups was consistent with other research findings on the Colorado Plateau, which showed shrubs as dominant where winter soil moisture was high and seasonal temperature variable, and grasses as dominant where summer moisture was available (Gremer et al. 2018). That study pointed out that rising temperature and increasing temperature variability, associated with climate change, will result in conditions more favorable to shrubs because the change in temperature is expected to overwhelm the role of available soil moisture by late century. It also noted that shrubs are better adapted to large temperature fluctuations than grasses are. This study showed a stronger relationship between vegetation production and water availability than between production and temperature across alliance groups. Longer-term changes due to temperature trends and variability can be explored in the future. A review of woody-plant proliferation (Barger et al. 2011) found that seasonality of precipitation, land use, and atmospheric CO_2 concentrations were all important drivers of woody-plant expansion in semi-arid regions where annual PET was greater than annual P, as is the case at Colorado NM.

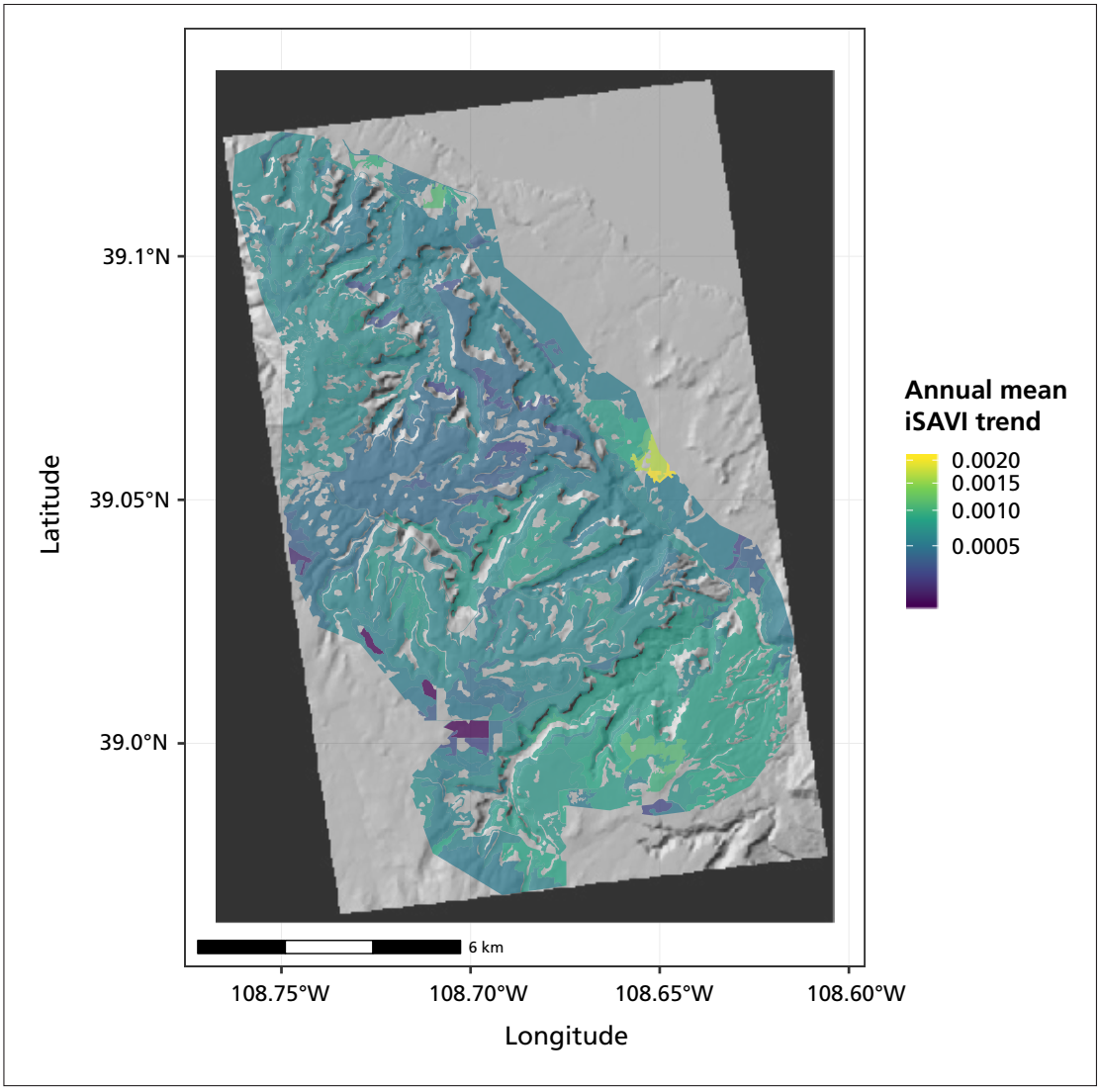


Figure 3-3. Spatial pattern of trends in mean annual iSAVI. Trend is average change in iSAVI per year for 2000–2019.

3.4 Climate relations

3.4.1 Qualitative patterns in annual precipitation and production

Between 2000 and 2019, precipitation increased parkwide, as did most measures of production in this semi-arid, water-limited environment. Improved water-use efficiency due to the fertilization effect of rising atmospheric CO_2 concentrations may explain some of the increase in production, but precipitation increase was likely the largest contributor (Sorokin et al. 2017). Plotting the iSAVI difference from long-term average iSAVI with precipitation showed a relatively tight temporal correspondence of interannual variation in annual precipitation and production (Figure 3-4), whereas CO_2 concentrations increased monotonically on an annual basis during the study period (https://gml.noaa.gov/ccgg/trends/).

While peaks and valleys in the timeseries roughly coincided, there were differences in the magnitude of vegetation response to precipitation, and evidence of a response delay that varied by alliance group. iSAVI peaks in annual production corresponded with interannual precipitation peaks in most alliance groups, but a lag in vegetation response can be caused by legacy effects of vegetation condition in prior years that carry over to subsequent years.

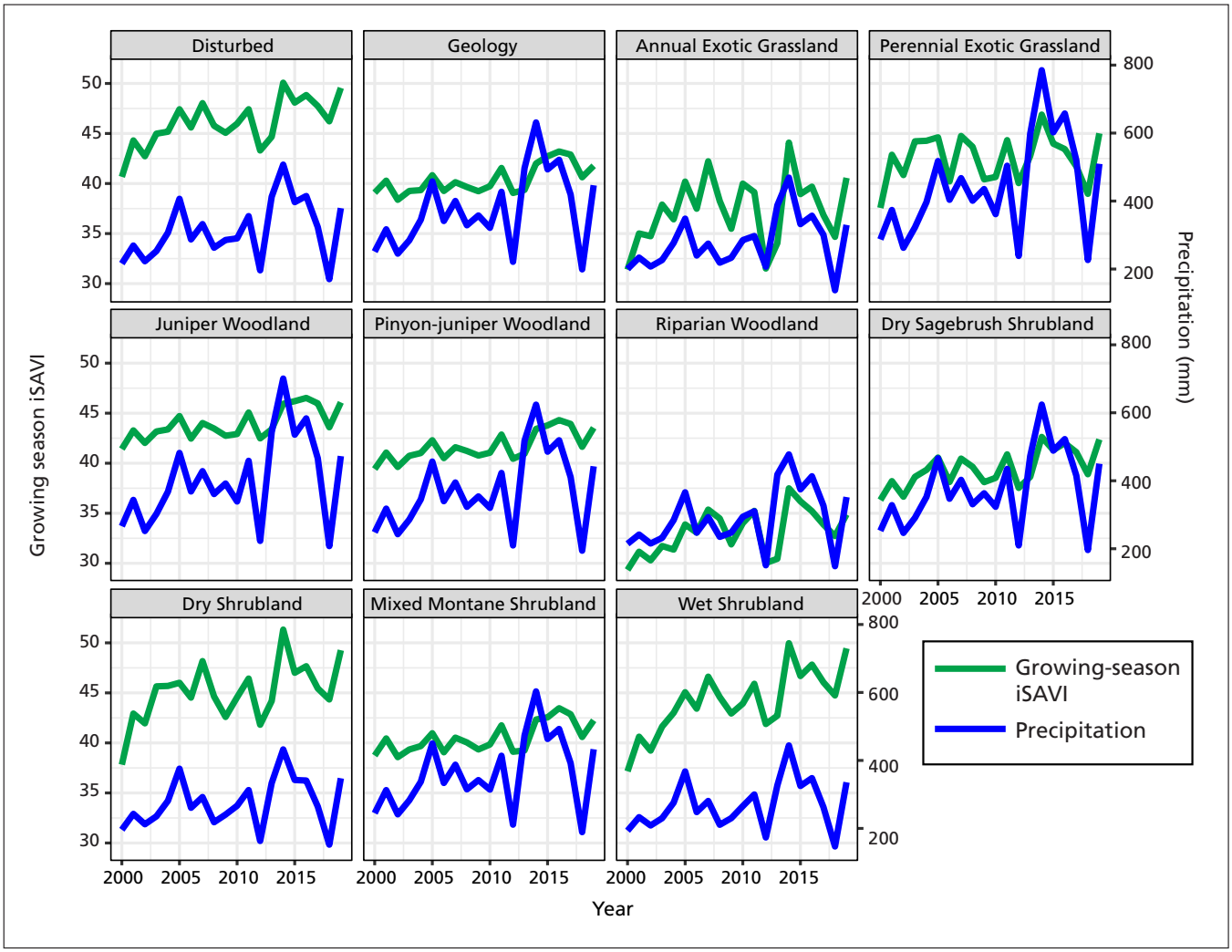


Figure 3-4. Co-variation in growing-season production, estimated as the iSAVI between March and October and water-year cumulative precipitation averaged within alliance groups, demonstrating the link between climate and vegetation production at Colorado NM at the annual scale. The timeseries shown here is intended to illustrate precipitation as a master climate driver of production in semi-arid environments. Statistical analyses of the relation of production to precipitation and all other climate variables is the subject of following sections.

Such legacy effects have been noted in semi-arid vegetation response to precipitation where prior conditions set the stage for current-year production. For example, a wet year following a drought may not be as productive as a wet year following an average precipitation year due to legacies in tillers, stems, root density, and seed production, which are limited in a drought (Noy-Meir 1973; Thoma et al. 2016). Because of prior conditions, the largest peaks in annual production do not always coincide with the largest peaks in annual precipitation.

In addition, the timing and magnitude of response to precipitation are affected by the structural and physiological traits of plants, including rooting depths, stomatal control of gas exchange, leaf morphology, annual or perennial life cycle, and the site conditions where they grow (Munson et al. 2015). Plant physiology may explain why peaks and valleys in annual production are more pronounced in grasslands and shrublands, but muted in woodland alliance groups. Additionally, evergreens that retain leaves for multiple years have lower-amplitude seasonal cycles (Yang et al. 2019). Grasslands are generally more responsive to interannual weather variation, while woodlands with deeper rooting systems can be buffered from short-term droughts. Additionally, variation in the magnitude of vegetation response to variation in precipitation could be due to higher runoff in high precipitation years if a large proportion of precipitation fell in a few storm events.

Collectively, the response of vegetation to interannual variation in weather is complex. The study of these interactions across space and time is greatly aided by the high frequency of satellite observations coupled with continuous daily climate observations over the same period of time. Organizing the remotely sensed observations by management-relevant vegetation types provides insight to differential responses of vegetation to climate—even in a relatively small area, such as a single park unit. Some of these interactions are explored in the remainder of this report.

3.4.2 Single-variable drivers of production

At the park level, relationships between growth and climate variables were generally weak due to the highly variable response relationships with climate across vegetation types. However, when examined by alliance groups, better relationships emerged (Figure 3-5).

Vegetation production in most alliance groups was correlated with multiple aspects of climate. Across alliance groups at Colorado NM, the water-abundance variables (P, RAIN, SNOW, AET, SOIL) were positively correlated with annual production. Variables representing heat, unmet water need, or atmospheric dryness (T, GDD, D, VPD) were negatively correlated with production. Within alliance groups with multiple polygons, there was variation in the strength of relationships, with climate variables indicated by error bars in Figure 3-5 (also see Table S-2 in Thoma 2022). This can be caused by variation in species assemblages and abundances that differ among map units of the same alliance.

Generally, annual precipitation, rain, and soil moisture had the strongest positive relationships with production in most alliance groups. Deficit had the strongest negative relationship with production (Figure 3-5). However, on an annual basis, most of the water-balance variables were no better correlated with production than annual precipitation. Every polygon that had a significant relationship with a temperature variable (PET, T, GDD) exhibited a decrease in production with warmer temperature (Table S-2 in Thoma 2022). This is typical in water-limited environments, where warmer temperature increases evaporative demand that is often not met by available water.

Some vegetation types respond more strongly to seasonal weather than annual conditions. For these plants, warming temperatures in the spring initiate growth. Then, as soil moisture decreases throughout the growing season, other variables, such as water deficit, typically take on greater

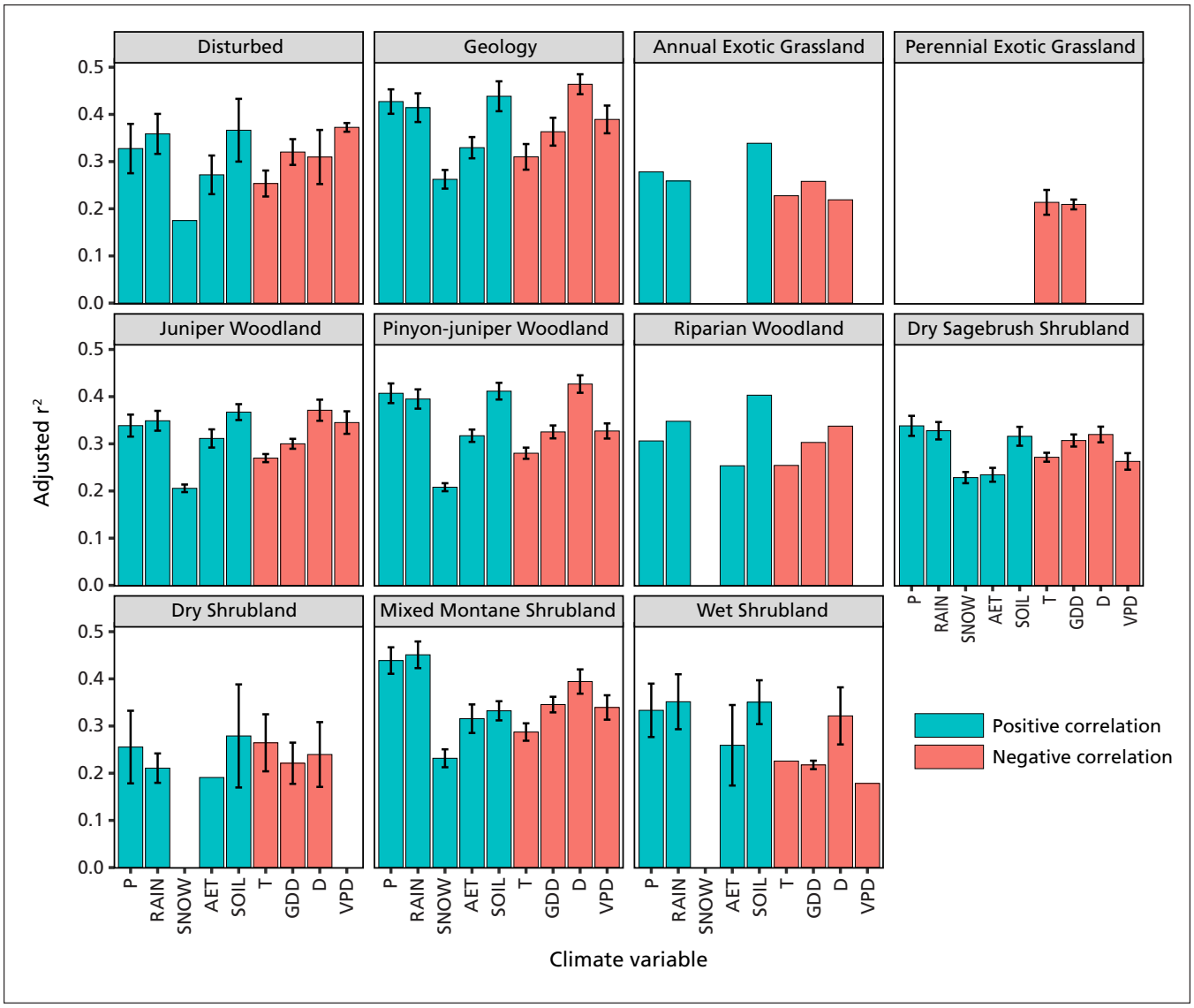


Figure 3-5. Relationships between water-year climate variables and first difference of growing season iSAVI, 2000–2019. Bar height is the mean variation in iSAVI explained by variation in climate or water-balance variable on the x-axis. Bars are standard error. Blue bar color indicates positive correlation. Red bar color indicates negative correlation. P = precipitation (mm), RAIN = precipitation as rain (mm), SNOW = precipitation as snow (mm of water), AET = actual evapotranspiration (mm), SOIL = average soil moisture (mm), T = average temperature (°C), GDD = growing degree days (°C), D = water deficit (mm), VPD = vapor-pressure deficit (Pa).

importance. Depending on the species, most growth may occur in spring or late summer. Thus, the timing of seasonal water and energy availability may be more important to annual vegetation production than annual water and energy availability (Barnes et al. 2016). These kinds of seasonal responses to weather are difficult to characterize on an annual basis with a single variable because the important climate drivers switch seasonally and there may be long-term memory effects from earlier growing seasons that affect current-year production (Thoma et al. 2016).

In other words, multiple aspects of climate and water balance act over both short and long periods to affect annual production. Thus, a simple linear-regression approach that considers single-variable influences on production over the course of an entire year is an oversimplification of important vegetation–climate feedbacks. This may explain coefficients of determination of <0.5 (Figure 3-5), which may seem unimpressive but are similar to results of species responses to single variables in plot studies (Munson et al. 2011).

Nevertheless, there is value in determining single-predictor regressions because they can identify important drivers that result in increases or decreases in annual production and represent a practical way to derive critical water needs and drought-stress indicators (Munson et al. 2016; Thoma et al. 2019) that can be tracked using data from weather stations. Which climate variable is the best single-variable indicator of annual vegetation production can be determined by alliance group from visual inspection of Figure 3-5 (tallest bar = best relationship), or by polygon from Table S-2 in Thoma (2022).

Annual precipitation at Colorado NM was generally among the climate or water-balance variables most strongly correlated with annual production, so it is used in the following sections that further explore climate/vegetation relationships. Multiple predictors and time lags of annual production response are considered in a later section.

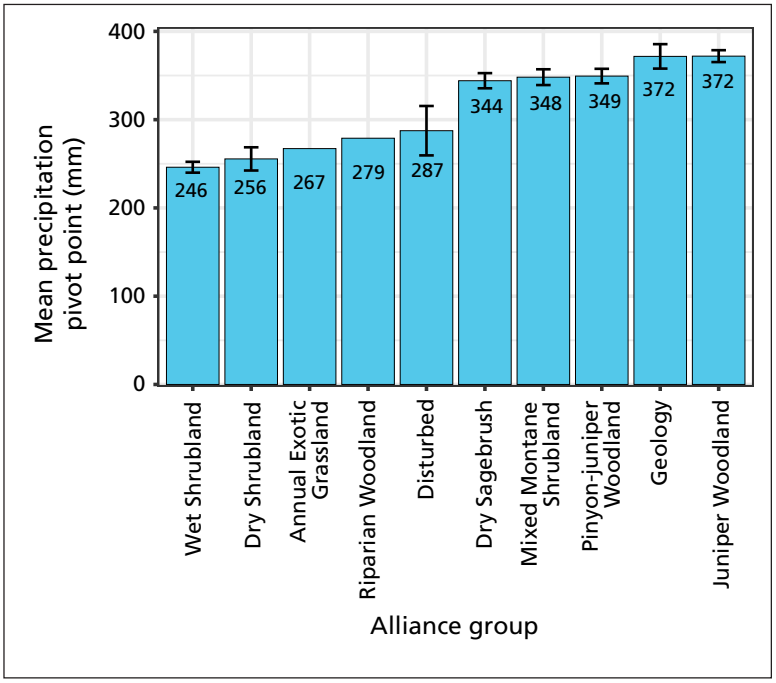


Figure 3-6. The mean precipitation pivot-point values shown here represent critical water needs for the different alliance groups. Standard error bars indicate range in variability of pivot points among polygons of an alliance group if more than one polygon of an had a statistically significant relationship ($p < 0.05$) with precipitation. Pivot points identify the critical water need that achieves average production for each alliance group.

3.5 Pivot points

3.5.1 Pivot points indicate drought tolerance

Plant species with smaller pivot points for water-abundance variables (e.g., precipitation, rain, snow, actual evapotranspiration, soil type) demonstrated a higher degree of drought tolerance, because less water was needed to achieve above-average production (Thoma 2022, Tables S-2 and S-4).[2] Conversely, larger pivot points for variables representing heat, unmet water need, or atmospheric dryness indicated a higher degree of drought tolerance, because more drought was tolerated before production drops below average.

At Colorado NM, the most drought-tolerant alliance group (i.e., the one with the lowest precipitation pivot point) was Wet Shrubland (Figure 3-6). The low pivot point of Wet Shrubland, which exists at the lowest elevations, may be due to accumulation of water from upslope positions that make this habitat less droughty in low-precipitation years. Because this habitat collects water from upslope, it can perform above average even when annual precipitation is low. The water-balance model used in this report does not accumulate flow from upslope positions, so it cannot account for the process of flow accumulation that is likely the cause of drought tolerance in this alliance group.

Exotic grassland types and other shrublands were more drought-tolerant than the Juniper or Pinyon-Juniper woodland groups, likely due to seasonal growth traits and dormancy during the driest times of year.

Pivot points for a specific geographic area are related to but not always equal to the

[2]The pivot points differed among water-abundance variables because they represent different periods and magnitudes of water availability. For example, soil moisture is only a fraction of total precipitation (P), because some P runs off and is not available to plants. Similarly, rain and snow represent fractions of total P that supply water for vegetation at different times of the year. Thus, each variable represents a different "pool" and phase of water (solid, liquid, or gas) that may be seasonally active or present during different seasons.

mean annual climate value where a pivot point is determined. For this reason, spatial patterns in pivot points often follow precipitation and temperature gradients with elevation. This can be seen in the order of alliance-group pivot points at Colorado NM. Lower-elevation alliance groups have lower precipitation pivot points, suggesting they are the most drought-tolerant (see Figure 3-6).

There are caveats to this generalization. At Colorado NM, the least drought-tolerant alliance group was Juniper Woodland, which requires the most precipitation before it switches from below- to above-average condition (see Figure 3-6). This finding was unexpected, because pinyon trees are generally thought to be less drought-tolerant than juniper trees on the Colorado Plateau, where juniper usually grow at lower and drier elevations than pinyon (Dickman et al. 2015; Gottfried et al. 1995). Alliance groups consist of many species and, in this case, include overstory and understory components. This could explain the counterintuitive finding if the understory beneath juniper trees was less drought-tolerant than those beneath pinyon at this park.

An alternative explanation involves the soil properties where the trees grow. On average, Juniper Woodland required more precipitation (pivot point = 371 mm) for above-average performance than Pinyon-Juniper Woodland (pivot point = 349 mm). This suggests the pinyon-juniper group is more drought-tolerant than the juniper group, contradicting the idea that juniper grow in drier conditions than pinyon trees. But in this case, the soils of Pinyon-Juniper Woodland have a higher water-holding capacity (42 mm) than those of the Juniper Woodland (35 mm). This may result in more soil-water storage in the pinyon-juniper group even though it receives less annual precipitation. A study of pinyon mortality in the southwestern US found that found soil properties explained more than 70% of the spatial pattern of pinyon mortality caused by the 2003–2004 drought (Peterman et al. 2012). Interactions between vegetation and precipitation that are modified by site conditions affecting water storage, such as soil properties, are an important aspect of this study.

3.5.2 Spatial patterns of drought tolerance

The map of precipitation pivot points shows that the amount of moisture required to increase production above that of the previous year generally increased with elevation (Figure 3-7). This pattern stemmed from the distribution of vegetation groups that generally followed changes in mean climate values. More specifically, it reflected the tendency of water availability (soil moisture) to increase with elevation, and unmet water need (deficit) to decrease with elevation (Stephenson 1998).

3.5.3 Pivot points for other climate variables

Pivot points for other climate and water-balance variables generally reflected the average climate conditions where alliance groups were found (Figure 3-8, Appendix A, Figure A-2). However, the range in pivot points within alliance groups, and the variation in species assemblages within and between polygons of each alliance group, reflected some variation beyond a pattern purely determined by elevation gradient. In semi-arid environments like Colorado NM, pivot points for variables AET, P, SOIL, Rain, and Snow are generally lower than the pivot point for D, an indicator of drought. This is because vegetation in these environments is adapted to handle relatively low water availability and high drought stress.

All results shown here are statistically significant. For this reason, any of these alliance group-level pivot points can be compared against historic, present, or future projected growing-season climate conditions to determine if those conditions are likely to result in below- or above-average vegetation production.

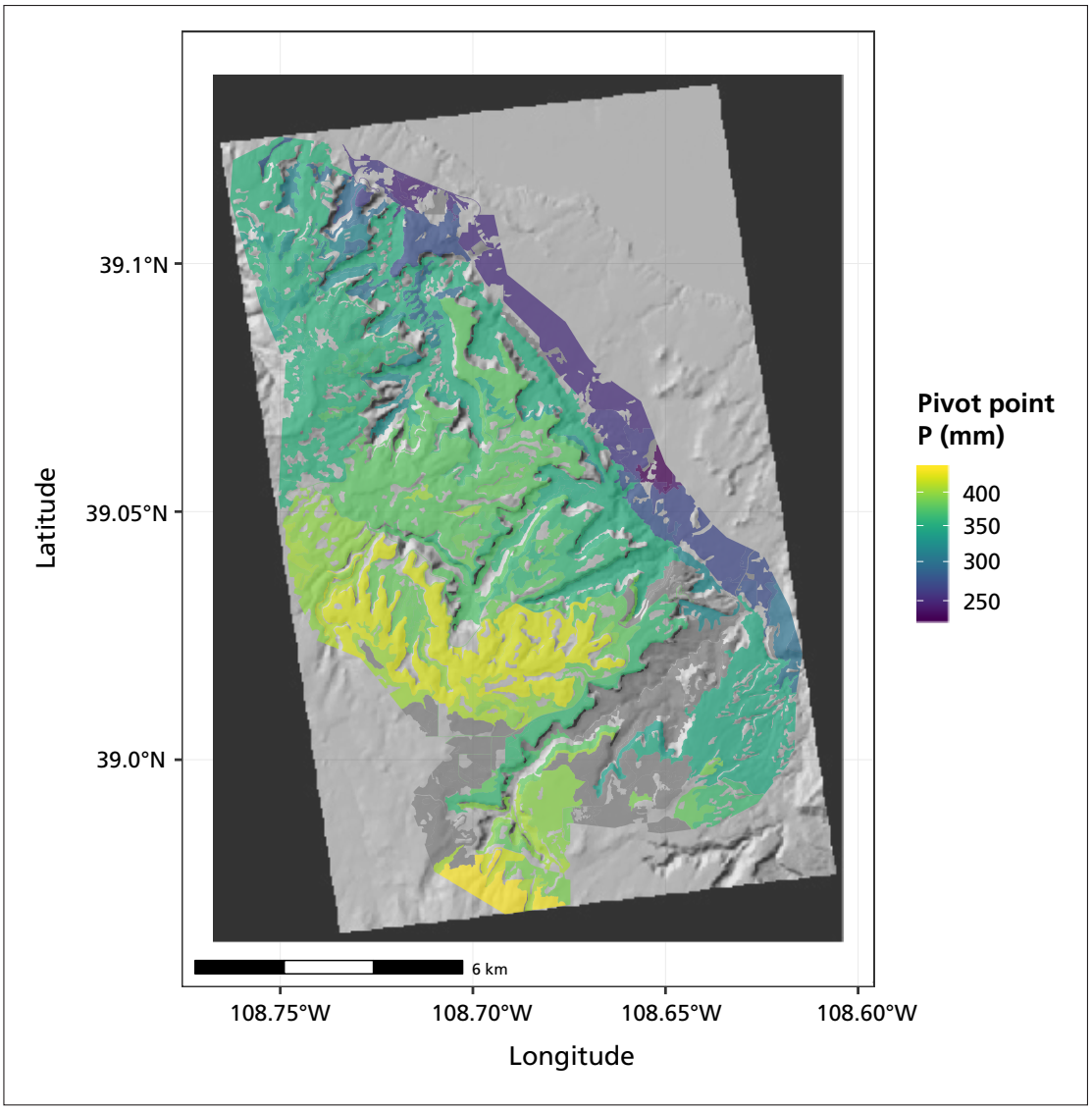


Figure 3-7. Precipitation pivot points for polygons with a significant relationship (p-value <0.05) between water-year annual precipitation and change in annual vegetation production, assessed as the interannual difference in iSAVI. The mean precipitation pivot-point values shown here represent spatial patterns in the critical water needs of vegetation.

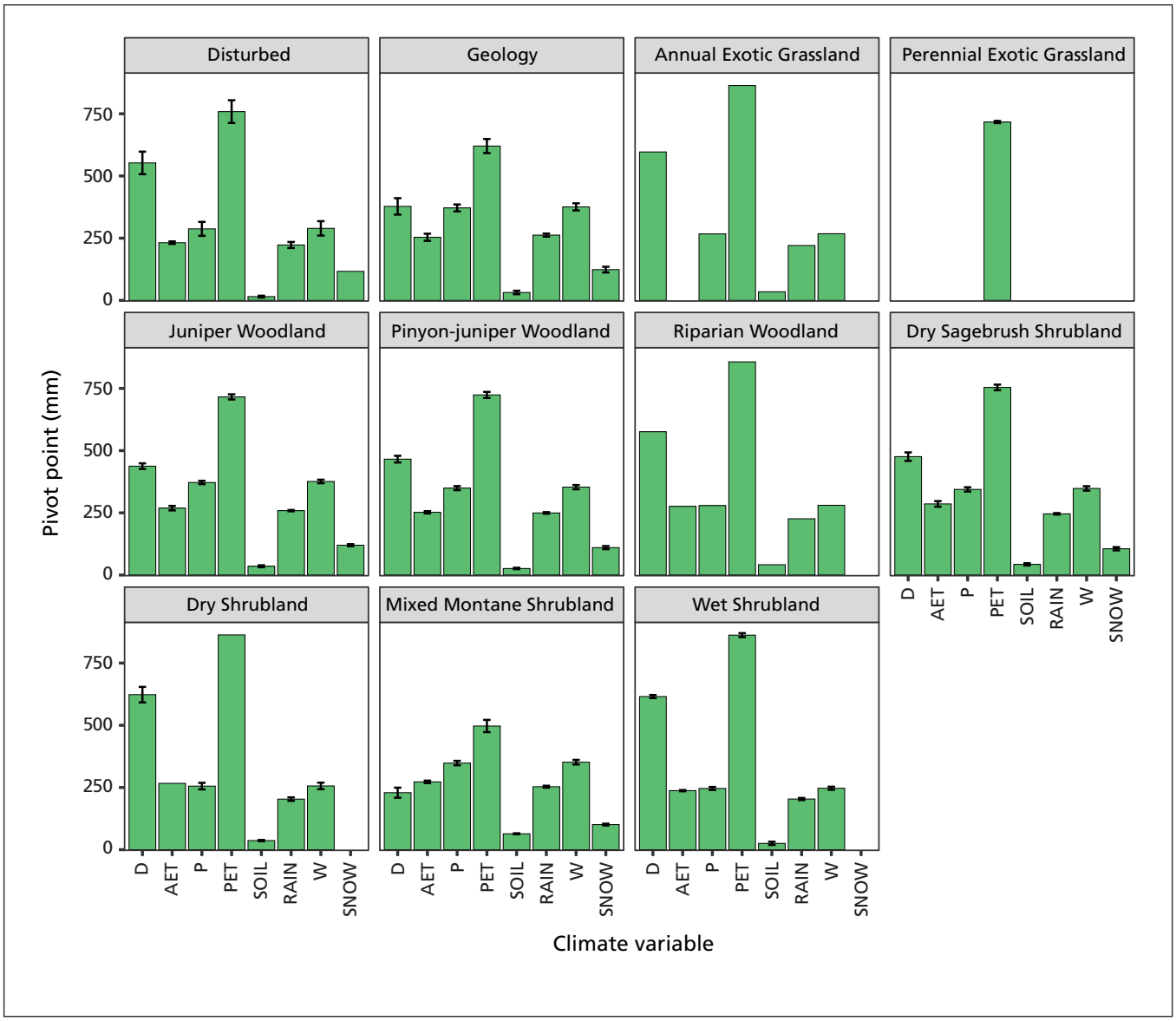


Figure 3-8. Significant ($p < 0.05$) water-related pivot points by alliance group. See Thoma (2022), Tables S-2 and S-4 for those pivot points. The magnitude of each pivot point reflects generally average conditions for polygons in each alliance group. The mean pivot-point values are the critical values where annual production switches from below to above average (relative to previous year) for the different alliance groups. P = precipitation (mm), RAIN = precipitation as rain (mm), SNOW = precipitation as snow (mm of water), AET = actual evapotranspiration (mm), SOIL = average soil moisture (mm), D = water deficit (mm).

Pivot points for each climate variable by polygon are provided in Table S-2 of Thoma (2022), and by alliance group in Table S-4. These can be used with data on climate exposure to identify conditions conducive to above- or below-average growth—information useful in vulnerability assessments associated with Climate Smart Conservation planning (Stein et al. 2014) (see Section 3.8).

3.6 Vegetation response

3.6.1 Vegetation response and climate sensitivity

When they interact with climate, plant traits determine which species grow under different conditions of water availability. The result is a spatial organization of alliance groups that reflect local climate and the sensitivity of vegetation to climate (Figure 3-9). The interactions between plant traits, site characteristics, and climate-determined patterns of vegetation distribution in the past will determine how vegetation in Colorado NM is shaped by climate in the future.

Vegetation response is a formal component of vegetation vulnerability assessments used in Climate Smart Conservation (Stein et al. 2014b). The importance of response is related to the need to understand which

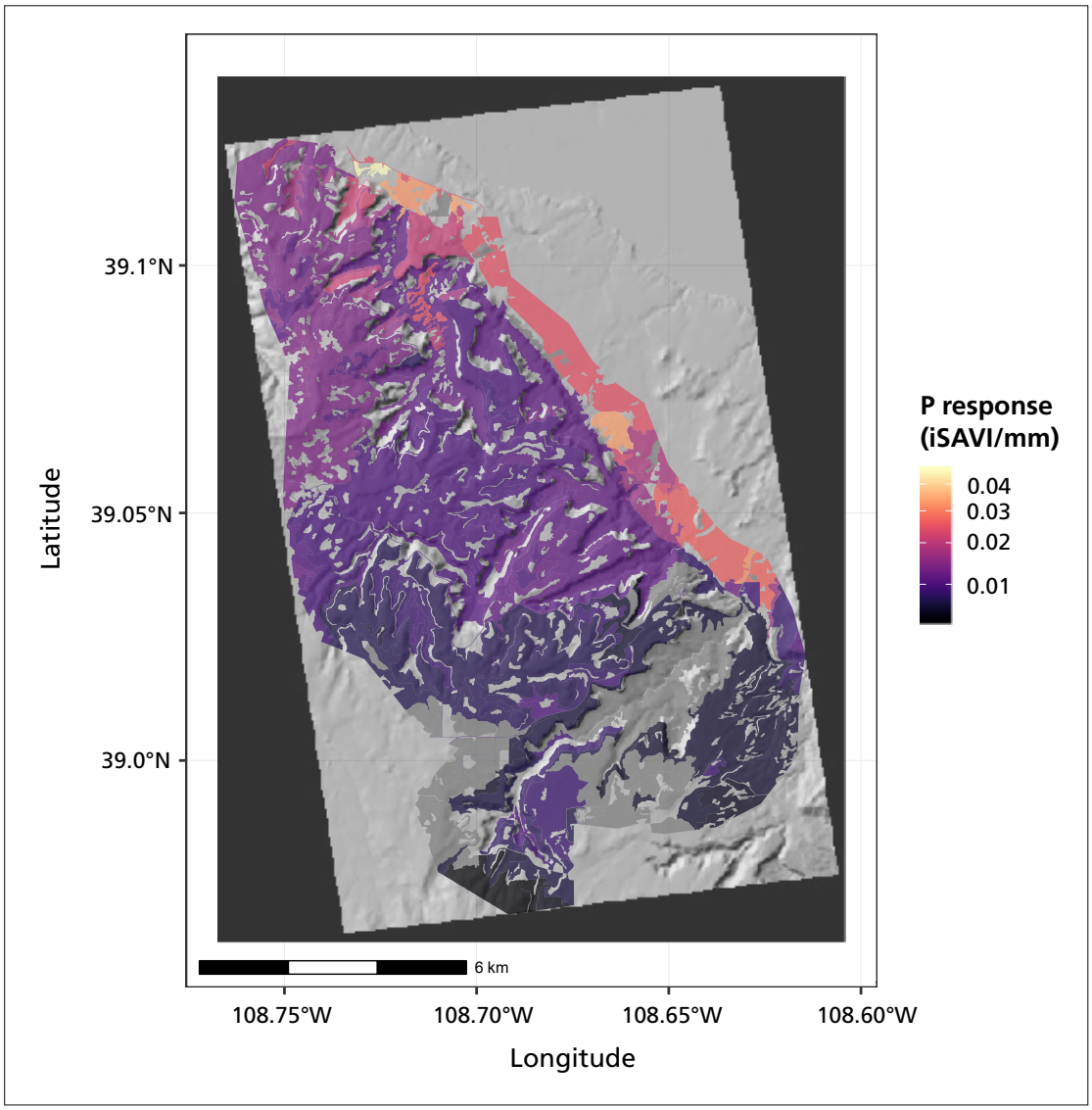


Figure 3-9. Responses of different vegetation alliance groups to precipitation. Standard error bars indicate range in variability of responses among polygons of an alliance group if more than one polygon of an alliance group had a statistically significant relationship ($p < 0.05$) with precipitation. Polygons most sensitive to precipitation were in the northern portion of the monument.

vegetation groups may respond sooner or more strongly to a given amount of climate exposure. While a unit change in iSAVI is not quantitatively linked to vegetation cover or biomass in this analysis, it is representative of change in both of those attributes. In this way, the iSAVI response indicates where change is likely to happen first and fastest as the climate shifts.

At Colorado NM, Annual Exotic Grassland had the highest response rate and sensitivity to annual precipitation (Figure 3-10). Juniper Woodland was least sensitive. Alliance-group sensitivities to other water-balance variables can be found in Appendix A, Figure A-3.

Generally, there was a pattern across the monument in which sensitivity increased at lower elevations, where precipitation was least. This was partly due to vegetation structure: the woodland alliance groups occur at higher elevations, grasslands and shrublands at lower elevations. If disturbance, such as fire or forest disease, replaced the woodland alliance groups with grassland or shrubland, then the response would shift to reflect the dominant vegetation structure.

Higher elevations dominated by slow-growing and slow-responding Juniper and Pinyon-Juniper woodlands were less sensitive to variation in annual precipitation. This partly explains the pattern of response, also related to duration of greenness, in which species with longer seasons of green leaves were less responsive to weather or water balance.

Responsiveness generally increased from high to low elevation along a decreasing precipitation gradient. Annual Exotic Grassland and Dry Shrubland responded most rapidly when water was abundant. In years when precipitation is higher than normal, vegetation in the Disturbed and Annual Exotic Grassland groups could become management concerns because their rate of response to precipitation input is greater than that of native vegetation.

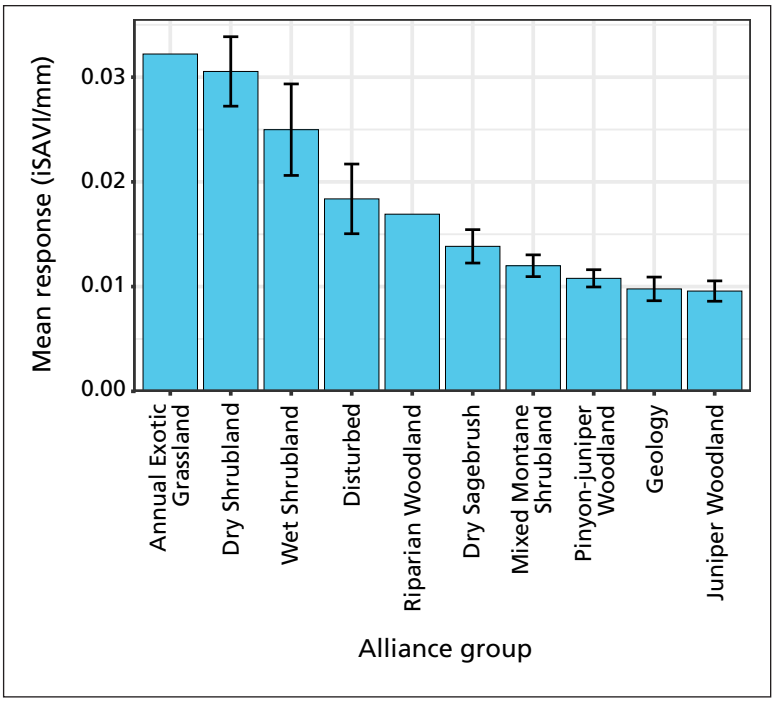


Figure 3-10. Sensitivity of growing-season vegetation production to annual water-year precipitation. This figure shows which vegetation types will experience change first. Groups with highest response rates are most likely to see change happen first and fastest as the climate shifts. Response is the slope of the linear-regression relationship between annual precipitation and iSAVI change from the previous year. It is the change in iSAVI expected per millimeter of change in annual precipitation. Areas without color were either smaller than the minimum area required for mapping (<8.3 ha) or did not have a significant relationship with annual precipitation. Areas that were not significantly related to annual precipitation may be related to other climate metrics. Statistics for sensitivity of each polygon to each climate metric, including quality of relationships and regression coefficients, can be found in Table S-2 of Thoma (2022).

3.6.2 Spatial patterns of response

The alliance groups most sensitive to precipitation were disturbed areas, geology, and the two exotic grasslands. The polygons most sensitive to precipitation were in the northern portion of the monument (see Figure 3-9). Additional response maps, found in Appendix A, Figure A-3, illustrate spatial patterns in the sensitivity of alliance groups to precipitation and deficit, and more pronounced variation in sensitivity to soil moisture.[3]

[3]Response to soil moisture is greater than sensitivity to precipitation or deficit because incremental changes in soil moisture in this analysis are expressed as a water-year mean, whereas precipitation and deficit are sums (see Table 1-1). However, the pattern in response to soil moisture is tied to spatial variation in soil properties that play important roles in storing precipitation between events.

3.6.3 *Influence of site characteristics*

Spatial patterns in soil and site properties, including percent sand and clay, depth to root-restrictive layers, water-holding capacity, slope, and aspect, influenced drought tolerance and sensitivity to climate variables. This was apparent from similar patterns seen in the soil-properties maps (Figure 3-11) and the response maps (e.g., Figure 3-9). This correspondence was further evidence of the interactions between climate, site properties, and vegetation traits (deep- or shallow-rooted, perennial or annual) that influence vegetation condition and trends.

By relating pivot points and responses with site properties (see Table S-2 in Thoma 2022), we can quantify the strength of influence that site properties have in modifying climate effects. Steeper regression slopes (such as those in Appendix A, Figure A-4) indicate a stronger effect of a given site property on either the pivot point or response to climate. For example, juniper alliance groups may have a stronger negative response to sand content and stronger positive response to clay content than pinyon-juniper alliance groups. Generally, precipitation pivot points increased with depth to restrictive layer, clay content, and water-holding capacity (see Figure 3-11). For pinyon-juniper woodlands, precipitation pivot points decreased with sand content and site slope. Site properties affected drought tolerance and sensitivity to climate by influencing water retention and distribution in the soil profile, as well as heat-loading due to the slope and aspect of the site relative to the sun.

These site-specific properties locally modified the influence of climate and were important determinants of vegetation condition and patterns on the landscape. They can be quantitatively introduced into vulnerability assessments at the polygon scale by use of a water-balance model that accounts for these complex interactions. Although the relationships of site properties and vegetation with climate relationships are shown graphically only for the Pinyon-Juniper and Juniper woodland groups, relationships like these for other alliance groups can be constructed as needed using the data in Table S-4 of Thoma (2022).

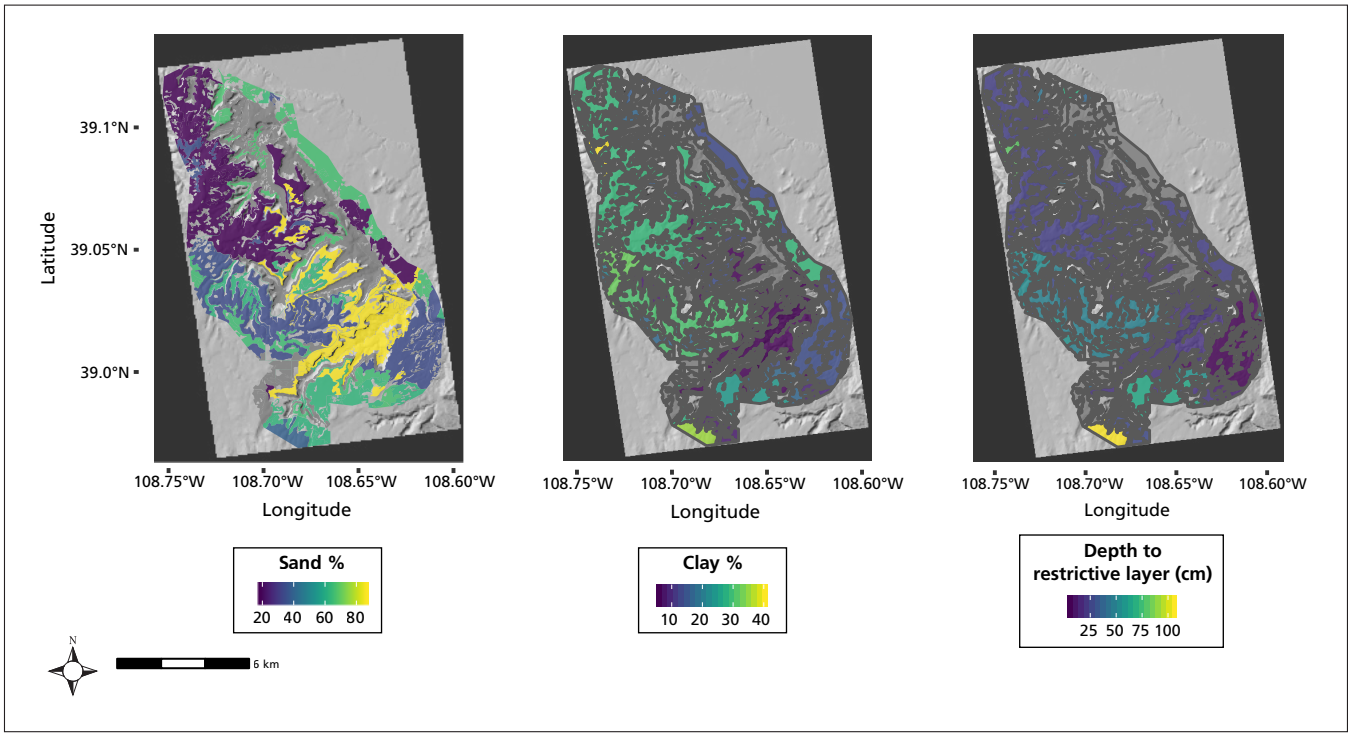


Figure 3-11. Maps of percentage sand content in top meter of soil, percentage clay content of soil, and depth to restrictive layer in alliance groups. Spatial patterns of soil properties correspond with patterns in vegetation response to climate. Areas of no color fill indicate missing soil properties data or depth is greater than 100 centimeters.

3.6.4 *Patterns within alliance groups*

While pivot points and responses provide different information, they are linked by steeper line slopes: as precipitation pivot points decrease (i.e., cross the horizontal "no change" line further to the left), response rate increases. (Figure 3-12). Alliance groups with steeper slopes (e.g., Annual Exotic Grassland and Wet Shrubland) are considered more responsive to changes in water availability. These groups increase production with less precipitation, demonstrating that responsiveness to precipitation is greatest where vegetation is most drought-tolerant.

There was a large range in pivot points and responses, reflecting a wide range of plant traits responding differently to climate variability across the park. The patterns of pivot points and responses quantify unique climatic habitats occupied by the different alliance groups in the park, and can serve as a guide to anticipate what, where, when, and why vegetation change may occur. For example, this analysis suggests that positive growth response to high precipitation will

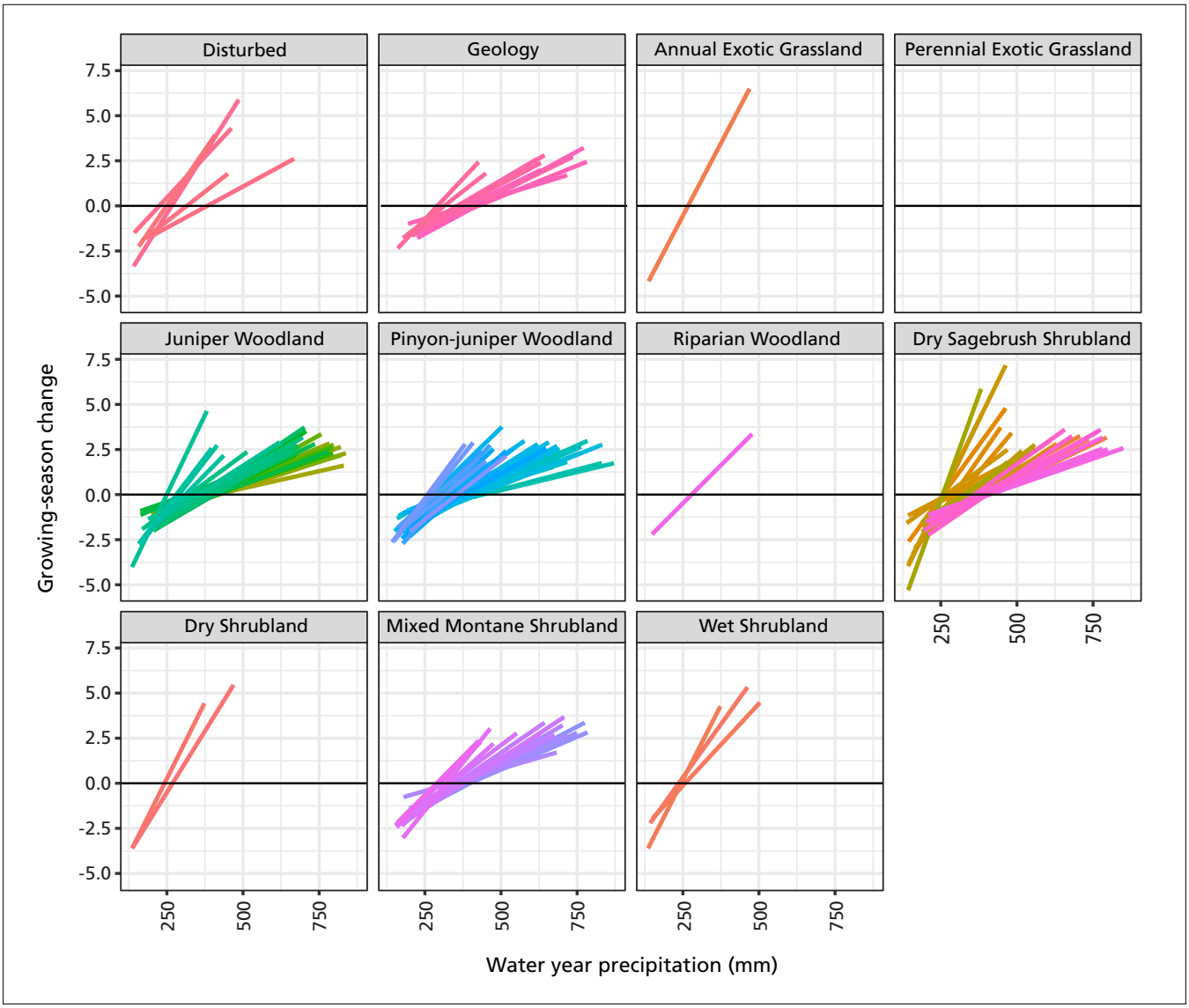


Figure 3-12. Graphical depiction of the relationship between pivot points and responses in polygons that had a significant relationship (p-val <0.05) between iSAVI and water-year precipitation (e.g., critical water need vs. rate of growing season iSAVI change per mm precipitation). Polygon-level pivot points and responses are provided in Table S-2 of Thoma (2022). Alliance groups with steeper slopes are considered more responsive to changes in water availability. Alliance groups and alliance polygons within alliance groups that cross the horizontal axis further left are more drought resistant. This is because they shift to above-average condition with less precipitation. Only significant relationships are shown. Panels without lines represent alliance groups with no significant relationships between iSAVI and climate variables. Colors help differentiate individual polygons within alliance groups.

be greater in Annual Exotic Grassland than in shrubland or woodland alliance groups.

Tracking weather conditions during the growing season allows a view into vegetation condition at the polygon or alliance-group scale, depending on management interest (Thoma 2022, Tables S-2, S-4). Generally, within alliance groups, vegetation response increased as precipitation decreased. The degree of responsiveness was determined by traits that allowed plants to either resist drought or rapidly respond to water availability. The end result was that vegetation response to climate could be considered coarsely at the alliance-group level, but at higher spatial resolution and often, with higher accuracy, at the polygon level. For example, in the Dry Sagebrush Shrubland alliance group, precipitation explained 34% of interannual variation in production. But by polygon (n = 33), precipitation explained between 16% and 65% of interannual variation in production.

Multiple factors can introduce additional variability in pivot points and responses within alliance groups. These include differences in species assemblages, spacing between plants, and soil properties that affect the retention and distribution of water in the soil profile that is accessible to different growth forms (e.g., plants with shallow or deep roots) (Thoma et al. 2019).

3.6.5 Production response to water and non-water variables

Assemblages with higher responses (steeper regression slopes) were more sensitive to climate. Depending on the climate variable, the slope could be positive (as with semi-arid environments and water variables, such as precipitation and actual evapotranspiration), or negative (in response to water deficit or potential evapotranspiration, which are related to temperature) (Figure 3-13; also see Thoma 2022, Tables S-2 and S-4).

Direct comparison of water variables to non-water variables, such as GDD and VPD, is difficult due to their different units of measure. Similarly, it is important to note that response to change in an average annual value, such as soil moisture, is strong partly because this variable is averaged (because soil has an upper limit of water-holding capacity), which weights its effect on vegetation more per unit change than other climate variables that are summed (see Table 2-2). This is why small changes in average soil moisture have a larger effect than small changes in annual precipitation. Responses to temperature variables GDD and T should also be considered similarly, because GDD is a summed variable, while T is averaged. Variable importance is considered in the following sections.

3.7 Multi-variable indicators of annual vegetation production

Pivot points and responses are ecological measures of annual production, but production is affected by multiple aspects of weather before and during a growing season, as well as conditions in prior growing seasons that set the stage for production potential in the current year (Sala et al. 2012).[4]

In the multi-model comparison of climate correlates with interannual differences in growing-season iSAVI across all alliance groups, climate indicators of annual production showed that regardless of alliance group, most (72%) polygons were influenced by three years of average annual soil moisture. The next most-common indicators of production were two years of soil moisture and the interaction between two years of soil moisture and prior-year deficit (Figure 3-14). Three years of precipitation was a competitive model in 43% of polygons. These patterns generally held within alliance groups. Two-to-three years of soil moisture were common indicators of production in most alliance groups (Figure 3-15). However, in models of Mixed Montane shrubland production, 2–3 years of precipitation were common indicators. In models of Dry Shrubland production, three years of soil moisture was the most-common indicator. A list of top-performing models by polygon can be found in Table S-5 of Thoma (2022).

[4]This is one reason why the annual relationships described above are not as strong as monthly relationships described in some of our earlier work (Thoma et al. 2016)

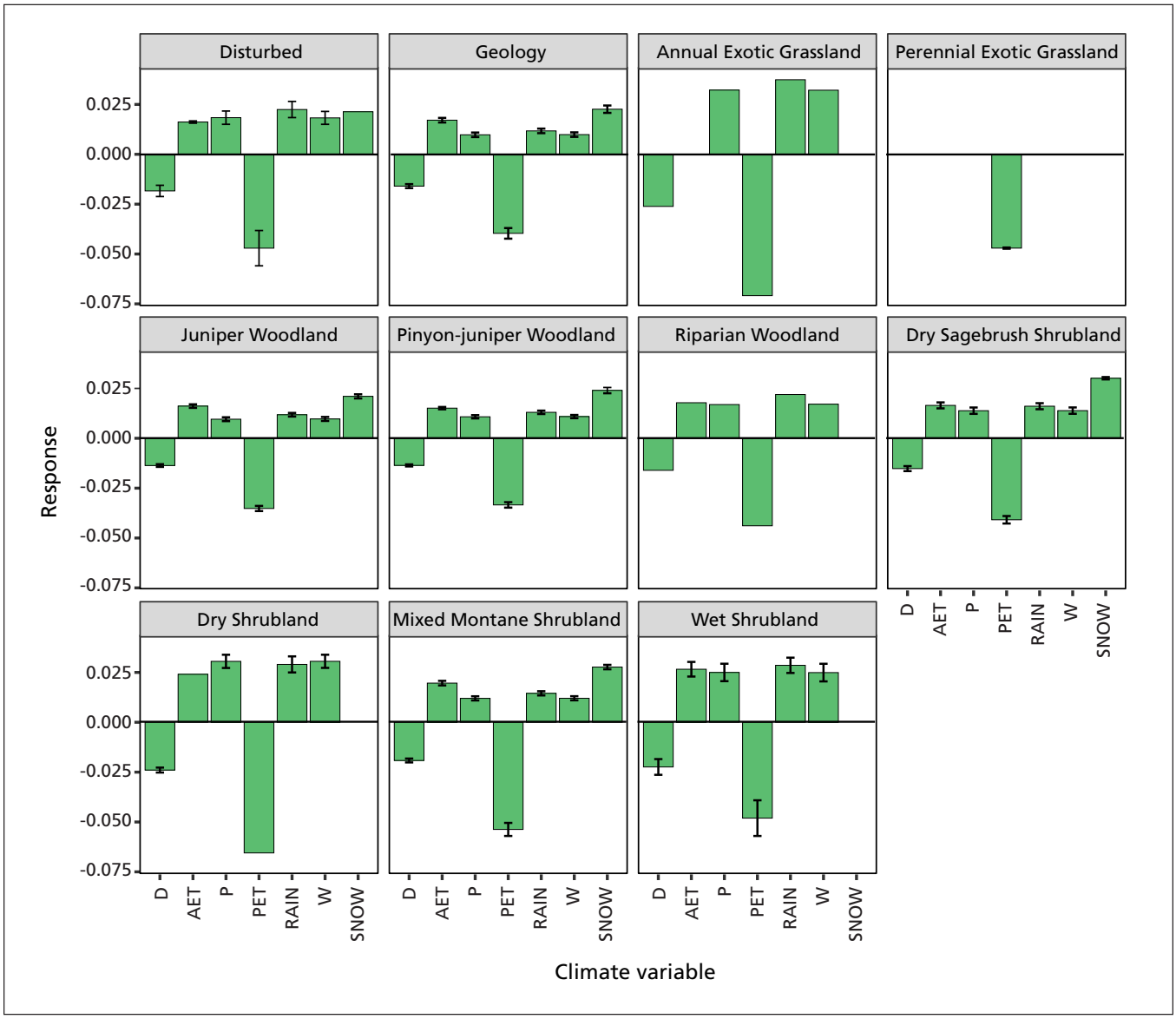


Figure 3-13. Vegetation response to summed water flux variables (regression slopes from ΔiSAVI versus annual climate-variable sum). Statistics for these relationships and all other variables can be found in Thoma (2022), Tables S-2 and S-4. D = deficit (mm), AET = actual evapotranspiration (mm), P = precipitation (mm), RAIN = precipitation as rain (mm), W = combination of rain and snowmelt (mm), SNOW = precipitation as snow (mm of water).

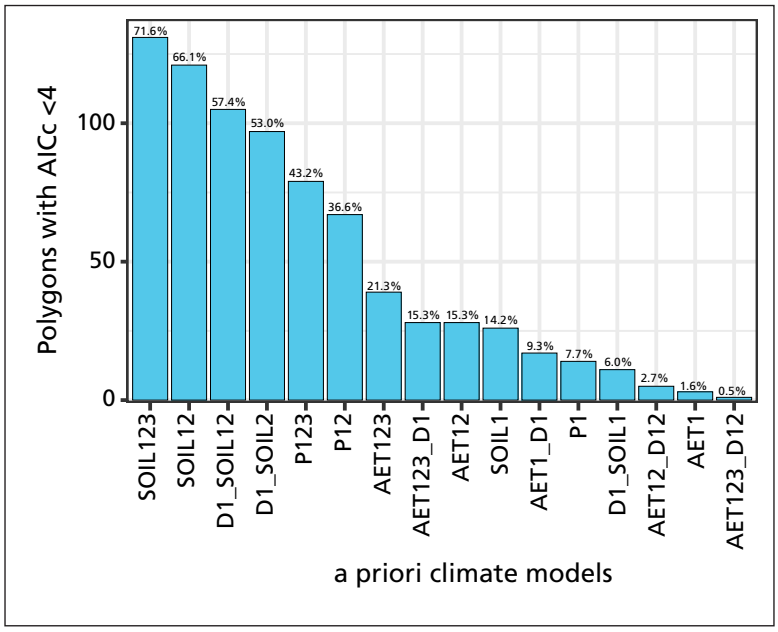


Figure 3-14. Top models in multi-model comparison of climate correlates with interannual differences in growing-season iSAVI across all alliance groups. Percentages indicate proportion of polygons where each model was competitive. Each polygon may have more than one competitive model; thus, the sum of percentages exceeds 100 across all models. The x-axis labels refer to the a priori climate models in Table 2-3. SOIL = annual average soil moisture; D = annual deficit; AET = annual evapotranspiration; P = annual precipitation. Numbers indicate current and prior years included in each model. 1 = current year; 12 = current and previous year; 123 = current and previous two years.

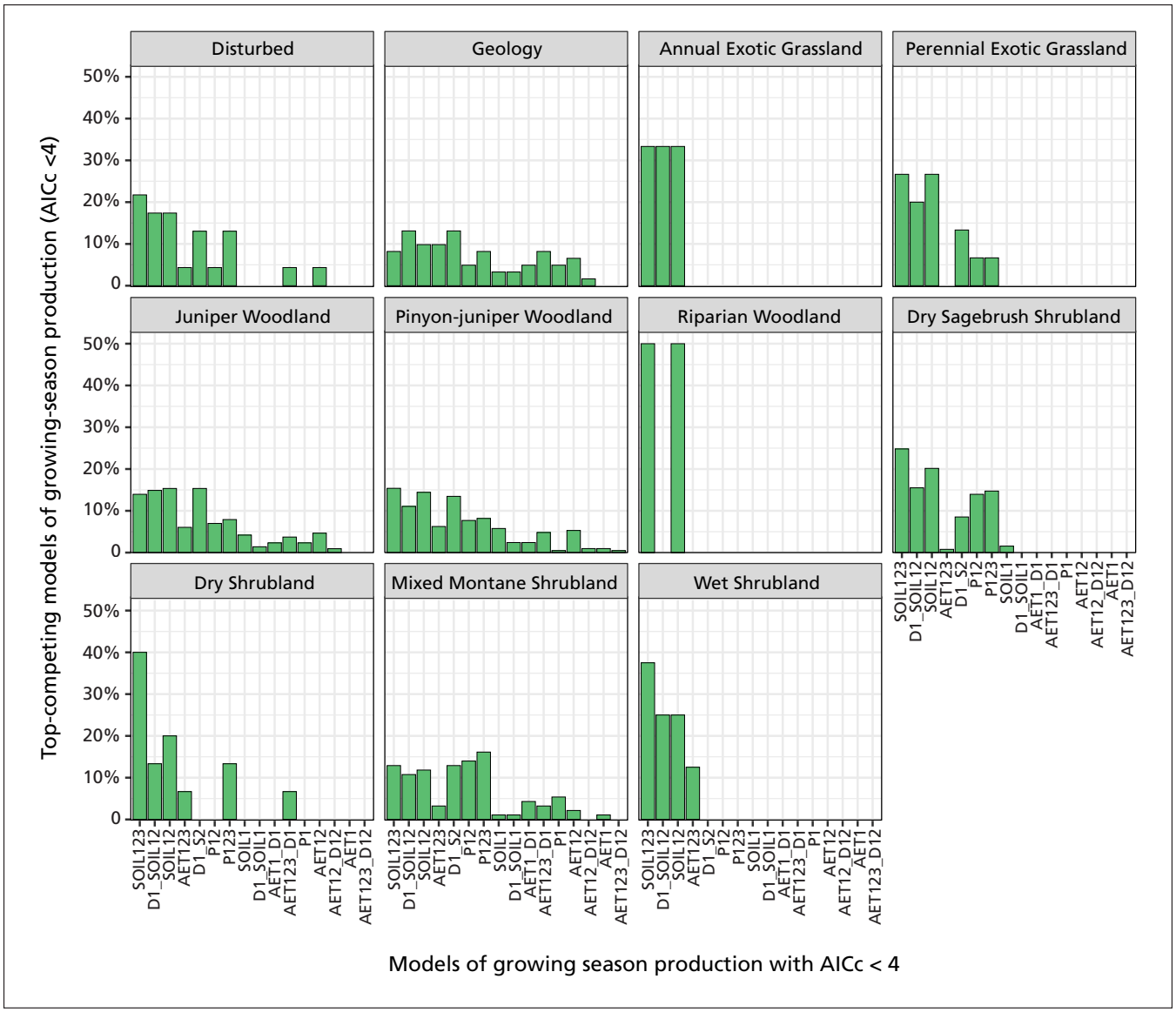


Figure 3-15. Top models of growing-season production by alliance group in multi-model comparisons of climate correlates with interannual differences in growing season iSAVI. The x-axis labels refer to the a priori climate models in Table 2-3. The y-axis represents the proportion of polygons in each alliance group where each model was competitive. Each polygon may have more than one competitive model; thus, the sum of percentages can exceed 1 across models. SOIL = annual average soil moisture, D = annual deficit, AET = annual evapotranspiration, P = annual precipitation. Numbers are 1 = current year, 12 = current plus previous year, 123 = current plus previous two years.

The majority of alliance groups responded to soil moisture, highlighting the importance of soil as a storage reservoir between precipitation events in a semi-arid environment where water is the growth-limiting factor in most years (Bisigato et al. 2013). Soil properties that help sustain higher average soil moisture, perhaps through reduced runoff or deep infiltration, provide additional benefit. This is apparent in the finding that two years of soil moisture were as competitive as three years of precipitation in some polygons.

3.8 Land-surface phenology trends at Colorado National Monument

A trend in earlier start of growing season occurred in all alliance groups except for Annual Exotic Grassland and Wet Shrubland (Table 3-2; Appendix A, Figure A-5). In recent years, the growing season was ending earlier for some alliance groups (Perennial Exotic Grassland, Juniper and Riparian woodlands, and Dry Shrubland) but ending later for others (Annual Exotic Grassland and Dry Sagebrush, Mixed Montane, and Wet shrublands). Collectively, these changes resulted in a longer growing season in all groups except Perennial Exotic Grassland. There, the growing season was shortened by 10 days, mostly due to a trend in earlier end-of-season. The timing of peak growth occurred later in the growing season for all alliance groups except Dry Shrubland, which in recent years was peaking an average of 13 days sooner than in 2000 (see Table 3-2).

By 2019, 86% of the park area consisting of Pinyon-Juniper Woodland, Juniper Woodland, and Dry Sagebrush Shrubland was greening up 7–11 days earlier than in 2000, and the growing season was an average of 24–30 days longer. These changes were consistent with rising temperatures and increasing annual growing degree days that can extend the growing season if moisture is available. It was also consistent with increasing CO_2 concentrations that increase vegetation production through a process known as CO_2 fertilization (Sorokin et al. 2017). However, the strength of the relationship between production and annual precipitation mediated through soil moisture over the study period (see Figure 3-5) and in findings from Section 3.7 suggested most of the increase in production was related to increases in water availability, rather than CO_2.

Table 3-2. Trends in phenology averaged across polygons in the same alliance group.[1]

Alliance group	Δ SOS	Δ EOS	Δ LOS	Δ POP	Hectares	Polygon count	% area
Disturbed	-5	-2	29	8	636.5	6	6.2
Geology	-12	5	28	6	165.3	11	1.6
Annual Exotic Grassland	5	22	22	10	10.1	1	0.1
Perennial Exotic Grassland	-2	-15	-10	18	81.4	5	0.8
Juniper	-10	-3	24	11	2,821.7	46	27.6
Pinyon-Juniper	-11	0	30	8	4,949.8	45	48.3
Riparian	-1	-1	1	16	11.4	1	0.1
Dry Sagebrush	-7	1	26	4	1,065.6	40	10.4
Dry Shrubland	-3	-9	21	-13	102.2	6	1
Mixed Montane Shrubland	-9	6	23	5	307.8	19	3
Wet Shrubland	0	6	27	4	89.0	3	0.9

[1]Change in days per year was obtained by multiplying the slope of the change over time by the number of years (20) in the study period. Phenology metrics for each polygon were derived for each year from the annual growing season iSAVI curves for 2000–2019. Confidence in phenology trends was low at the polygon level due to small sample size (n=20 years per polygon) and high variability, but higher as polygon count increased. ΔSOS = days of change in start-of-season, ΔEOS = days of change in end of season, ΔLOS = days of change in length of season, ΔPOP = days of change in period of peak production. Negative and positve numbers for SOS, EOS, and POP indicate that the metric started earlier and later, respectively, in the calendar year. Percent area is relative to the extent of alliance groups in and near the park shown in Figure 1-1.

Changes in land-surface phenology result from interactions between temperature, moisture, plant traits that control growth rates, and CO_2 concentrations that affect water-use efficiency. Generally, warming reduces growth rates in semi-arid environments, while elevated CO_2 increases water-use efficiency for the same amount of water, which can increase growth rates. Thus, warming may initiate an earlier start to the growing season and elevated CO_2 may increase water-use efficiency, resulting in a longer growing season. But efficiency is ultimately limited if conditions become sufficiently dry and growth ceases. For this reason, and given projected drying on the Colorado Plateau, increases in efficiency may be small and short-lived in the face of disturbance caused by drought or wildfire (Allen et al. 2015). Tracking changes in phenology in NCPN parks, and linking those changes to seasonal changes in temperature and CO_2 concentrations, could help further clarify the vulnerability of semi-arid vegetation to multiple aspects of climate change (Sorokin et al. 2017).

3.9 Drivers of green-up

3.9.1 A priori model selection method

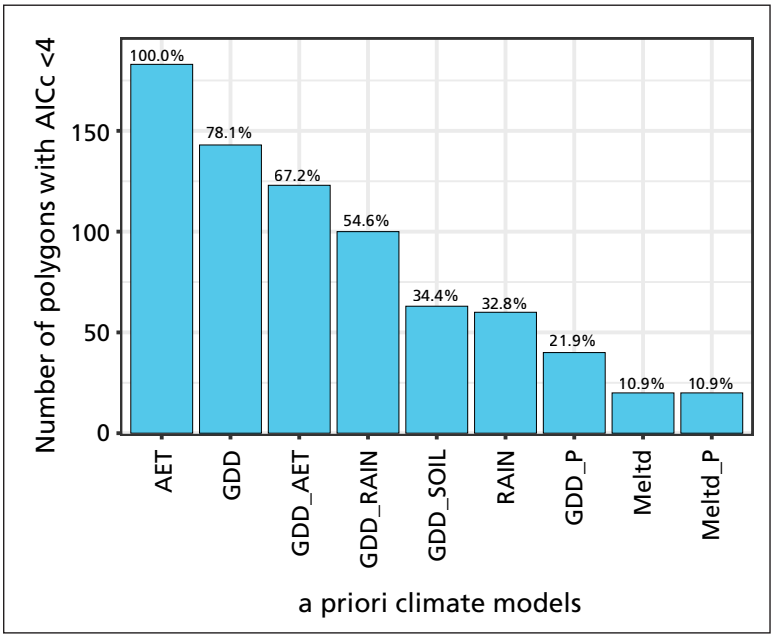


Figure 3-16. Top models in multi-model comparisons of climate correlates with start of growing season at the whole-park scale. The x-axis labels refer to a priori climate models as determinants of green-up, or start of season. Srad = solar radiation, Meltd = day of complete snowmelt, AET = actual evapotranspiration, P = precipitation, VPD = vapor-pressure deficit.

At the scale of both the park and alliance group, the most common a priori competitive model of green-up timing (see Table 2-4) was cumulative AET between January 1 to the SOS date. Actual evapotranspiration explained 48% of variation in SOS. Other competitive models included average maximum temperature since January 1 and cumulative growing degree days.

At the park level, AET was also the only variable important in every alliance group (Figure 3-16). At the alliance-group level, GDD and GDD_SOIL were frequently important (Figure 3-17).

Actual evapotranspiration is a highly integrative variable that includes moisture supply from soil, temperature warm enough for growth, day length, and solar incidence angle. It commences only after snowmelt is complete. Growing degree days are likely important because spring soil moisture is typically at its highest level after the winter recharge period and therefore not usually limiting. Rather, some amount of heat is needed to stimulate plant growth after winter dormancy. So, only unusually dry fall and winter periods would result in low moisture levels being a co-limiting factor to temperature.

3.9.2 Random-forest method

Variable importance plots showed the best predictors of start-of-season were date of snowpack melt, precipitation, and AET (Figure 3-18). These findings were similar to those in the multi-variable regression models, where AET was important, but with the addition of precipitation as an important variable.

Findings from the two modeling methods suggested a combination of temperature and moisture are important indicators of SOS, as is expected in semi-arid climates. The loss of snow cover that exposes vegetation to warming and solar radiation in spring makes intuitive sense as a driver for the start of growth, but the effect of precipitation is less intuitive unless the soil was not sufficiently replenished to meet plant needs with moisture over winter and early spring.

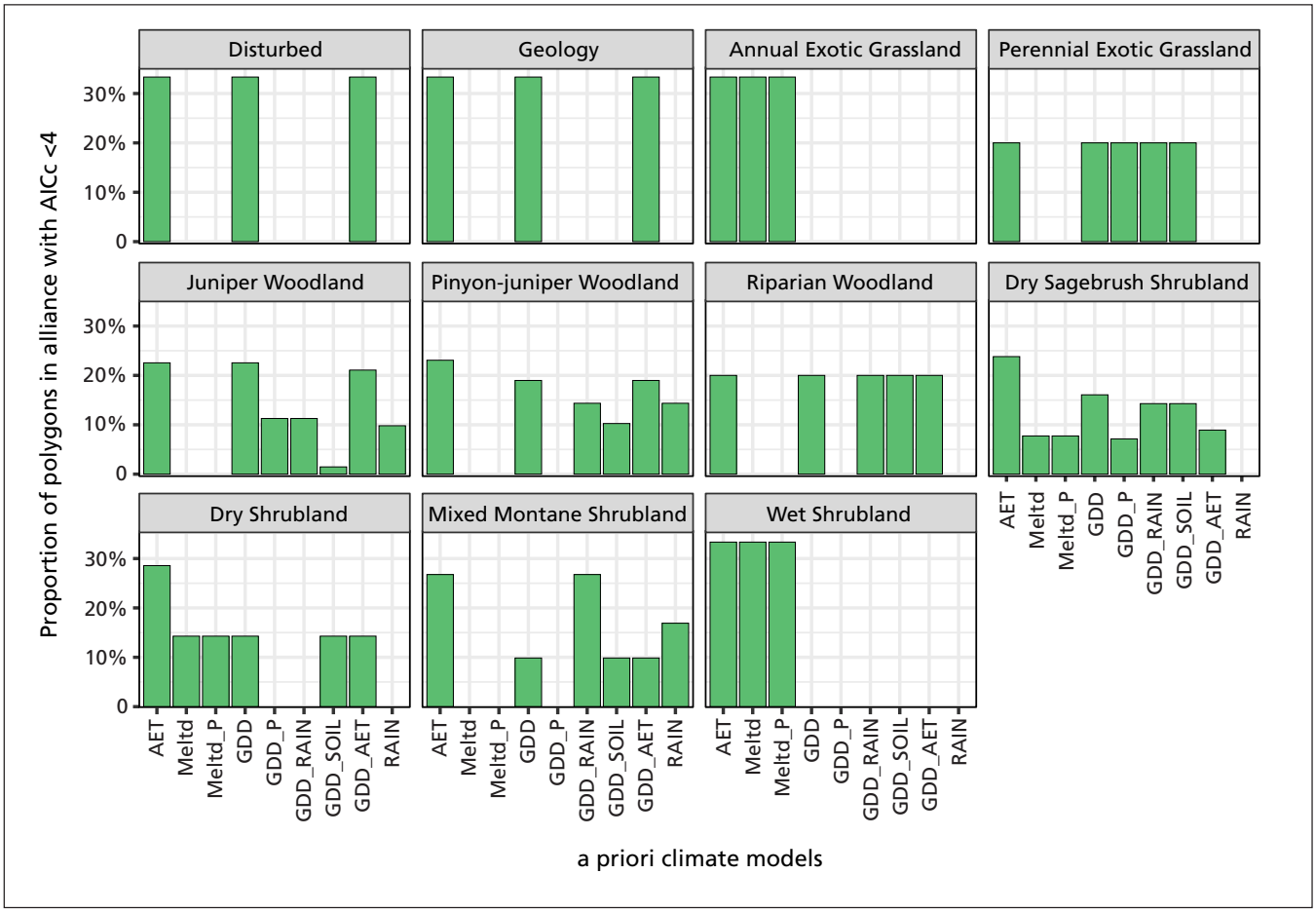


Figure 3-17. Top models in multi-model comparisons of climate correlates with start of growing season at the alliance-group scale. The x-axis labels refer to a priori climate models as determinants of green-up, or start of season. Srad = solar radiation, Meltd = day of complete snowmelt, AET = actual evapotranspiration, P = precipitation, VPD = vapor-pressure deficit.

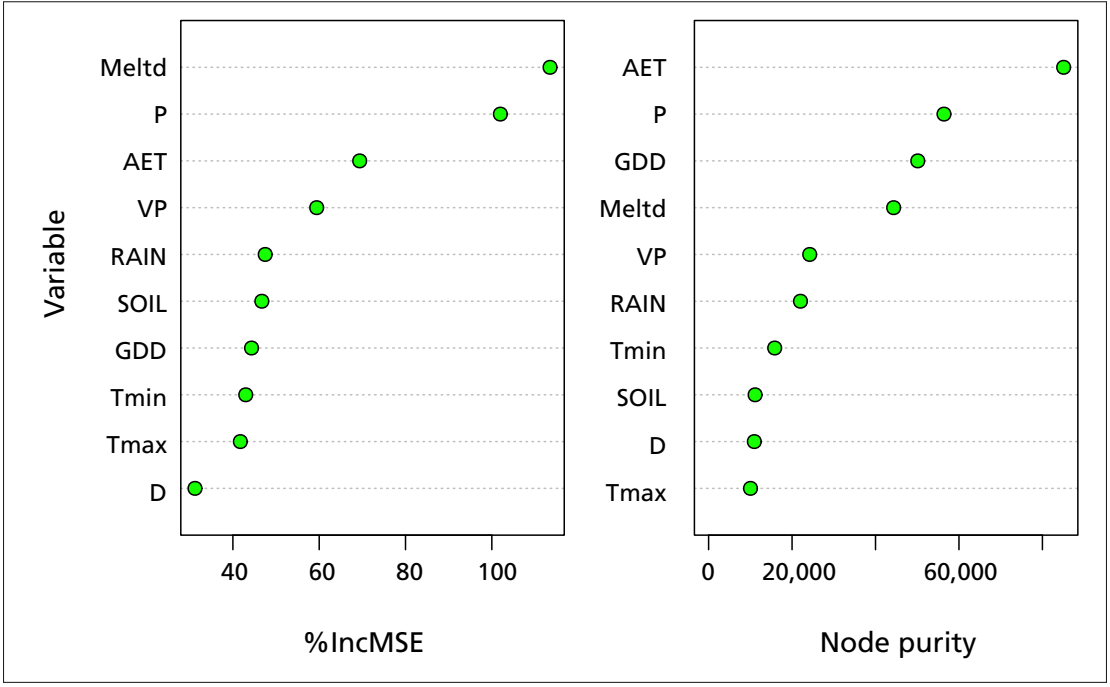


Figure 3-18. Variable importance in the random-forest machine-learning model of climate drivers of the start of growing season. Percent increase in mean square error (%IncMSE) is a measure of model performance with each variable. Increase in node purity (IncNodePurity) is the difference in residual sum of squares in regression with or without each variable.

The random-forest model obtained from the training dataset was used to model SOS in the validation dataset to determine predictive performance. It predicted SOS date at the park scale with a mean absolute error of +/- 1.9 days (Figure 3-19). When separated by alliance group, the model performed equally well (Figure 3-20).[5]

Inspection of SOS outliers in Figures 3-19 and 3-20 suggests they may have resulted from low amplitude and monotonic increase (straight line) in SAVI in some years. This combination may make it difficult to identify meaningful SOS dates using the derivative method that relies on change in the acceleration of growth rate in spring to determine when growth starts. Even though polygon/year combinations with winter SAVI peaks were screened out of the analysis (Norris and Walker 2020), it is not clear how SOS may be affected by the shadowing noted in pinyon-juniper and shrubland habitats by Norris and Walker. This is because the shadowing effect is partially dependent on vegetation structure and spacing, which is a continuum of conditions across landscapes. For this reason, modeled SOS dates should be considered with skepticism in the Pinyon-Juniper, Juniper and all shrubland alliance groups, as well as in polygons that yield outliers in the model of SOS.

Despite these potential shortcomings, the validation demonstrates a strong predictive model of SOS using climate data for most of the Colorado NM landscape. This means climate projections could be used to model SOS dates in the future. This could be helpful in assessing potential vulnerabilities caused by phenological mismatch between pollinators and flowering species, as well as potential impacts to migrating birds and mammals, such as deer. Mule deer in some western states "surf the green wave" of vegetation as it greens up progressively across gradients of latitude and elevation (Aikens et al. 2017; Merkle et al. 2016; van Wijk et al. 2012). Presently, it is unknown if animal species in NCPN parks time their movements with SOS or the green wave thereafter, but this information could be used to help assess if animals are keyed into this land-surface process.

[5]The analysis was conducted at the park scale, rather than by polygon (as in Section 3.7.2.1) to increase sample size for the modeling process.

3.10 Climate patterns

Annual temperature, precipitation, and estimates of AET, climatic water deficit, and soil moisture derived from the water-balance model for 1980–2019 exhibited high interannual variability (Figure 3-21 and Appendix A, Figure A-6). This variation caused large interannual changes in annual vegetation production.

During 2000–2019, there was a weak, though statistically significant ($p < 0.1$) increase in precipitation of 3–11 millimeters per year. Average annual temperature remained stable during the study period (see Figure 3-12 and Figure A-6). The increase in precipitation resulted in a corresponding increase in AET of 3–6 millimeters per year. The effect of these seemingly small changes was important as illustrated by the significant upward trends in production across alliance groups shown in Section 3.3.

An interesting decadal oscillation in precipitation was evident: peaks in the middle of each decade since 1980 translated to similar peaks in other water-balance variables. The same pattern was apparent in soil moisture, AET, and water deficit (Figure 3-22), although for deficit the peaks (maximum drought stress) coincided with the times of least precipitation (Appendix A, Figure A-6). If the periodicity of these cycles continues in the future, it could serve as a useful guide for timing restoration efforts that require substantial planning efforts, long-term investments, and multiple years of minimal drought stress for germination and establishment.

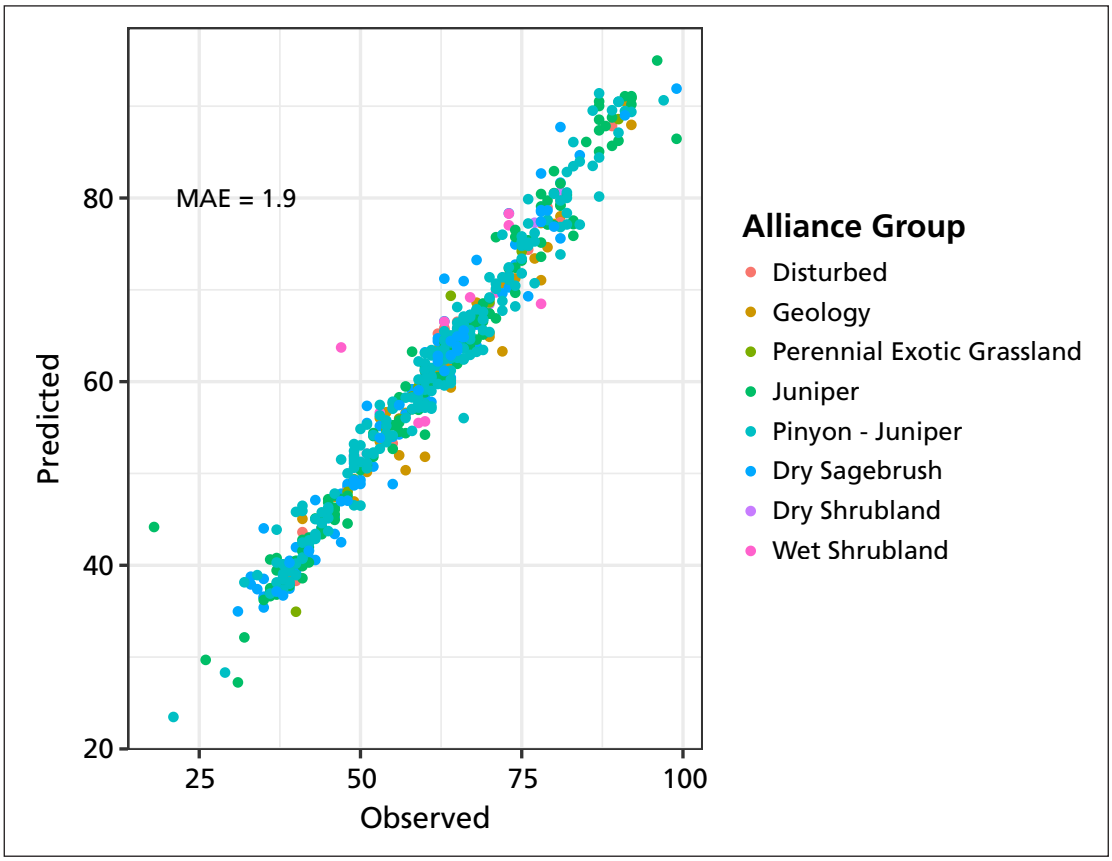


Figure 3-19. Predicted start-of-season date versus observed start-of-season date in the holdout dataset used for validation of the random-forests model for all polygons in Colorado NM. MAE is mean absolute error of prediction in days. Polygons with annual peaks (POP) occurring between November 1 and April 1 were removed prior to this analysis (Norris and Walker 2020).

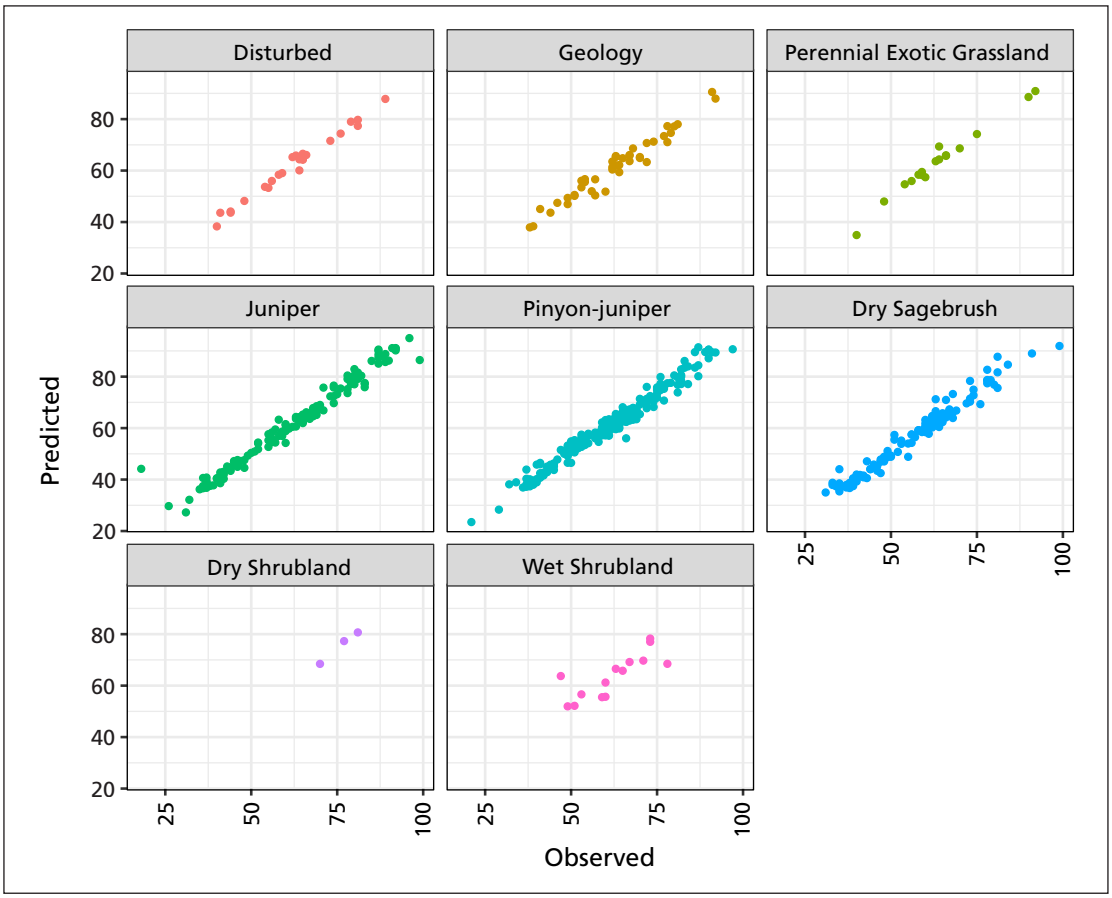


Figure 3-20. Predicted start-of-season date versus observed start-of-season date in the holdout dataset used for validation of the random-forests model for alliance groups. Polygons with annual peaks (POP) occurring between November 1 and April 1 were removed from this analysis. Outliers are likely due to difficulty in discriminating SOS when SAVI changes monotonically.

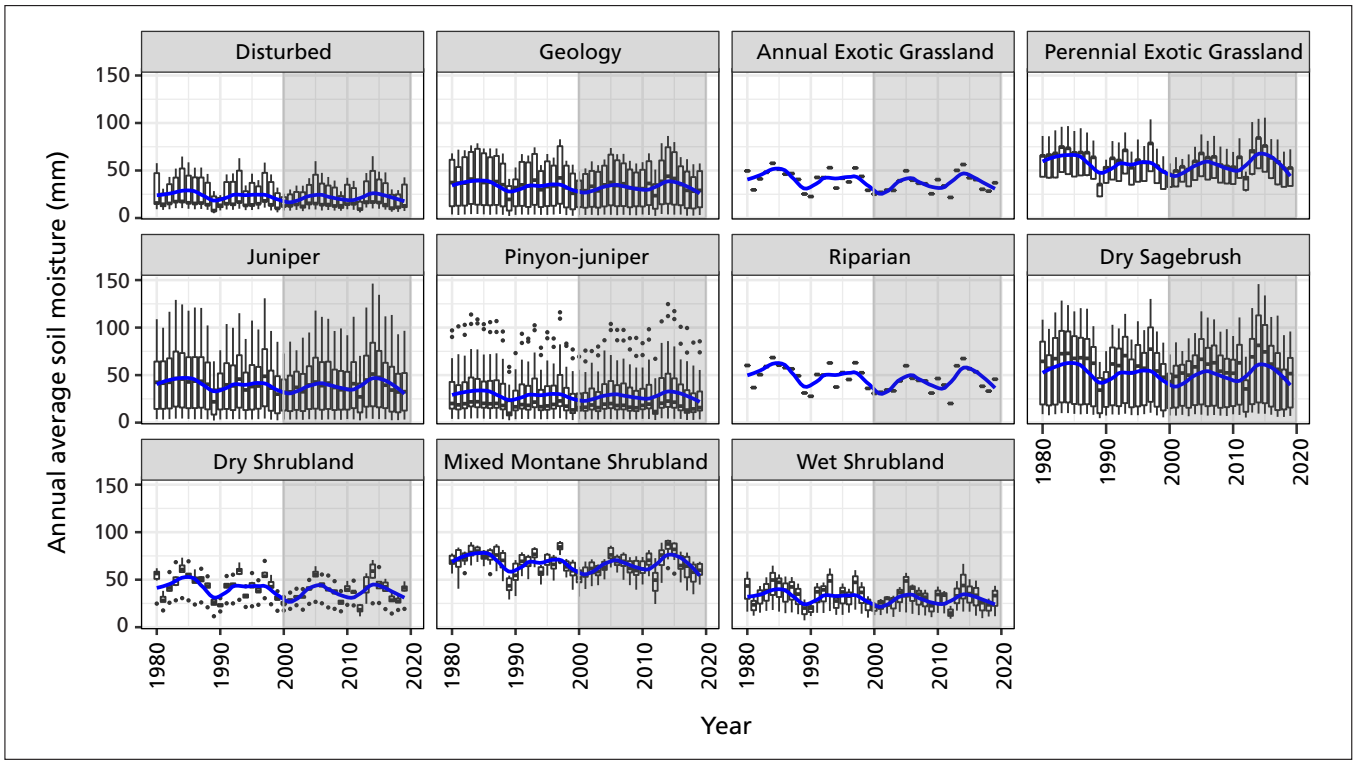


Figure 3-21. Long-term temporal patterns and variability in soil moisture in vegetation alliance groups at Colorado NM. Box plots demonstrate the range of variation by year. The line is a loess smooth with a 25% span to illustrate multi-year patterns. Gray shaded area includes the period between 2000 and 2019, investigated for relationships between production and climate when satellite imagery and climate data were both available. Study-period trends and associated statistics for the other water-balance variables are presented in Appendix A, Figure A-6.

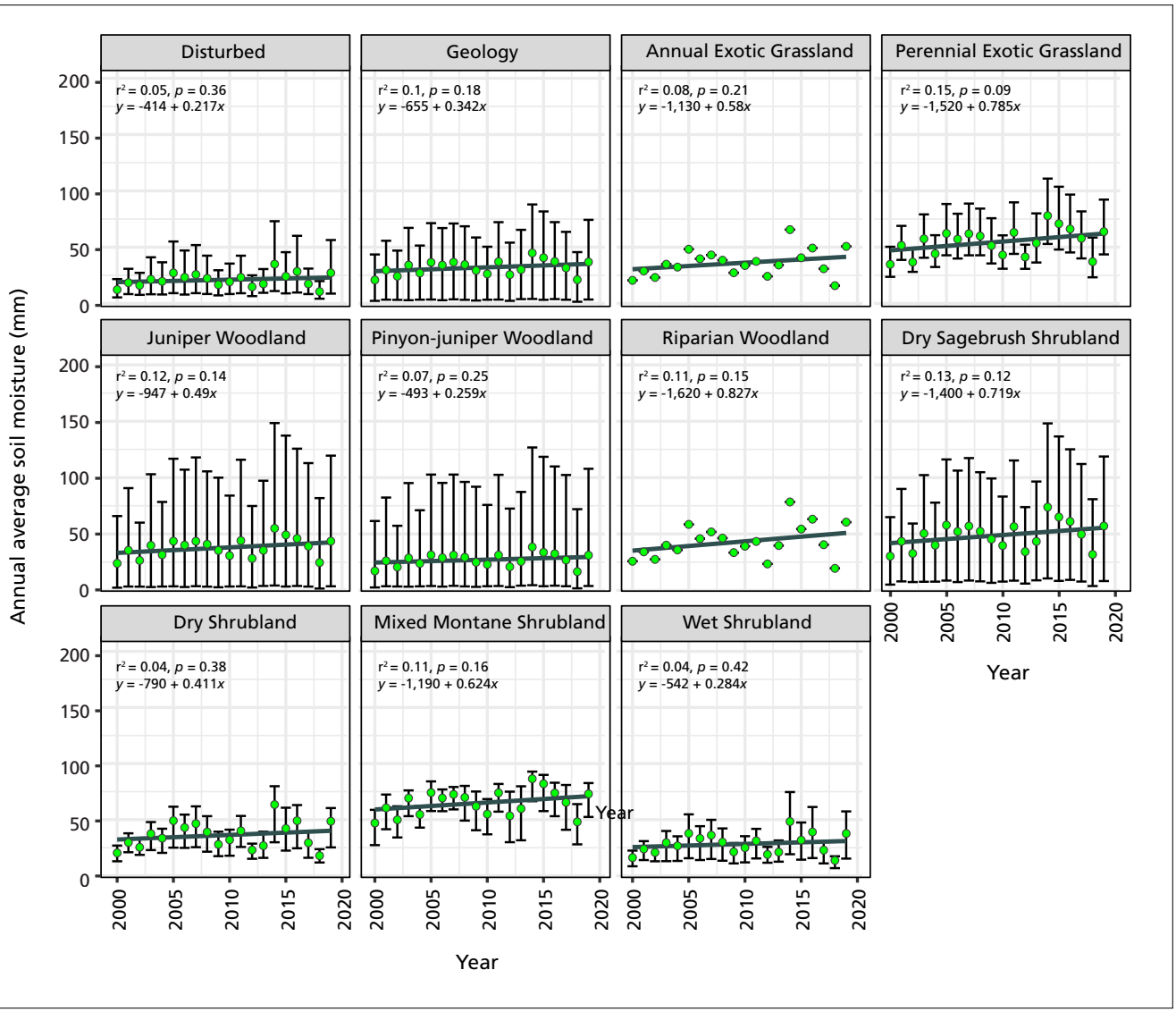


Figure 3-22. Soil-moisture trend over time, 2000–2019. Bars are standard error.

4 How to Use this Report in Climate Smart Conservation Planning

This report provides information that feeds directly into the Climate Smart Conservation Framework (Figure 4-1), the process used by the NPS Climate Change Response Program (CCRP) and other federal agencies to make climate-adaptation plans based on plausible future climate and resource responses in climate-scenario planning (NPS 2021; Stein et al. 2014). Results from this report inform Step 2 (Figure 4-1), which is an assessment of vegetation vulnerability to climate change that defines climate exposure, vegetation sensitivity, and vulnerability of vegetation to climate change considering inherent adaptive capacity and management actions that help reduce vulnerability (adapted from NPS (2021).

4.1 Identifying management goals

The first step in Climate Smart Conservation is to identify management goals that will inform the planning process. This is usually an iterative process where initial goals are periodically re-evaluated based on values, vulnerability, and adaptive management. Goals may be determined via planning processes, by current threats, or by changes that have already occurred. Clearly defined goals help make the rest of the Climate Smart Planning process more efficient. In addition to vulnerability and values, management goals may also consider management paradigms of resisting, accepting, or directing change (NPS 2021; Schuurman et al. 2020). The appropriate paradigm depends on the goals informed by values and vulnerability assessments. It may be necessary to implement strategies that reflect more than one paradigm to achieve goals.

4.2 Vulnerability assessment

This report advances understanding of climate as a driver of vegetation production and phenology at alliance-polygon, alliance-group, and whole-park scales at Colorado NM. The historical perspective in this report provides the necessary background for understanding the range in variability of climate and vegetation response while also informing how vegetation is likely to

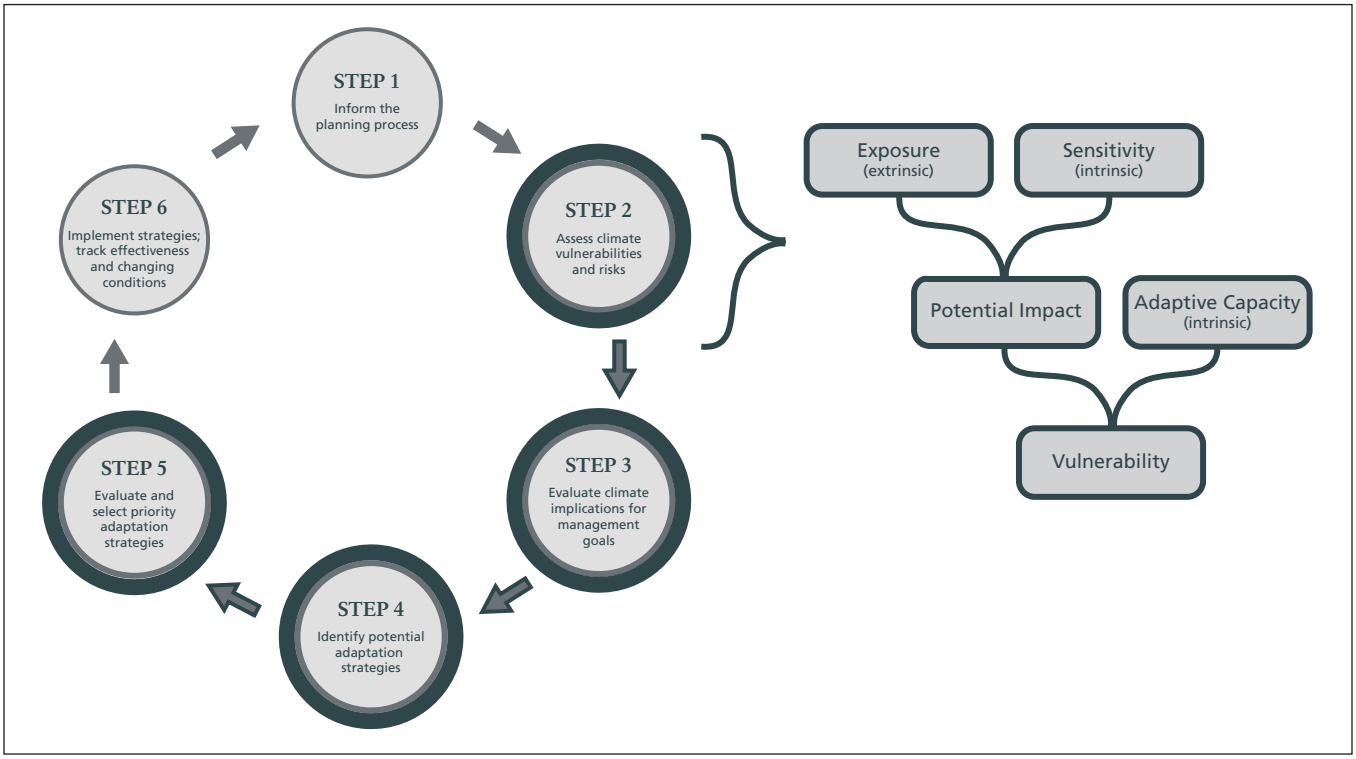


Figure 4-1. The Climate Smart Conservation framework. The concentric circles represent different scenarios that can guide the planning process.

respond to weather in the near term and climate change in the long-term. Specifically, results identify how vegetation condition and sensitivity are linked to incremental changes in weather and climate. Thus, this report can be used to determine how vegetation production and phenology may change (increasing or decreasing production) if the relationships described here carry into the future. Disruption of those relationships can be caused by gradual transitions of native vegetation, exotic-species invasions, disturbance, or land-use change.

Vegetation response in this report is synonymous with the concept of climate sensitivity in the Climate Smart Conservation context (see Figure 4-1), which is a critical step in determining vulnerability to climate change. Sensitivity to climate determines how much, and how rapidly, vegetation production changes with climate. Sensitivity is obtained from the slope of the regression line in the relationship between interannual variation in growing season iSAVI (surrogate for change in annual production) and any one climate variable (see Figure 2-3 and Thoma 2022, Tables S-2 and S-4).

Quantitative vulnerability assessments can help determine where, when, and which alliance groups and which polygons are likely to change (see Figures 3-9 and 3-10). The information in Thoma 2022 (Tables S-2 and S-4) of this report is designed for use as a landscape- and polygon-scale vegetation vulnerability assessment. A vulnerability assessment evaluates climate exposure and vegetation sensitivity, and how they will likely interact in the future to affect vegetation condition. Historic and future exposure to many climate variables are included in this report (Appendix A, Figure A-6; Christensen et al. 2021). Pivot points and sensitivity by polygon or alliance group are summarized in maps, charts, and tables (Appendix A, Figures A-2 and A-3; Thoma 2022, Tables S-2 and S-4), as is the role of site characteristics, such as soil properties, that modify sensitivity (see Figure 3-11). Future vulnerability (Figure 4-2) is determined by comparing different climate projections (climate scenarios in Christensen et al. 2021) to pivot points for each polygon (Table S-2 in Thoma 2022). This quantifies how frequently production falls below average conditions. If future production consistently falls below historic average conditions, then one vegetation assemblage is likely to transition into another better-suited to the new climate conditions. The following section demonstrates how to use data in this report for a polygon-level vulnerability assessment.

4.3 Using pivot points and responses in climate-adaptation planning

The annual pivot points and responses described here are useful for understanding how different aspects of climate (water availability, water use, water need, and temperature) affect vegetation. Additionally, pivot points and responses are integrative, useful ecological variables that complement assessments of exposure and sensitivity used for climate-adaptation planning. They combine effects of temperature, precipitation, and plant traits with site characteristics into single-variable descriptions of water use (AET) and unmet water need (D) (Tercek et al. 2021) that are place-based and uniquely identified for each alliance polygon.

Water-balance pivot points and responses are well-suited for applications that benefit from the simplicity of single-variable descriptions of climate exposure (such as temperature and precipitation), but are more biophysically related to natural-resource response (Stephenson 1998; Thoma et al. 2020). The quantitative assessment of vegetation sensitivity to climate and water-balance variables on an annual basis is a good starting point for the initial phase of long-range climate-adaptation planning.

4.4 Example vulnerability assessment

Below, an example of a quantitative vulnerability assessment for Colorado NM is presented using a pivot point and two future scenarios. Rather than considering all possible climate futures (currently 24 scenarios are available for consideration), which can be overwhelming, two scenarios shown in Christensen and others (2021)

were intentionally selected to bracket a wide range of plausible future conditions at Colorado NM. These include a best-case scenario of warming and increasing precipitation, and a worst-case scenario of warming and reduced precipitation. Climate exposure at Colorado NM will increase over time (Christensen et al. 2021) as declines in soil moisture and increases in water deficit play out under both a warmer and wetter and warmer and drier future. This is because the rate of warming under either scenario will result in drying that will outstrip projected changes in precipitation, even for the wetter scenario. The interaction of temperature and precipitation in both scenarios will result in earlier and longer dry seasons (Christensen et al. 2021).

For illustrative purposes, a vulnerability analysis for a single Juniper Woodland polygon in Colorado NM identifies exposure (change in climate over time), drought tolerance (pivot point determined from remote sensing), and vulnerability (frequency of pivot-point exceedance) in the future (Figure 4-2). The vulnerability assessment for this polygon, located near the park's center, was made by comparing pivot points (critical water need) to future water-balance conditions at Colorado NM. In this case, the annual-deficit pivot point for polygon Colorado NM_493 was 502 millimeters (calculated as the mean Gridmet deficit, which is the historic climate dataset appropriate for use with climate projections).

As the climate at Colorado NM warms, conditions will become drier as soil moisture declines and deficit increases (Christensen et al. 2021). Under the warm-and-dry (worst-case) scenario, deficit conditions will exceed the pivot point for the polygon in most years by 2030, suggesting a transition to more drought-tolerant vegetation may occur.

Under the warm-and-wet (best-case) scenario, annual deficit will remain near the historic range of variability, but multiple

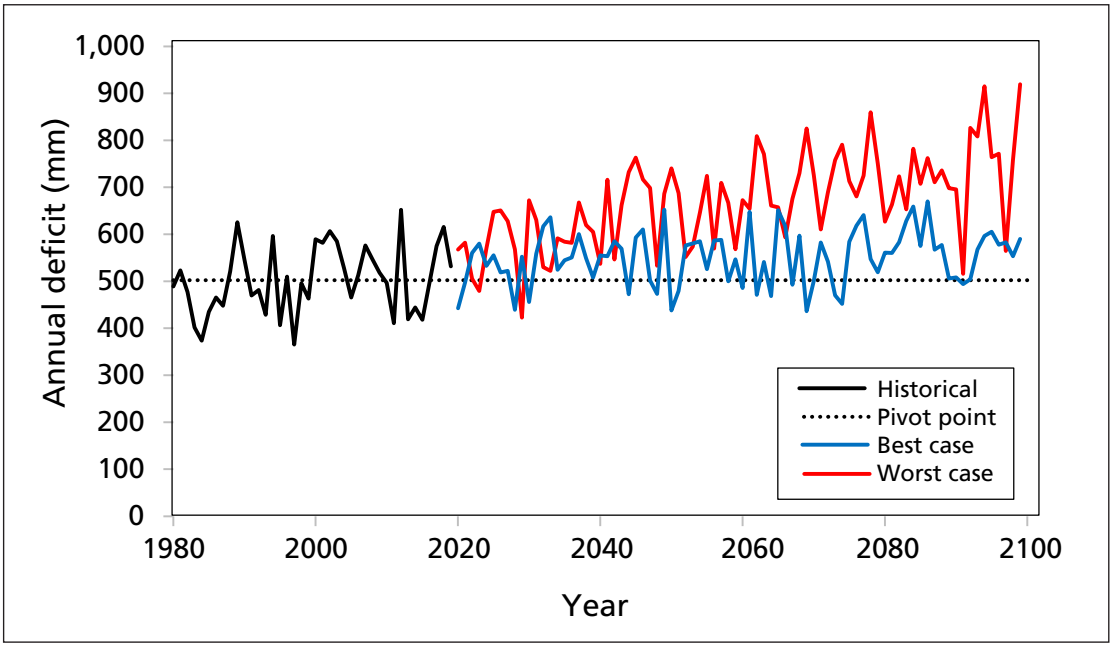


Figure 4-2. Quantitative vulnerability analysis for a single polygon in Colorado NM. Here, the projected change in annual water deficit relative to the pivot point is shown for a location at the park centroid (polygon Colorado NM_493), which falls in a Juniper Woodland alliance group. The deficit pivot point for this polygon was determined as 502 millimeters per year from the historical Gridmet climate dataset compatible with climate projections (screenedcleanedsummaries.s3-website-us-west-2.amazonaws.com). The best- and worst-case scenarios were selected from a range of many plausible futures derived from temperature and precipitation projections from the World Climate Research Program CMIP5 experiments (CMIP5; wcrp-climate.org). The temperature and precipitation data were passed through the water-balance model to generate future projections of the water-balance variables. The wetting scenario is the "best" case in this example. The projection data used to build this figure were from the climate exposure analysis summary report used to create the report in Christensen and others (2021).

years of drought stress above the pivot point may exceed the adaptive capacity of the Juniper group, leading to transition due to acute drought or fire disturbance in a few successive dry years. The effect of consecutive years of above-normal deficit was made clear by the widespread juniper mortality in southeast Utah noted by NCPN resource managers in 2019, following two years of high deficit (Figure 4-3). As noted earlier, annual and perennial grasses are more sensitive to deficit than pinyon and juniper—but this drought was sufficiently long and deep to kill trees that have multiple drought-resistance mechanisms via osmotic regulation and stomatal closure (Dickman et al. 2015).

From this analysis, it may seem that anything is possible—from no change to complete transition—which could lead to inaction due to uncertainty. However, the greatest uncertainty in this analysis is the representative concentration pathway (RCP) (4.5/best-case or 8.5/worst-case) that models CO_2 emissions—far moreso than the uncertainty in vegetation response to climate. For this reason, the next decade will be important to determining the trajectory of exposure.

The analysis demonstrated here can be recreated to determine site-specific vulnerability for any polygon in Colorado NM. Until such analyses using climate projections are quantitatively linked to pivot points in this report (as in Figure 4-2), users can gain a sense of vulnerability by sorting on pivot or slope in Tables S-3 and S-4 of Thoma (2022) to identify the most-sensitive and most drought tolerant polygons and alliance groups.

4.5 Identify and implement management actions

In planning for the future, the importance of vulnerability assessments for understanding and managing through climate change is underscored by statements from the Intergovernmental Panel on Climate Change (IPCC). As the summary for policymakers of their recent report states, "Global surface temperature will continue to increase until at least the mid-century under all emissions



NPS/DANA WITWICKI

Figure 4-3. A patch of dying junipers with the Abajo Mountains in the background, Cedar Mesa, Utah, 2019. In the two years before this photo was taken, water deficit was higher than at any time since 1980.

scenarios considered. Global warming of 1.5°C and 2°C will be exceeded during the 21st century unless deep reductions in carbon dioxide (CO_2) and other greenhouse gas emissions occur in the coming decades." It goes on to say, "Continued global warming is projected to further intensify the global water cycle, including its variability, global monsoon precipitation and the severity of wet and dry events" (IPCC 2021).

Vulnerability assessments can help identify the timing and type of management actions needed to achieve management goals in the face of an uncertain future. Additionally, they can help determine if existing actions are likely to achieve existing goals, if new management strategies are needed to achieve goals, or if management goals are unrealistic and need to be revised. After management goals and vulnerability assessments are reconciled, management options likely to achieve management goals can be identified and implemented (Steps 3–6 in Figure 4-1).

4.6 Tools to inform near-term management

Tracking weather conditions that lead up to or surpass pivot points during the growing season is a useful climate-based tool for assessing vegetation condition—but it provides an indirect assessment. Additional tools can provide real-time assessments of vegetation condition by identifying both trends in vegetation greenness and the vegetation anomaly (a comparison of current growing conditions versus past conditions). With these tools, users can iteratively identify the spatial pattern and strength of trends and where disturbance or unusual events are happening in near-real time.[1]

Interpreting the link between those patterns and climate requires contemporaneous climate data. Gridded climate data used in this report were created from weather-station data, typically in the year following a full year of data collected at weather stations. Weather-station data are better suited to investigations of real-time change in conditions, especially extreme events that garner interest as they happen or soon after—as was the case when park managers noted juniper mortality in 2018 and 2019.

The NCPN supports ClimateAnalyer.org, which makes accessing weather-station data easy (Figure 4-4). Data from the park weather station and other sources can be used to determine how weather and vegetation condition vary together in near real-time. This could be the basis for real-time condition assessments used in the tactical decisions needed to achieve long-range management goals. Care must be taken when analyzing trends from weather-station data due to missing values and outliers. Nevertheless, over the period of time analyzed in this report, the upward trend in station precipitation and no-trend in average temperature were consistent with the trends found using Daymet, the gridded climate data used in analysis for this report.

[1]More information on these tools can be obtained from the author of this report.

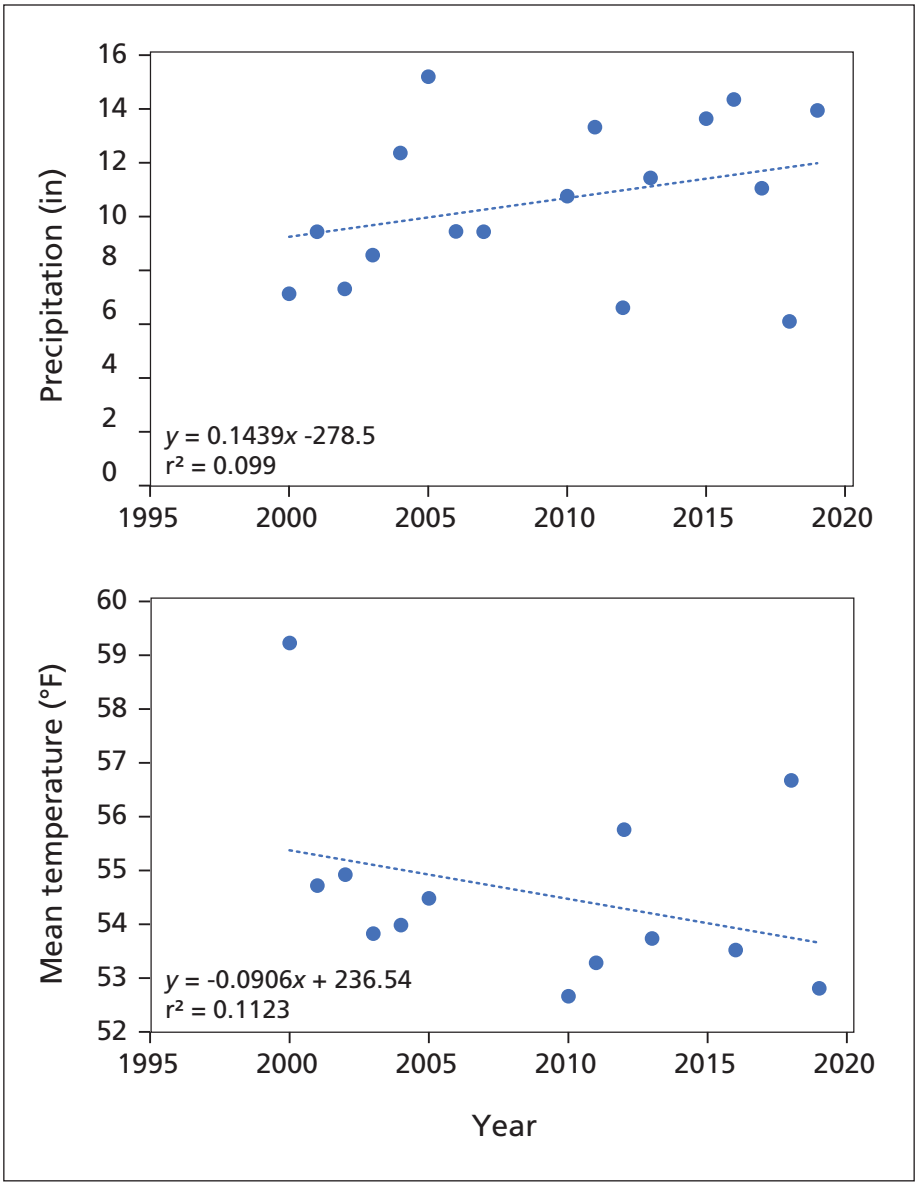


Figure 4-4. Annual trends in water-year precipitation and temperature obtained from Colorado NM weather station via ClimateAnalyzer.org. Years with more than 15 missing days were excluded. The data were exported to Excel for plotting.

5 Conclusions

Since 2000, primary production has increased at Colorado NM. The increase coincided with a slight increase in precipitation over the same period. However, over this period, there were dry years and dry periods extending for several years that resulted in substantial declines in vegetation cover that largely rebounded by the end of the study.

The variation in vegetation condition across wet and dry years was evaluated to identify which alliance groups were most drought-tolerant (Wet Shrubland), and which were least drought tolerant (Juniper Woodland). Similarly, variation in climate over the study period was used to determine that Annual Exotic Grassland was most sensitive to precipitation, while Juniper Woodland was least sensitive.

The climate variable most strongly correlated with vegetation production was two or more years of average annual soil moisture. Timing of snowmelt, solar radiation, and actual evapotranspiration were the primary determinants of green-up timing. Over the study period, the start of growing season shifted earlier, and the length of growing season increased, likely due to an increasing trend in precipitation. The variation in weather conditions and corresponding vegetation response provide a window into the past that will inform understanding and management of vegetation that always has and will continue to respond to climate at Colorado NM.

Much of the information in this report will soon be outdated. However, some of the findings described here have long-term value and are unlikely to change in the near future, such as pivot points and sensitivity of vegetation to weather and climate. Those factors are mostly inherent to the vegetation and where it grows. However, climate is changing rapidly, and extreme weather events are becoming more frequent. The tools developed for these analyses can help National Park Service managers to anticipate and plan for climate change—and to manage change as it happens. This report demonstrates how combining satellite observations of vegetation condition with climate data can help determine the right time and place for action needed in the near term to help achieve long-range management goals for stewarding park resources through continuous change.

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Appendix A. Supplemental Figures for Landscape Phenology, Vegetation Condition, and Relations with Climate at Colorado National Monument, 2000–2019

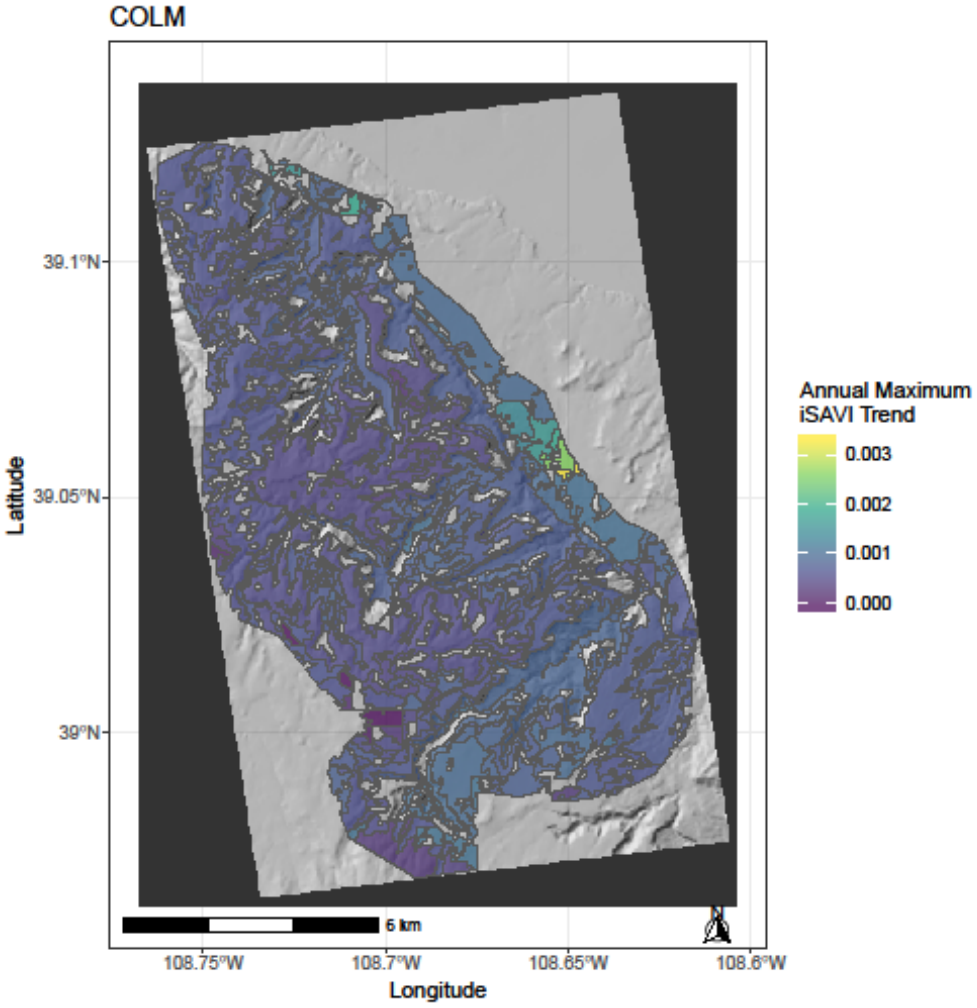


Figure A-1. Spatial pattern of trends in maximum annual iSAVI. Trend is average change in iSAVI per year for the period 2000-2019.

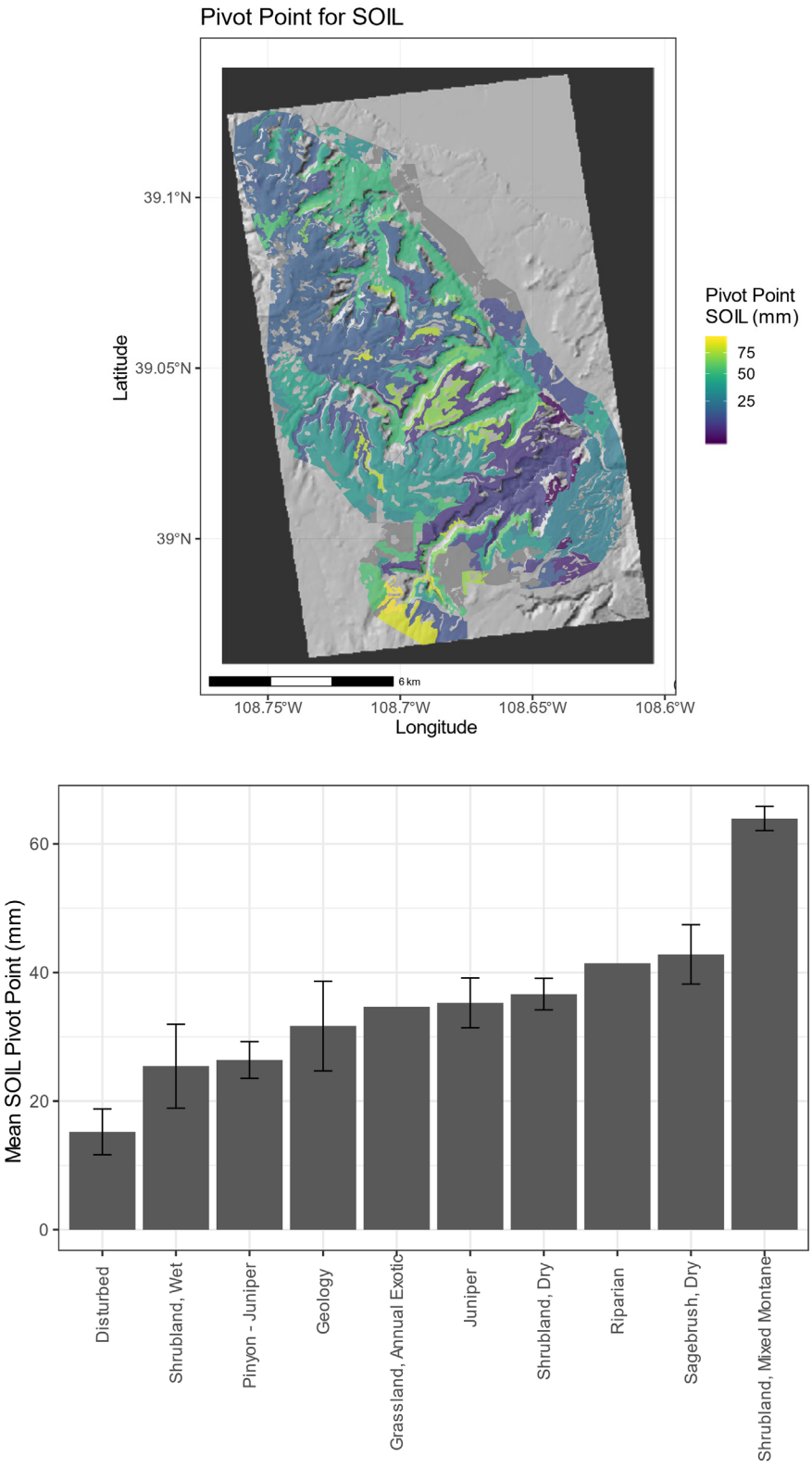


Figure A-2a. Pivot points for polygons where climate variables were significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.

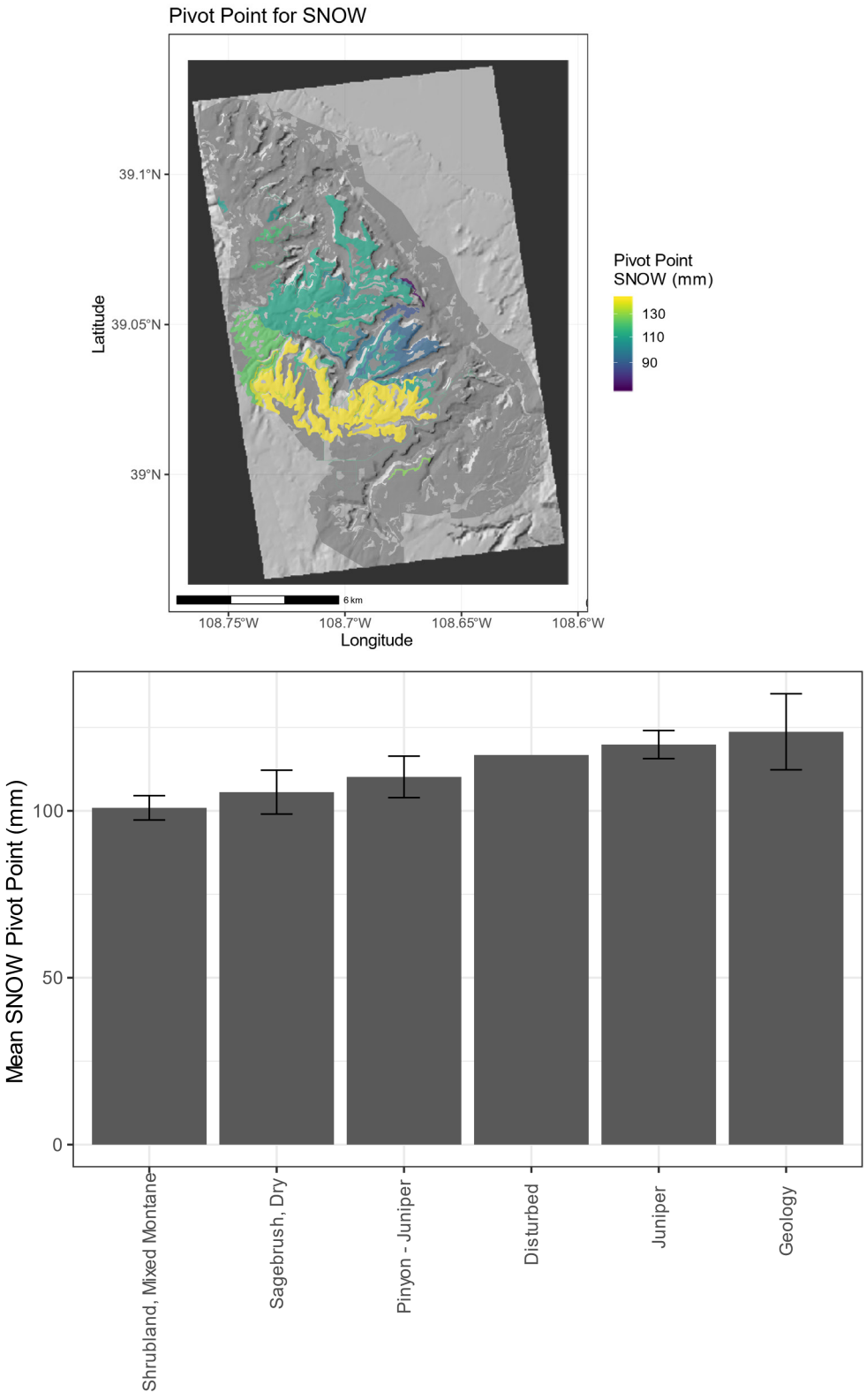


Figure A-2b. Pivot points for polygons where climate variables were significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.

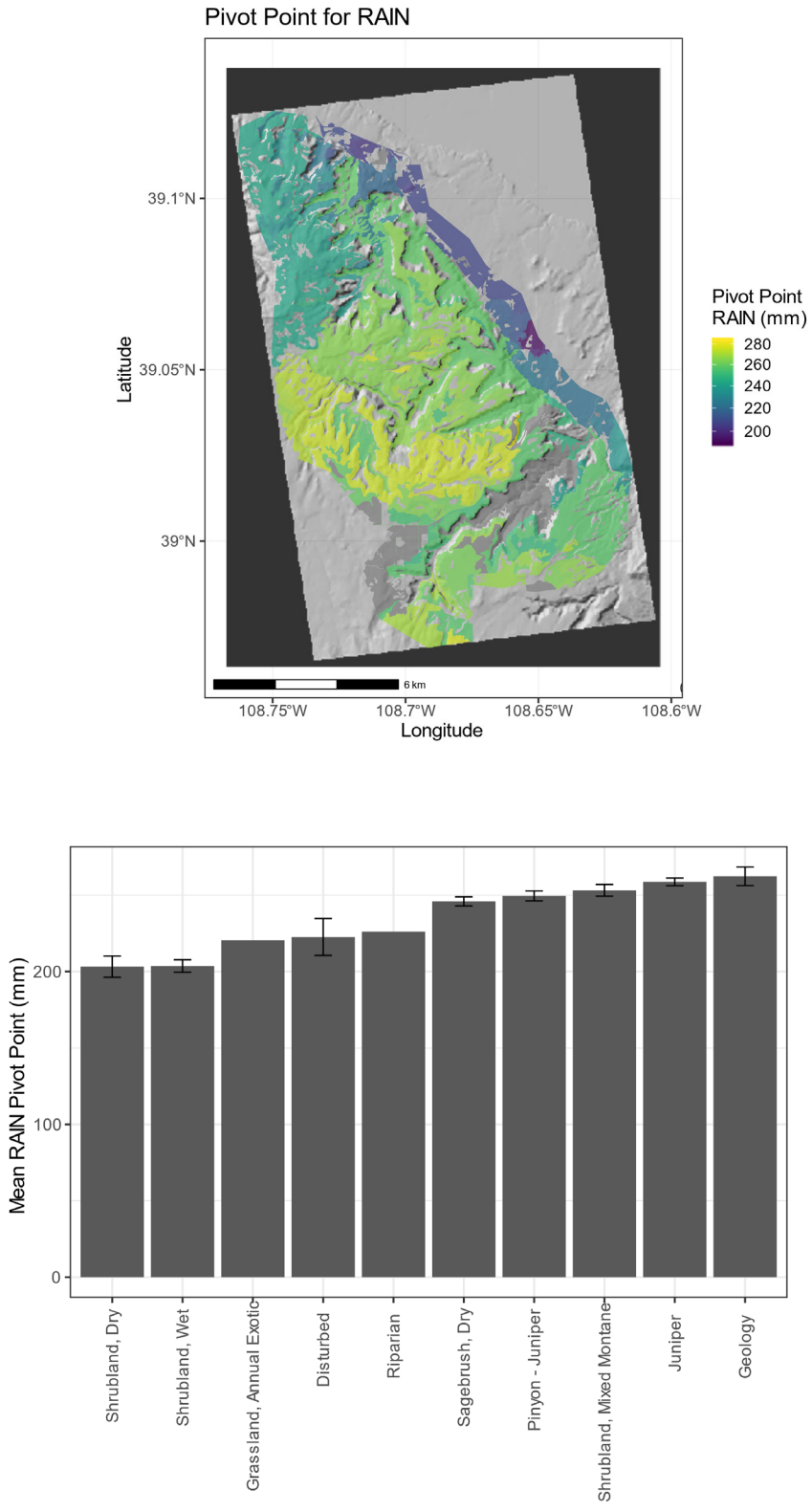


Figure A-2c. Pivot points for polygons where climate variables were significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.

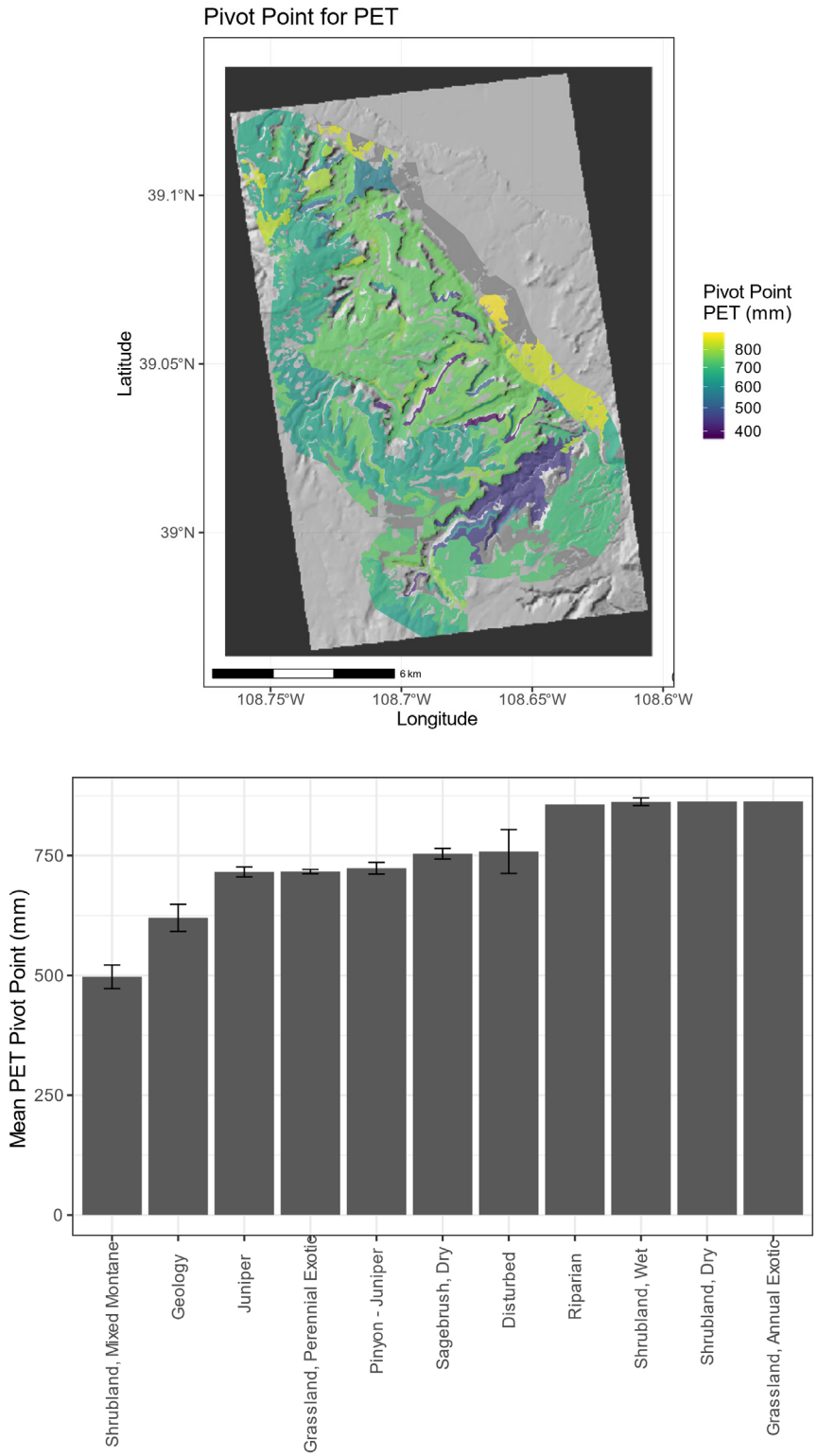


Figure A-2d. Pivot points for polygons where climate variables were significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.

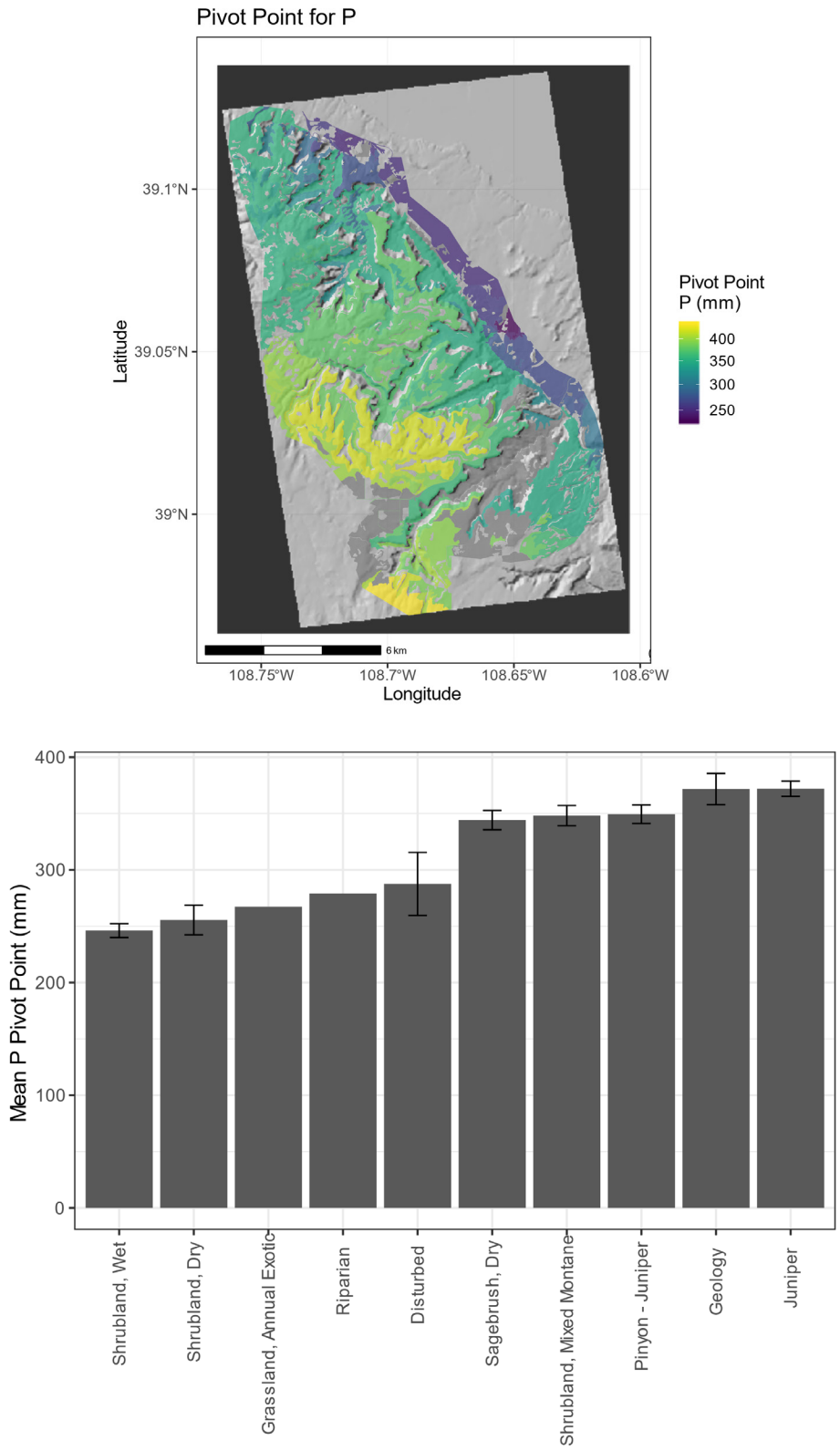


Figure A-2e. Pivot points for polygons where climate variables were significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.

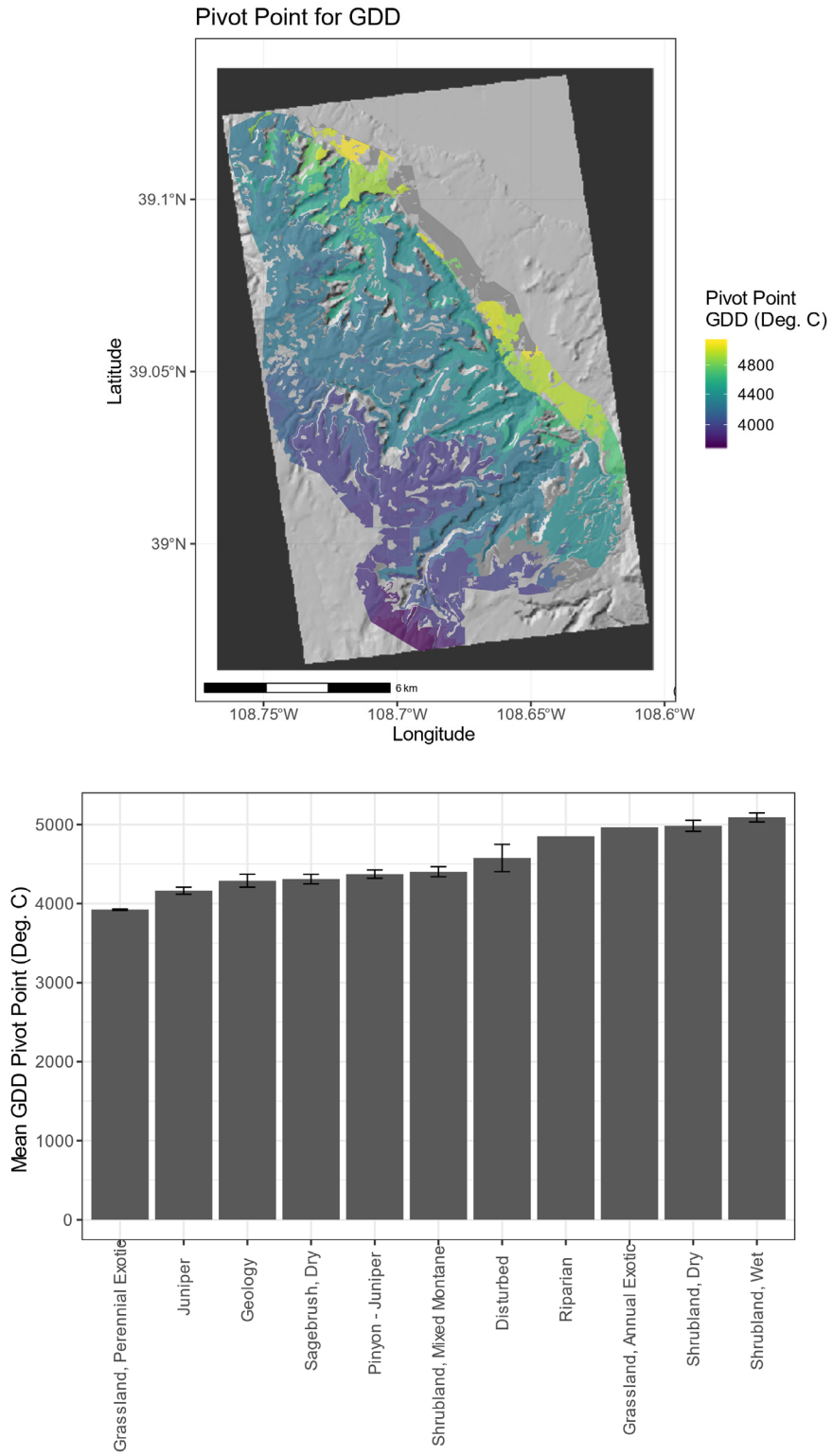
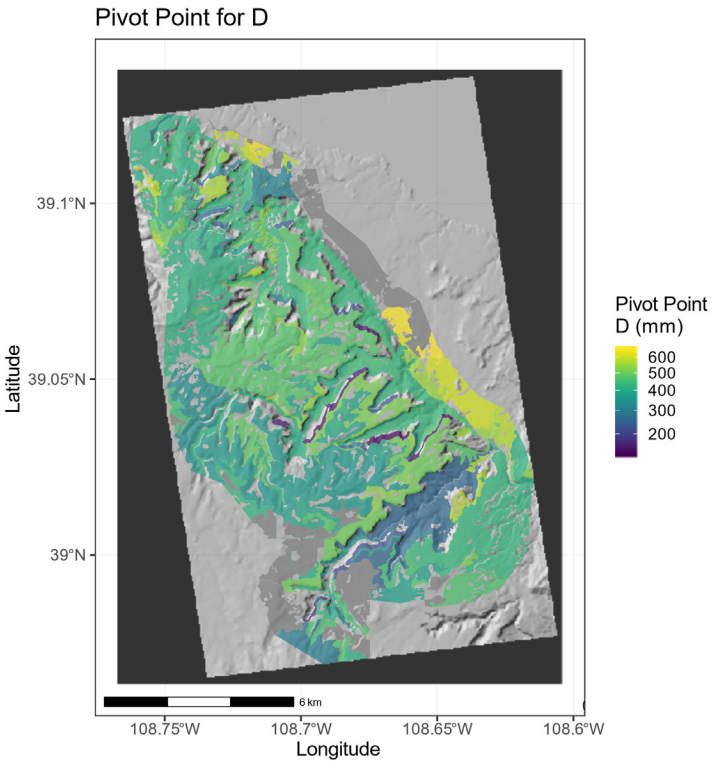


Figure A-2f. Pivot points for polygons where climate variables were significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.



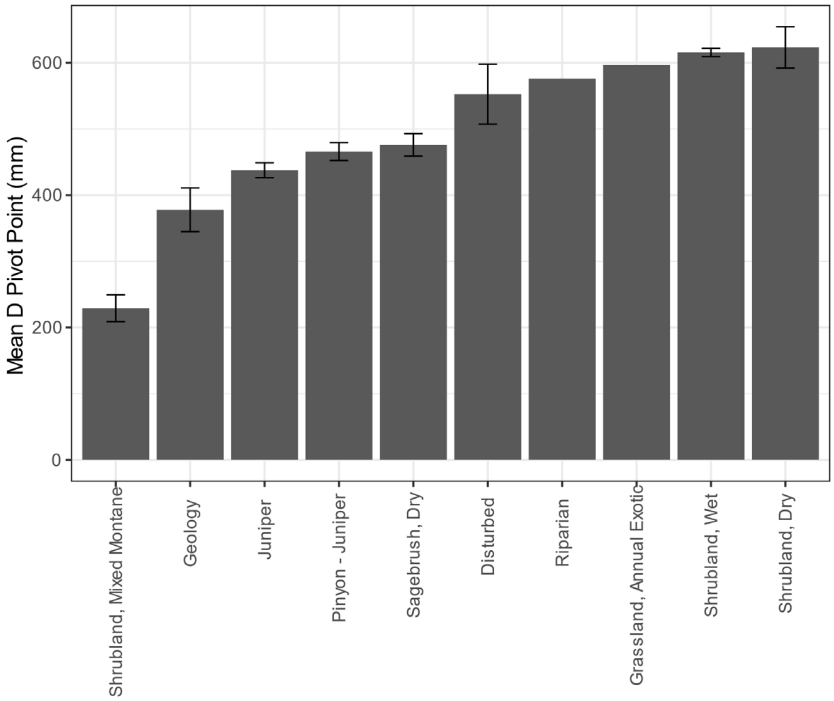


Figure A-2g. Pivot points for polygons where climate variables were significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.

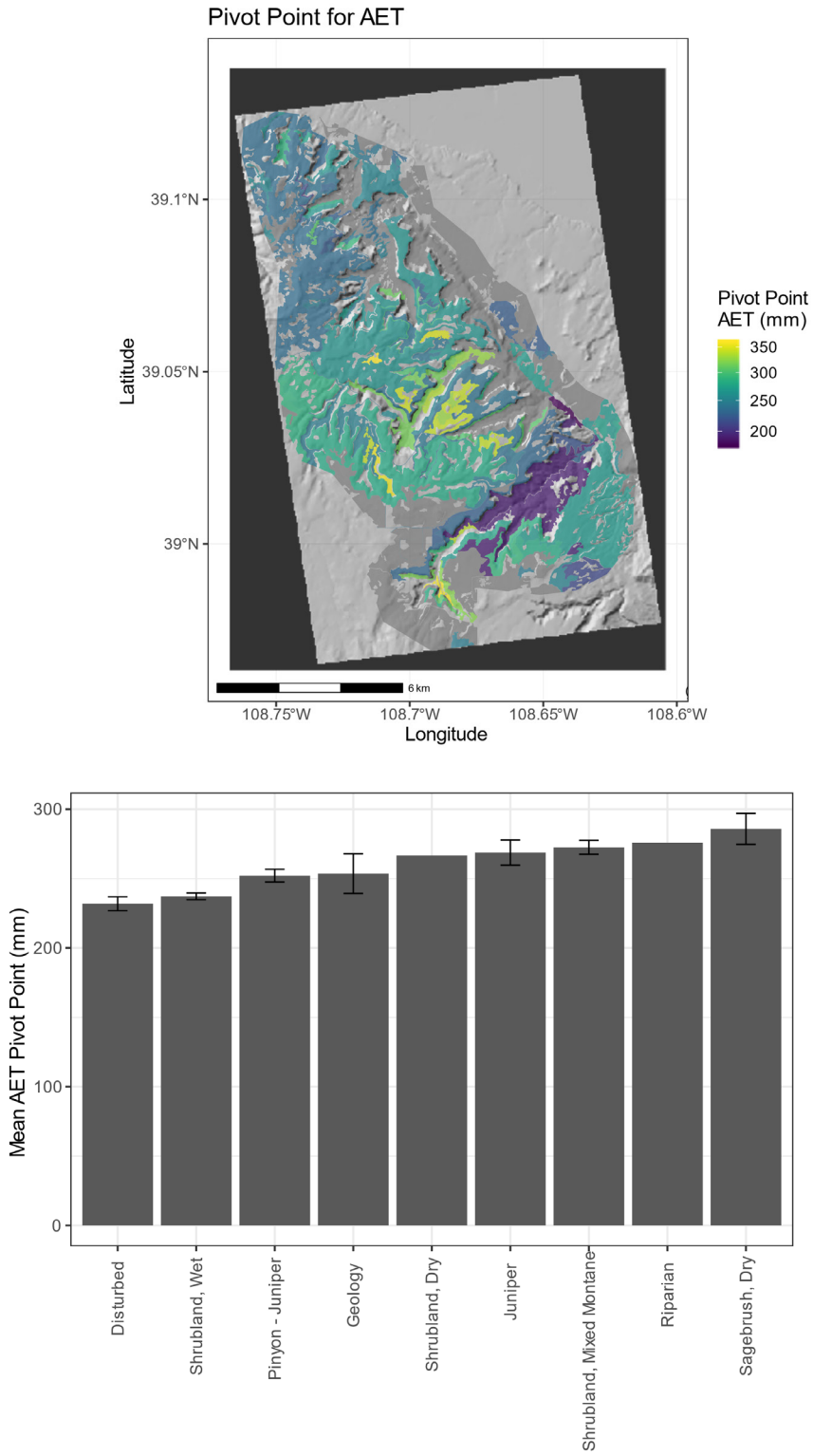


Figure A-2h. Pivot points for polygons where climate variables were significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.

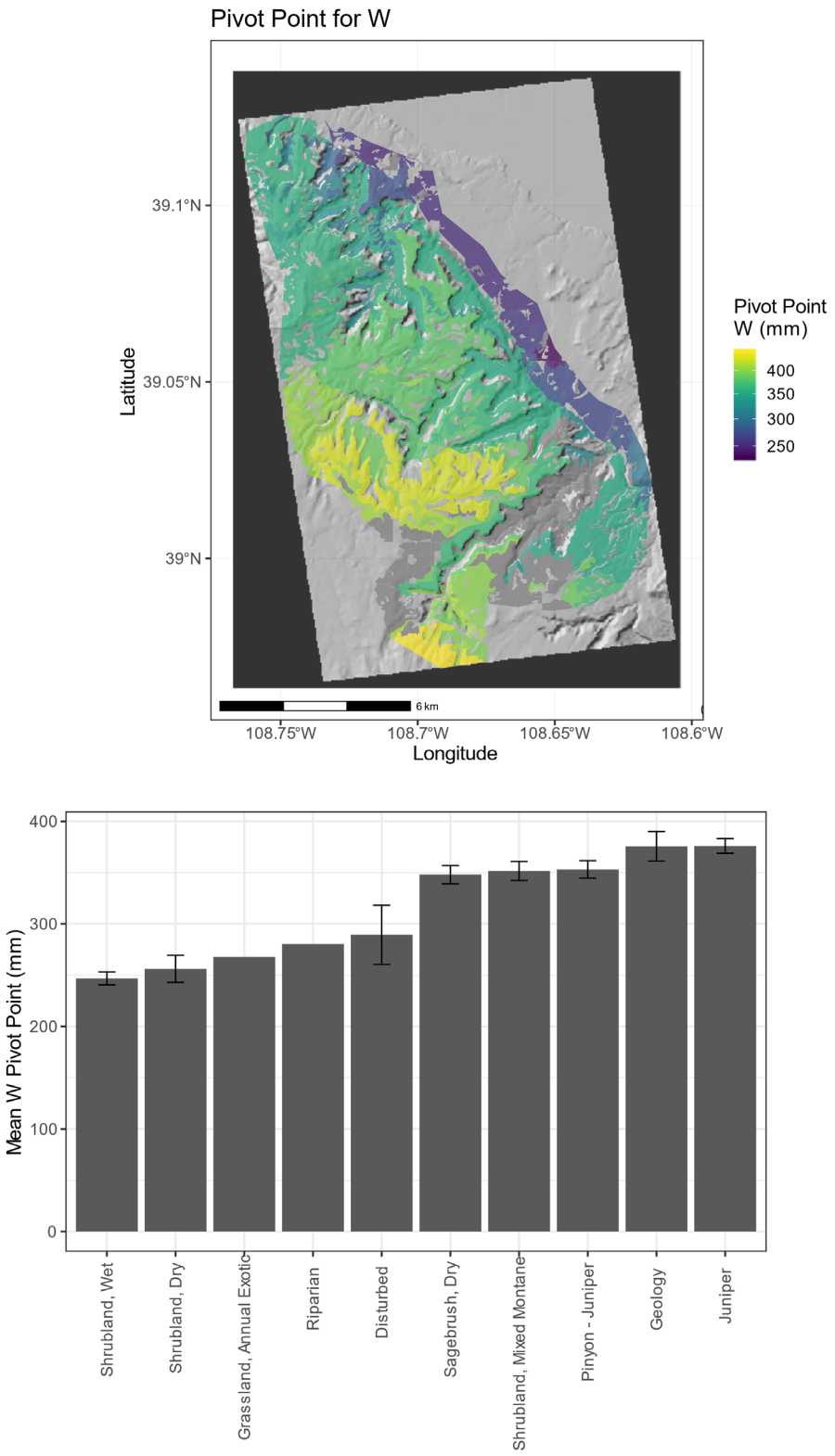
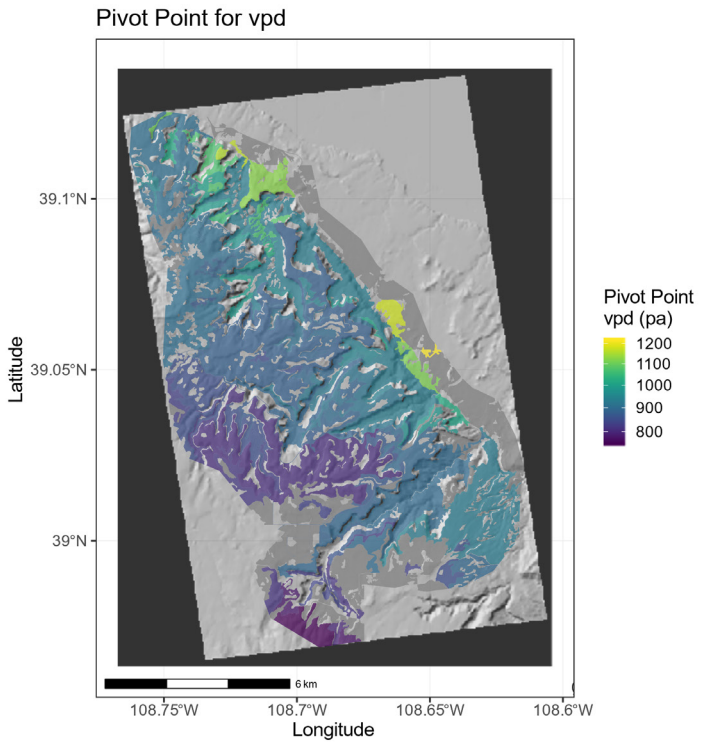


Figure A-2i. Pivot points for polygons where climate variables were significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.



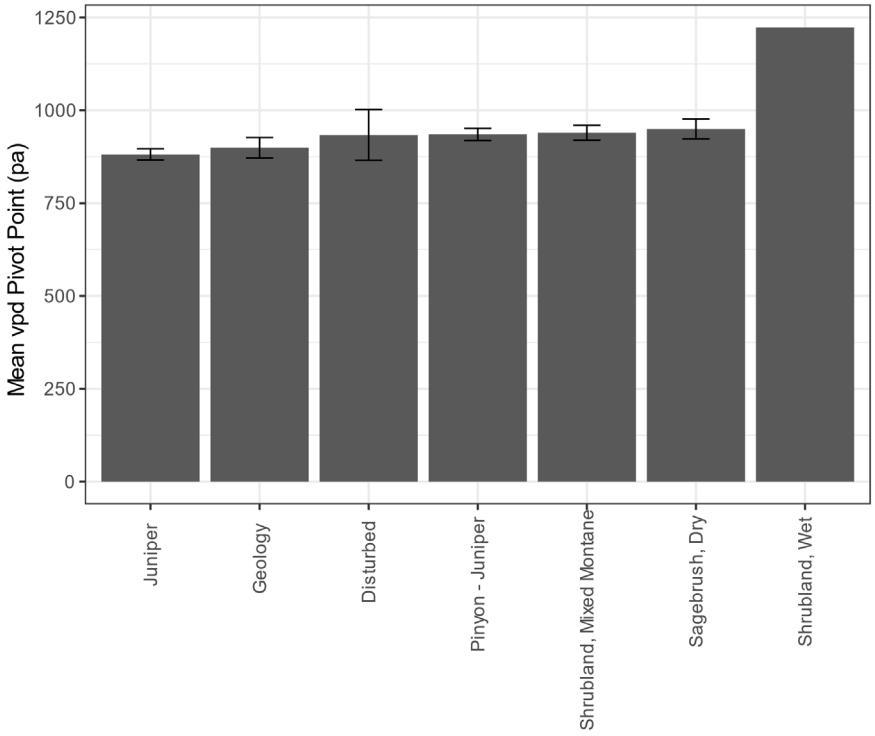


Figure A-2j. Pivot points for polygons where climate variables were significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.

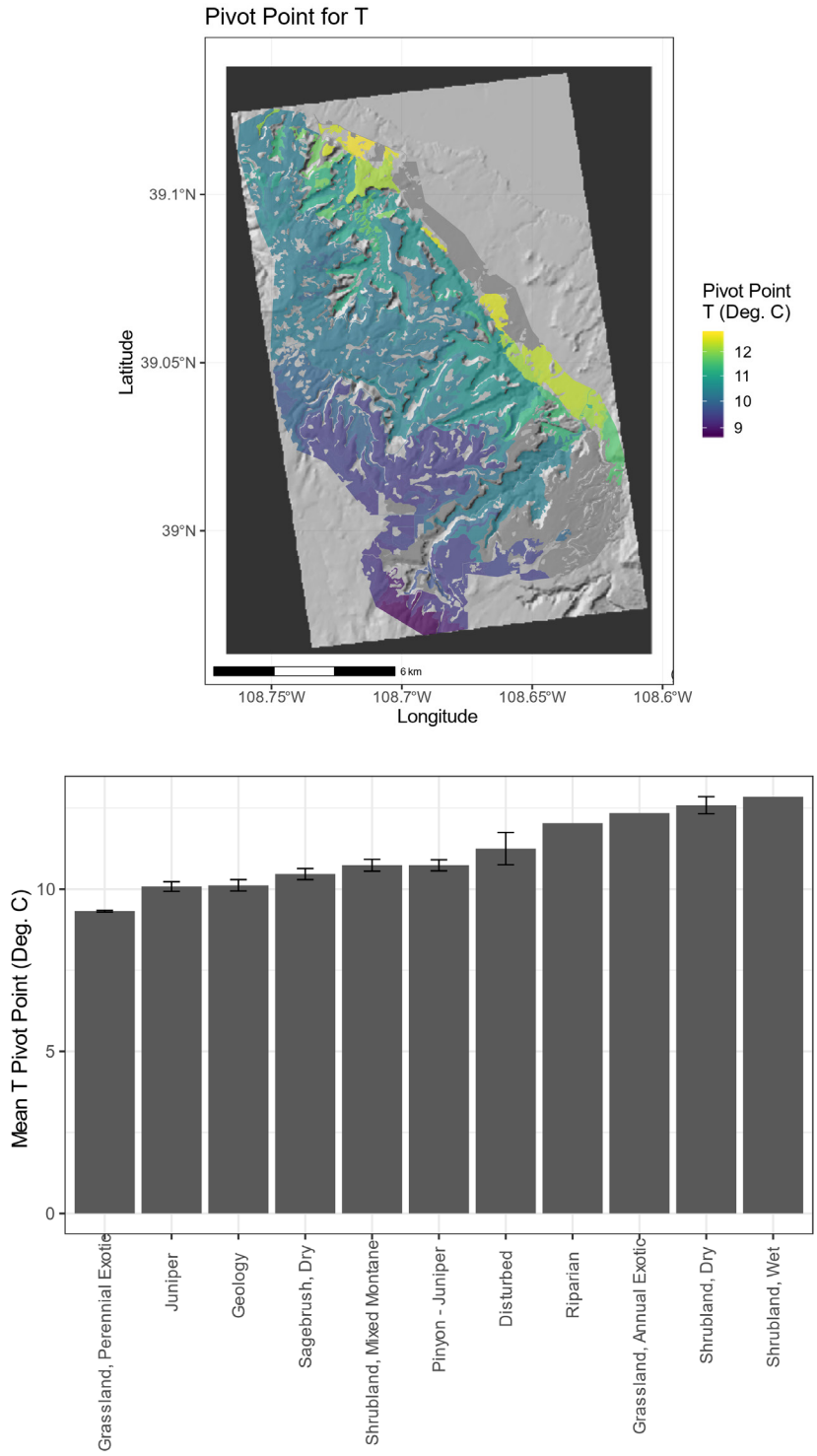
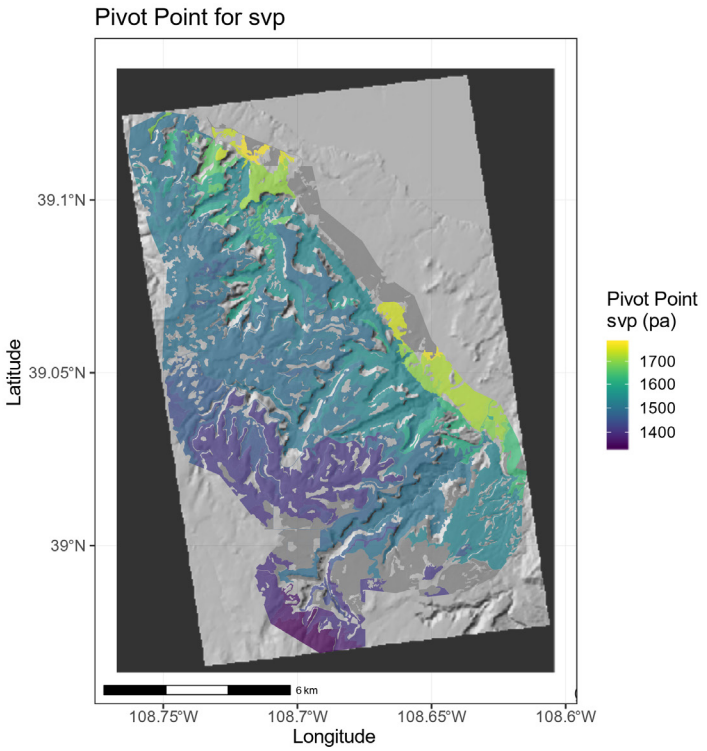


Figure A-2k. Pivot points for polygons where climate variables were significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.



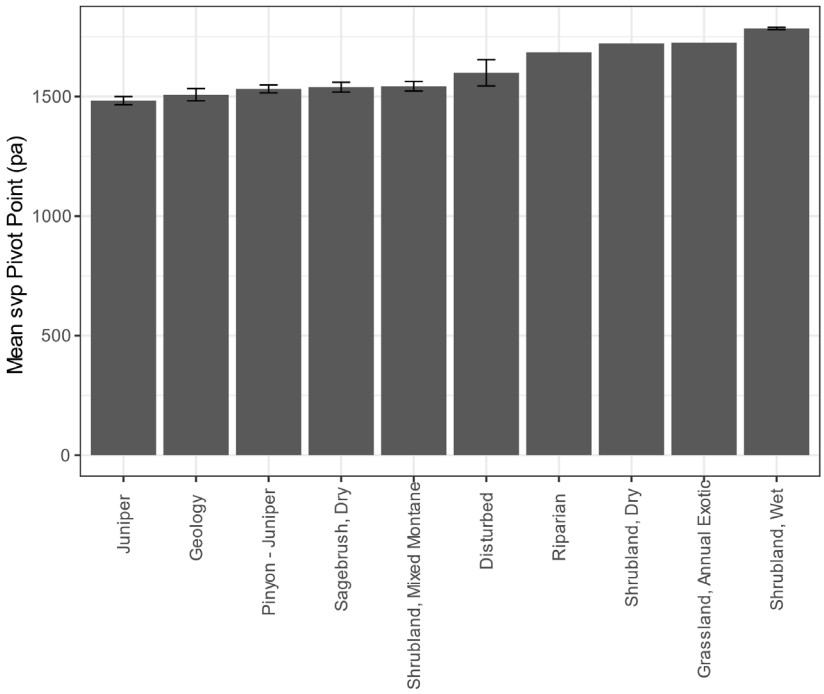


Figure A-2l. Pivot points for polygons where climate variables were significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.

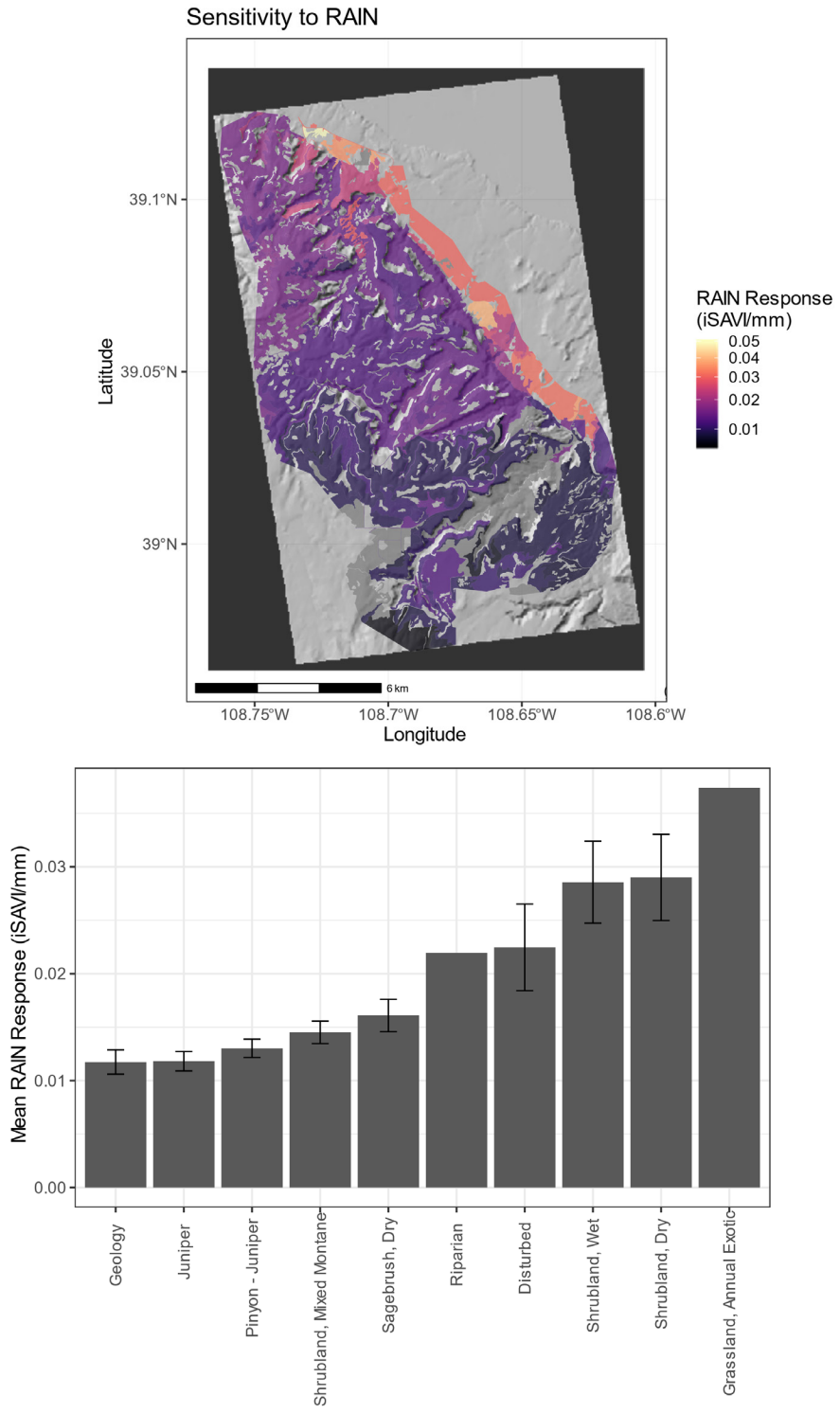


Figure A-3a. Sensitivity of growing season vegetation production to climate variables, where the relationship was significant (p-value < 0.05). Climate data summarized by water year.

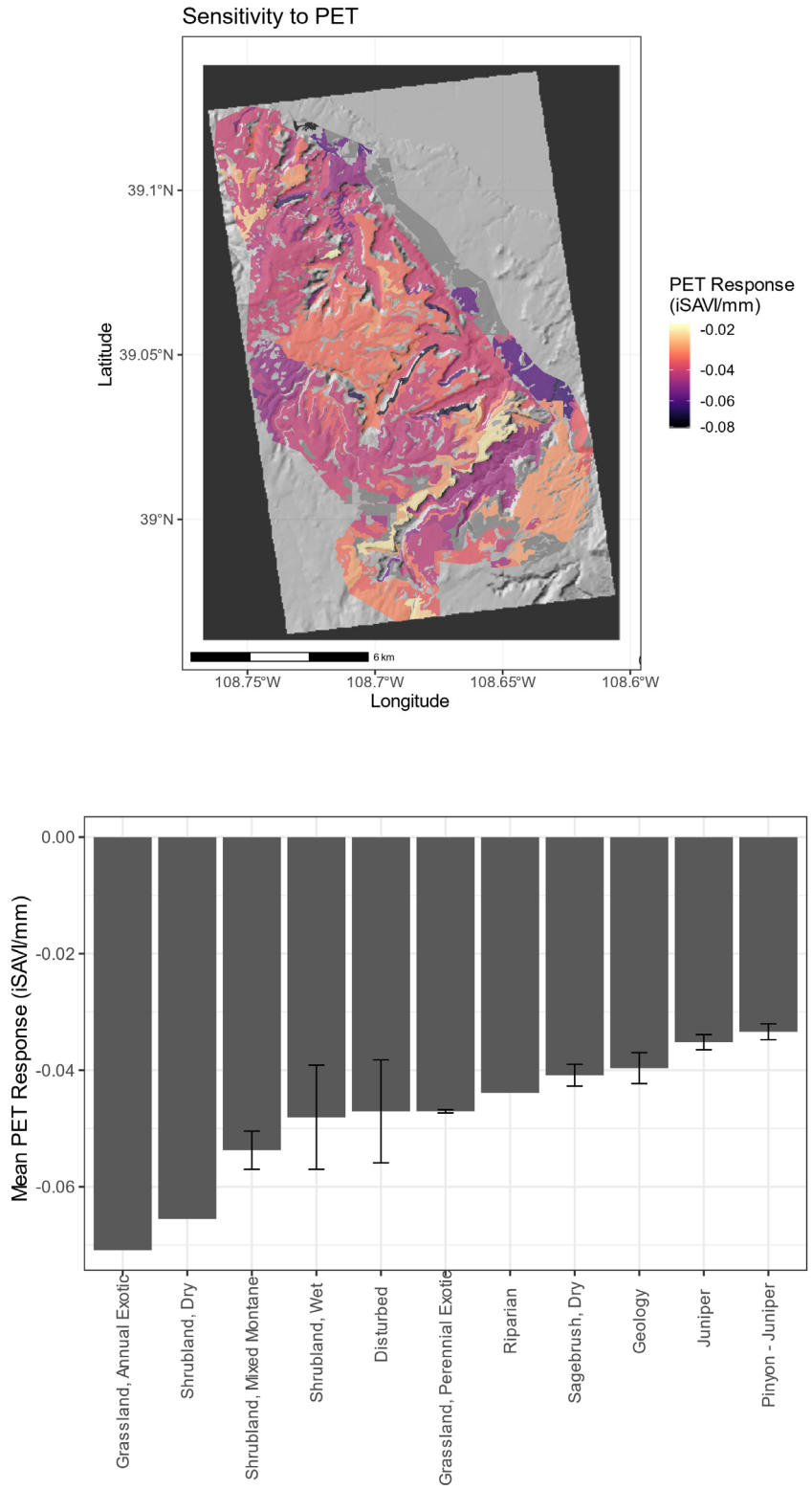


Figure A-3b. Sensitivity of growing season vegetation production to climate variables, where the relationship was significant (p-value < 0.05). Climate data summarized by water year.

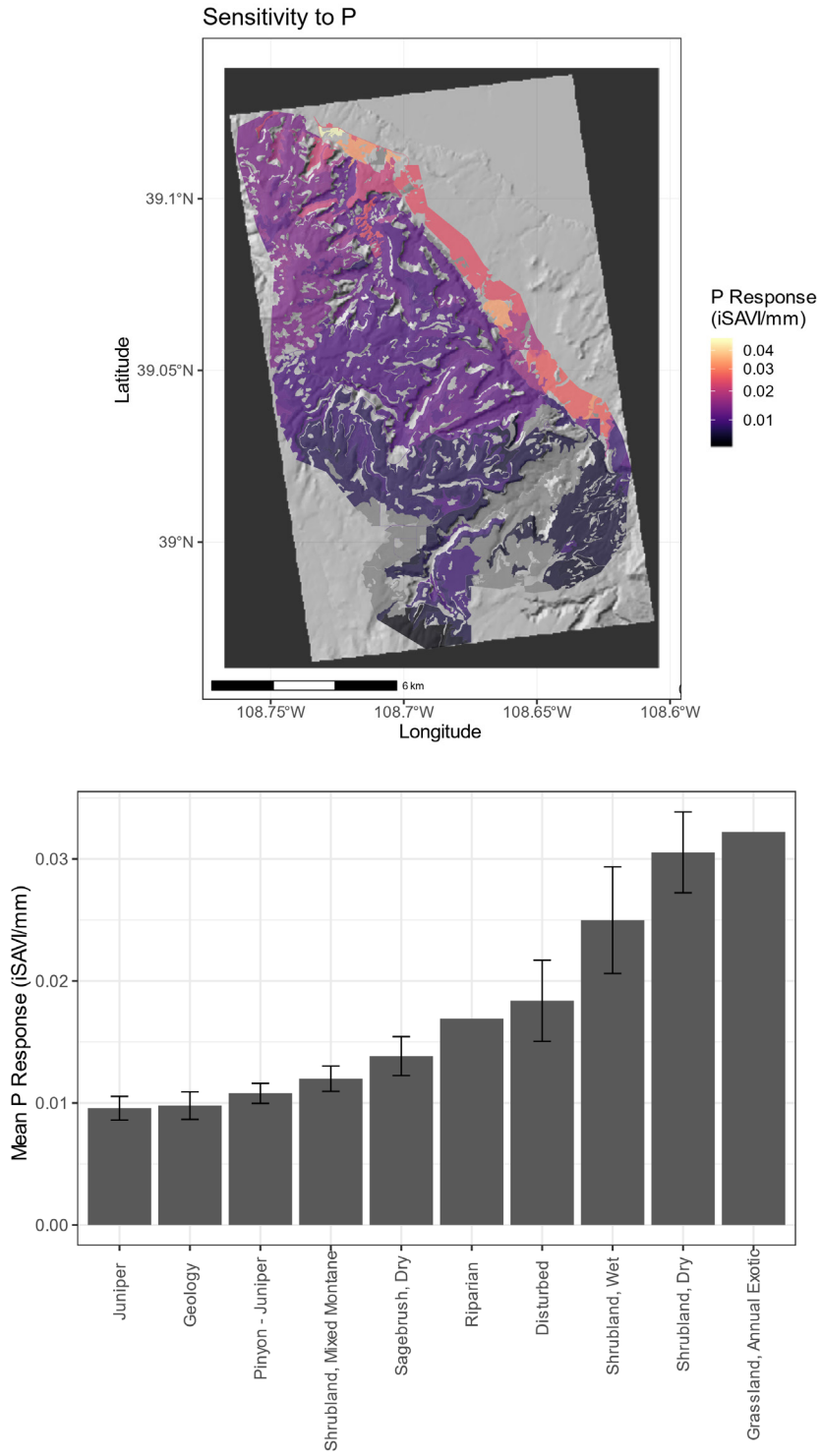


Figure A-3c. Sensitivity of growing season vegetation production to climate variables, where the relationship was significant (p-value < 0.05). Climate data summarized by water year.

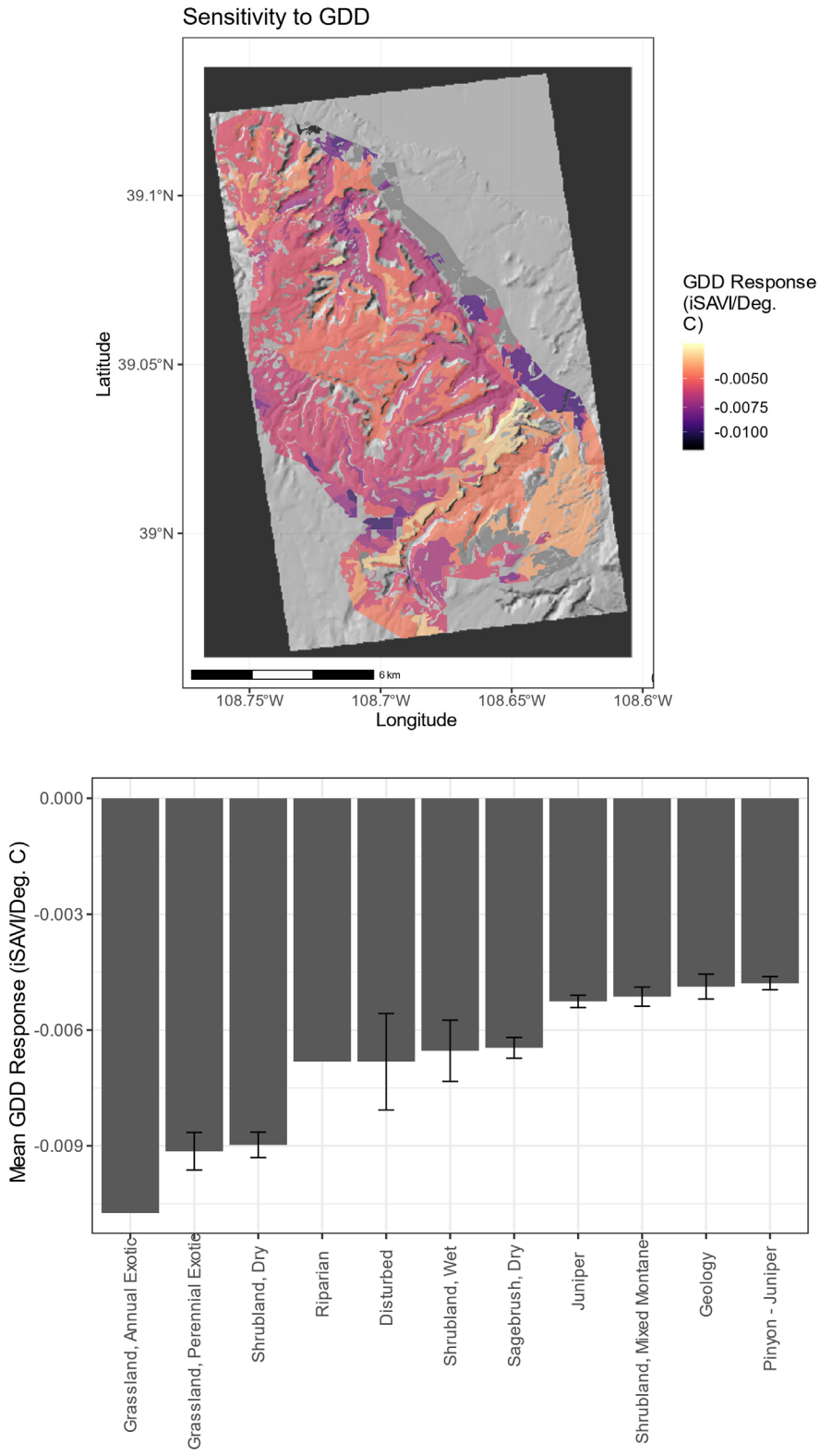


Figure A-3d. Sensitivity of growing season vegetation production to climate variables, where the relationship was significant (p-value < 0.05). Climate data summarized by water year.

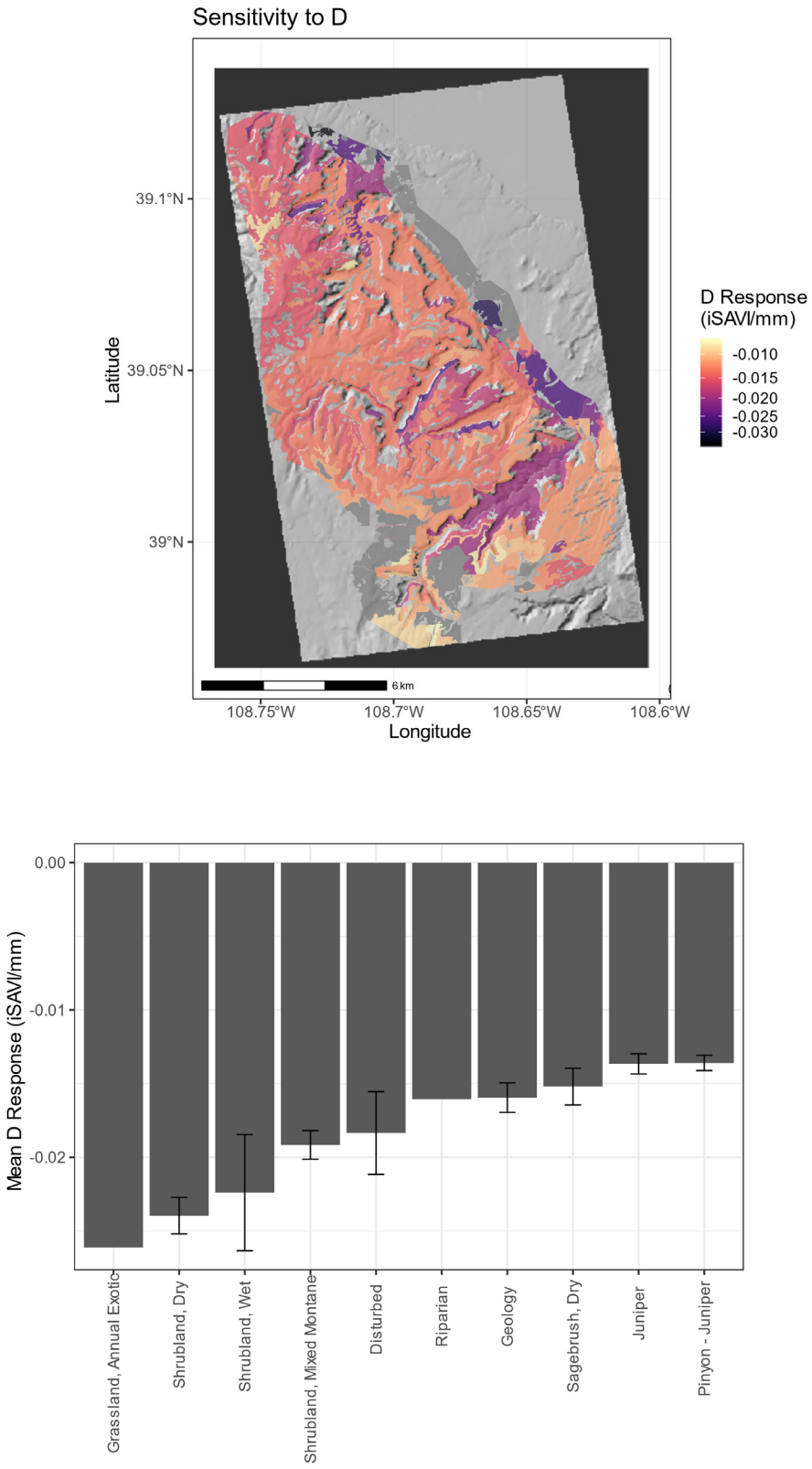


Figure A-3e. Sensitivity of growing season vegetation production to climate variables, where the relationship was significant (p-value < 0.05). Climate data summarized by water year.

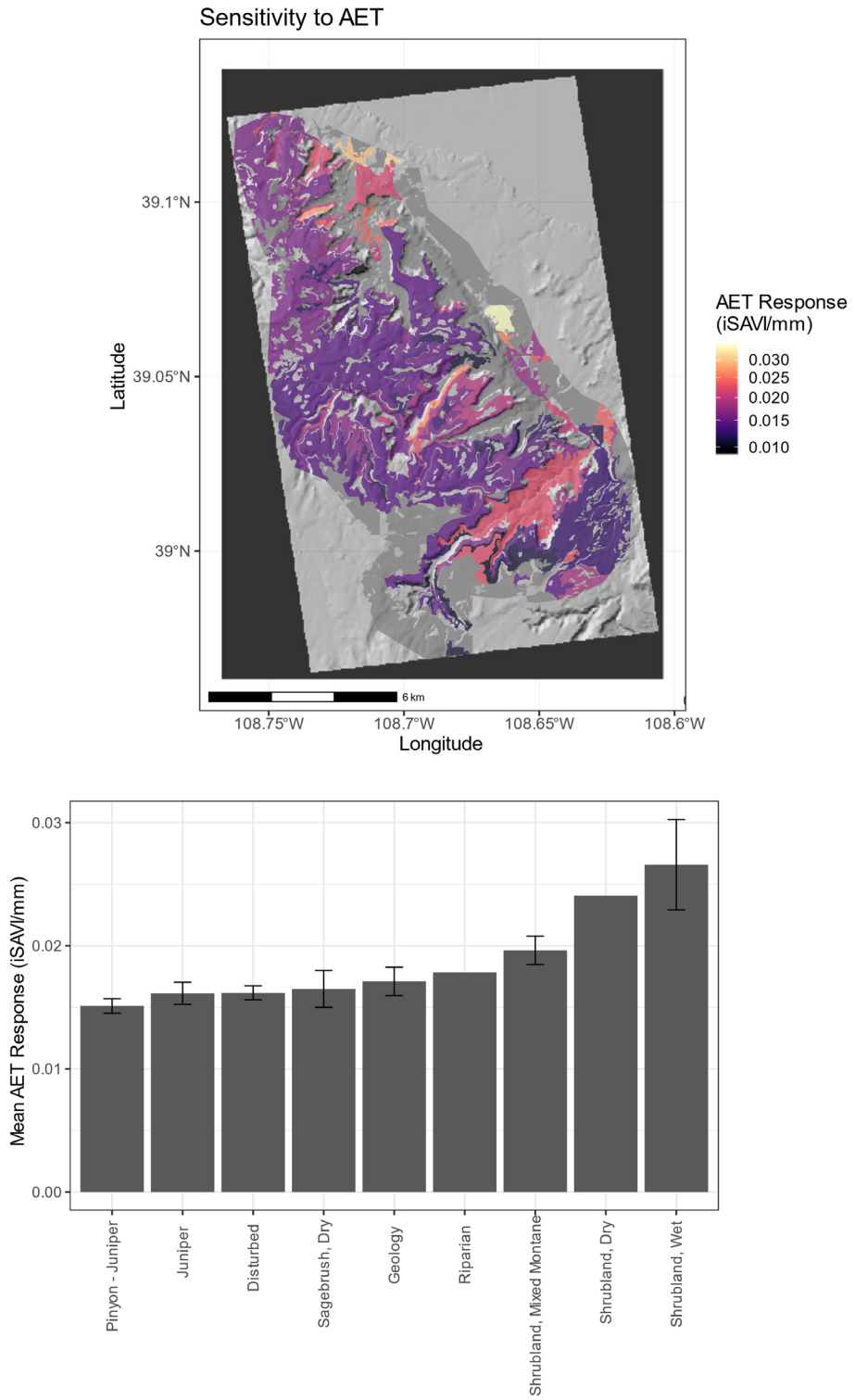
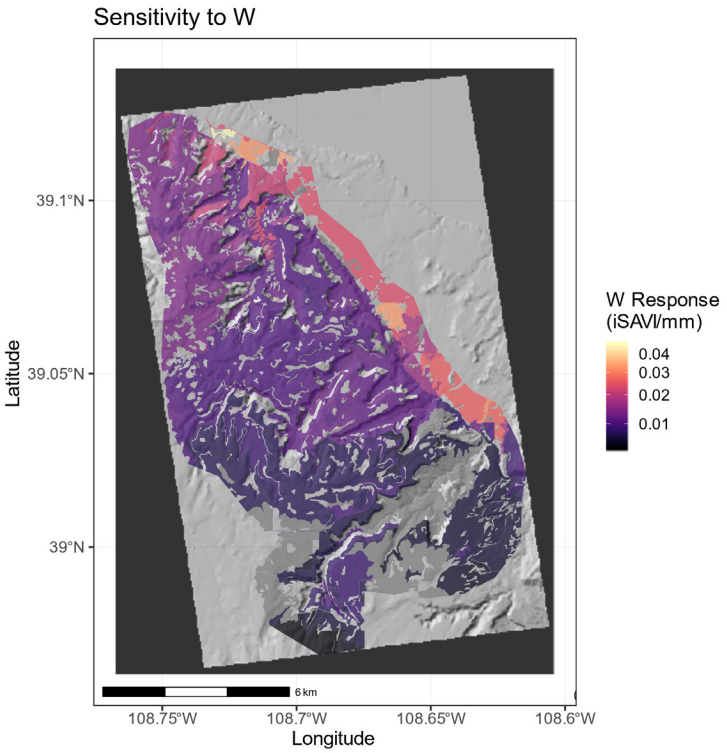


Figure A-3f. Sensitivity of growing season vegetation production to climate variables, where the relationship was significant (p-value < 0.05). Climate data summarized by water year.



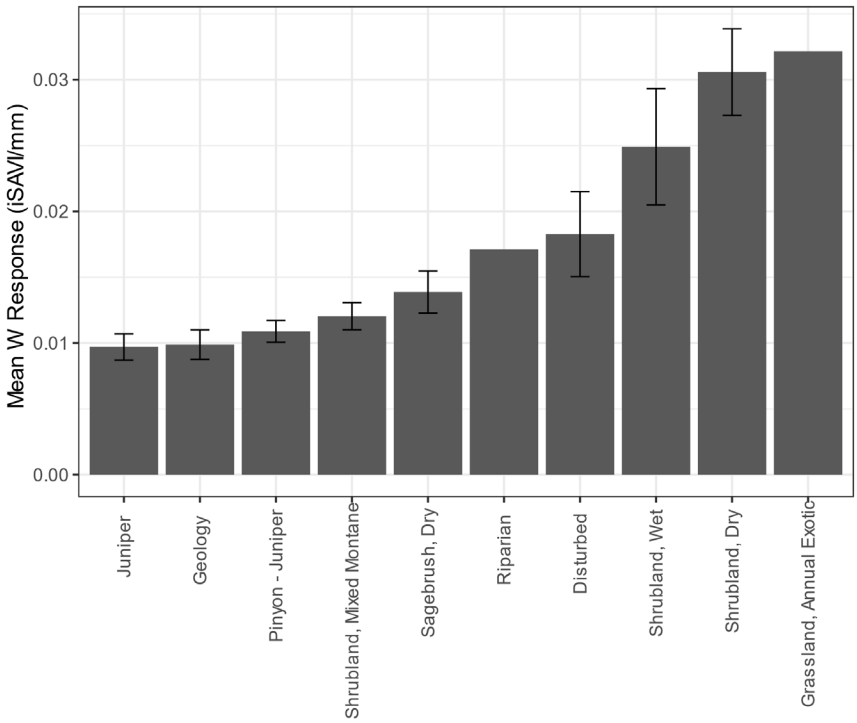


Figure A-3g. Sensitivity of growing season vegetation production to climate variables, where the relationship was significant (p-value < 0.05). Climate data summarized by water year.

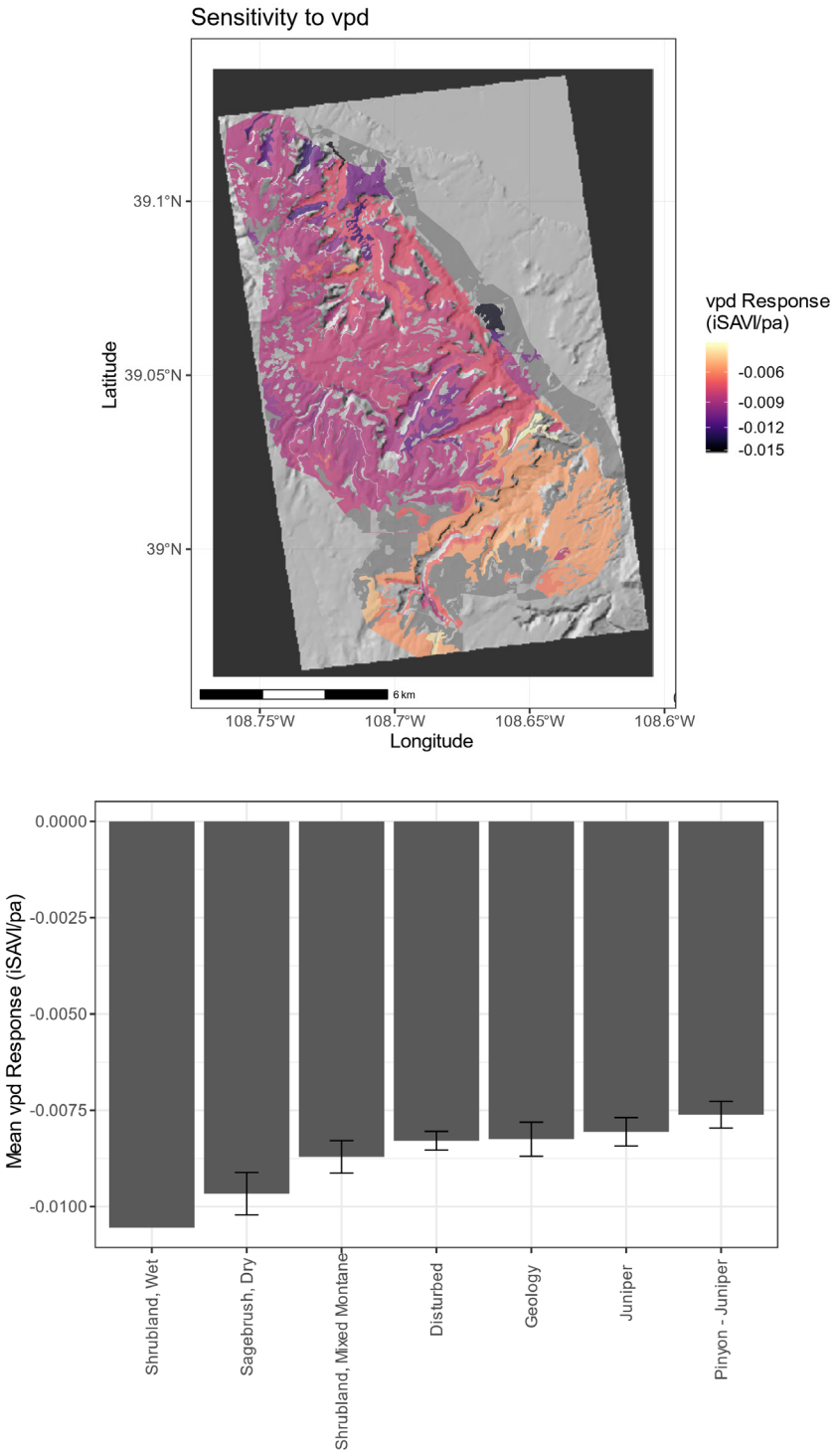


Figure A-3h. Sensitivity of growing season vegetation production to climate variables, where the relationship was significant (p-value < 0.05). Climate data summarized by water year.

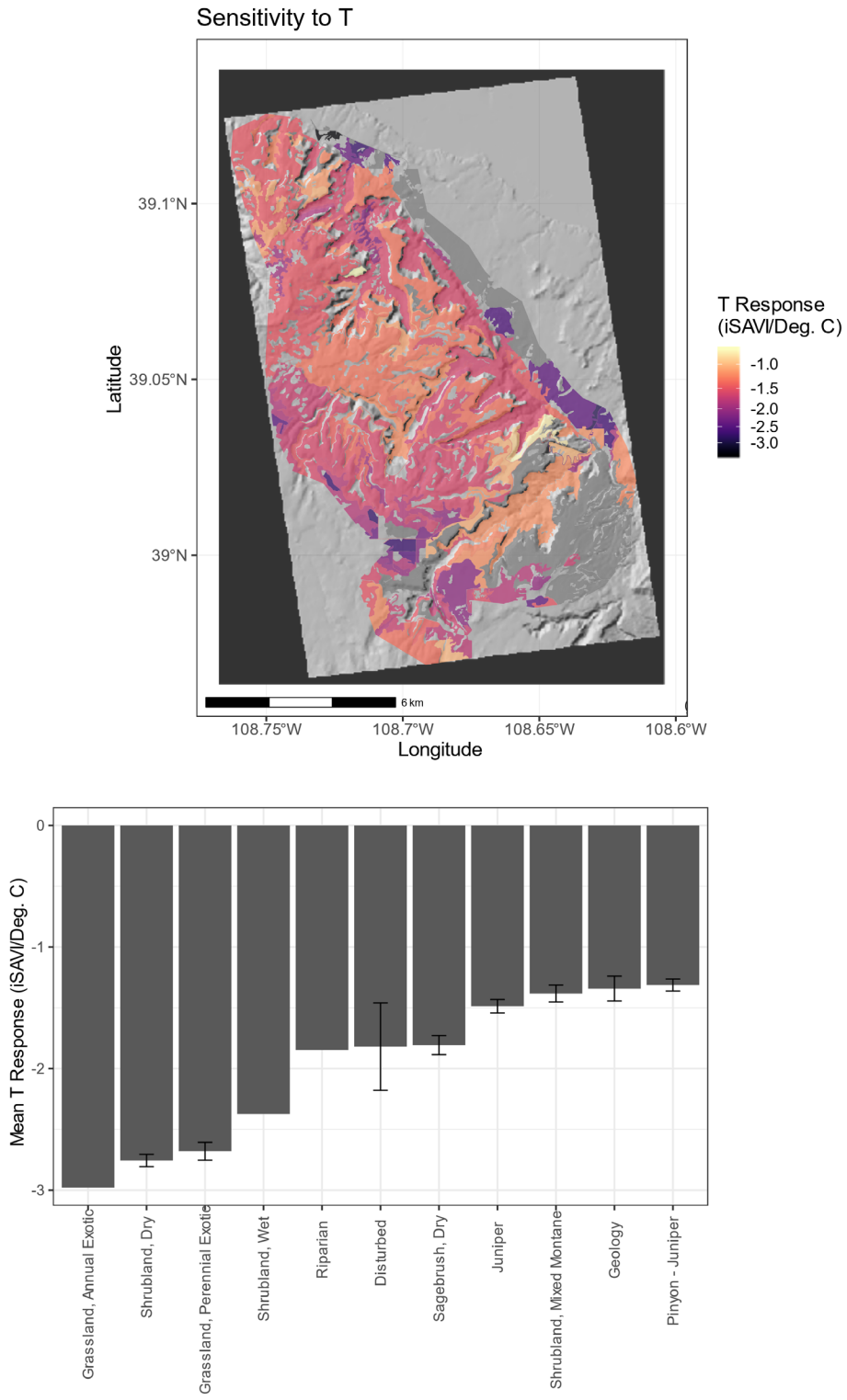


Figure A-3i. Sensitivity of growing season vegetation production to climate variables, where the relationship was significant (p-value < 0.05). Climate data summarized by water year.

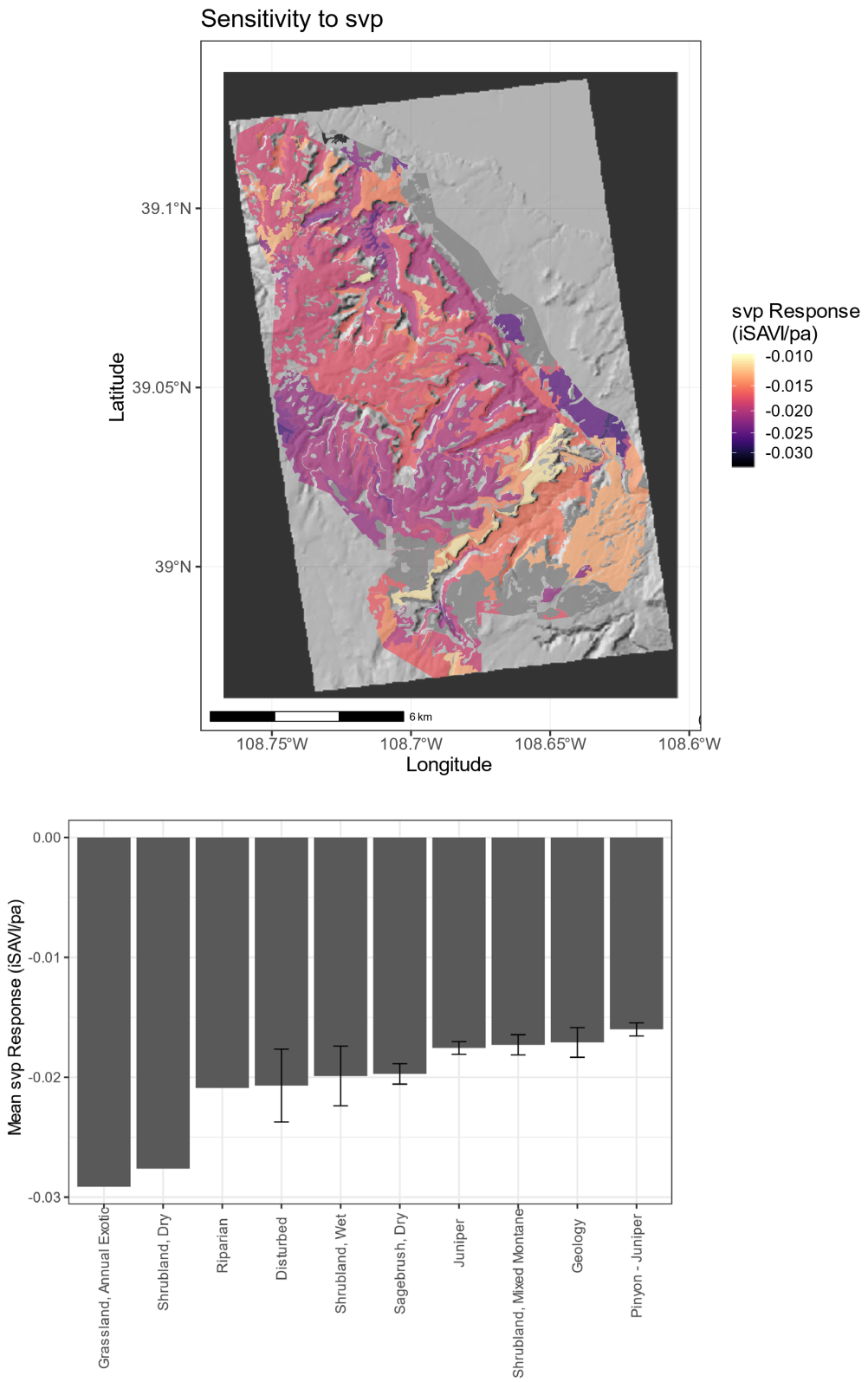


Figure A-3j. Sensitivity of growing season vegetation production to climate variables, where the relationship was significant (p-value < 0.05). Climate data summarized by water year.

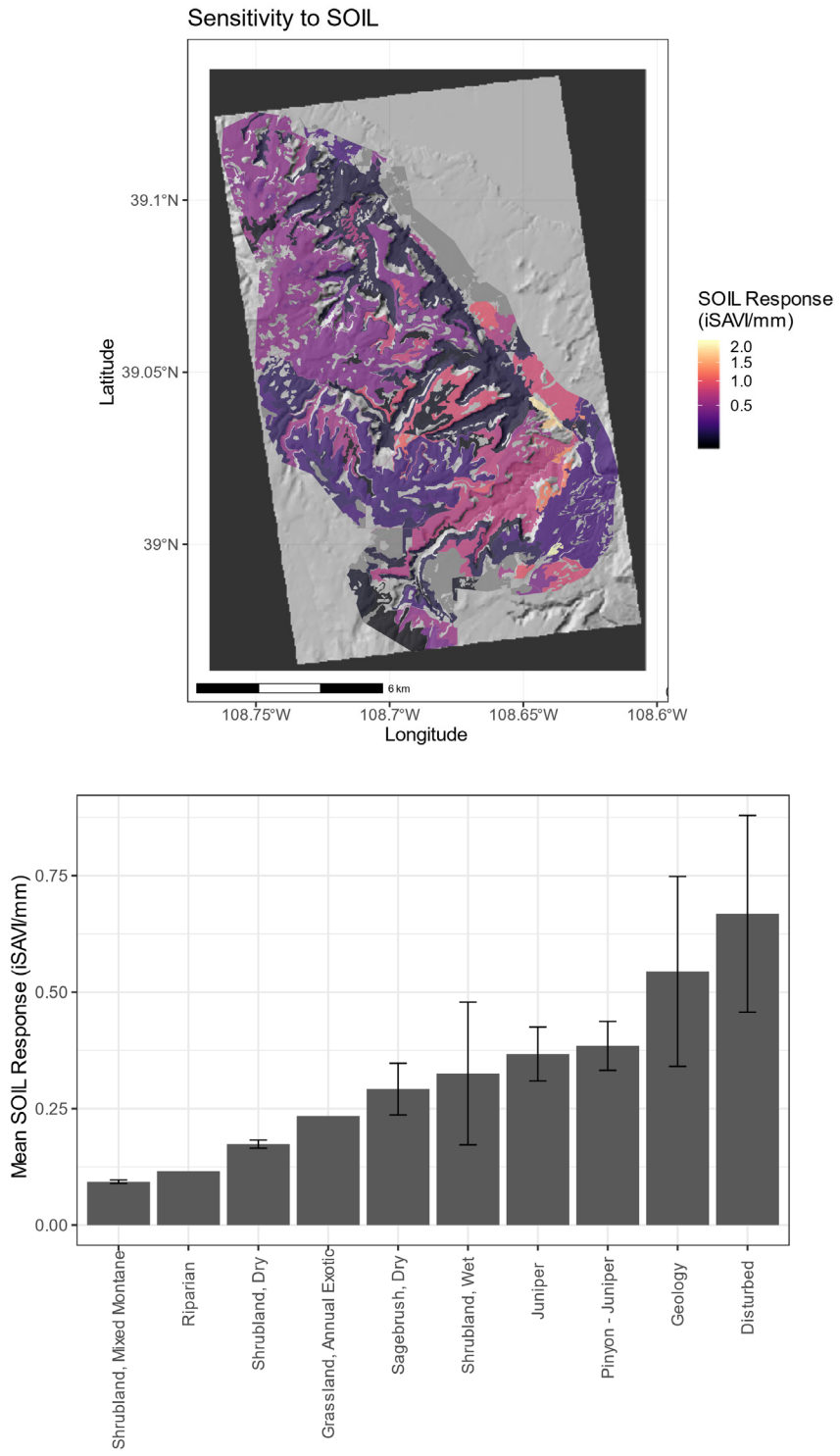


Figure A-3k. Sensitivity of growing season vegetation production to climate variables, where the relationship was significant (p-value < 0.05). Climate data summarized by water year.

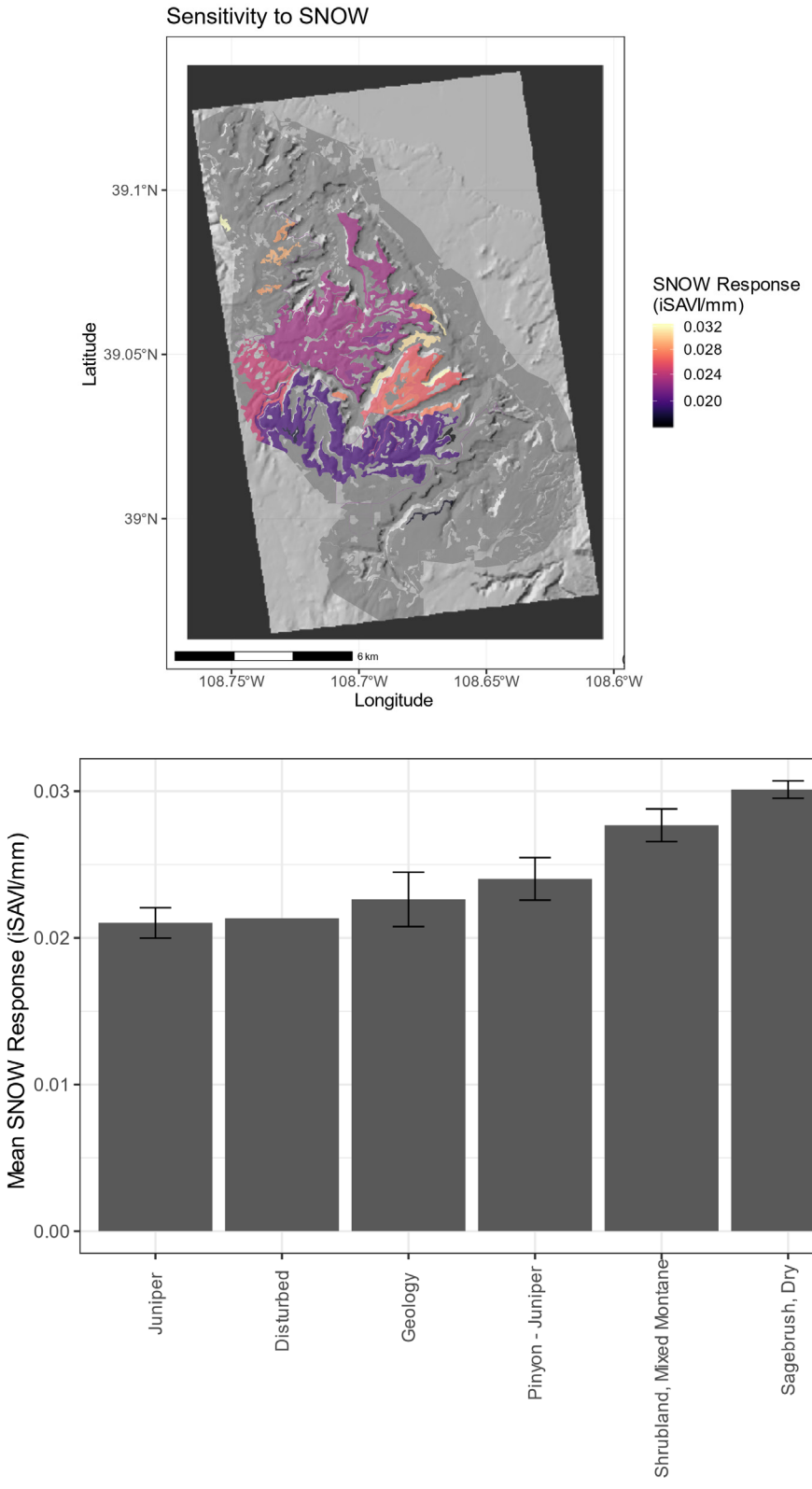


Figure A-3l. Sensitivity of growing season vegetation production to climate variables, where the relationship was significant (p-value < 0.05). Climate data summarized by water year.

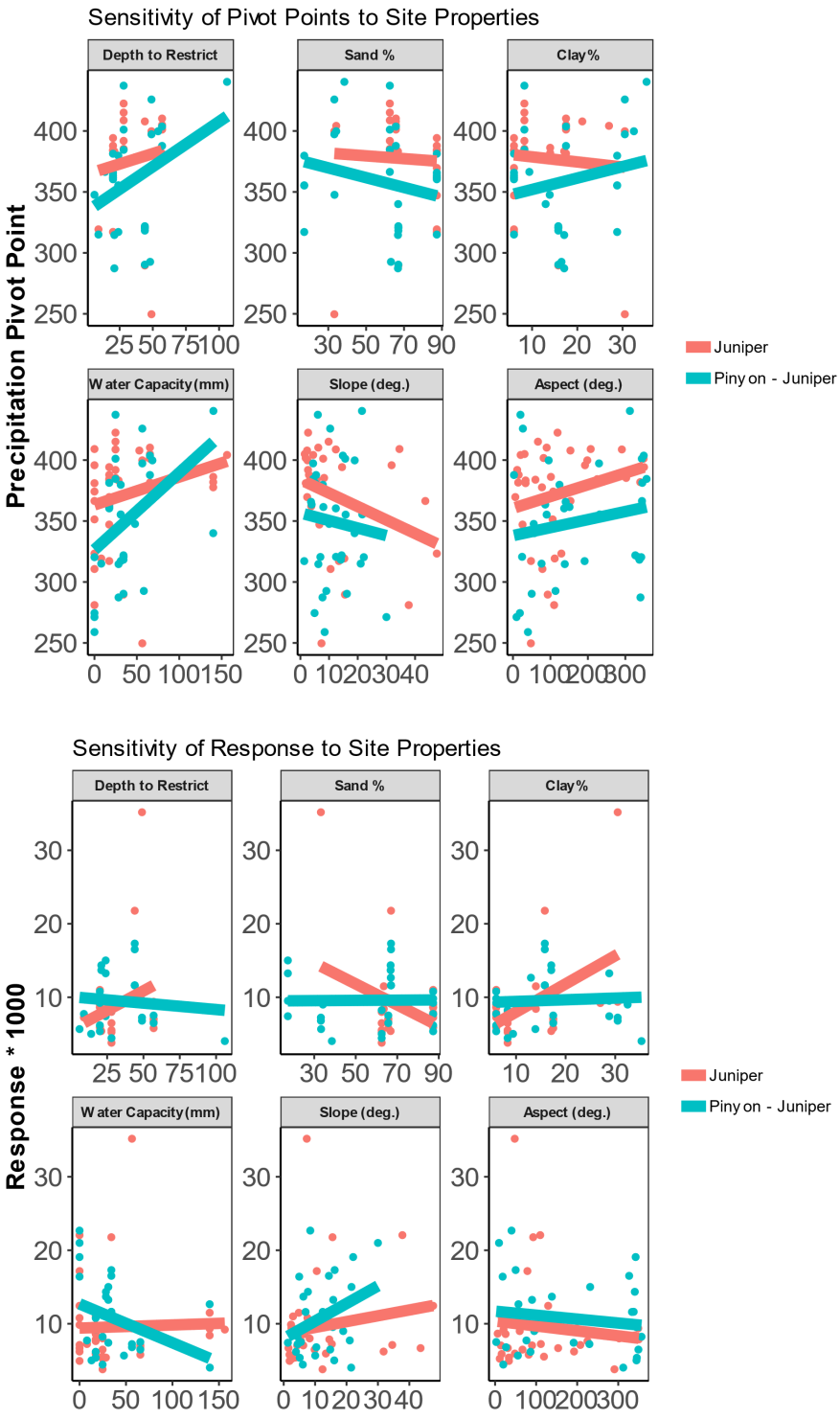


Figure A-4. Variation in a) precipitation pivot points and b) responses to precipitation as related to soil and site characteristics in Pinyon – Juniper woodlands. Steeper slopes indicate greater sensitivity of either pivot points or responses to site properties. These site properties are important modifiers of climate because they control water retntion and distribution in the soil profile and in the case of site slope and aspect because they affect the heat load on vegetation.

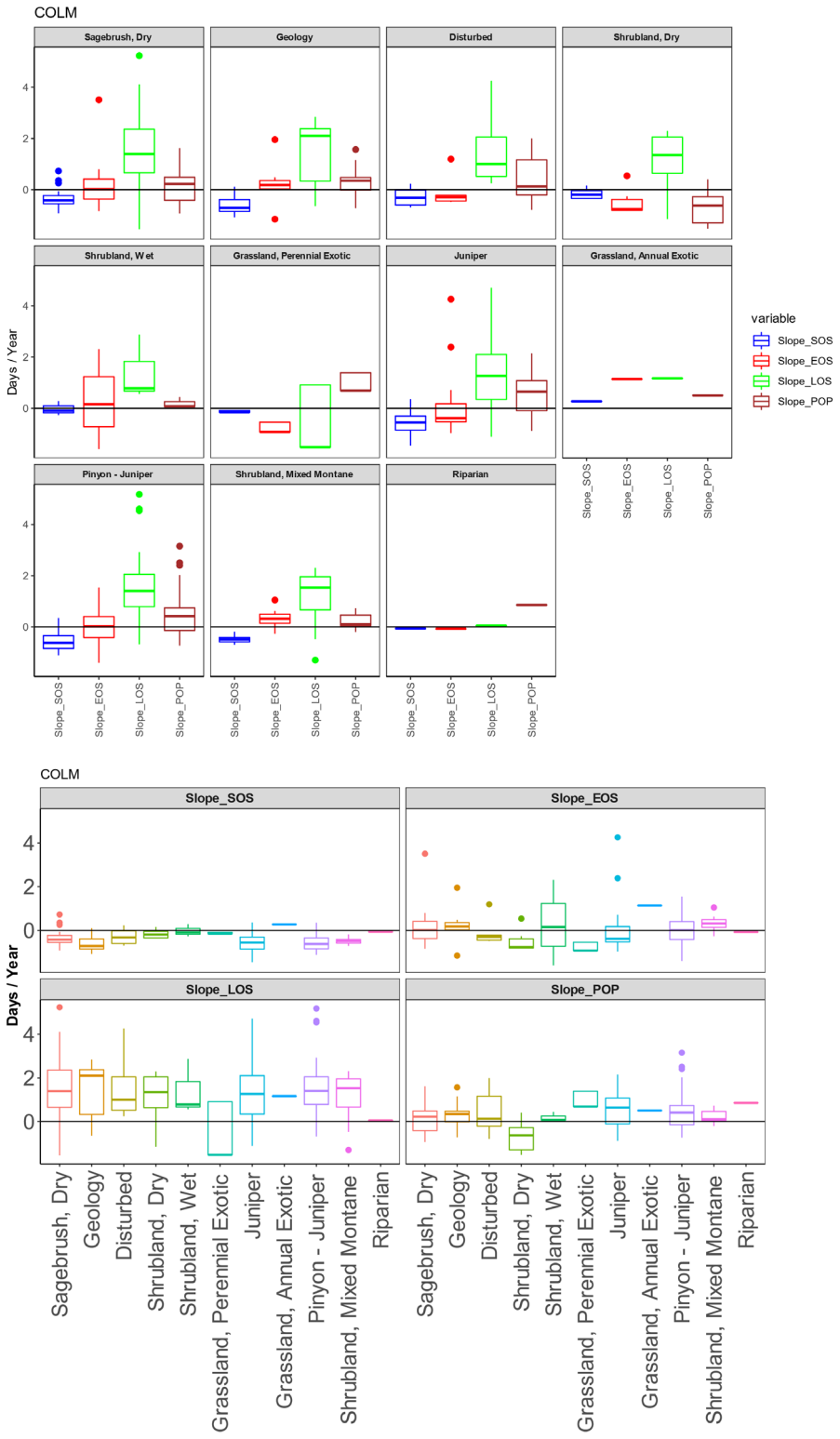


Figure A-5. (a) Direction and magnitude of change rate in land surface phenology metrics determined as +/-days per year for start of season (Slope SOS), end of season (Slope EOS), length of season (Slope LOS) and timing of peak SAVI (Slope POP). (b) rates of change in phenology metrics by alliance group. Slope refers to the slope of linear regression of phenology metric versus year for the period 2000-2019.

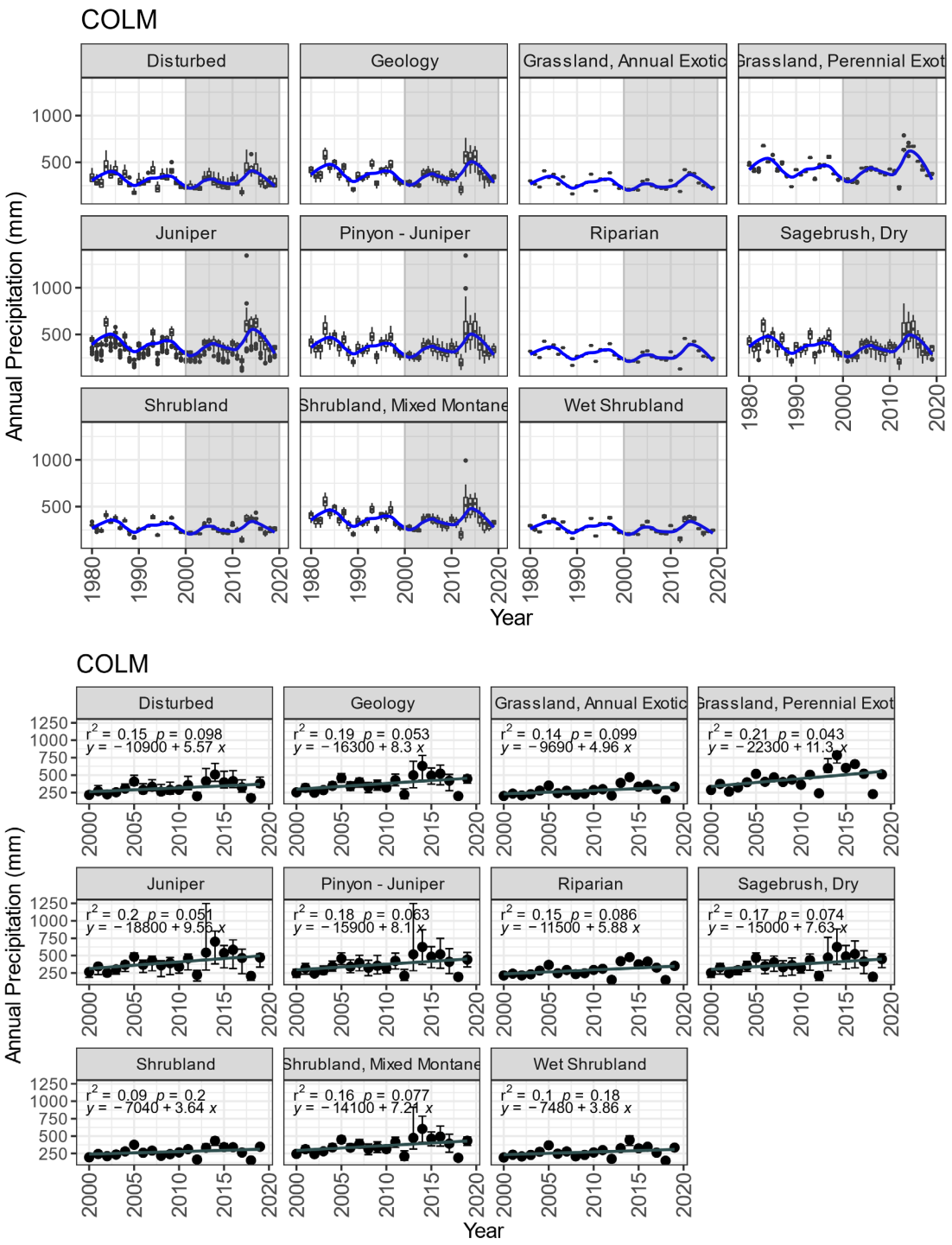


Figure A-6a. Cumulative annual water balance variables over time in vegetation alliance groups at COLM. Box plots demonstrate the range of variation within alliance groups by year. The blue line is a loess smooth with a 25 percent span to illustrate multi-year patterns. Gray shaded area includes the period investigated for relationships between production and climate when satellite imagery and climate data were both available. In the lower panel, trend over time is shown for the period in gray in the top panel. Bars are standard error.

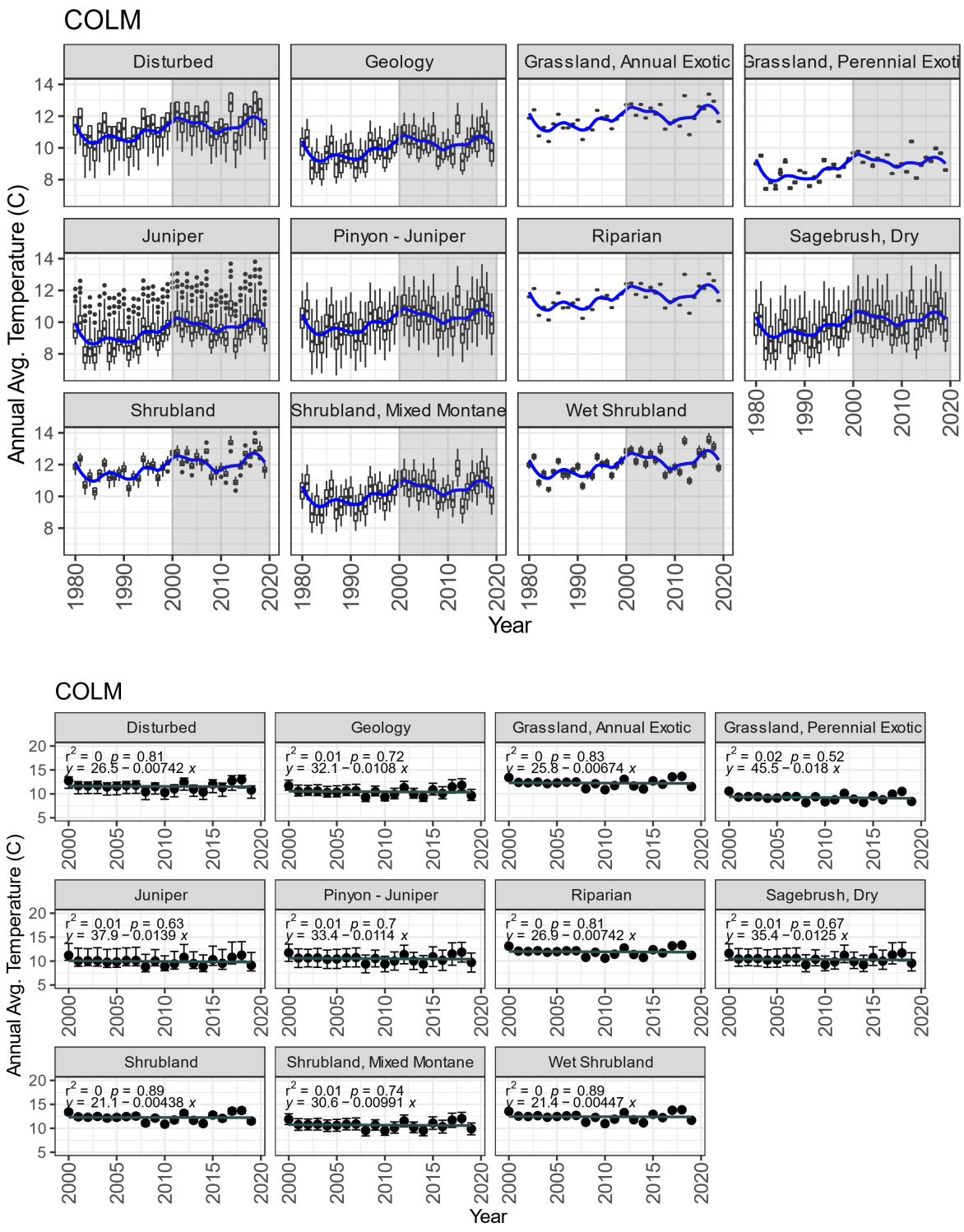


Figure A-6b. Cumulative annual water balance variables over time in vegetation alliance groups at COLM. Box plots demonstrate the range of variation within alliance groups by year. The blue line is a loess smooth with a 25 percent span to illustrate multi-year patterns. Gray shaded area includes the period investigated for relationships between production and climate when satellite imagery and climate data were both available. In the lower panel, trend over time is shown for the period in gray in the top panel. Bars are standard error.

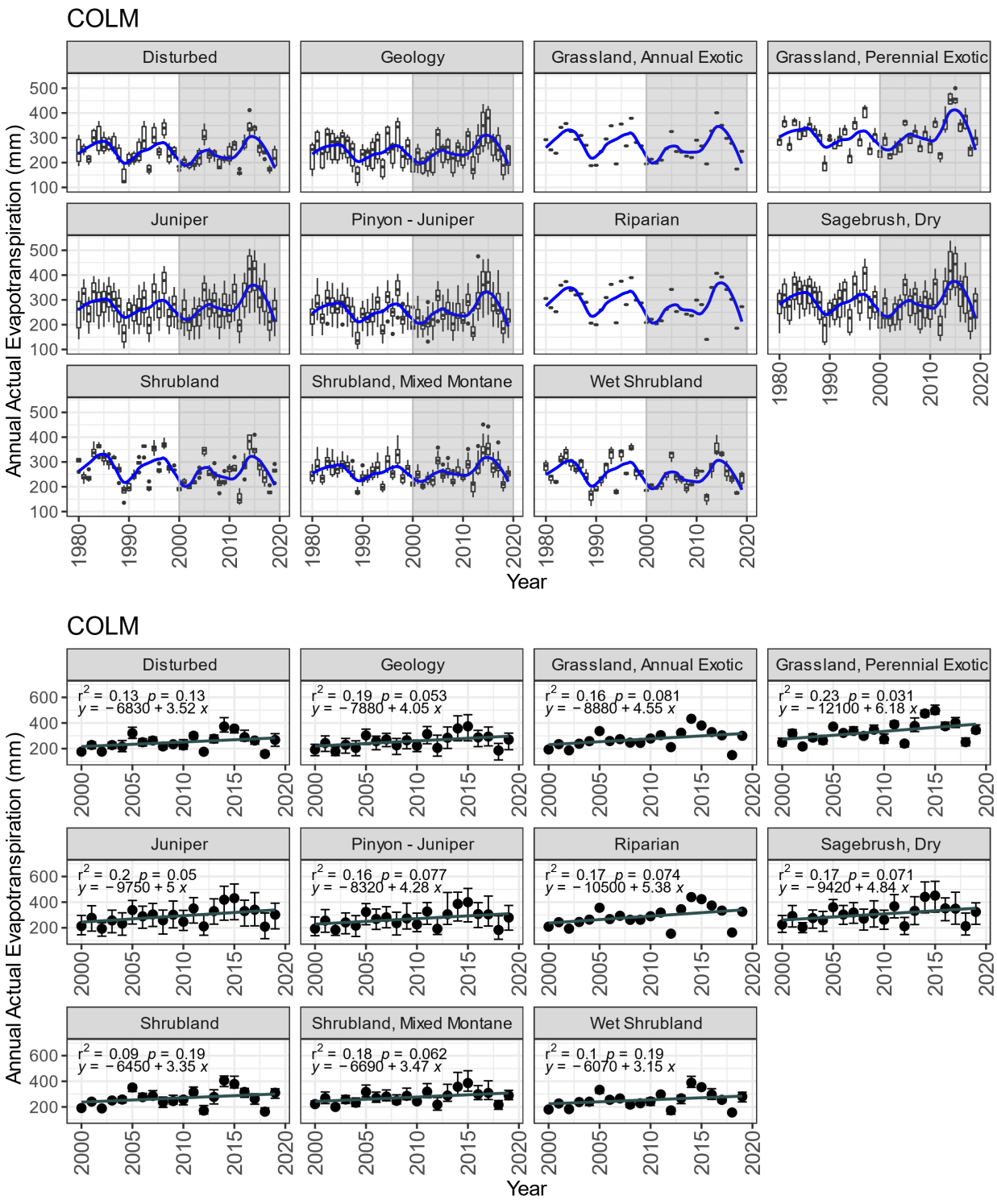


Figure A-6c. Cumulative annual water balance variables over time in vegetation alliance groups at COLM. Box plots demonstrate the range of variation within alliance groups by year. The blue line is a loess smooth with a 25 percent span to illustrate multi-year patterns. Gray shaded area includes the period investigated for relationships between production and climate when satellite imagery and climate data were both available. In the lower panel, trend over time is shown for the period in gray in the top panel. Bars are standard error.

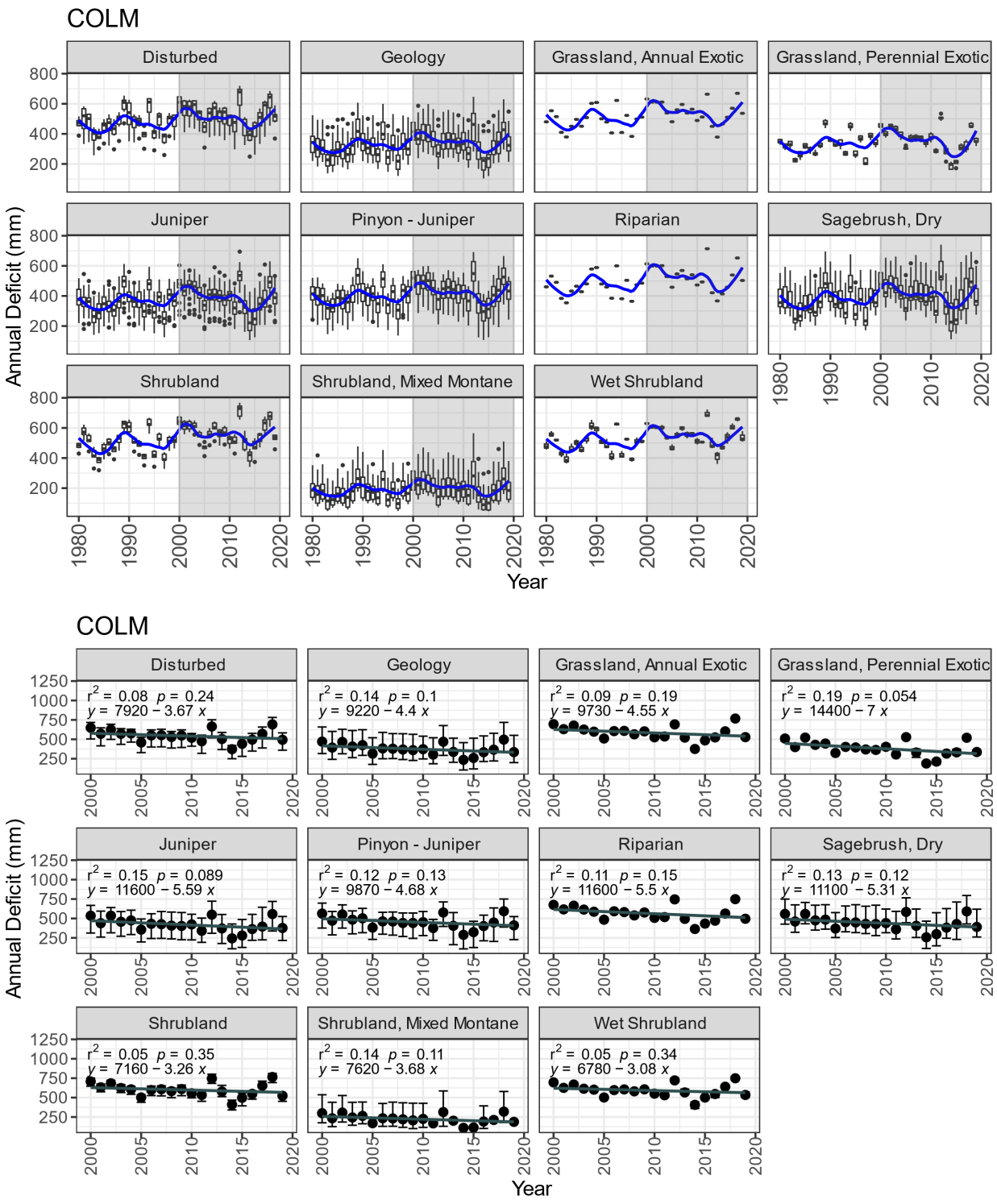


Figure A-6d. Cumulative annual water balance variables over time in vegetation alliance groups at COLM. Box plots demonstrate the range of variation within alliance groups by year. The blue line is a loess smooth with a 25 percent span to illustrate multi-year patterns. Gray shaded area includes the period investigated for relationships between production and climate when satellite imagery and climate data were both available. In the lower panel, trend over time is shown for the period in gray in the top panel. Bars are standard error.

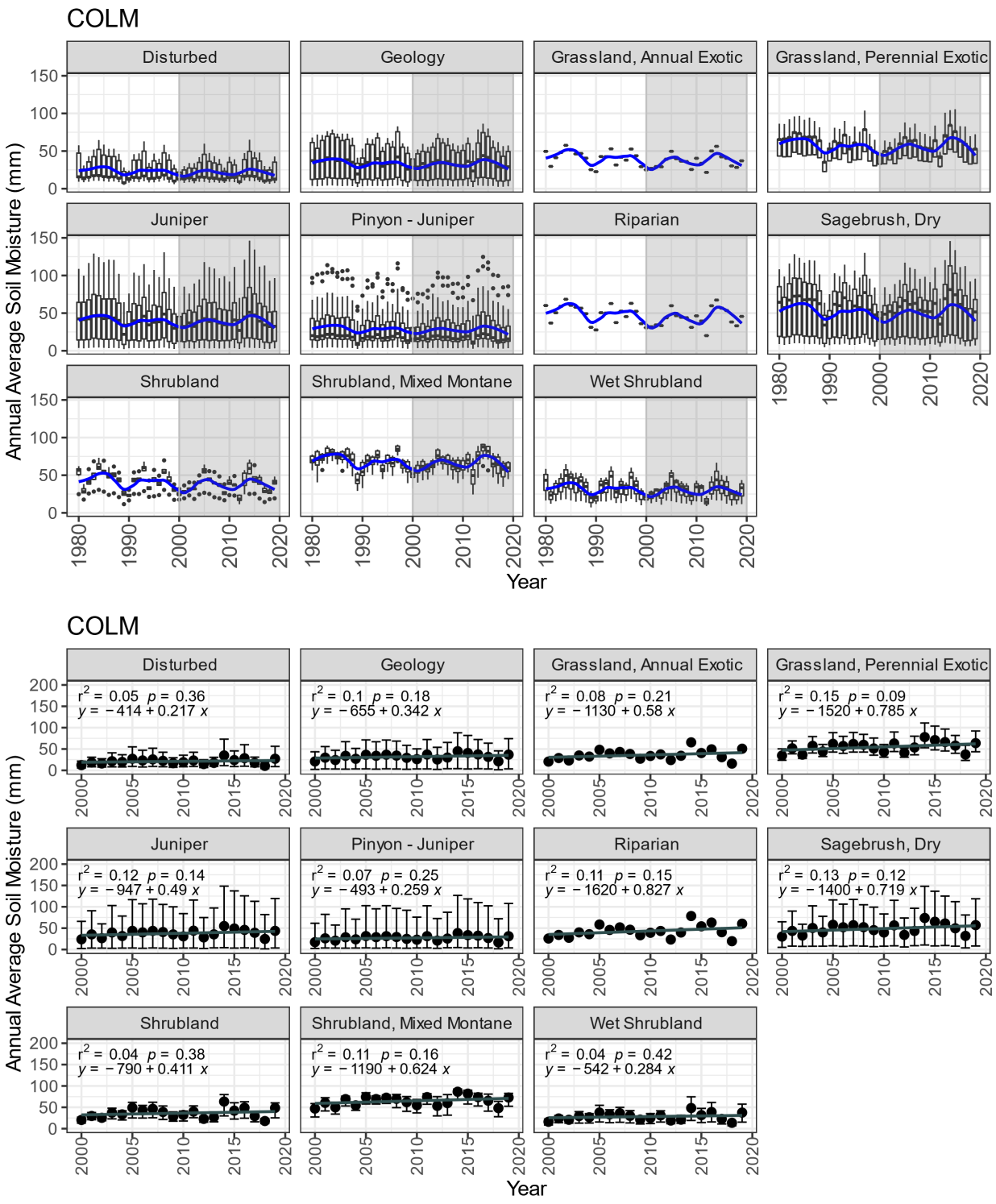


Figure A-6e. Cumulative annual water balance variables over time in vegetation alliance groups at COLM. Box plots demonstrate the range of variation within alliance groups by year. The blue line is a loess smooth with a 25 percent span to illustrate multi-year patterns. Gray shaded area includes the period investigated for relationships between production and climate when satellite imagery and climate data were both available. In the lower panel, trend over time is shown for the period in gray in the top panel. Bars are standard error.

The Department of the Interior protects and manages the nation's natural resources and cultural heritage; provides scientific and other information about those resources; and honors its special responsibilities to American Indians, Alaska Natives, and affiliated Island Communities.

NPS 119/180421, May 2022

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