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

The “blue marble” image is the most detailed true-color image of Earth to date. Much of the information contained in this image came from a single remote-sensing device: NASA’s Moderate Resolution Imaging Spectroradiometer, or MODIS. Flying more than 700 kilometers above Earth onboard the Terra satellite, MODIS provides an integrated tool for observing a variety of terrestrial, oceanic, and atmospheric features of the Earth.
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Landscape phenology, vegetation condition, and relations with climate at Fossil Butte National Monument, 2000–2019

Science Report NPS/SR—2025/304

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Abstract

Climate plays a major role in determining vegetation composition in parks, and changes in climate will affect vegetation conditions and composition in the future. This study, which examined changes in climate, water availability, and vegetation from 2000 to 2019 in Fossil Butte National Monument (NM) in Wyoming, USA, evaluates vegetation sensitivity to weather and climate to understand climate-vegetation relationships that can be used to predict what vegetation types may change. Specifically, it evaluates where change is likely in the monument, when change may happen, and why change may occur. This information is needed to help avoid surprises and can be used to plan for inevitable change. Satellite images were analyzed with climate data to quantify vegetation sensitivity to climate and drought tolerance. Historic trends in vegetation production and phenology were evaluated, and analysis with climate data identified which aspects of climate were most important to annual production and phenology for different vegetation types. Additionally, trends in climate and climate drivers of vegetation phenology were also identified. Since 2000, a very dry period, primary production has increased in and near Fossil Butte NM. The increase coincided with an increase in precipitation over the same period. However, over this period, both isolated dry years and prolonged droughts occurred, resulting in substantial declines in vegetation cover, which largely rebounded by the end of the study. The information generated in this study can be applied to long-term management and planning, which can help preserve the natural resources of the National Park System for the enjoyment, education, and inspiration of this and future generations.

Executive Summary

Quantitatively linking satellite observations of vegetation condition and climate data over time provides insight into 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.

This report provides baseline information about vegetation production and condition over time at Fossil Butte 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 drivers 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 monument planning and management. Patterns of pivot points and responses can serve as a guide to anticipate what, where, when, and why vegetation change may occur.

For this analysis, vegetation alliance groups were derived from vegetation-map polygons (Friesen et al. 2010) 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 alone. By accounting for the interactions between temperature, precipitation, and site characteristics, water balance helps make regional climate assessments relevant to local scales.

The results provide a foundation for interpreting weather and climate as drivers of change in primary production over a 20-year period at the polygon and alliance-group scale. Additionally, they demonstrate 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.

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 vegetation production was stable in and near Fossil Butte National Monument between 2000 and 2019.

- Mixed montane shrubland was the only alliance group that increased in mean and maximum annual measures of production, representing less than one percent of the analysis area. There were no decreasing trends in annual measures of production.
- There was a statistically significant increase in growing season production in all alliance groups.
- Measures of water stress were negatively correlated with production, while measures of water abundance were positively correlated with production, which suggests a water-limited environment. This also explains increases in growing season production with increasing annual precipitation during the study.
- Based on water deficit pivot points, Mesic Sagebrush alliance group was the least drought tolerant, while Disturbed and Wet Meadow were most drought tolerant.
- Quaking Aspen, Mesic Sagebrush, and Mixed Montane Shrublands were the alliance groups most sensitive to variation in annual actual evapotranspiration. Sensitivity to precipitation was similar across alliance groups.
- Three years of actual evapotranspiration was the best indicator of annual production at the monument scale. This was also generally true at the alliance-group scale.
- By the end of the study period, the growing season was starting later for most alliance groups, but earlier for Dry Shrubland and Wet Meadow alliance groups.
- By the end of the study period, the growing season was ending later for most alliance groups, but earlier for Quaking Aspen.
- During the study period, the growing season lengthened for most alliance groups except Quaking Aspen.
- By the end of the study, the timing of peak growth occurred later in all alliance groups and was 6.4 days later on average.
- Day of snowmelt and precipitation were the most important determinants of the start of growing season.

This report provides a foundation for interpreting weather and climate as drivers of change in primary production over a 20-year period at the polygon, alliance-group, and park scales. It can be used to determine what, when, where, and why future changes in climate may impact vegetation.

List of Acronyms

AET: actual evapotranspiration

D: climatic water deficit

EOS: end of growing season

GDD: growing degree days

iSAVI: integrated growing season soil adjusted vegetation index

LOS: length of season

Meltd: date of complete snowmelt

MODIS: moderate resolution imaging spectroradiometer

NCPN: Northern Colorado Plateau Network

NDVI: normalized difference vegetation index

NM: national monument

NVC: National Vegetation Classification

NVCS: National Vegetation Classification Standard

P: annual precipitation

PACK: snowpack water equivalent

PET: potential evapotranspiration

POP: timing of peak growth

RAIN: rain

SAVI: soil adjusted vegetation index

SNOW: snow

SOIL: soil moisture

SOS: start of season/green-up

SRAD: solar radiation

T: temperature (annual average)

Tmax: temperature (maximum)

Tmin: temperature (minimum)

VP: vapor pressure

VPD: vapor-pressure deficit

W: water as rain plus snowmelt

Acknowledgments

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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 three scales: park, vegetation-alliance group, and vegetation-alliance polygon. The objective is to demonstrate the methods of analysis, share standardized findings, and document historic climate exposure and sensitivity to weather and climate as drivers of vegetation change at Fossil Butte NM.

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 change in vegetation condition.

It provides a foundation for interpreting weather and climate as drivers of change 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 changes in climate in the future.

1.1 The importance of primary production

Photosynthesis is the process in plants that converts sunlight, CO_2, water, and minerals into the 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 semiarid environments like the Colorado Plateau, sunlight and CO_2 are abundant and rarely limit production. However, primary production is controlled by different environmental variables in different places. In tropical forests, primary production may be controlled by the 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., a 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 into 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 are ideal for assessing seasonal as well as annual conditions and trends. The imagery also provides insight into 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 into 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" judgment (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. Although disturbances can be detected, it is beyond the scope of this analysis to do so, because it requires different methods than those used here. However, all the data used to detect disturbance are available and can be made available via the author.

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 (resilience or susceptibility) and recovery from disturbance (speed of recovery, 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 type of information can be used to assess vulnerability of vegetation assemblages to changes in climate.

1.4 Pivot points and responses

In semiarid 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 into 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 production increases or decreases given the water available for growth. A pivot point is 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. Semiarid plants generally respond more positively than humans to water that exceeds minimum needs. However, 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' 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 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, or it can 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 if 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 monument 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 (de 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 is 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 into cascading effects on pollinators and migrating animals that depend on growth initiation, forage production, and the length of the growing season.

2 Methods

2.1 Overview

A variable project boundary ranging between approximately 1.6 km (1 mile) and 9.5 km (6 miles) around the edge of the monument (environs) was chosen by network and monument staff over the course of several scoping meetings held in 2002 (Figure 1). The total project mapping area is 161,169 hectares (398,258 acres). Of this area, 85,096 ha (210,278 acres) are within the monument boundary and 76,073 ha (187,980 acres) are in the environs. The environs were extended on Douglas Mountain to include an important part of the Yampa River watershed.

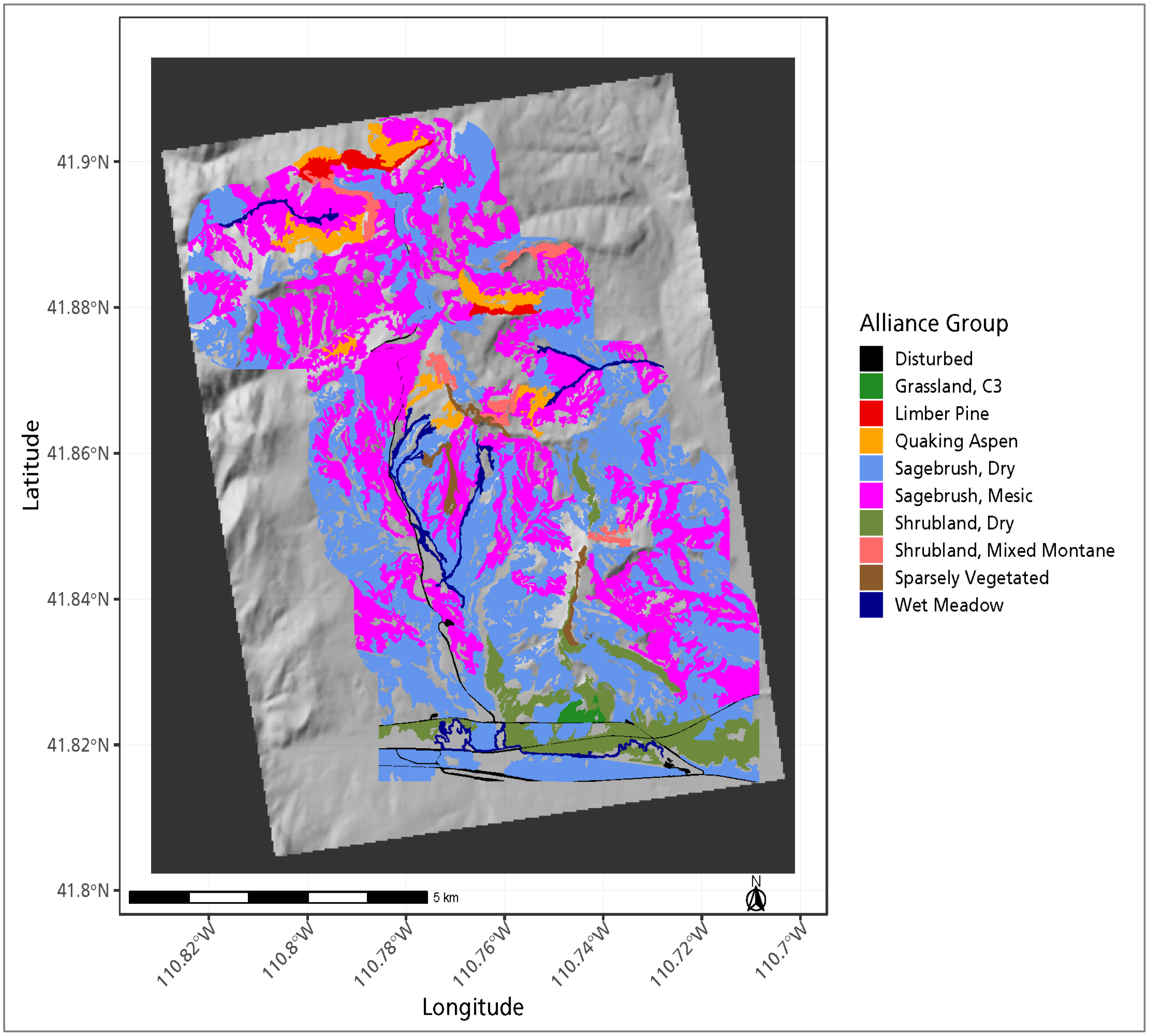

Figure 1. NCPN alliance groups analyzed for trends in production, phenology, and climate relations at Fossil Butte National Monument. Areas not colored within the study boundary are alliance polygons smaller than the minimum target area of 8.3 hectares.

NPS

This report was compiled by comparing climate data with variation in land-surface greenness over time, as measured in satellite imagery of the monument's vegetation-mapping project area (Friesen et al. 2010). A large archive of 460 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 monument landscapes and over time for trends.

2.2 Remote-sensing targets

Three scales of analysis are presented in this report: vegetation-alliance polygon, vegetation-alliance group, and park-wide. 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 (Friesen et al. 2010; 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. The park-scale analysis is achieved by lumping all alliance polygons into a single analysis or by averaging analysis results across alliances to the park scale.

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 forested 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. Alliances reflect 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 monument vegetation maps (Friesen et al. 2010).

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 (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 communication) 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 (NVC) alliances mapped consistently across NCPN park units, we created 32 alliance groups based on floristics, canopy structure, and local environmental conditions. Of those, 10 occurred in Fossil Butte NM (Table 1; Figure 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 NVC. A key that links each NCPN alliance group to vegetation-mapping units familiar to NCPN managers can be found in Table S-1 of NPS (2025). The image-analysis targets were the ungrouped alliance polygons, so while results reported in the body of this report are for NCPN alliance groups, results are also available by polygon for ungrouped alliances in the supplemental tables (NPS 2025).

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

Table 1. NCPN alliance groups and corresponding National Vegetation Classification alliances, Fossil Butte National Monument.

NCPN alliance group	National Vegetation Classification alliance(s) [A]
Disturbed	Non-natural
Grassland, C3	Arizona Fescue - Mountain Muhly - Muttongrass Southern Rocky Mountain Montane Grassland Alliance
Limber Pine	Limber Pine Intermountain Basins Forest & Woodland Alliance
Quaking Aspen	Quaking Aspen Rocky Mountain Forest & Woodland Alliance
Sagebrush, Dry	Wyoming Big Sagebrush Mesic Steppe & Shrubland Alliance
Sagebrush, Dry	Basin Big Sagebrush - Foothill Big Sagebrush Dry Steppe & Shrubland Alliance
Sagebrush, Dry	Alkali Sagebrush Steppe & Shrubland Alliance
Sagebrush, Mesic	Spiked Big Sagebrush - Mountain Big Sagebrush Steppe & Shrubland Alliance
Sagebrush, Mesic	Mountain Big Sagebrush - Mixed Steppe & Shrubland Alliance
Shrubland, Dry	Shadscale Saltbush Scrub Alliance
Shrubland, Mixed Montane	Utah Serviceberry - Alderleaf Mountain-mahogany - Littleleaf Mountain-mahogany Shrubland Alliance
Sparsely Vegetated	Joint-fir species - Saline Wildrye - Crispleaf Buckwheat Badlands Cold Desert Sparse Vegetation Alliance
Wet Meadow	Baltic Rush - Mexican Rush Wet Meadow Alliance

[A] The alliance names shown in this table do not match those found in Friesen et al. (2010) because alliance names and codes in that report were subsequently updated to USNVC Version 2.01, released March 30, 2017. The names from 2010 were cross-walked to the current names displayed here. For information on nomenclature, see FGDC (2008).

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. 2015).

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 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 semiarid 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 semiarid environments (Huete 1988). It is calculated as

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

where L is the soil background adjustment factor (L = 0.5), 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 semiarid 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 time series 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 the 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 time step for the pixels within a polygon target, missing polygon-average values were interpolated.

Missing daily values were a consequence of the 16-day periodicity of observations and quality screening in earlier steps. Finally, a smoothing filter was used to remove high-frequency noise from the time series of each polygon. After smoothing across large gaps in winter, prominent dips in the time series (artificially low values that were an artifact of the smoothing) were truncated to a minimum winter value based on pixel values that were likely reflectance from bare soil or senesced vegetation (Wang et al. 2018). This process resulted in a smoothed and complete daily time series for each polygon.

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 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 Wilhelm 1997).

This study also evaluated two variables that could influence vegetation production and phenology: vapor-pressure deficit (VPD, Pa) and solar radiation (SRAD, 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, T, VPD), are averaged (Table 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 would be physically impossible.

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

Variable	Abbreviation	Units	Type	Temporal summary
Precipitation	P	mm	flux	sum
Rain	RAIN	mm	flux	sum
Snow	SNOW	mm	flux	sum
Snow Pack Water Equivalent	PACK	mm	flux	sum
Water as Rain plus Snow Melt	W	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

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 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 date (Meltd) 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 the day of melt begins by searching backward from May 1 (user-specified date) for PACK values greater than four 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 time series of daily PACK values confirmed this was a reasonable approach to differentiating between periods that were predominantly snow covered or snow-free.

2.7 Measures of vegetation production

Because net primary production is generated through photosynthesis and spectral indices 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). We determined trends in three variables derived from the SAVI time series 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).

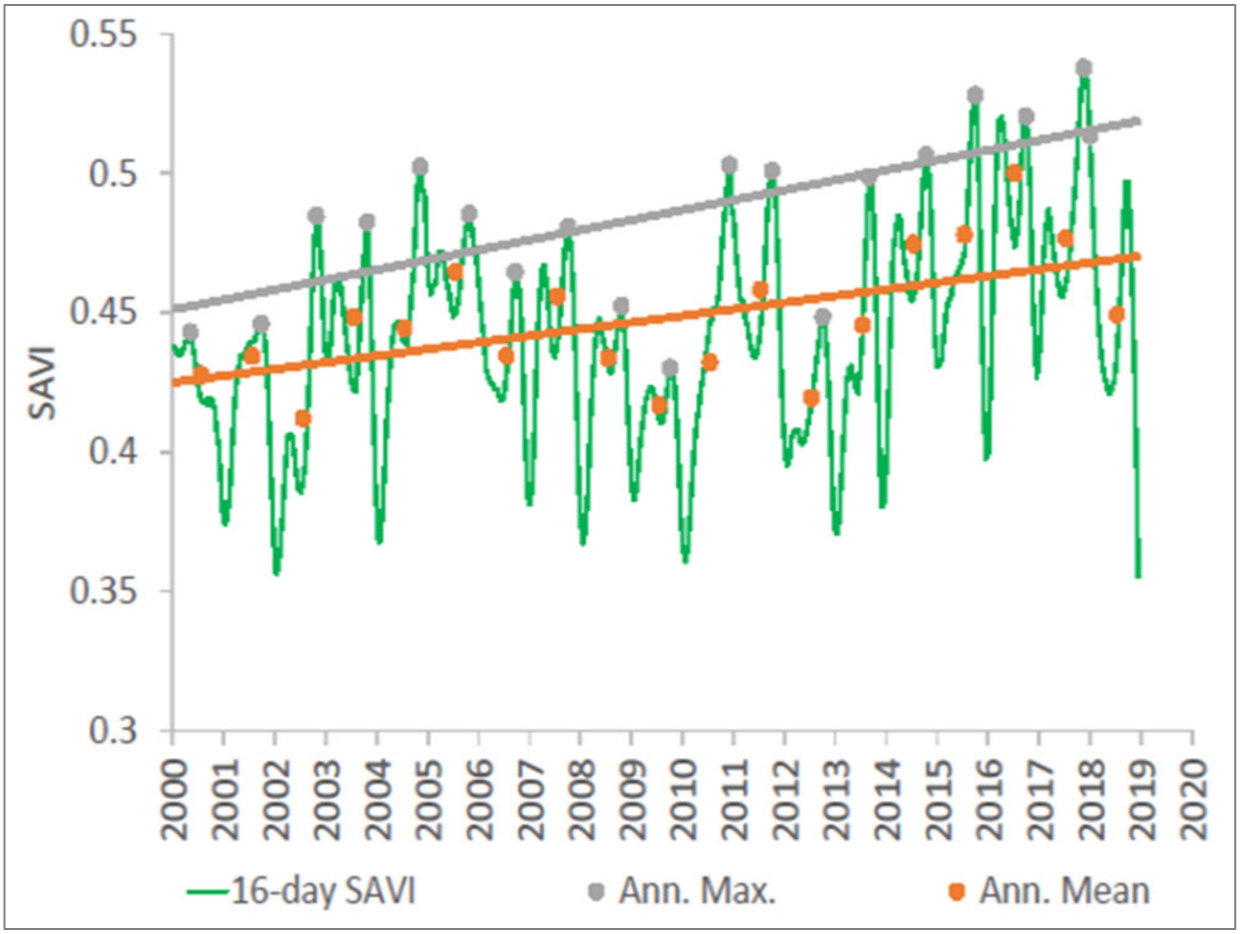

Figure 2. Measures of annual production from a time series of 16-day soil adjusted vegetation index (SAVI) derived from MODIS imagery. Linear trends against time for annual maximum and annual mean values are shown as straight lines.
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2.8 Calculating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

Trends in production were assessed by tracking changes in maximum and mean annual SAVI for 2000–2019 using the annual aggregated time series method (AAT) and Mann-Kendall trend test (Forkel et al. 2013) (see Figure 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 a holistic measure of the cumulative production of actively photosynthesizing vegetation (Mendez-Barroso et al. 2009; Reed et al. 1994). This proxy for aboveground net primary production results from the intentional construction of spectral indices, 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 time series 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 time series. 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 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.

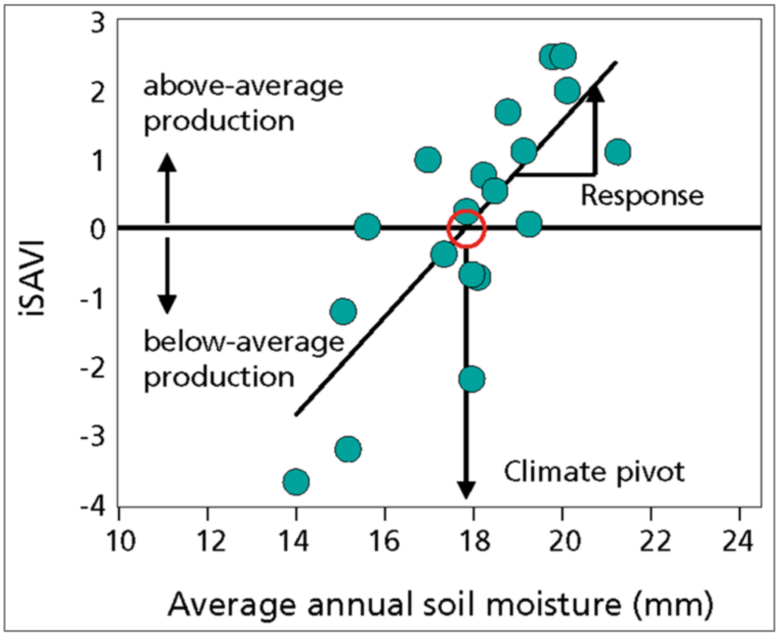

Figure 3. Conceptual diagram of soil-moisture pivot point and response of a single vegetation-alliance map unit to variation in annual average soil moisture. Vegetation production transitions from below- to above-average condition at the soil moisture pivot point. The response is the rate of change in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

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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.

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 D, 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 3) based on expected vegetation responses to climate variables and lags from our earlier experience working in semiarid 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.

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

Model [A]	Climate variables [B]											
	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

[A] See Table 2 for acronyms.

[B] X = variable used in model, – = variable not used in model. Lags refer to models that include the water balance term for the preceding one (lag1) or two (lag2) years.

We then competed the models against each other using multiple regression models and identified competitive models based on delta AICc values < 4 to determine the combination of climate variables acting over one or more years that have the most influence on growing-season production. Models that did not compete well (delta 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 monument level by aggregating results from all polygons in the monument. 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.

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 3).

Pivot points and responses are depicted graphically (see Figure 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 dry-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 dry-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 dry-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.[2]

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.

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 monument 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.

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

[2] Although not shown graphically, the standard error of pivot points is available for every polygon (Table S-2 in NPS 2025).

accelerates (start), peaks (maximum), and decelerates (end) (Figure 4). Length of growing season is the span of time between start and end. These values were determined for every polygon-year combination where possible. In some cases, phenology metrics could not be determined because the amplitude of annual variation was small, which made it impossible to find inflection points. The length-of-season metric was dropped if either start or end of season could not be determined. Start, end, and length-of-season metrics were also dropped if start of season occurred in winter between November 1 and April 1 due to vegetation shadows that confound satellite-based phenology assessments (Norris and Walker 2020).

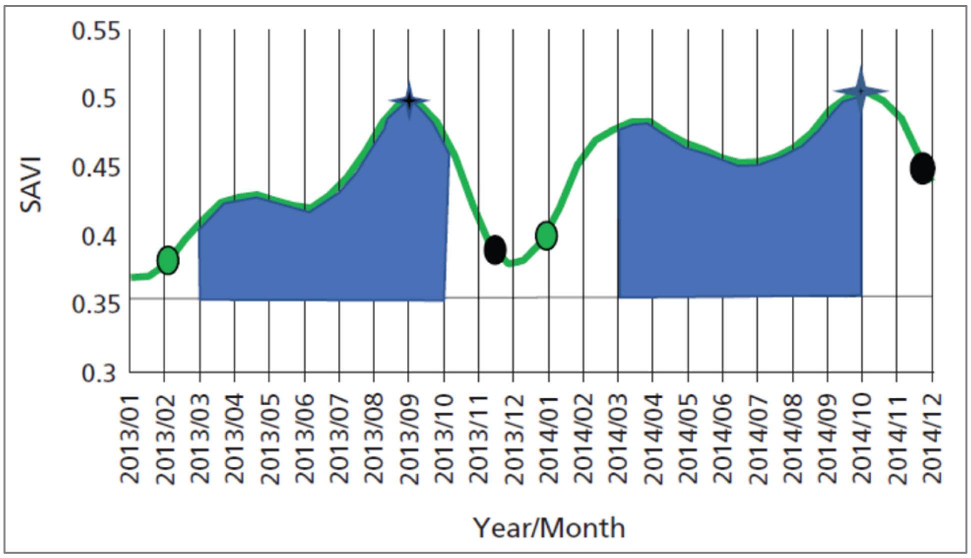

Figure 4. Integrated area under the growing-season curve (shaded area) for one polygon over two calendar years. The months used to calculate growing-season production are fixed and include March through October. Phenology metrics are derived using a process that determines inflection points on the annual curves using the derivative (rate of change in growth rate) method. In some years, phenology cannot be determined in semiarid 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.

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Polygon-level phenology metrics were summarized across alliance groups. The summary involved averaging linear-regression slopes (days of change per year) across polygons within an alliance type, then multiplying the slope by the number of years (20 years) in the study to determine the average days of change in each phenology metric over the course of the study. Due to variation in the regression relationships and using regression slope to convert to days of change in each metric, the change in length of season in summary tables is similar to, but not equal to the length of time between start and end of season.

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.

The timing of SOS, peak greenness and its magnitude, senescence, and LOS 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).

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, polygon-year combinations that exhibit winter peaks cannot be used in phenology analysis. These polygon-years were removed by determining if their annual peak of greenness occurred 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 removed from analysis for that year. This allowed retention of 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 SOS, or greenup. 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 4) (St. Peter 2015). These models were competed against one another to determine top models of SOS.

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

Model [A]	Climate variable [B]											
	AET	**GDD**	**P**	**RAIN**	**D**	**VPD**	**SRAD**	**Tmax**	**Tmin**	**VP**	**SOIL**	**Meltd**
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

[A] 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. See Table 2 for acronyms.

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

Second, the random forests machine-learning technique was used to determine important drivers of phenology and provide predictive models of SOS (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 randoms forest 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 holdout 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 SOS predictions could be compared against observations in the validation dataset. The accuracy of predictions for SOS was 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.

3 Results and Discussion

3.1 Completeness of satellite observations

Completeness of growing-season observations was 82.6% across all targets for the 20-year period of analysis. Clouds, aerosols, and snow cover reduced the average completeness of high-quality observations to 61% of potential observations on an annual basis across all polygon targets. The minimum completeness for any single polygon on an annual or seasonal basis was 62% and 63%, respectively.

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

3.2 Time series

At Fossil Butte NM, SAVI observations reflected differences in vegetation response to climate that were apparent when observations were organized by NCPN alliance group (Figure 5). 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.

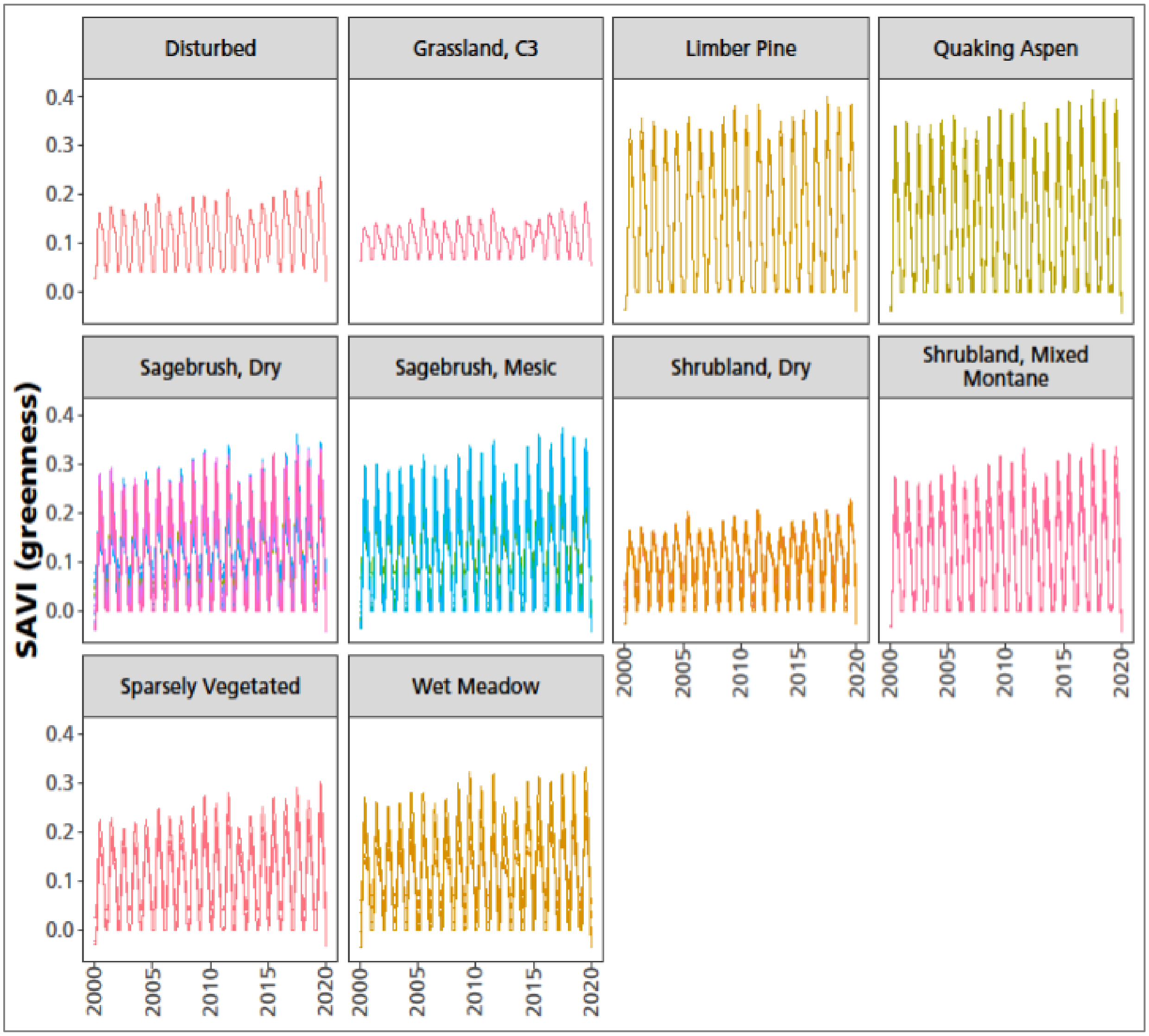

Figure 5. Soil-adjusted vegetation index time series by alliance group for 145 polygons analyzed for 2000–2019. Colors help differentiate individual polygon time series traces. Each polygon time series was filtered to include only high-quality pixel values, with minimum values truncated to winter minimum, 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.
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Gap-filled and smoothed time series illustrated a broadly similar upward trend in all alliance groups during the study period (Figure 5). However, the alliance groups showed a high degree of variability in amplitude and timing of peak values. It is typical for some polygons in an alliance group to exhibit "outlying character," indicating they are not a good fit with other polygons in the group. However, this issue was not noticed at Fossil Butte NM, which suggests the members of each alliance group respond similarly to weather and climate.

3.3 Trends in indicators of annual production

Significant upward trends (p-value < 0.05) in maximum and mean annual SAVI occurred in two of five polygons of Mixed Montane Shrubland alliance group representing less than one percent (24.4 ha) of the study area (Figure 6). No other trends were found for these measures of annual production in any of the other alliance groups. Results by polygon for significant trends in maximum and mean annual SAVI are in Table S-3 in NPS (2025).

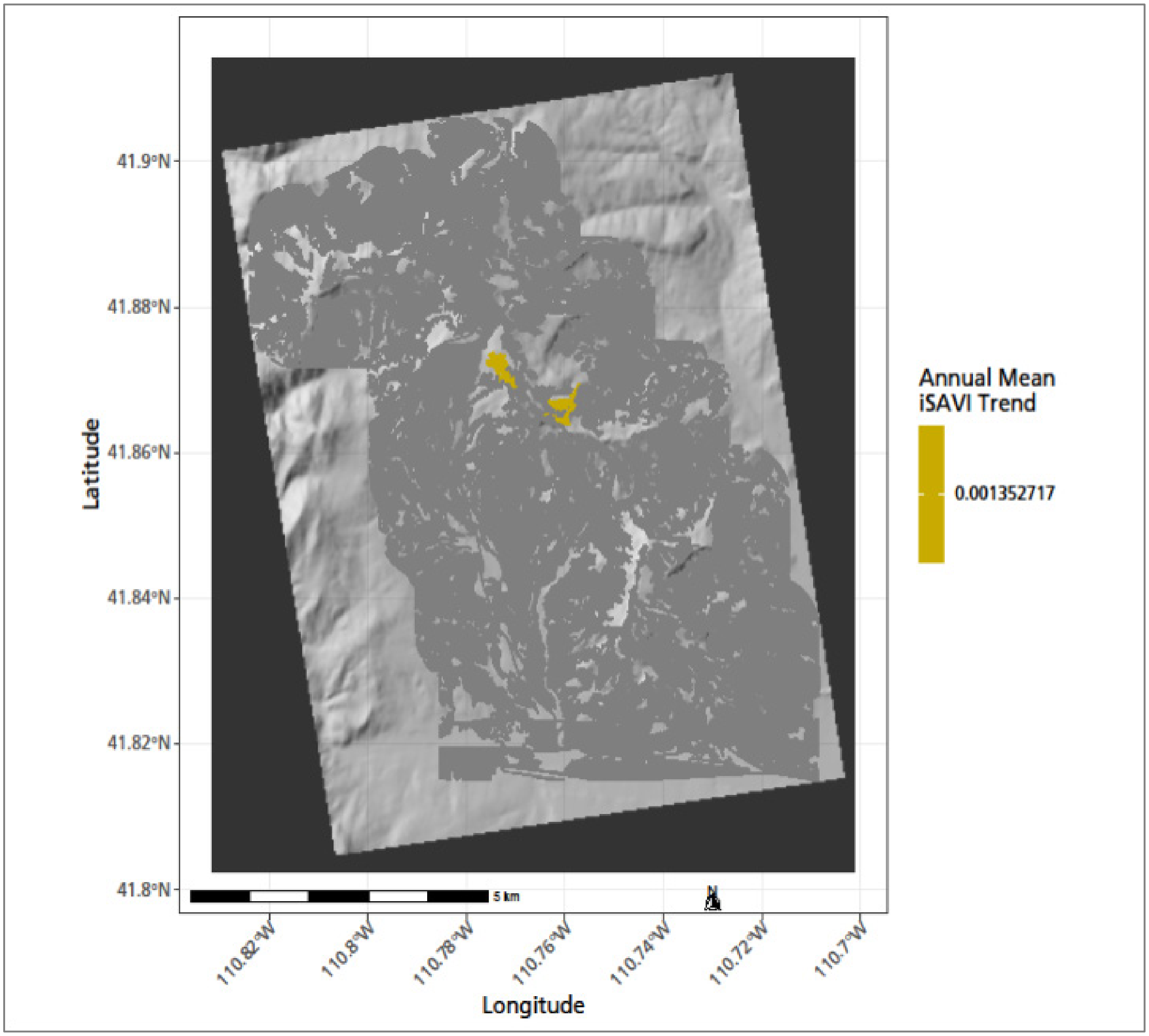

Figure 6. Spatial pattern of trends in mean annual iSAVI. Trend represents the average change in iSAVI per year from 2000 to 2019. Yellow areas indicate a positive trend in iSAVI. Gray areas represent locations with no significant trend, that were not analyzed or were outside the study area.
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3.4 Trends in indicators of growing season production

Significant upward trends in growing-season iSAVI, determined via simple linear regression, were found for all alliance groups (Figure 7). Evaluation of simple linear-regression slopes show that Mixed Montane Shrubland production increased at the fastest rate followed by Mesic Sagebrush and Wet Meadow alliance groups (Figure 7).

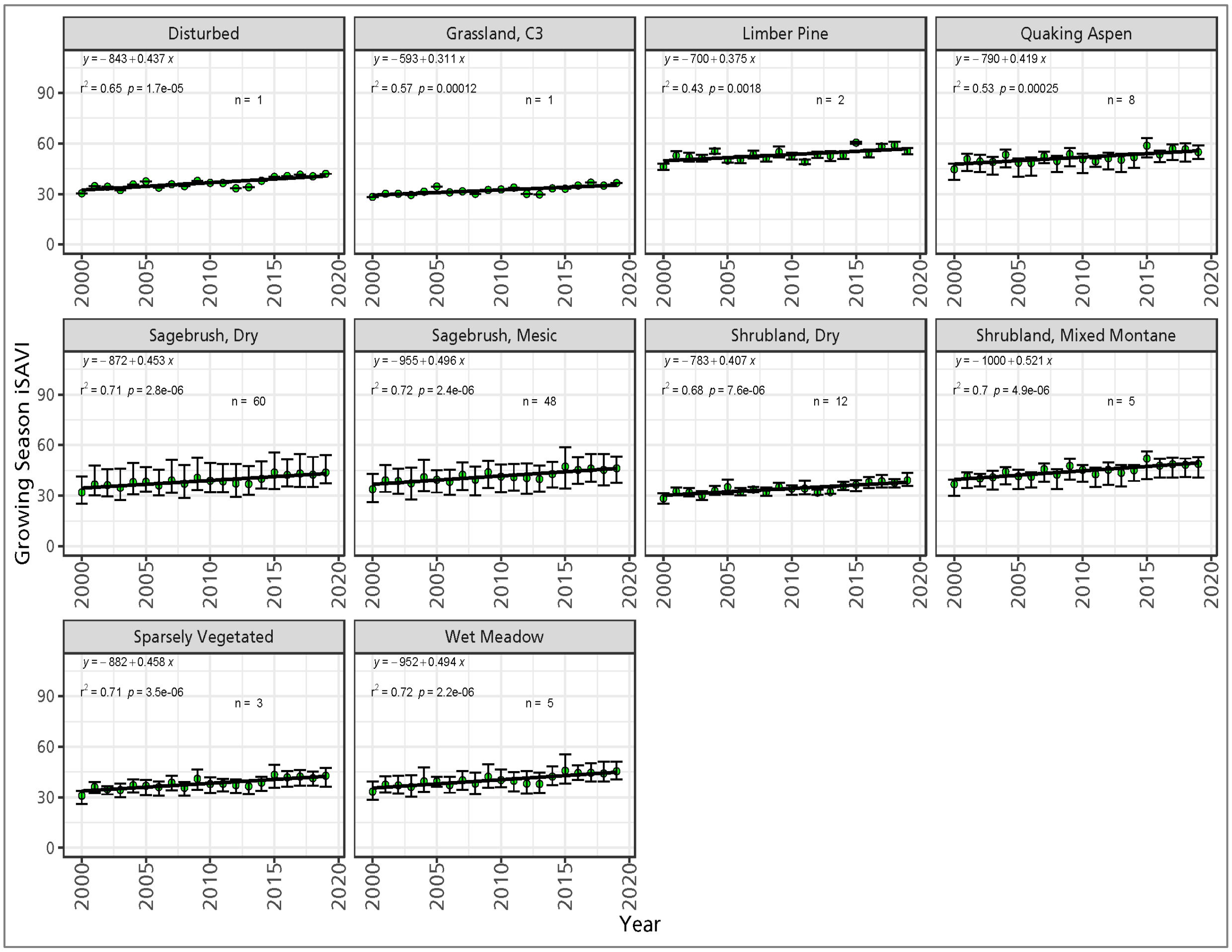

Figure 7. Trends in mean growing-season iSAVI by alliance group, determined via simple linear regression. Bars are standard error among polygons within each alliance group. n = number of polygons analyzed in each alliance group, r^2 = coefficient of determination, p = p-value, y = growing season iSAVI, x = year.

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As a subset of the annual period, the growing-season iSAVI focused on the March through October period, revealing climate-driven temporal patterns in all alliance groups. The study began in 2000, which had the lowest annual precipitation since 1988. Following 2000, precipitation trended upward, but other low production years coincided with low precipitation years 2012 and 2018. In 2012, growing season production fell most dramatically in the C3 Grassland and Dry Shrubland Alliance groups (Figure 8). Production in the low-precipitation year 2018 was not nearly as low as that in 2012, perhaps due to the abundant precipitation in 2017. By the end of the study, above-average levels of production were observed in most alliance groups (Figures 7 and Figure 8), demonstrating the resilience of Fossil Butte NM vegetation production to short term drought stress during the study.[3]

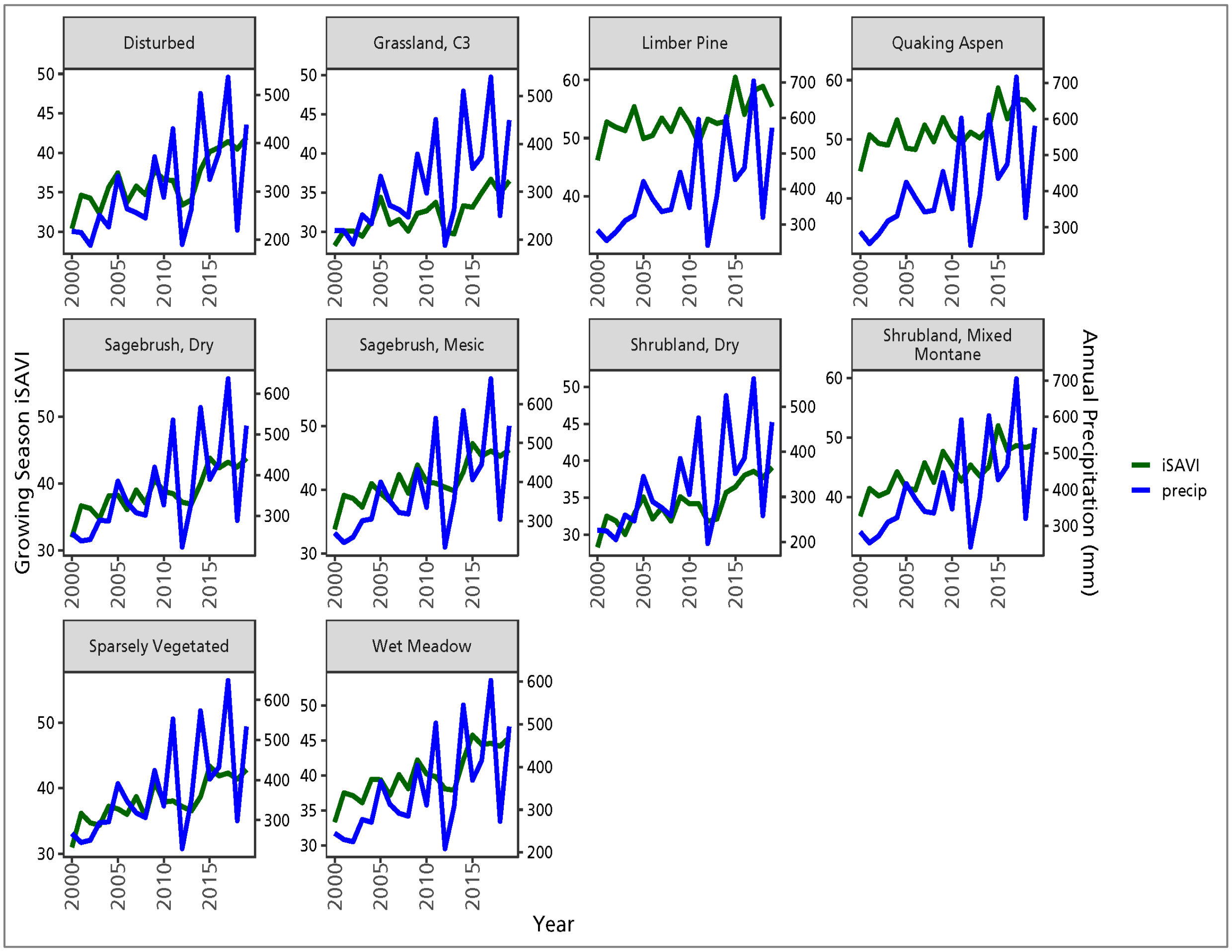

Figure 8. Co-variation in growing-season production, estimated as the iSAVI between March and October and water-year cumulative precipitation averaged within alliance groups, demonstrating the link between climate and vegetation production in the monument at the annual scale. The time series shown here is intended to illustrate precipitation as a master climate driver of production in semiarid environments. Statistical analyses of the relation of production to precipitation and all other climate variables is the subject of following sections.
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[3] This finding does not imply vegetation composition was not affected or did not change. Composition change cannot be determined from this analysis.

3.5 Climate relations

3.5.1 Qualitative patterns in annual precipitation and production

Between 2000 and 2019, precipitation increased in most alliance groups, as did growing-season production in this semiarid, 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 shows the temporal correspondence of interannual variation in annual precipitation and production (Figure 8), whereas CO_2 concentrations increased monotonically on an annual basis during the study period (https://gml.noaa.gov/ccgg/trends/). The link between precipitation and production is most obvious in the C3 Grassland and Dry Shrubland alliance groups in Figure 8. This provides qualitative evidence that variation in production is more strongly related to precipitation than CO_2.

While peaks and valleys in the time series 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, such as seen in Limber Pine can be caused by legacy effects of vegetation condition in prior years that carry over to subsequent years. More evidence of legacy effects comes from the relatively minor 2018 decline in production, which followed the wettest year in the study.

Such legacy effects have been noted in semiarid 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. Organizing the remotely sensed observations by management-relevant vegetation types provides insights that may be useful in climate adaptation planning.

3.5.2 Single-variable drivers of production

At the monument level, relationships between growth and climate variables were generally weak due to the highly variable response relationships with climate across vegetation types (not shown). However, when examined by alliance groups, better relationships emerged (Figure 9).

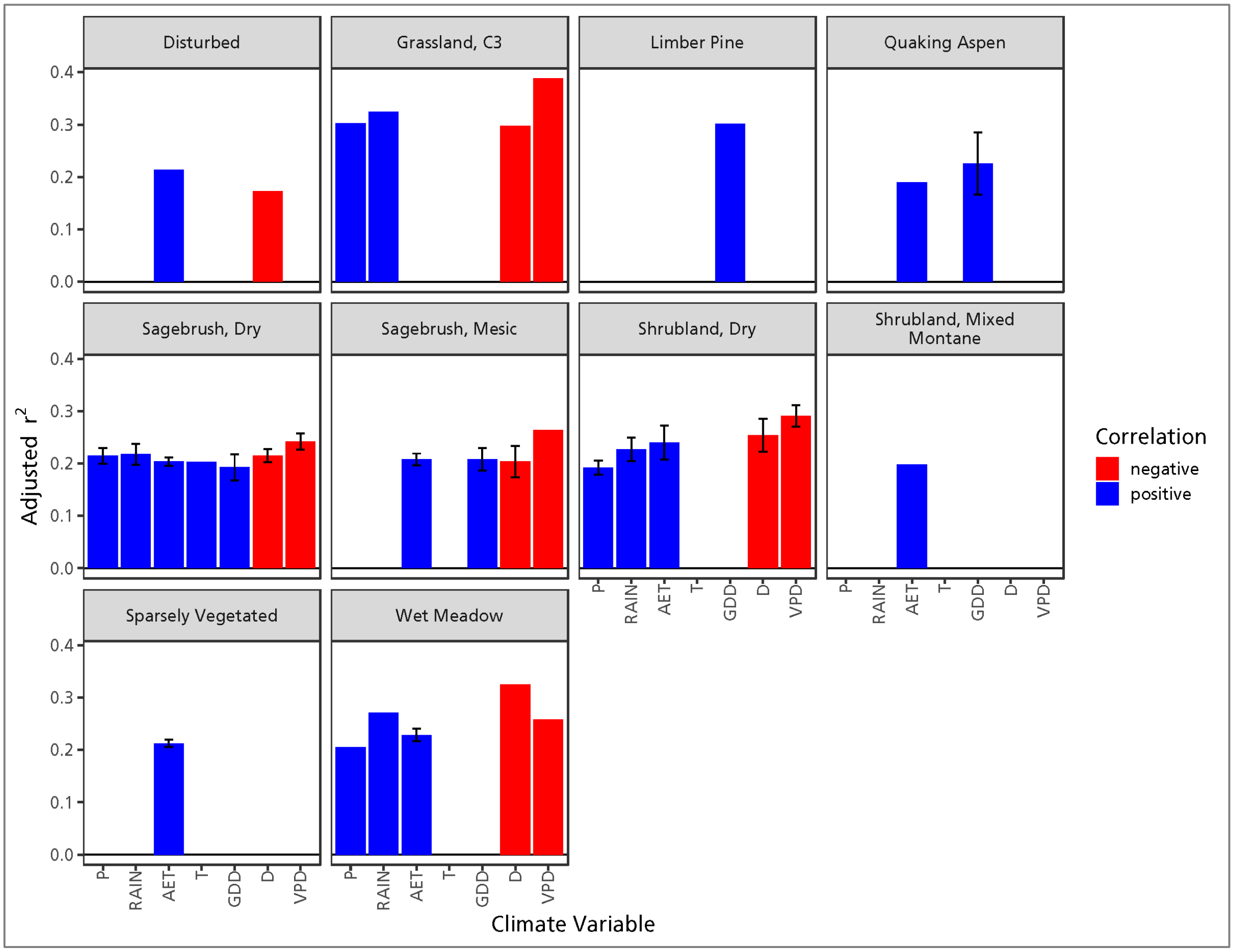

Figure 9. Significant (p-value < 0.05) relationships between water-year climate variables and first difference of growing season iSAVI, 2000–2019. Bar height is the mean variation in iSAVI explained by variation in climate or water-balance variable on the x-axis. Error bars are standard error. Blue bar color indicates positive correlation. Red bar color indicates negative correlation. P = precipitation (mm), RAIN = precipitation as rain (mm), AET = actual evapotranspiration (mm), T = average temperature (°C), GDD = growing degree days (°C), D = water deficit (mm), VPD = vapor-pressure deficit (Pa).
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Vegetation production in all alliance groups was correlated with multiple aspects of climate. Across alliance groups at Fossil Butte 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, except for Limber Pine, Dry Sagebrush, and Mesic Sagebrush alliance groups. A positive correlation with growing degree days in these arid-adapted alliance groups suggests that production is somewhat temperature limited. That is, they may have sufficient water to meet metabolic needs most years, but growth is limited by available heat needed for growth. Within alliance groups with multiple polygons, there was variation in relationship strength among polygons, indicated by error bars in Figure 9 (also see Table S-2 in NPS 2025). 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 actual evapotranspiration had the strongest positive relationships with production in most alliance groups. Vapor pressure deficit had the strongest negative relationship with production in most alliance groups (Figure 9). However, on an annual basis, most of the water-balance variables were no better correlated with production than annual precipitation, where precipitation had a significant relationship with production. There was a mixture of responses to temperature variables (PET, T, GDD), where some alliance groups exhibited a decrease in production with warmer temperature and some an increase (Table S-2 in NPS 2025). Decreases in production with temperature are typical in water-limited environments, whereas increases in production with warmer temperatures are typical in heat-limited environments. The mixed response to temperature by alliance group at Fossil Butte NM likely explains why actual evapotranspiration is an important climate variable because it integrates the effect of precipitation inputs and water used by vegetation driven by heat available to move water from soil to the atmosphere.

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 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 relations. This may explain coefficients of determination of <0.5 (Figure 9), 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. The best single-variable indicator of annual vegetation production can be determined by alliance group from visual inspection of Figure 9 (tallest bar = best relationship), or by polygon from Table S-2 in NPS (2025).

Annual precipitation at Fossil Butte 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.

3.6 Pivot points

3.6.1 Pivot points indicate drought tolerance

Plant species with smaller pivot points for water-abundance variables (e.g., precipitation, rain, snow, actual evapotranspiration, soil moisture) demonstrated a higher degree of drought tolerance, because less water was needed to achieve above-average production (NPS 2025, Tables S-2 and S-4).[4] Conversely, larger pivot points for variables representing heat, unmet water need, or atmospheric dryness also indicated a higher degree of drought tolerance, because more drought was tolerated before production drops below average.

At Fossil Butte NM, the most drought-tolerant alliance groups (i.e., the ones with the highest deficit pivot point) were Disturbed and Wet Meadow alliance groups (Figure 10). In the case of Wet Meadows, this is likely due to the low-lying places where accumulation of water from upslope positions makes these alliance groups less drought-prone in low-precipitation years. Because this alliance group 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. Nevertheless, the physical processes that collect water in these locations will continue to collect water in the future, which will likely make this alliance group less susceptible to drought than other upland alliance groups. It is unclear why Disturbed areas are drought tolerant relative to other alliance groups. It could be due to management actions or the species assemblage in those areas that are more well adapted to dry conditions than other native vegetation in the monument.

[4] The pivot points differed among water-abundance variables because they represent different pools, 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.

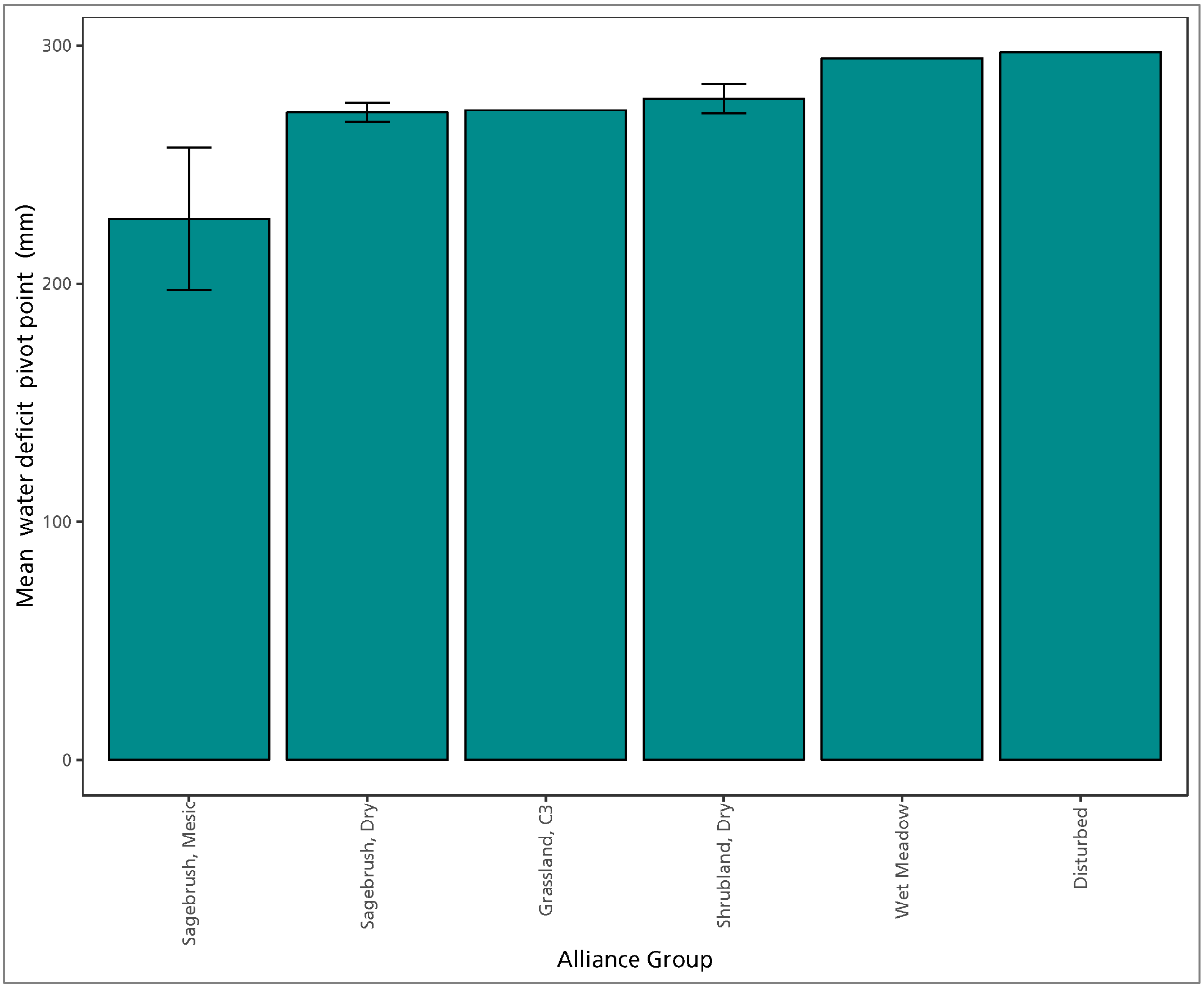

Figure 10. The mean deficit pivot-point values shown here represent critical water needs for the different alliance groups. Standard error bars indicate range in variability of pivot points among polygons of an alliance group if more than one polygon had a statistically significant relationship (p-value < 0.05) with precipitation. Deficit pivot points identify the drought stress where production switches from above to below average production for each alliance group.
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Forest alliance groups did not show a significant relationship with deficit. This could be due to adaptations to dry conditions (Limber Pine) or to where they grow in areas of water accumulation (Quaking Aspen). Grasslands and other shrublands were more drought-tolerant than the Wet Meadow group, likely due to seasonal growth traits and dormancy during the driest times of year.

3.6.2 Spatial patterns of drought tolerance

Pivot points for a specific geographic area are related to but not always equal to the 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 spatial pattern of significant (that is, where different variables were significantly related to production) drought tolerance and temperature pivot points at Fossil Butte NM. Lower-elevation alliance groups were significantly related to production via deficit, suggesting those alliance groups are water limited. On the other hand, higher elevation alliance groups were significantly related to production via growing degree days, suggesting they are growth-limited more by cold temperature than water availability (Figure 11; Appendix A).

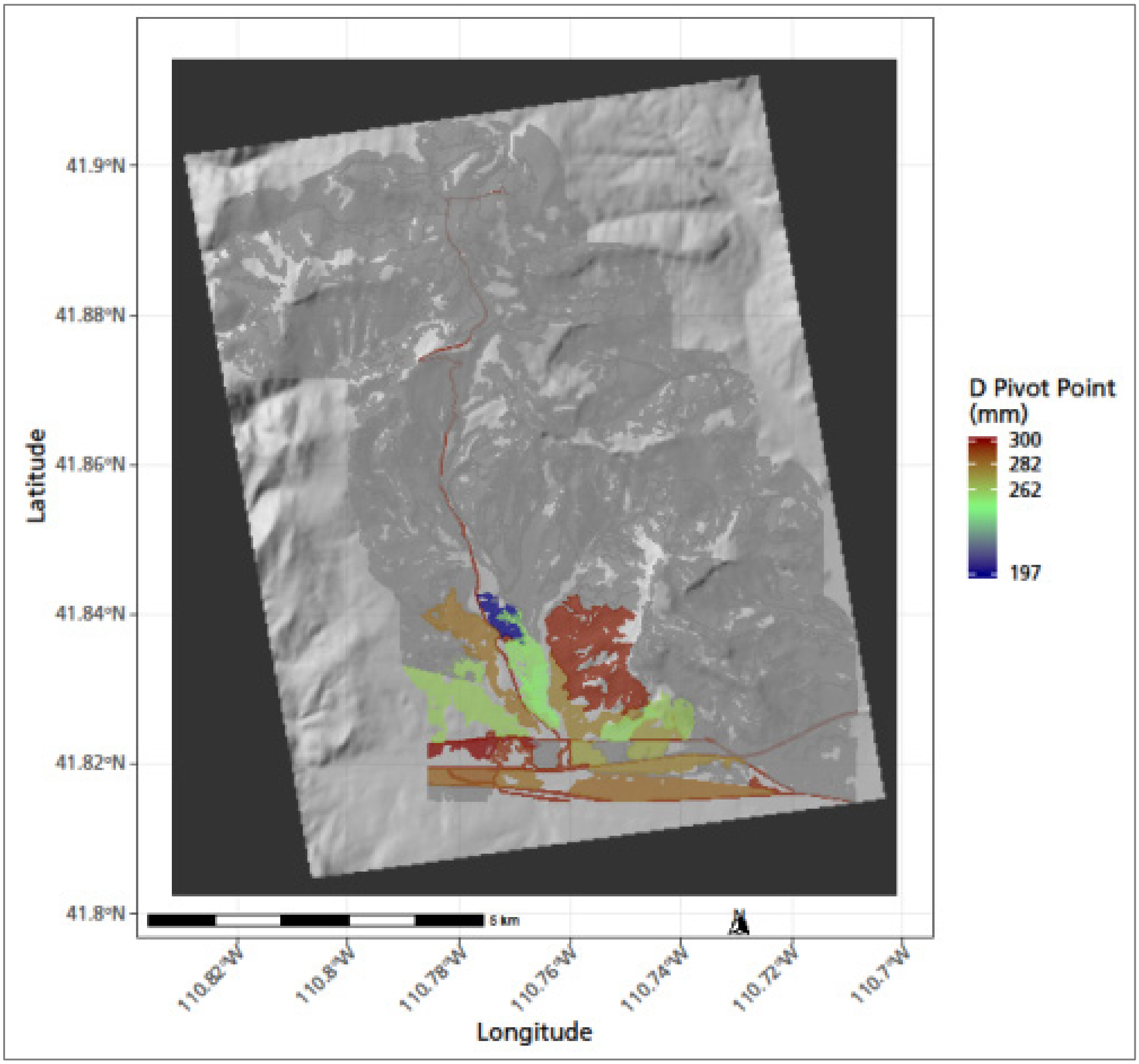

Figure 11. Deficit pivot points for polygons with a significant relationship (p-value < 0.05) between water-year annual deficit and change in annual vegetation production, assessed as the interannual difference in iSAVI. The mean deficit pivot-point values shown here represent spatial patterns in the critical water needs of vegetation.
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A study of pinyon mortality in the southwestern US found that 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 considered by using water-balance variables as indicators of climate. For this reason, pivot points for other water-balance variables are included in the appendix figures and tables (see Appendix A; Tables S-2 and S-4 in NPS 2025).

3.6.3 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 12; Appendix A). 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 environments like Fossil Butte NM, where low elevations are water limited and higher elevations are temperature limited, a variable like actual evapotranspiration explains vegetation production better for more alliance groups than variables that only describe water abundance (P, RAIN, SNOW, SOIL) or heat (T, GDD).

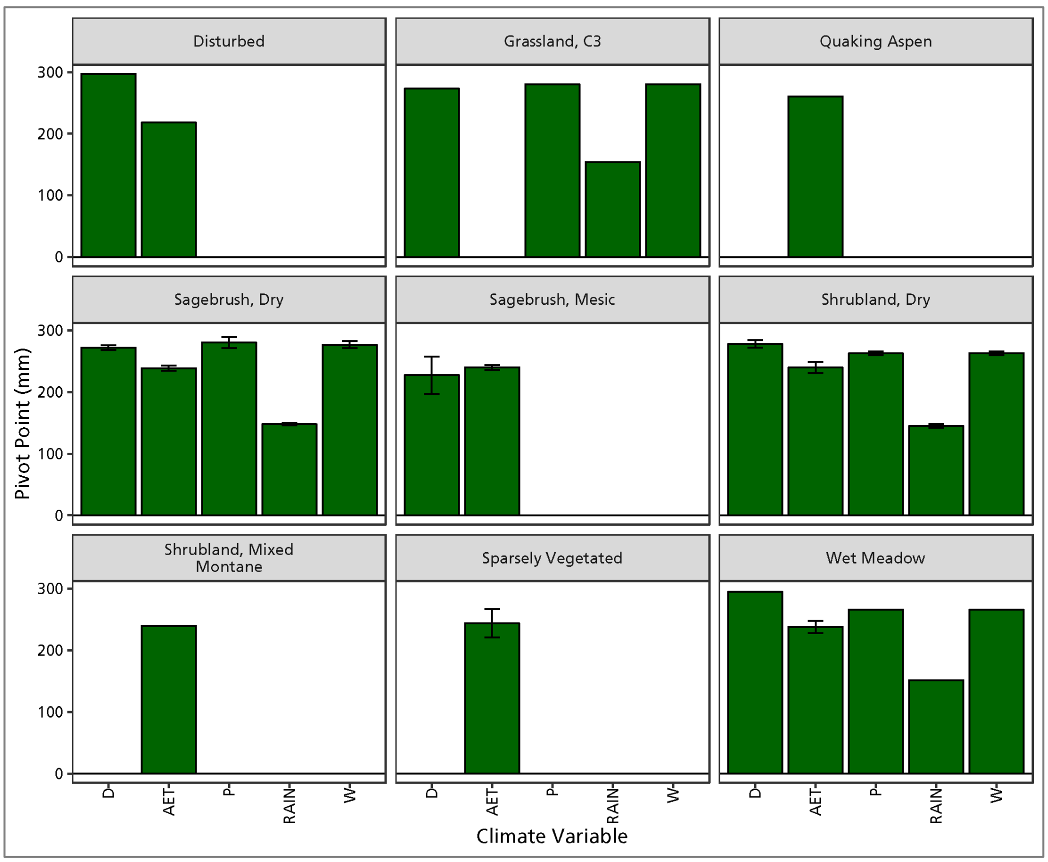

Figure 12. Significant (p-value < 0.05) water-related pivot points by alliance group. See Table S-4 in NPS (2025) for the pivot point values. The magnitude of each pivot point reflects generally average conditions for polygons in each alliance group. The mean pivot-point values are the critical values where annual production switches from below to above average (relative to previous year) for the different alliance groups. D = water deficit (mm), AET = actual evapotranspiration (mm), P = precipitation (mm), RAIN = precipitation as rain (mm), W = snowmelt plus rain (mm).

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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.

Pivot points for each climate variable by polygon are provided in Table S-2 of NPS (2025), 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 4).

3.7 Vegetation response

3.7.1 Vegetation response and climate sensitivity

When they interact with climate, plant traits determine which species grow under different conditions of water availability and cold tolerance. The result is a spatial organization of alliance groups that reflect local climate and the sensitivity of vegetation to climate (Figure 13). The interactions between plant traits, site characteristics, and climate-determined patterns of vegetation distribution in the past will determine how vegetation in Fossil Butte NM is shaped by climate in the future.

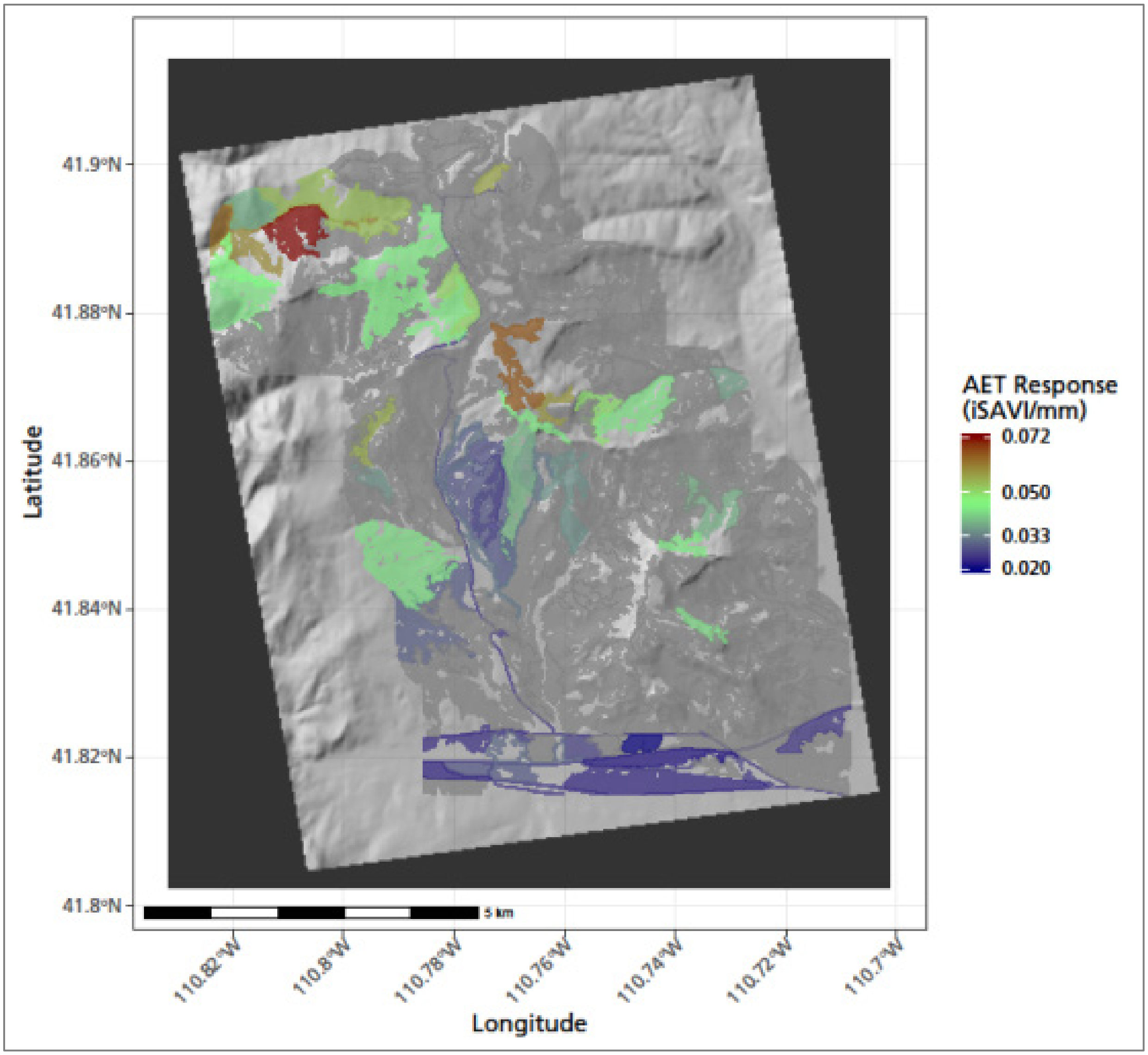

Figure 13. Sensitivity of growing-season vegetation production to annual water-year actual evapotranspiration. This figure shows which vegetation types will experience change first. Groups with highest response rates are most likely to see change happen first and fastest as the climate shifts. Response is the slope of the linear-regression relationship between annual actual evapotranspiration and iSAVI change from the previous year. It is the change in iSAVI expected per millimeter of change in annual actual evapotranspiration. 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 actual evapotranspiration. Areas that were not significantly related to annual actual evapotranspiration 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 NPS (2025).

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Vegetation response is a formal component of vegetation vulnerability assessments used in Climate Smart Conservation (Stein et al. 2014). The importance of response is related to the need to understand which 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 Fossil Butte NM, Quaking Aspen and Mesic Sagebrush had the highest response rate and sensitivity to annual actual evapotranspiration (Figure 14). Dry Shrubland and Disturbed alliance groups were least sensitive. Alliance-group sensitivities to other water-balance variables can be found in Appendix A.

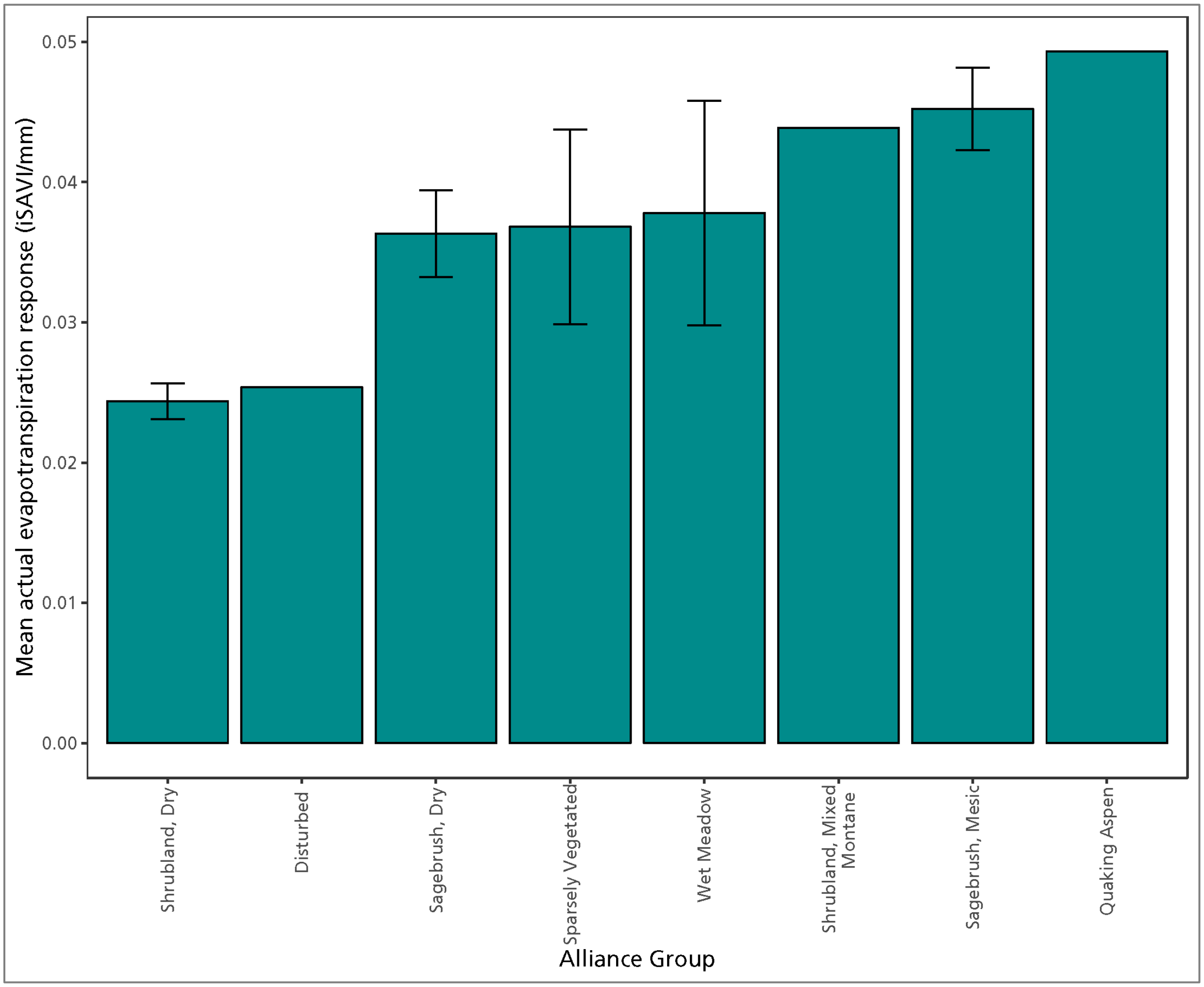

Figure 14. Responses of different vegetation alliance groups to actual evapotranspiration. Standard error bars indicate range in variability of responses among polygons of an alliance group if more than one polygon of an alliance group had a statistically significant relationship (p-value < 0.05) with actual evapotranspiration.

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Generally, there was a pattern across the monument in which sensitivity increased at higher elevations. This was partly due to vegetation structure: the Quaking Aspen alliance group grows in higher elevations in the monument, but Mesic Sagebrush alliance group occurs throughout. 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. Additional response maps, found in Appendix A, illustrate spatial patterns in the sensitivity of alliance groups to deficit and growing degree days.

3.7.2 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. There are patterns in the soil-properties maps (Figure 15) that may align with patterns in the response maps (e.g., Figure 13 and Appendix A). However, holes or gaps in the response maps make it difficult to see qualitatively and the sample sizes needed for statistical evaluation are too small. More analysis is needed to determine quantitatively how soil properties affect pivot points and responses, but it is likely that interactions between climate, site properties, and vegetation traits (deep- or shallow-rooted, perennial or annual) have influenced and will continue to influence vegetation condition and trends.

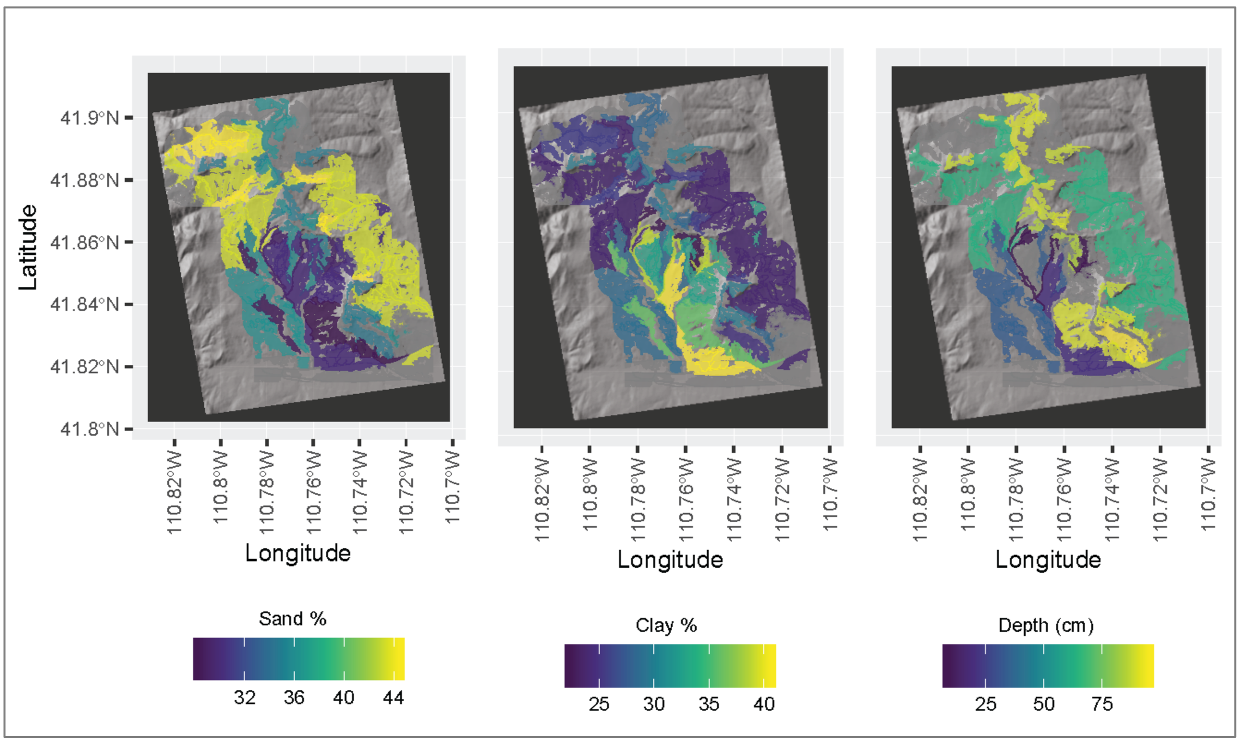

Figure 15. Maps of percentage sand content in top meter of soil, percentage clay content of soil, and depth to restrictive layer in alliance groups. Spatial patterns of soil properties correspond with patterns in vegetation response to climate. Areas of no color fill indicate missing soil properties data or depth is greater than 100 centimeters.

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3.7.3 Patterns within alliance groups

While pivot points and responses provide different information, they are linked by plant traits: as precipitation pivot points decrease (i.e., cross the horizontal “no change” line further to the left), response rate increases (Figure 16). Alliance groups with steeper slopes (e.g., Quaking Aspen and Mesic Sagebrush) are considered more responsive to changes in water availability. These groups increase production with less actual evapotranspiration, demonstrating that responsiveness to actual evapotranspiration is greatest where vegetation is most drought-tolerant.

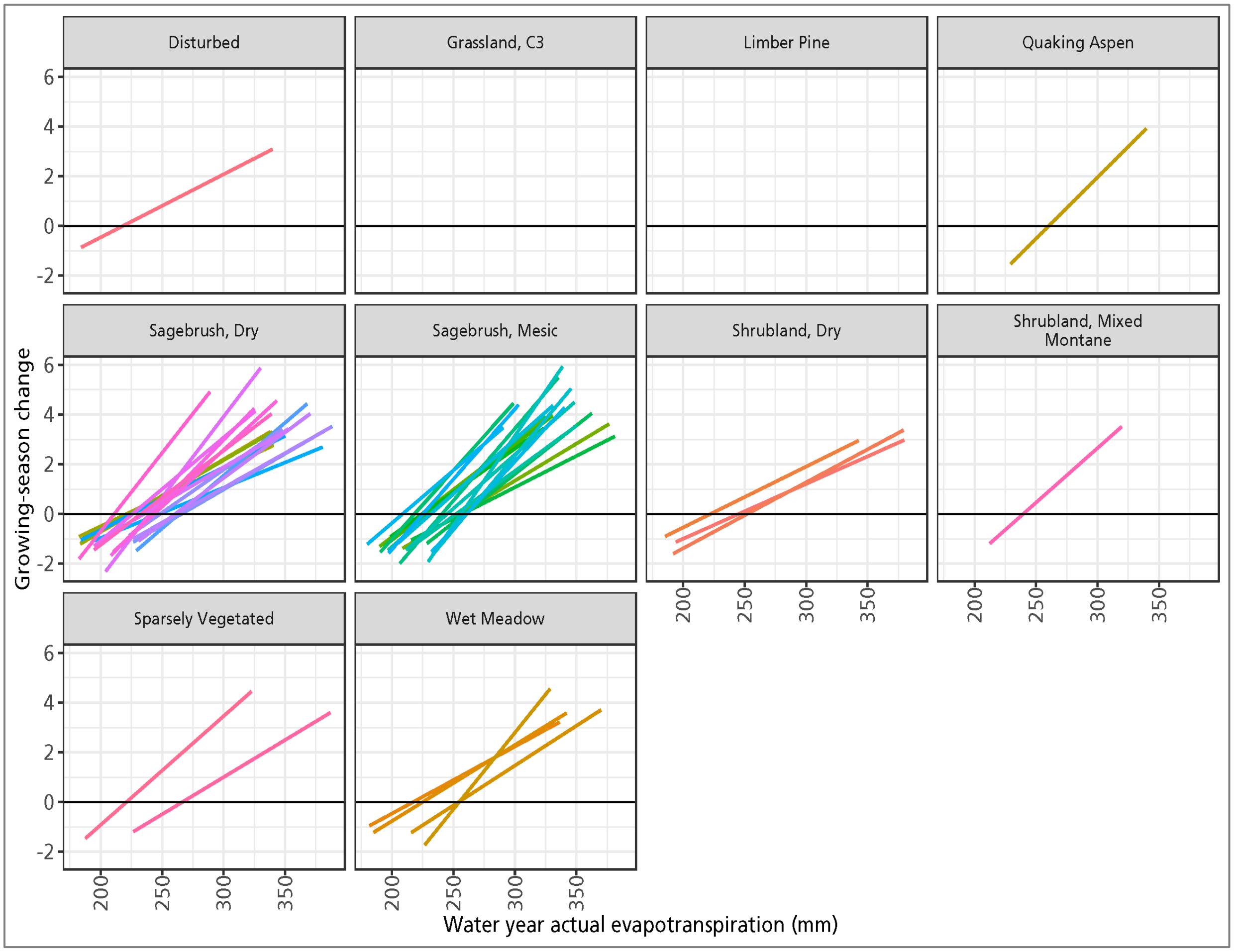

Figure 16. Graphical depiction of the relationship between pivot points and responses in polygons that had a significant relationship (p-value < 0.05) between iSAVI and water-year actual evapotranspiration (e.g., critical water use vs. rate of growing season iSAVI change per mm precipitation). Polygon-level pivot points and responses are provided in Table S-2 of NPS (2025). 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 actual evapotranspiration. Only significant relationships are shown. Panels without lines represent alliance groups with no significant relationships between iSAVI and the climate variable. Colors help differentiate individual polygons within alliance groups.

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There was a large range in pivot points and responses, reflecting a wide range of plant traits responding differently to climate variability across the monument. The patterns of pivot points and responses quantify unique climatic habitats occupied by the different alliance groups in the monument, 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 actual evapotranspiration will be greater in Quaking Aspen and Mesic Sagebrush areas, more so than in Dry Shrubland or Disturbed areas.

Tracking weather conditions during the growing season allows a view into vegetation condition at the polygon or alliance-group scale, depending on management interest (NPS 2025, Tables S-2, S-4). Generally, within alliance groups, vegetation response increased as actual evapotranspiration decreased. The degree of responsiveness was determined by traits that allowed plants to either resist drought or rapidly respond to water availability. The 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 C3/C4 Grassland alliance group, precipitation explained 21% of interannual variation in production. But by polygon (n = 17), precipitation explained between 16% and 34% of interannual variation in production.

Multiple factors 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).

3.7.4 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 semiarid environments and water variables, such as precipitation, rain and snow), or negative (in response to water deficit or potential evapotranspiration, which are related to temperature) (Figure 17; also see NPS 2025, Tables S-2 and S-4). However, these relationships switch with elevation at Fossil Butte NM, which could create confusion. That is, across the elevation gradient at Fossil Butte, water is limiting at lower elevations and temperature limiting at higher elevations, so it is better to focus on climate variables that integrate the effects of temperature and precipitation like AET and D. With these variables, if a statistically significant relationship exists with production, response to deficit is always negative and response to actual evapotranspiration is always positive across all elevations at Fossil Butte NM.

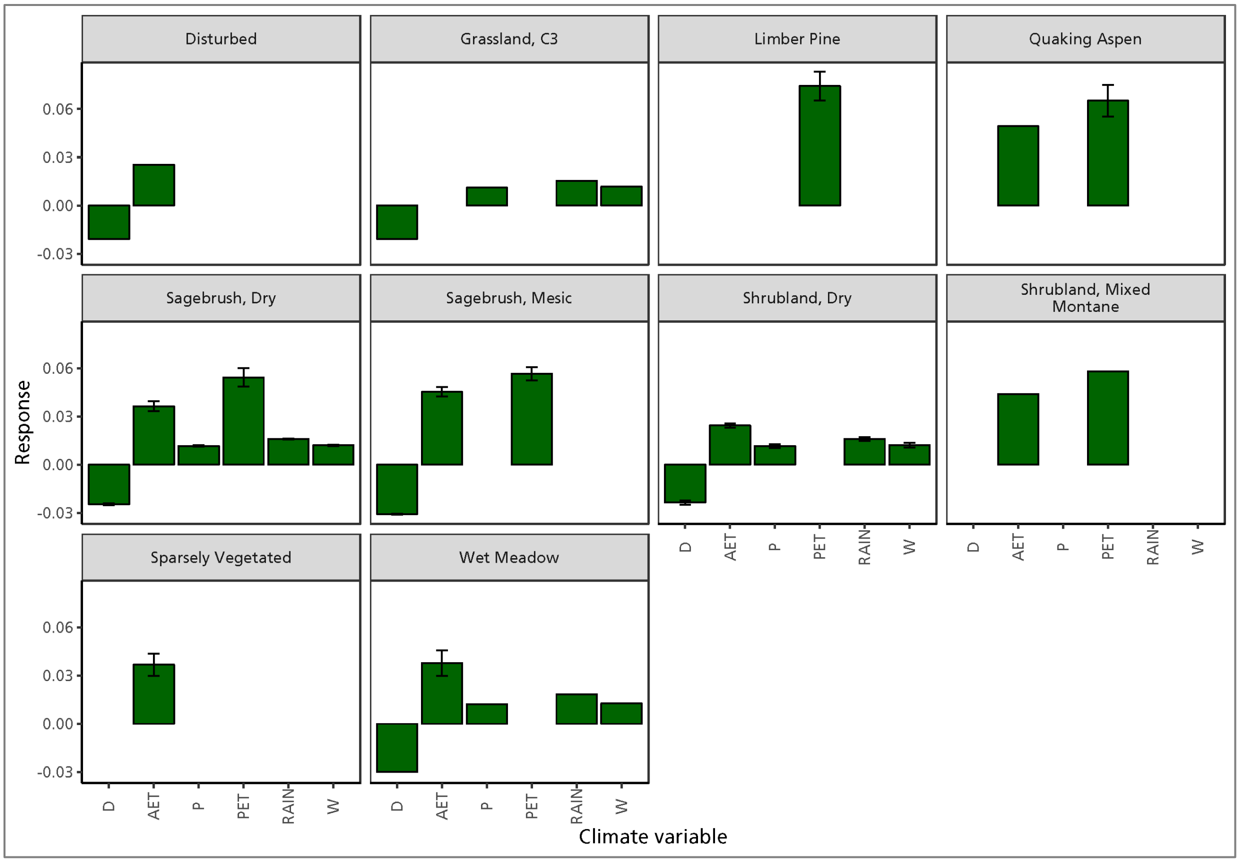

Figure 17. Vegetation response to summed water flux variables (regression slopes from iSAVI versus annual climate-variable sum). Statistics for these relationships and all other variables can be found in Table S-4 in NPS (2025). D = climatic water deficit (mm), AET = actual evapotranspiration (mm), P = precipitation (mm), PET = potential evapotranspiration (mm), RAIN = precipitation as rain (mm), W = combination of rain and snowmelt (mm).
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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, can be 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). However, no significant relationships with soil moisture were found at Fossil Butte NM. 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.

3.8 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).[5]

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 (76%) polygons were influenced by three years of actual evapotranspiration (Figure 18). These patterns generally held within alliance groups (Figure 19). A list of top-performing models (AICc < 4) by polygon can be found in Table S-5 of NPS (2025).

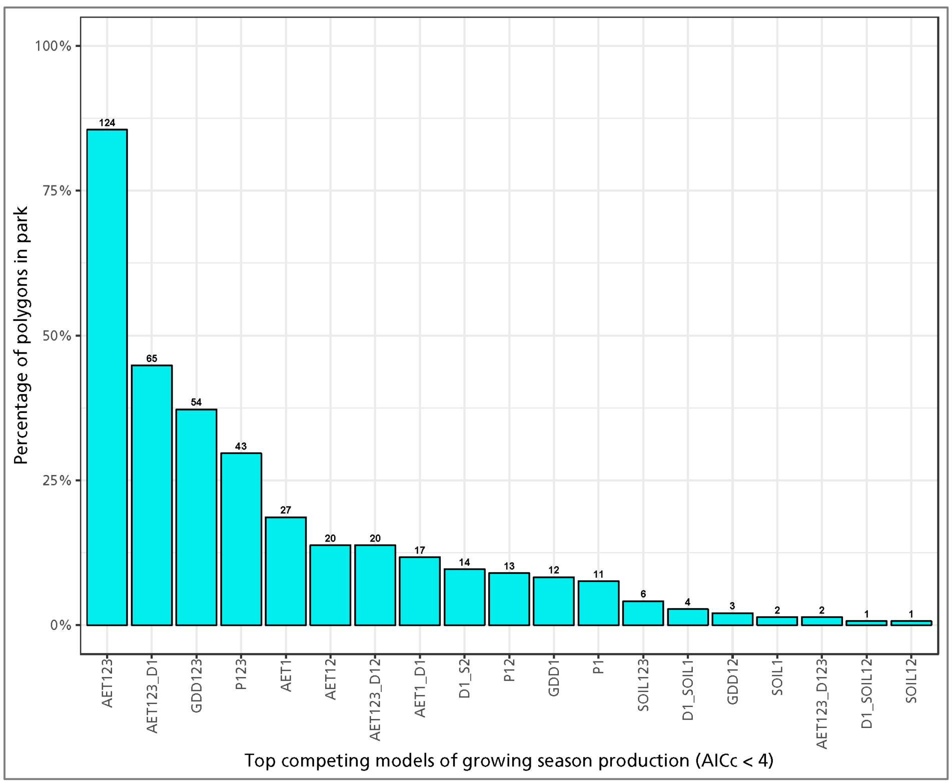

Figure 18. Top models in multi-model comparison of climate correlates with interannual differences in growing-season iSAVI across all alliance groups. Percentages indicate proportion of polygons where each model was competitive. Numbers above bars indicate polygon count. Each polygon may have more than 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 3. AET = annual evapotranspiration (mm), GDD = growing degree days, P = annual precipitation (mm), D = climatic water deficit (mm), SOIL = annual average soil moisture (mm). Numbers indicate current and prior years included in each model. 1 = current year; 12 = current and previous year; 123 = current and previous two years.

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[5] 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).

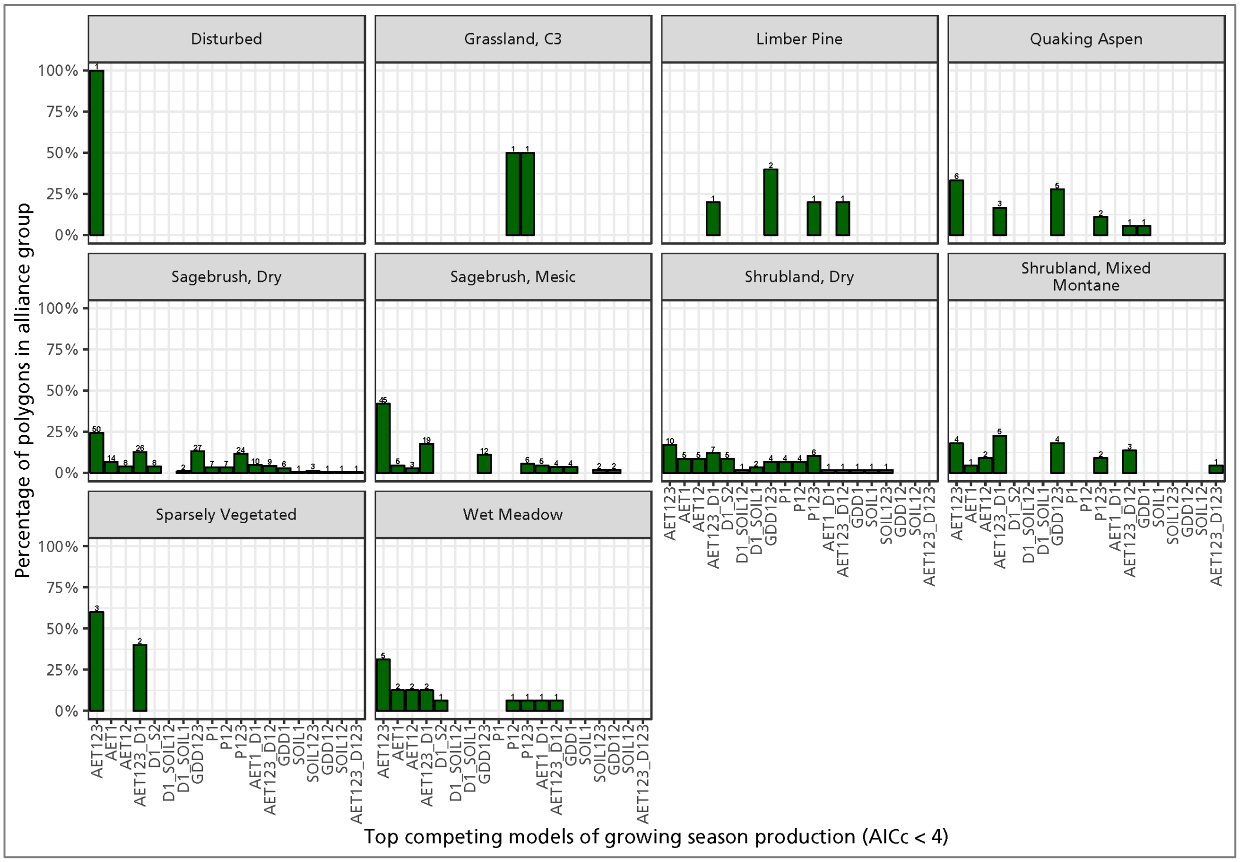

Figure 19. Top models of growing-season production by alliance group in multi-model comparisons of climate correlates with interannual differences in growing season iSAVI. The x-axis labels refer to the a priori climate models in Table 3. The y-axis represents the proportion of polygons in each alliance group where each model was competitive. Numbers above bars indicate polygon count. Each polygon may have more than one competitive model; thus, the sum of percentages can exceed 1 across models. AET = annual evapotranspiration (mm), D = climatic water deficit (mm), SOIL = annual average soil moisture (mm), GDD = growing degree days, P = annual precipitation (mm). Numbers indicate current and prior years included in each model. 1 = current year; 12 = current and previous year; 123 = current and previous two years.

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Most alliance groups responded to multiple years of actual evapotranspiration, highlighting the importance of legacy effects across years in a semiarid 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.

3.9 Land-surface phenology trends at Fossil Butte National Monument

At the monument scale, the start of growth advanced 16 days earlier and the end of growth occurred 5 days later. Collectively, these changes resulted in a growing season that was on average 27 days longer by the end of the study. At the end of the study, timing of peak growth occurred 5.5 days earlier for shrublands and grasslands, representing 41% of the study area (Table 5).

Table 5. Trends in phenology averaged across polygons in the same alliance group.

Alliance group	ΔSOS	ΔEOS	ΔLOS	ΔPOP	Hectares	Polygon count	% area
Sagebrush, Dry	2.1	8.7	6.1	4.7	2103	60	46.9
Sagebrush, Mesic	2.1	6.5	4.7	5.1	1625.6	48	36.2
Shrubland, Dry	−1.5	12.8	17.2	3.2	284.8	12	6.4
Quaking Aspen	4.7	−8.5	−11.4	7.8	154.5	8	3.4
Wet Meadow	−1.6	15.0	15.1	4.0	79.6	5	1.8
Shrubland, Mixed Montane	2.4	5.1	2.1	11.8	69.6	5	1.6
Disturbed	N/A	12.6	N/A	5.4	63.5	1	1.4
Limber Pine	3.8	N/A	N/A	7.0	51.6	2	1.2
Sparsely Vegetated	1.4	13.6	10.9	9.2	35.1	3	0.8
Grassland, C3	N/A	7.4	N/A	6.2	17.3	1	0.4

A trend in earlier start of the growing season occurred in all alliance groups except for Quaking Aspen and Mesic Sagebrush (Table 5; Appendix A). In recent years, the growing season was ending later for most alliance groups, but earlier for Dry Shrubland, and Wet Meadow. Collectively, these changes resulted in a longer growing season in 99.7% of the study area, including all groups except Quaking Aspen, which shortened by 11 days, respectively.

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) that increases water-use efficiency. However, the strength of the relationship between production and annual precipitation over the study period (see Figure 9) and in findings from Section 3.7 suggested most of the increase in production was related to increases in water availability during the study, which may have been augmented by increases in CO_2.

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 semiarid environments, while elevated CO_2 increases water-use efficiency of production for the same amount of water. 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 semiarid vegetation to multiple aspects of climate change (Sorokin et al. 2017).

3.10 Drivers of green-up

3.10.1 A priori *model selection method*

At the scale of both the monument and alliance group, the most common a priori competitive model of green-up timing (see Table 4) was growing degree days and cumulative precipitation between January 1 and the SOS date (Figures 20 and 21). Other competitive models included growing degree days, actual evapotranspiration, and rain. At the alliance group level, growing degree days and precipitation were the only variables important in every alliance group (Figure 21).

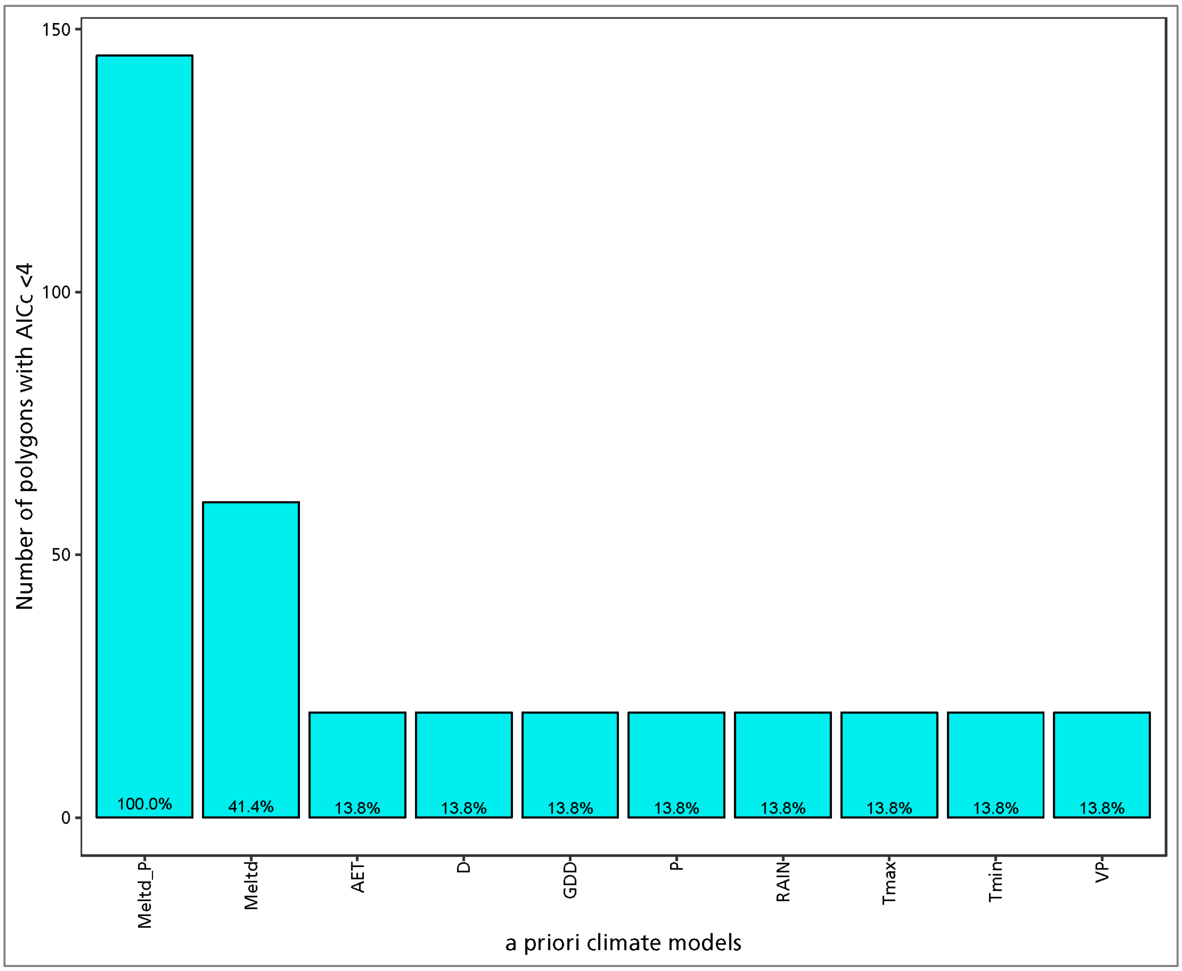

Figure 20. Top models in multi-model comparisons of climate correlates with start of growing season at the whole-park scale. The x-axis labels refer to a priori climate models as determinants of green-up or start of season. Meltd = day of complete snowmelt (day-of-year), AET = actual evapotranspiration (mm), D = climatic water deficit (mm), GDD = growing degree days, P = precipitation (mm), RAIN = precipitation as rain (mm), Tmax = maximum temperature (°C), Tmin = minimum temperature (°C), VP = vapor pressure (Pa).

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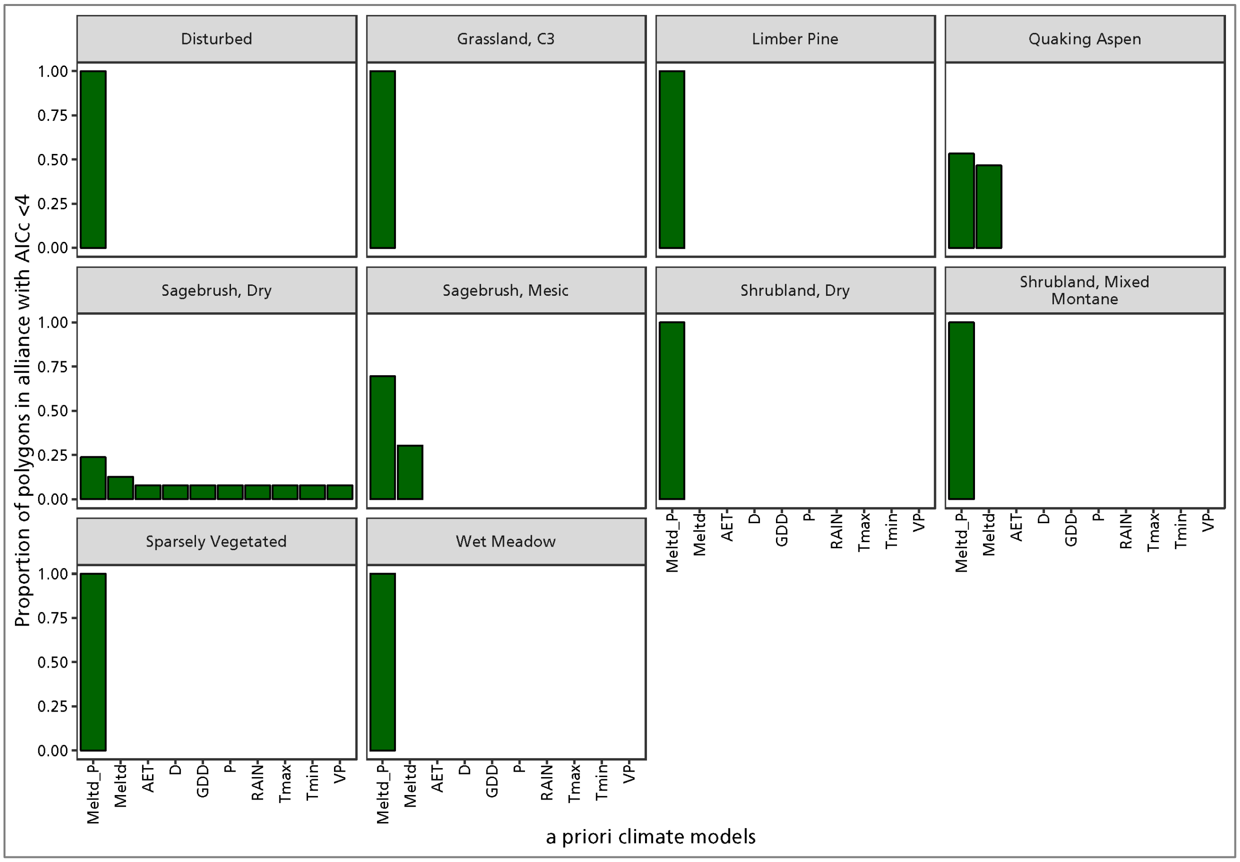

Figure 21. Top models in multi-model comparisons of climate correlates with start of growing season at the alliance-group scale. The x-axis labels refer to a priori climate models as determinants of green-up or start of season. Meltd = day of complete snowmelt, AET = actual evapotranspiration (mm), D = climatic water deficit (mm), GDD = growing degree days, P = precipitation (mm), RAIN = precipitation as rain (mm), Tmax = maximum temperature (°C), Tmin = minimum temperature (°C), VP = vapor pressure (Pa). *NPS / DAVID THOMA*

Day of snow melt is likely important as a growth release due to cold and light limitation beneath snowpack. The importance of precipitation during the calendar year may indicate that the soil-water holding capacity requires spring precipitation to fill and for continuously wet near surface conditions for germination. Otherwise, insufficient precipitation may be a growth-limiting factor for initiating growth. This may be a consequence of typically dry fall and winter periods, which would result in low moisture levels in the absence of spring precipitation.

3.10.2 Random-forests method

Variable importance plots also showed the best predictors of start-of-season were date of snowpack melt, and precipitation. Growing degree days and rain were also important (Figure 22). These findings were similar to those in the multi-variable regression models, where date of snow melt and precipitation were important, but with the addition of growing degree days and rain as important variables.

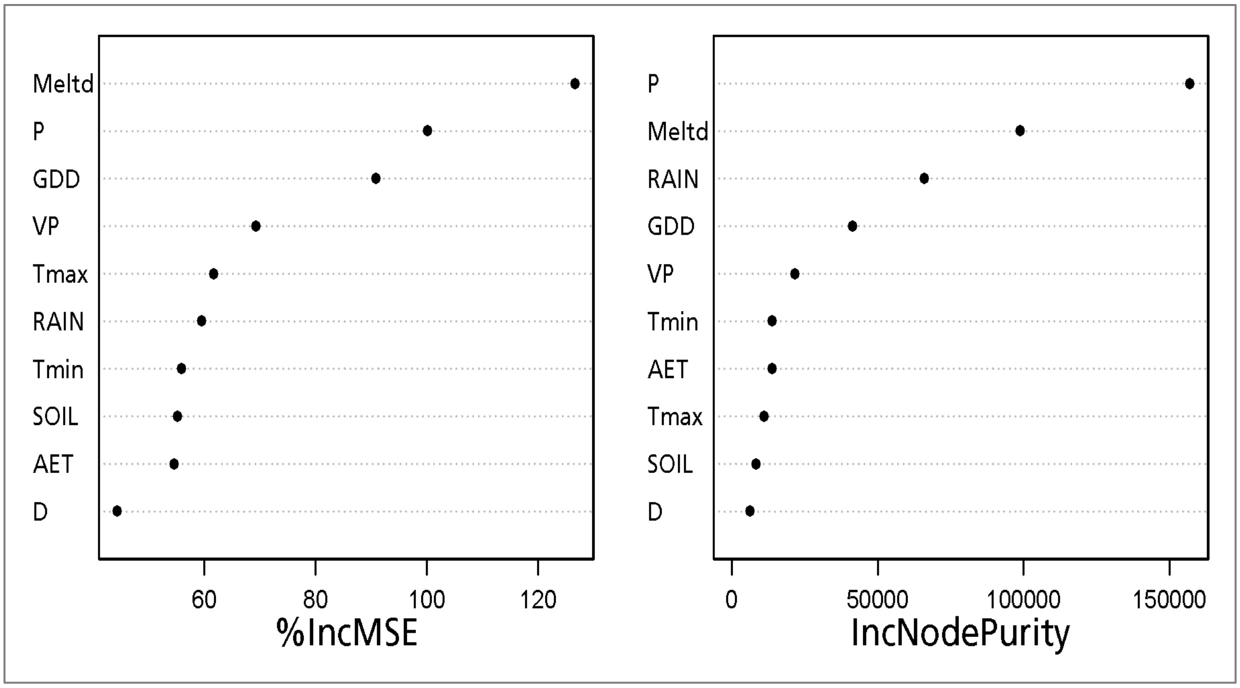

Figure 22. Variable importance in the random-forest model of climate drivers of the start of growing season. Percent increase in mean square error (%Inc-MSE) is a measure of model performance with each variable. Increase in node purity (IncNodePurity) is the difference in residual sum of squares in regression with or without each variable.
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Findings from the two modeling methods suggested a combination of snowmelt date and moisture are important indicators of SOS, as is expected in cold, semiarid 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 at higher elevations where snow accumulates over winter, but the effect of spring precipitation is less intuitive unless the soil moisture was not sufficiently replenished over winter to meet plant needs.

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 monument scale with a mean absolute error of ± 1.3 days (Figure 23). When separated by alliance group, the model performed equally well (Figure 24).[6]

[6] The analysis was conducted at the park scale, rather than by polygon (as in Section 3.9) to increase sample size for the random forests modeling process.

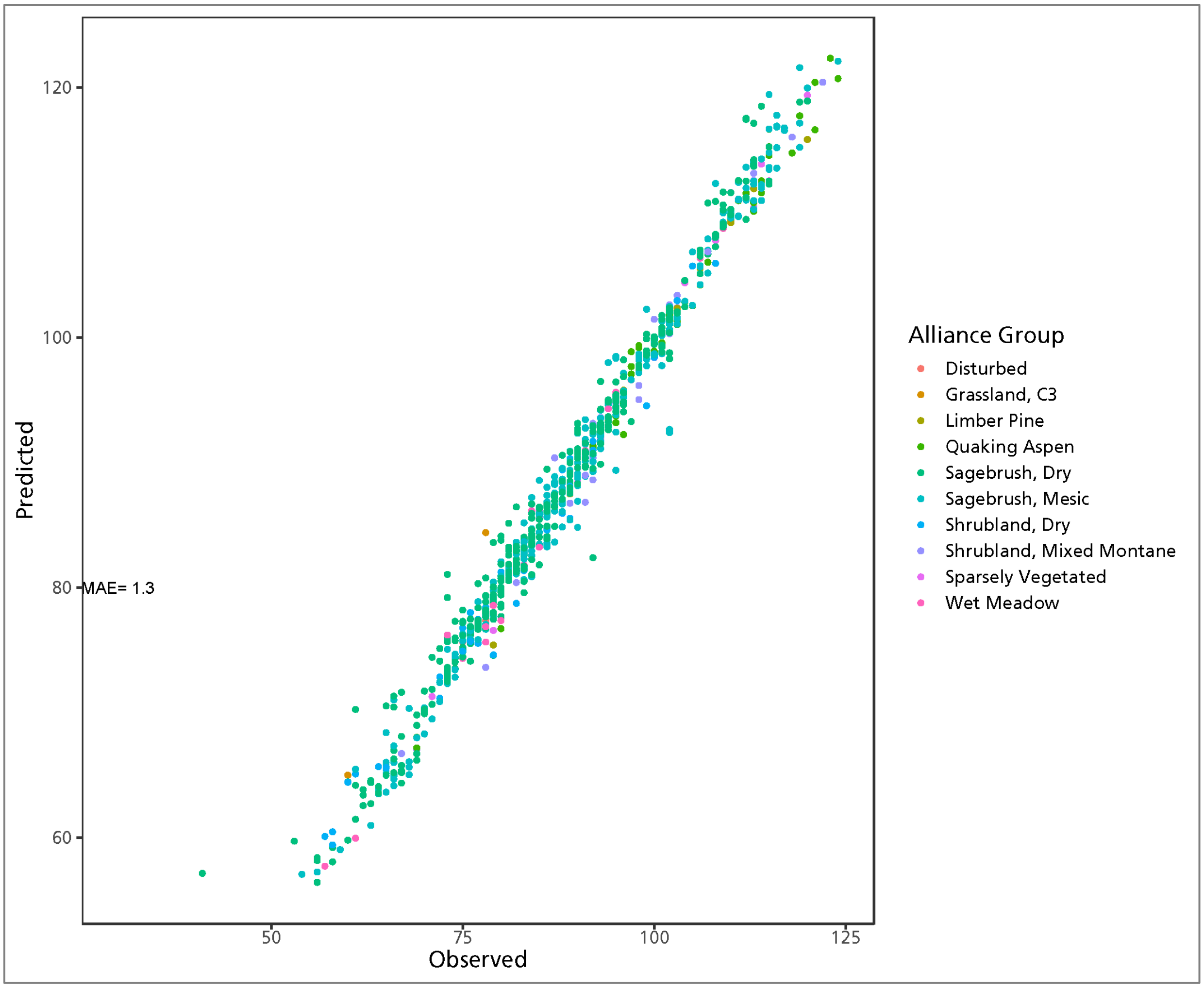

Figure 23. Predicted start-of-season date versus observed start-of-season date in the holdout dataset used for validation of the random-forests model for all polygons in Fossil Butte NM. MAE is mean absolute error of prediction in days. Polygons with annual peaks (POP) occurring between November 1 and April 1 were removed prior to this analysis (Norris and Walker 2020).
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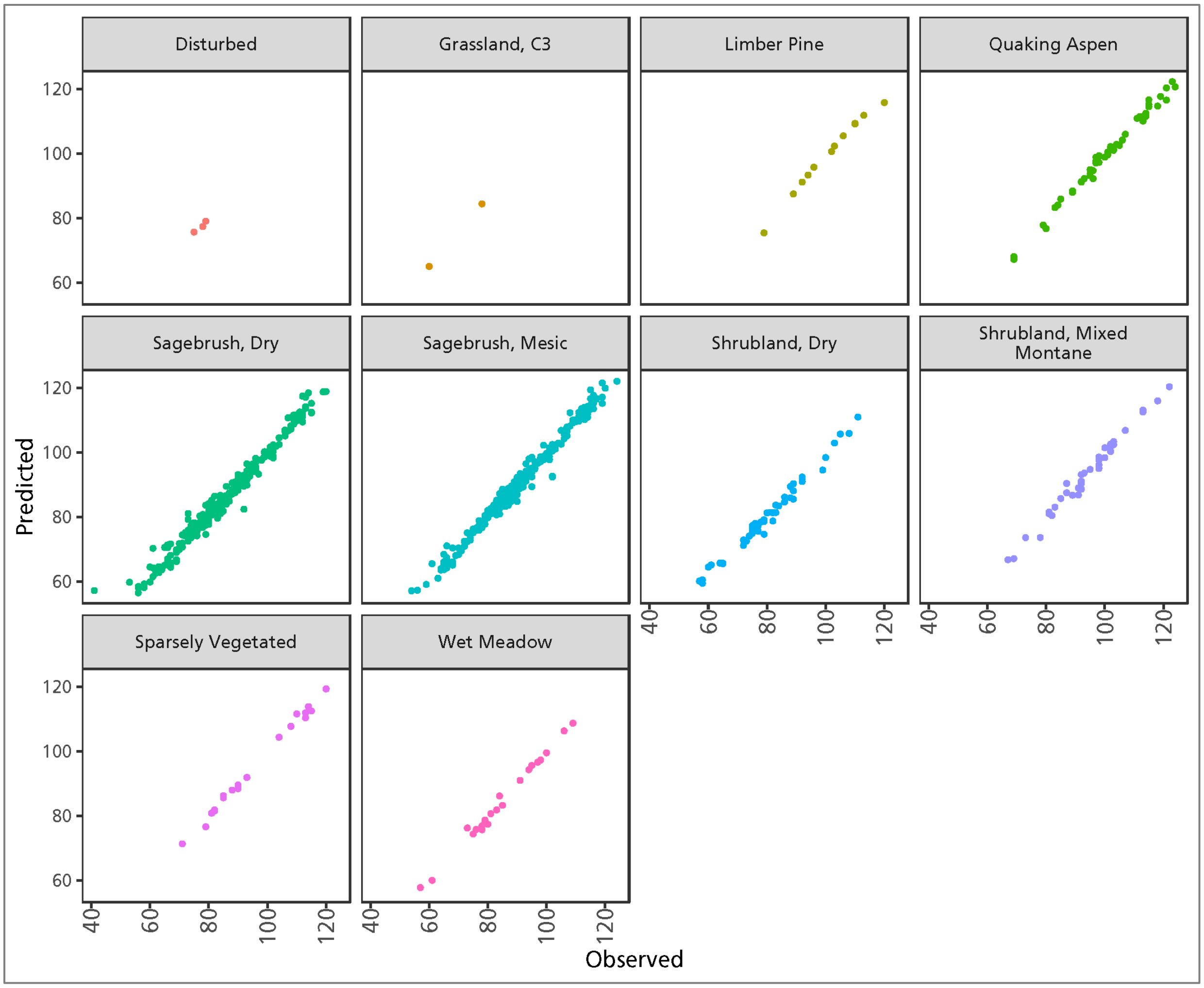

Figure 24. Predicted start-of-season date versus observed start-of-season date in the holdout dataset used for validation of the random-forests model for alliance groups. Polygons with annual peaks (POP) occurring between November 1 and April 1 were removed from this analysis. Outliers are likely due to difficulty in discriminating SOS when SAVI changes monotonically during a growing season in low productivity years.
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Inspection of SOS outliers in Figures 23 and 24 suggests they may have resulted from low amplitude and monotonic increase (straight line) in SAVI in some years. This combination makes 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 (per Norris and Walker 2020), it is not clear how SOS may be affected by the shadowing noted in 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 shrubland alliance groups.

Despite these potential shortcomings, the validation demonstrates a strong predictive model of SOS using climate data for most of the Fossil Butte 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.

3.11 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 25; Appendix A). This variation caused large interannual changes in annual vegetation production.

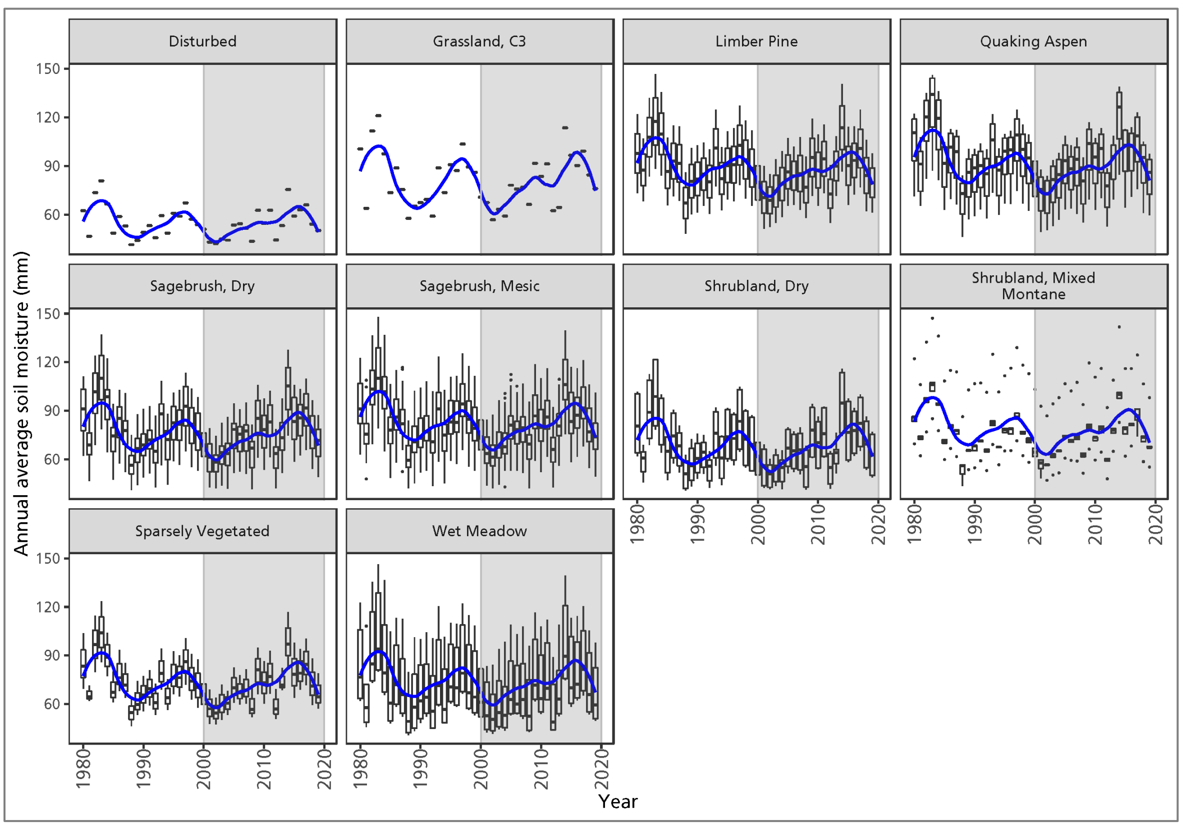

Figure 25. Long-term temporal patterns in precipitation in vegetation alliance groups. Box plots demonstrate the range of variation by year. The line is a loess smooth with a 25% span to illustrate multi-year patterns. Gray shaded area includes the period between 2000 and 2019, investigated for relationships 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.

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During 2000–2019, there was a statistically significant (p-value < 0.05) increase in precipitation of 1–2 millimeters per year (Figure 26). Average annual temperature also increased (approximately 0.05°C/year) but the trend was not statistically significant (p-value > 0.05) (see Figure 16; Appendix A). The increase in precipitation resulted in a corresponding increase in AET of 2–4 millimeters per year. The effect of these seemingly small changes was important as illustrated by the significant upward trends in production shown in Section 3.3.

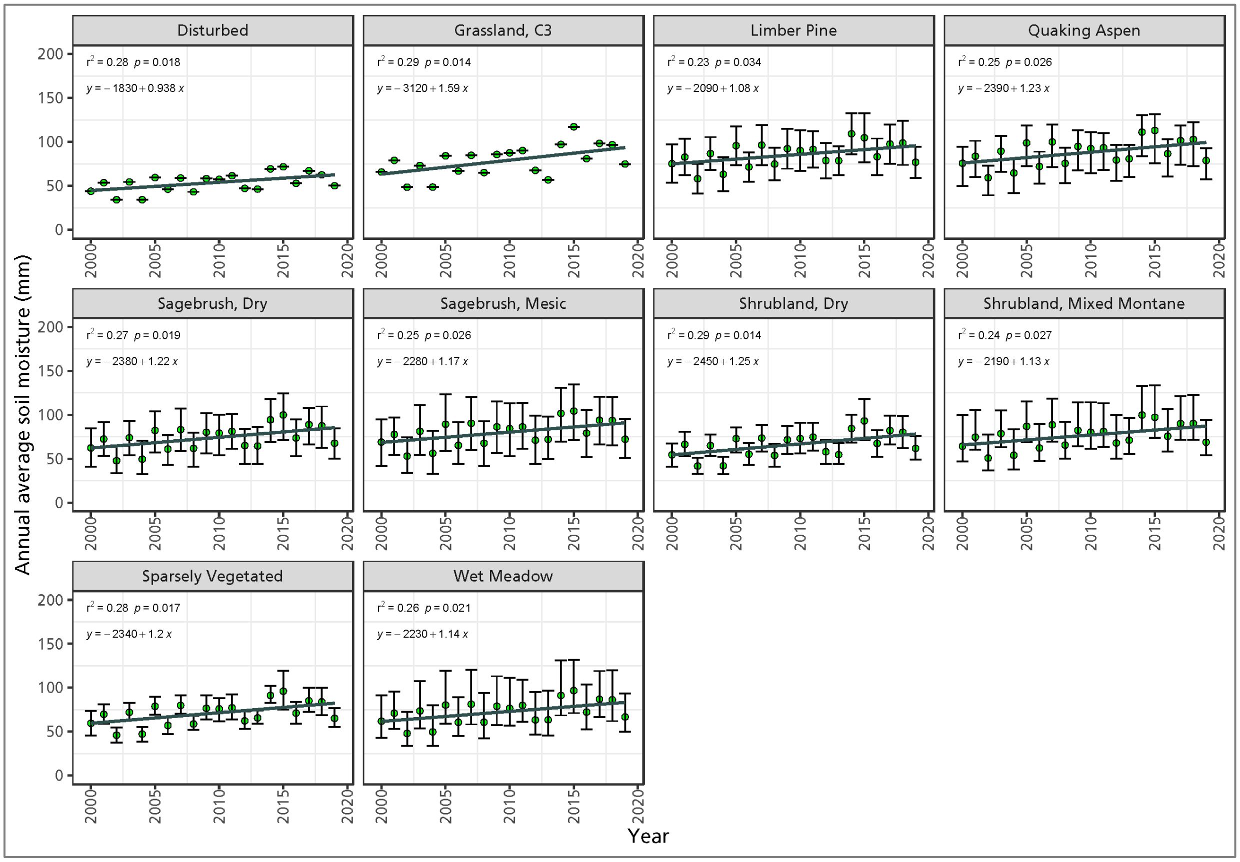

Figure 26. Annual precipitation trend over time, 2000–2019. Error bars are standard error.
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An interesting long-term oscillation in precipitation was evident: peaks in the middle of each decade since 1980 translated to similar peaks in other water-balance variables. The same pattern was apparent in soil moisture, AET, and water deficit (Appendix A), although for deficit the peaks (maximum drought stress) coincided with the times of least precipitation (Appendix A). 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.

4 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.[7]

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 monument managers noted juniper mortality in 2018 and 2019.

The NCPN supports ClimateAnalyzer.org, which makes accessing weather-station data intuitive and easy. Data from the monument 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.

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

5 Conclusions

Since 2000, a very dry period, primary production has increased in and near Fossil Butte NM. The increase coincided with an increase in precipitation over the same period. However, over this period, both isolated dry years and prolonged droughts occurred resulting 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 (Disturbed and Wet Meadow), and which were least drought tolerant (Mesic Sagebrush). Similarly, variation in climate over the study period was used to determine that Quaking Aspen, Mesic Sagebrush, and Mixed Montane Shrublands were the most sensitive to actual evapotranspiration, while sensitivity to precipitation was similar across alliance groups.

The climate variable most strongly correlated with vegetation production was three years of actual evapotranspiration. Timing of snowmelt and calendar year precipitation were the primary determinants of green-up timing. Over the study period, the start and end of the growing season shifted later, and the length of growing season increased for most alliance groups, likely due to warming and an increase in precipitation during the study.

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 Fossil Butte 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 until vegetation composition changes in the future, such as pivot points and sensitivity of vegetation to weather and climate. This is because drought tolerance and response to weather are factors 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 changes in climate —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 monument resources through continuous change.

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

Figures 27 to 78 present information about the landscape phenology, vegetation condition, and relations with climate that were observed in Fossil Butte National Monument during the study period from 2000 to 2019.

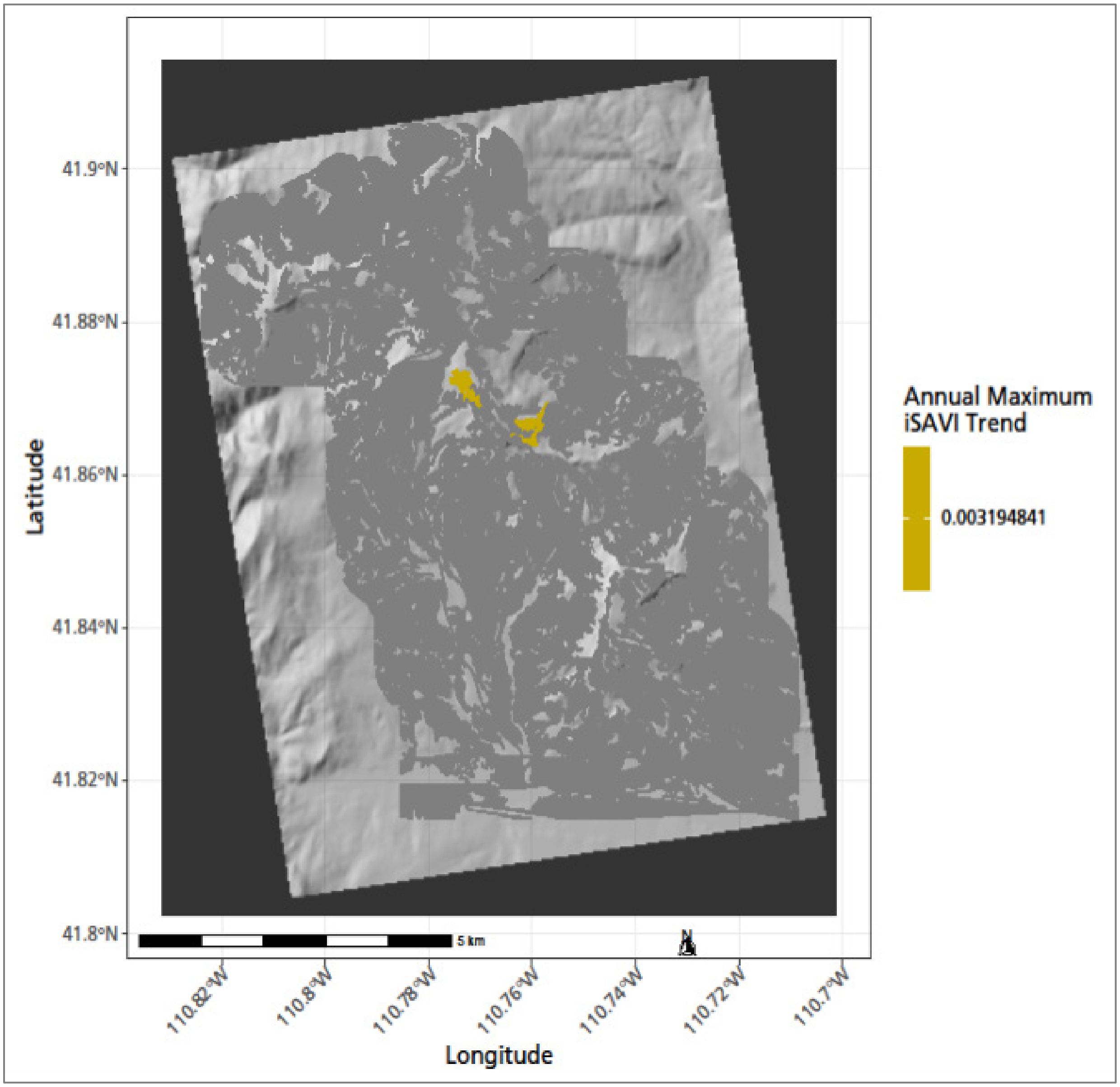

Figure 27. Spatial pattern of trends in maximum annual iSAVI. Trend is average change in iSAVI per year for the period 2000–2019.
NPS

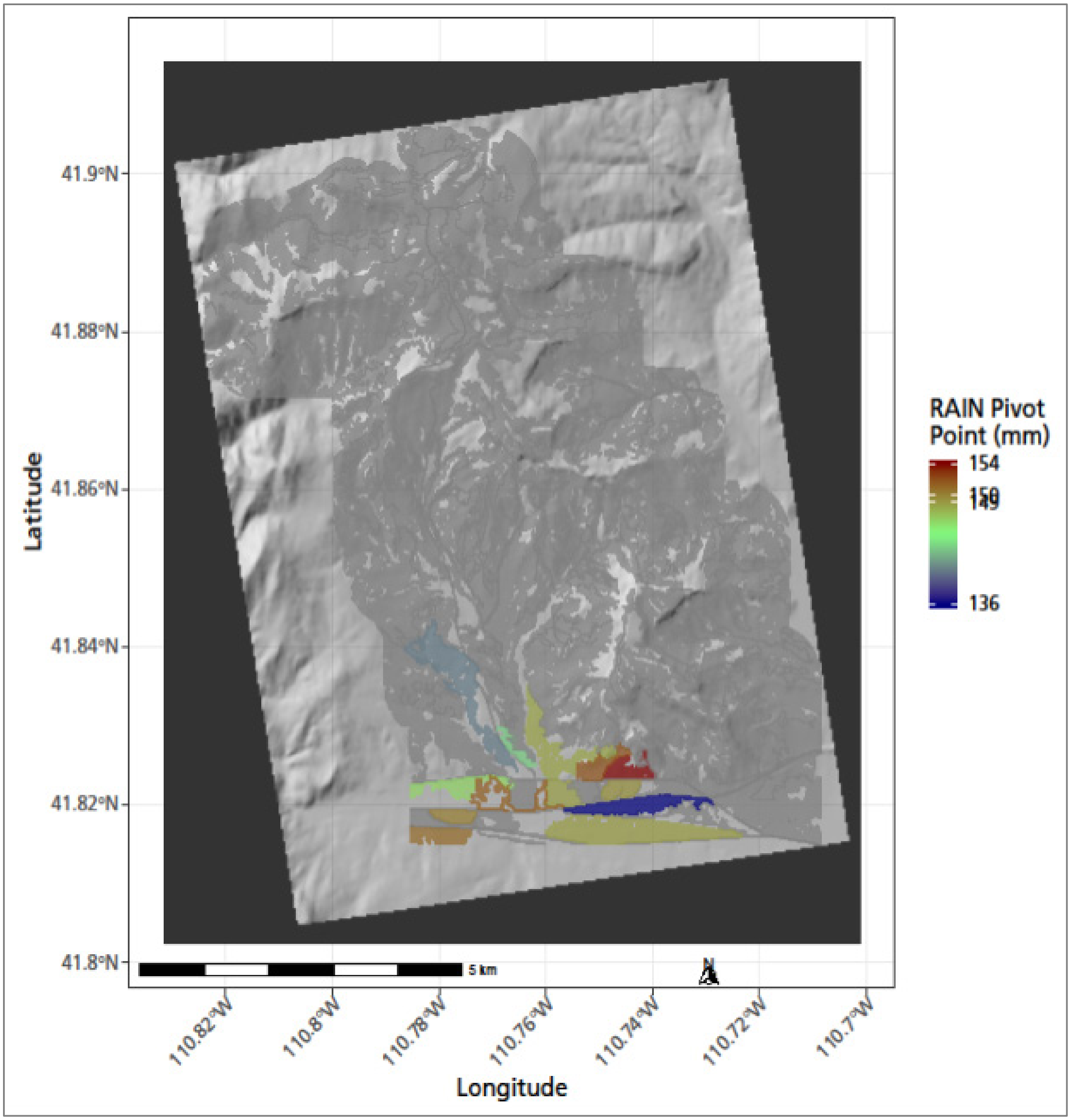

Figure 28. A map showing the locations of polygons where rain was significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.
NPS

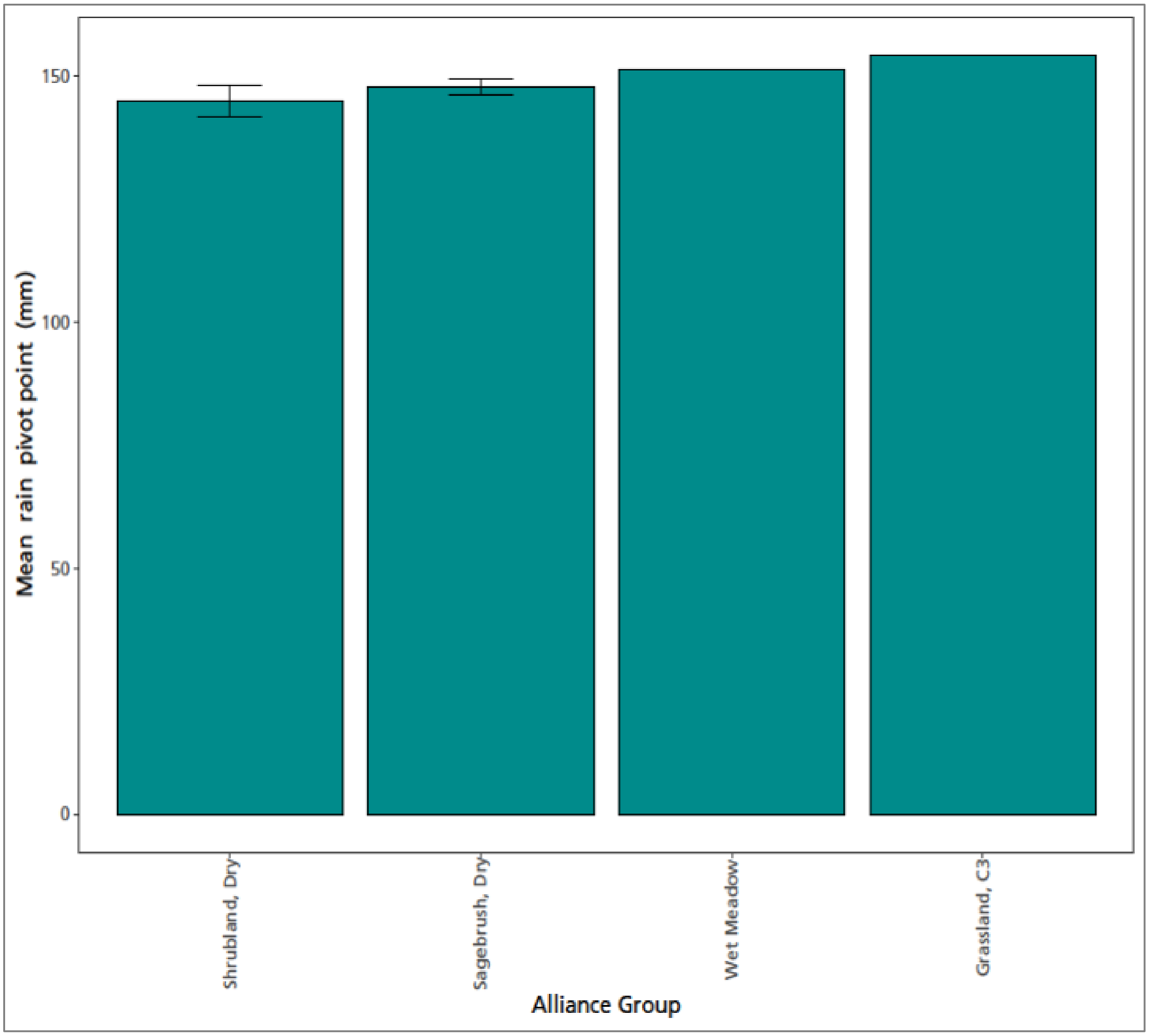

Figure 29. Pivot points for polygons where rain was significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.
NPS

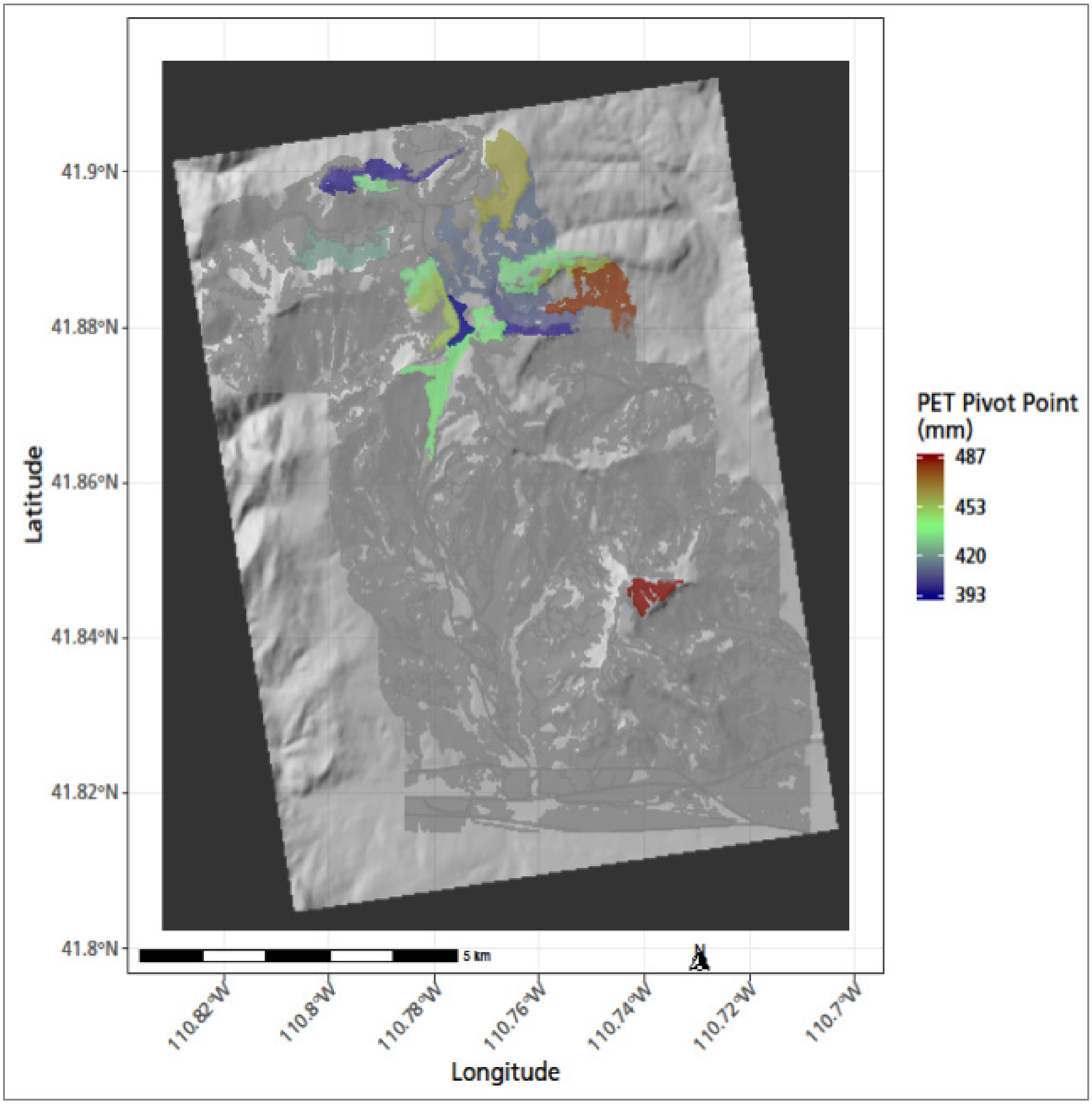

Figure 30. A map showing the locations of polygons where potential evapotranspiration was significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year. *NPS*

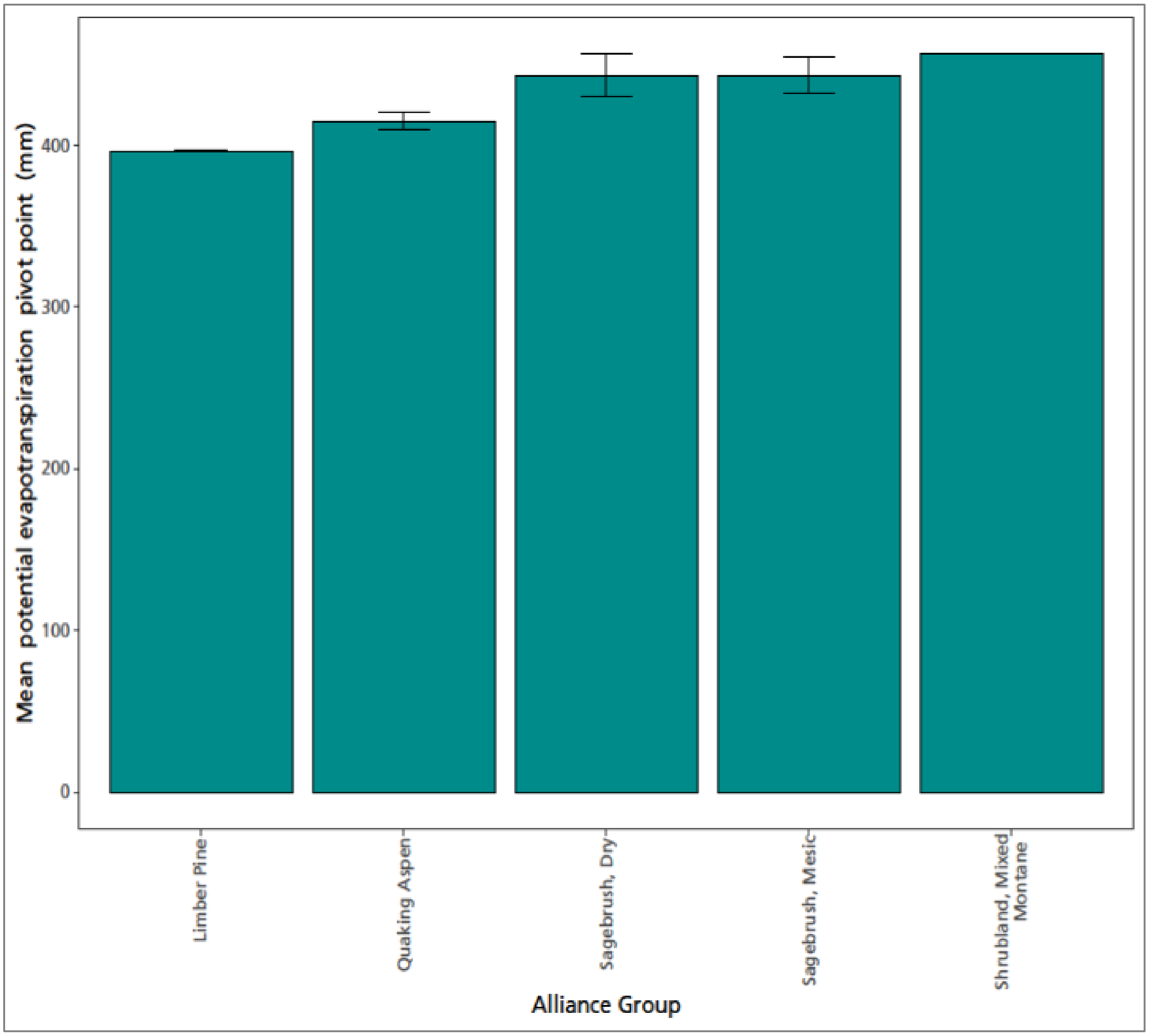

Figure 31. Pivot points for polygons where potential evapotranspiration was significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.
NPS

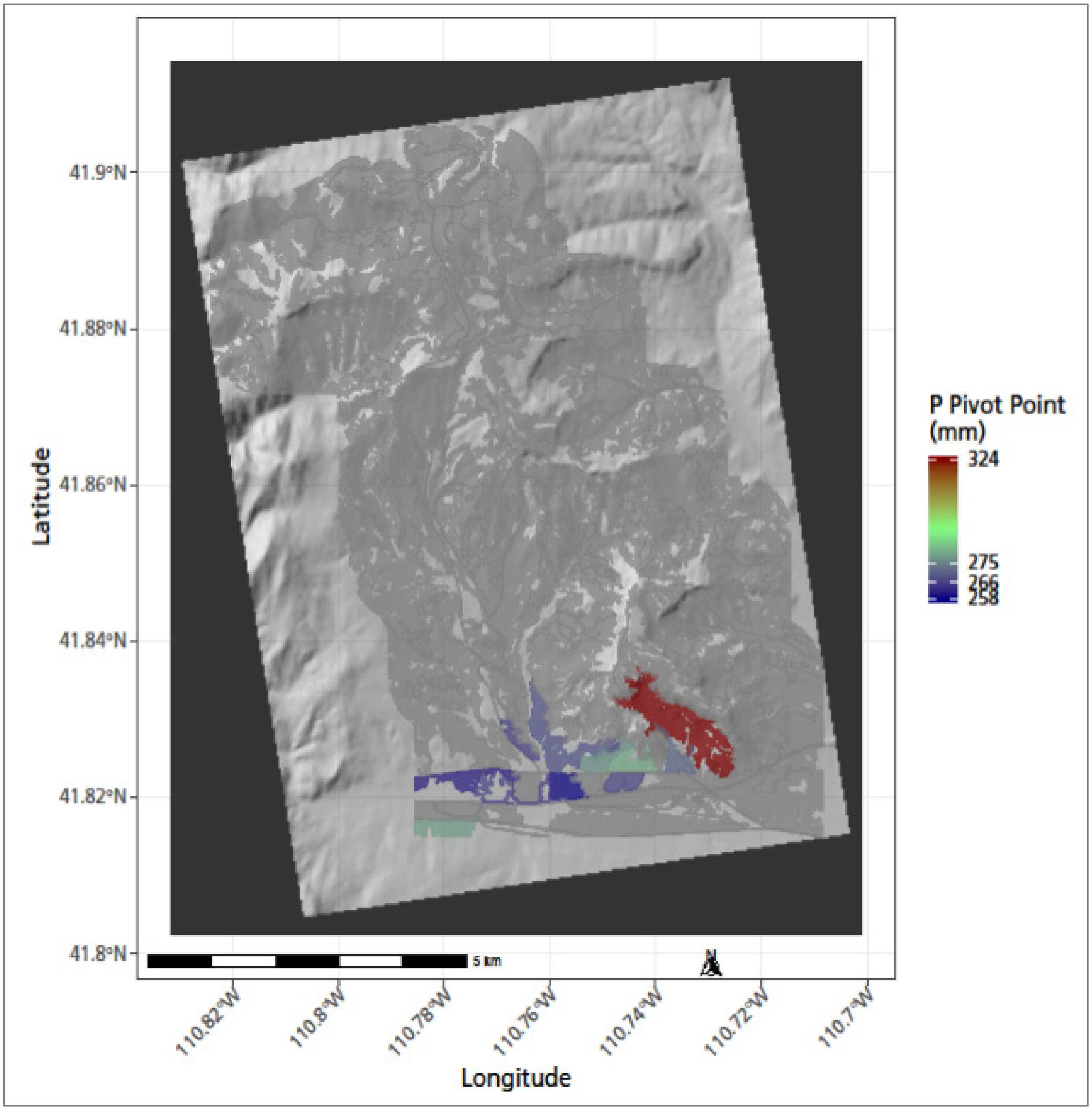

Figure 32. A map showing the locations of polygons where precipitation was significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.
NPS

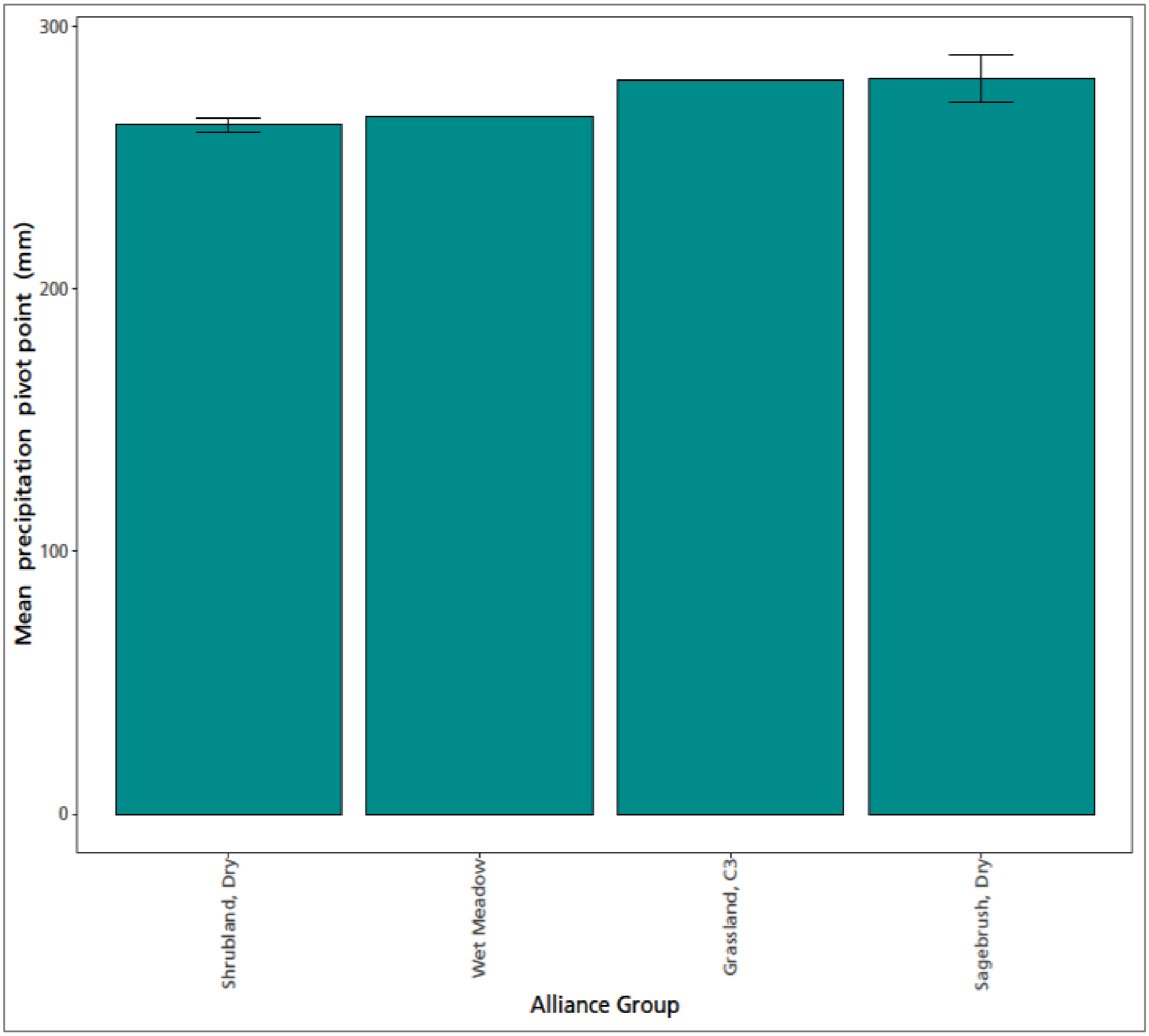

Figure 33. Pivot points for polygons where precipitation was significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.
NPS

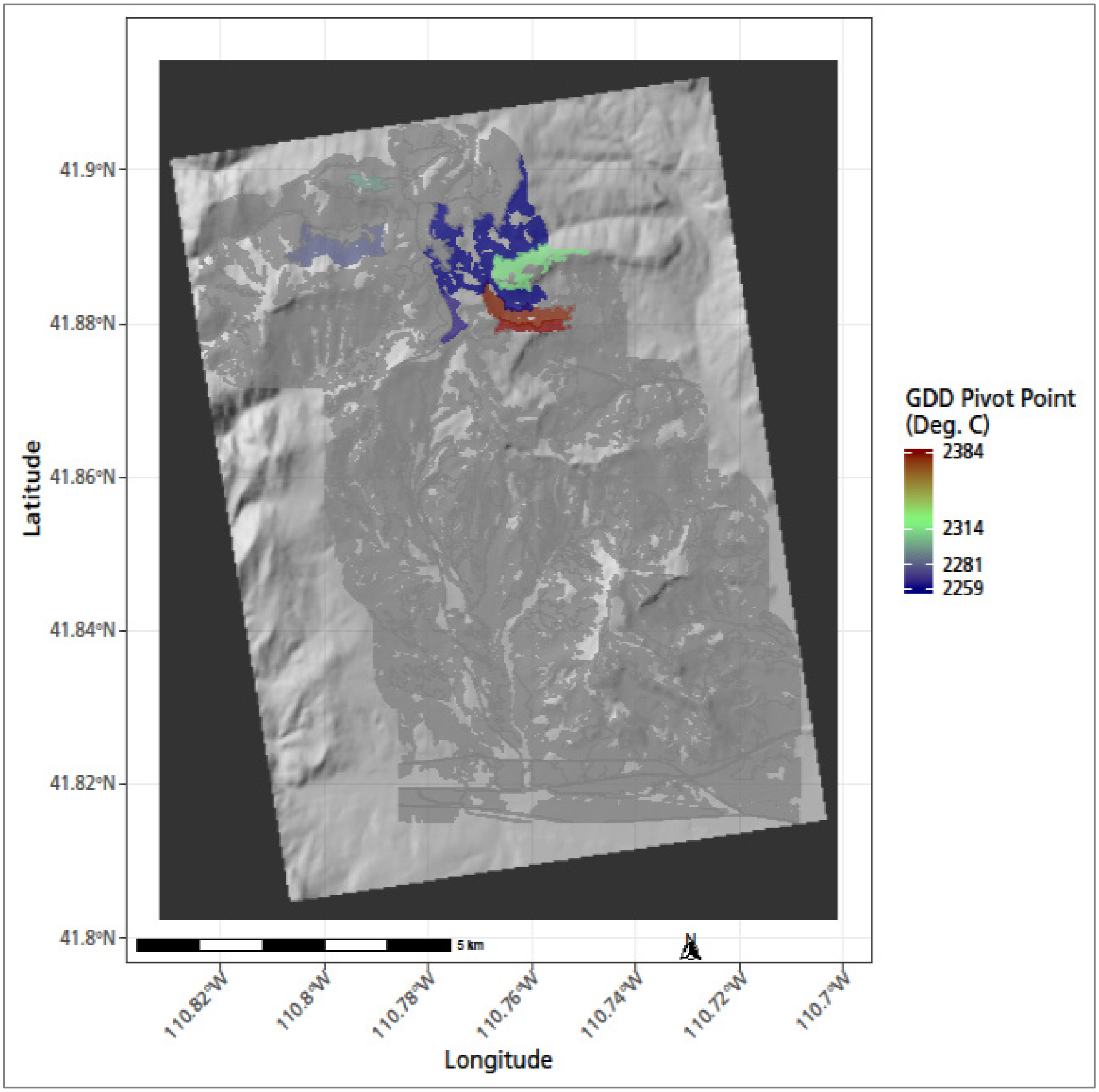

Figure 34. A map showing the locations of polygons where growing degree days were significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year. *NPS*

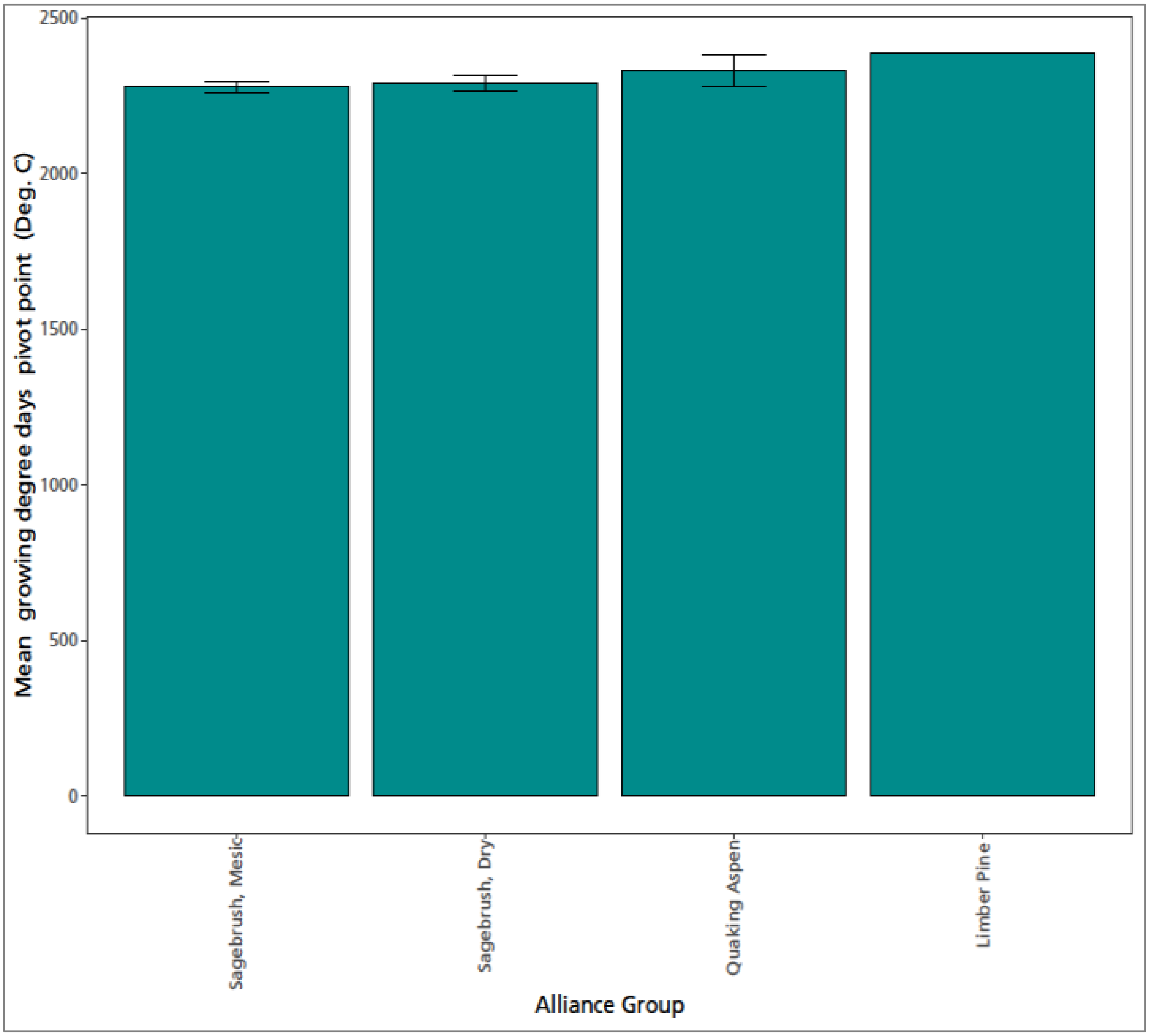

Figure 35. Pivot points for polygons where growing degree days were significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.

NPS

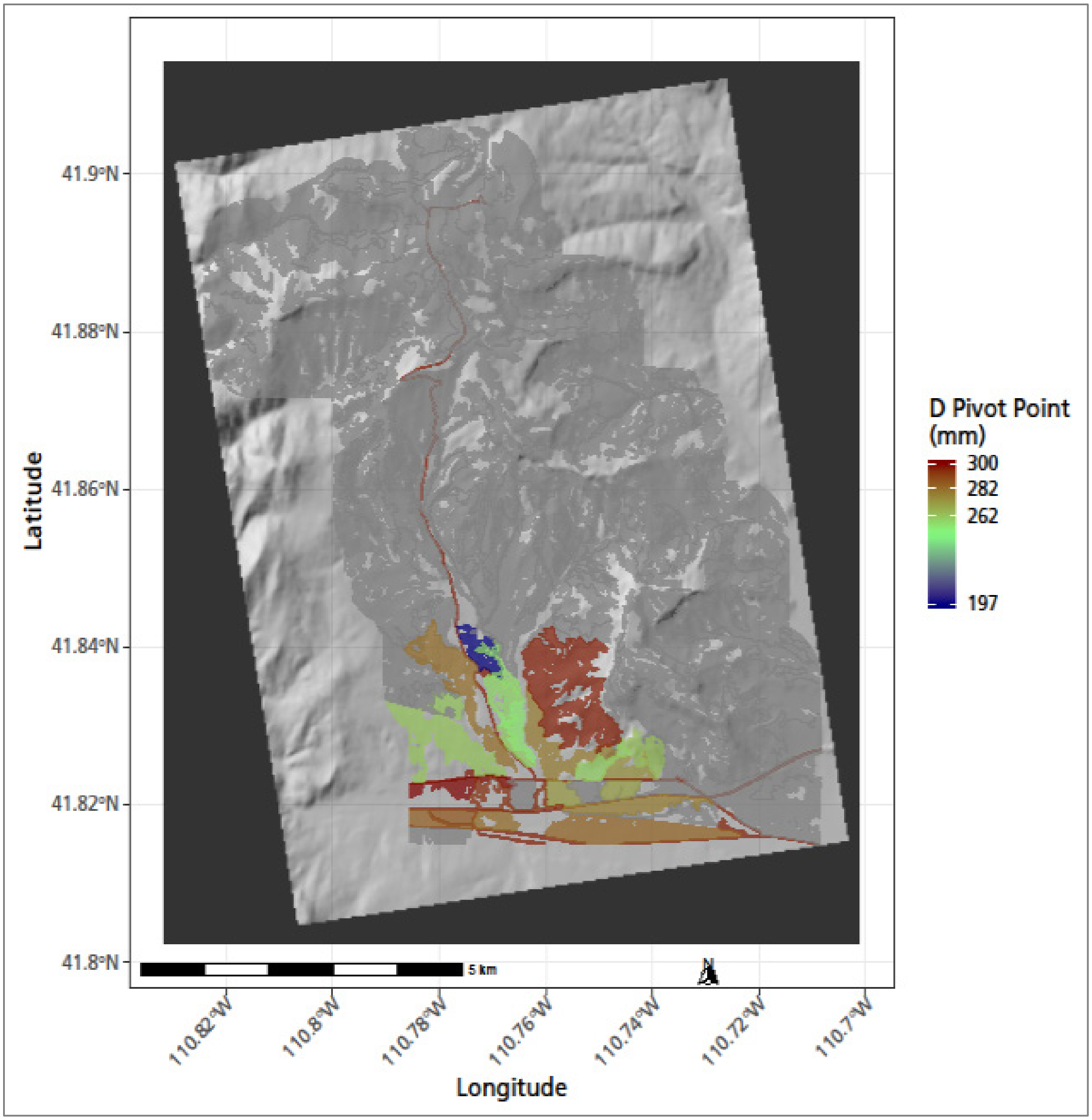

Figure 36. A map showing the locations of polygons where water deficit was significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.
NPS

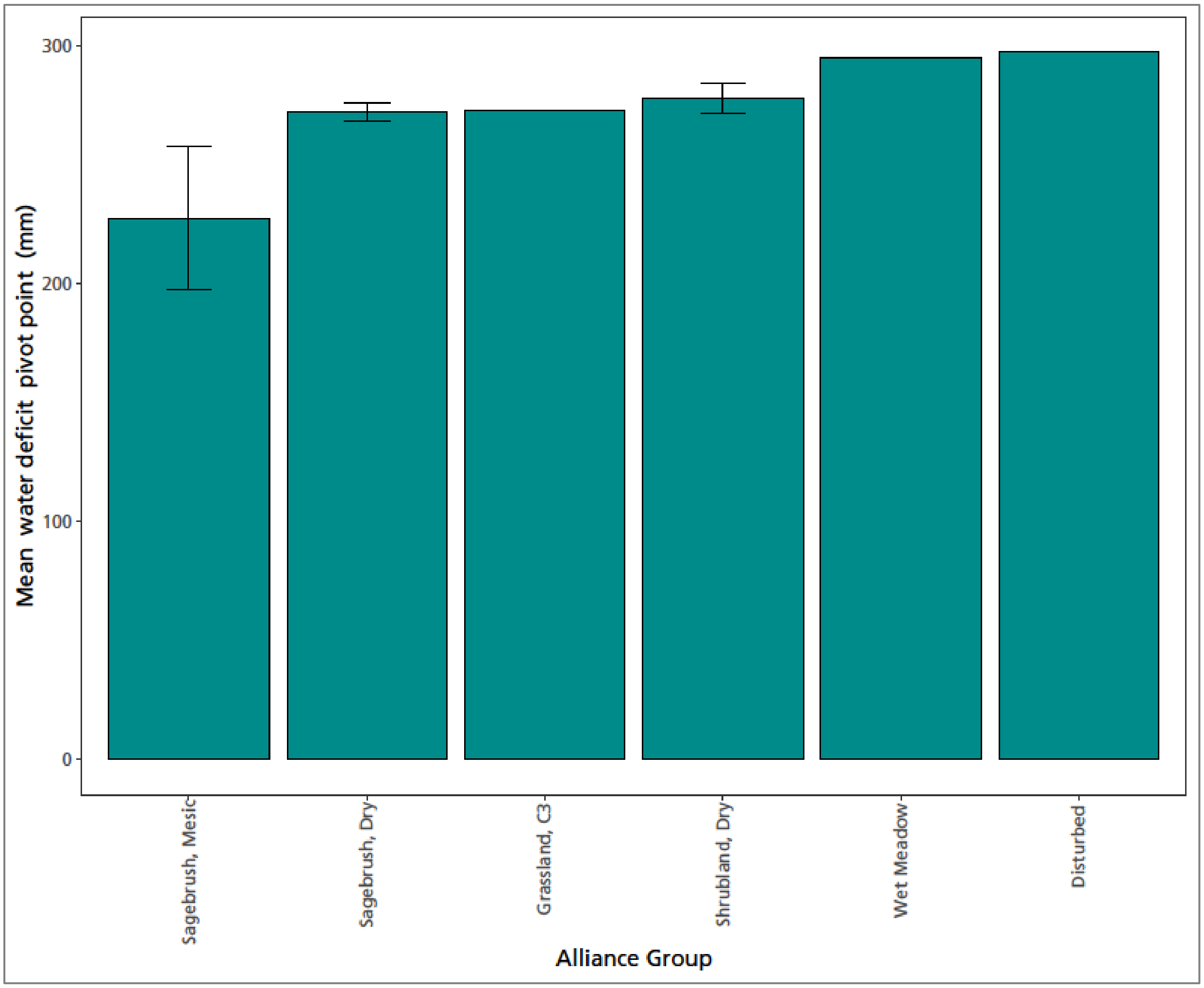

Figure 37. Pivot points for polygons where water deficit was significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.

NPS

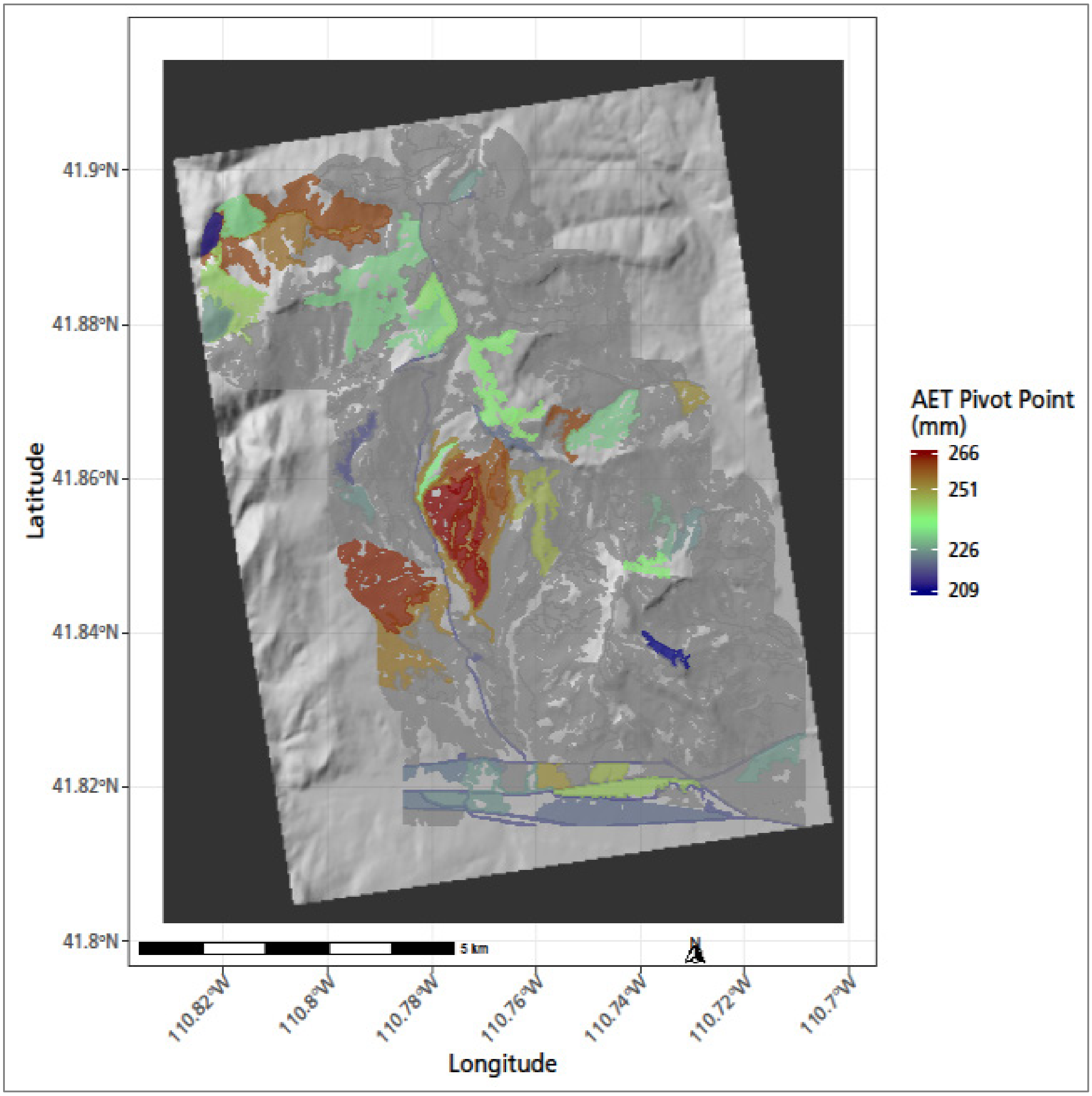

Figure 38. A map showing the locations of polygons where actual evapotranspiration was significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year. *NPS*

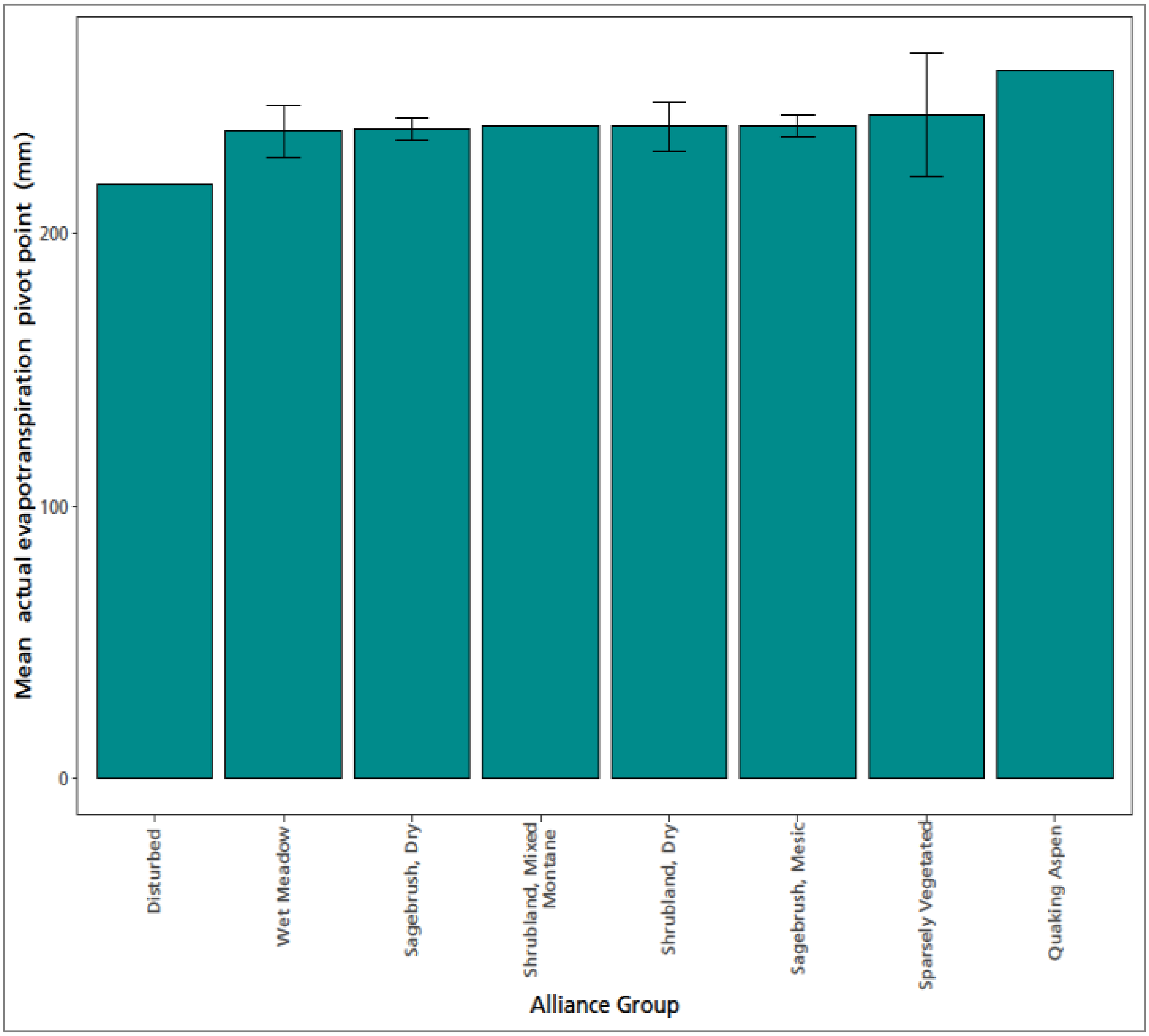

Figure 39. Pivot points for polygons where actual evapotranspiration was significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.
NPS

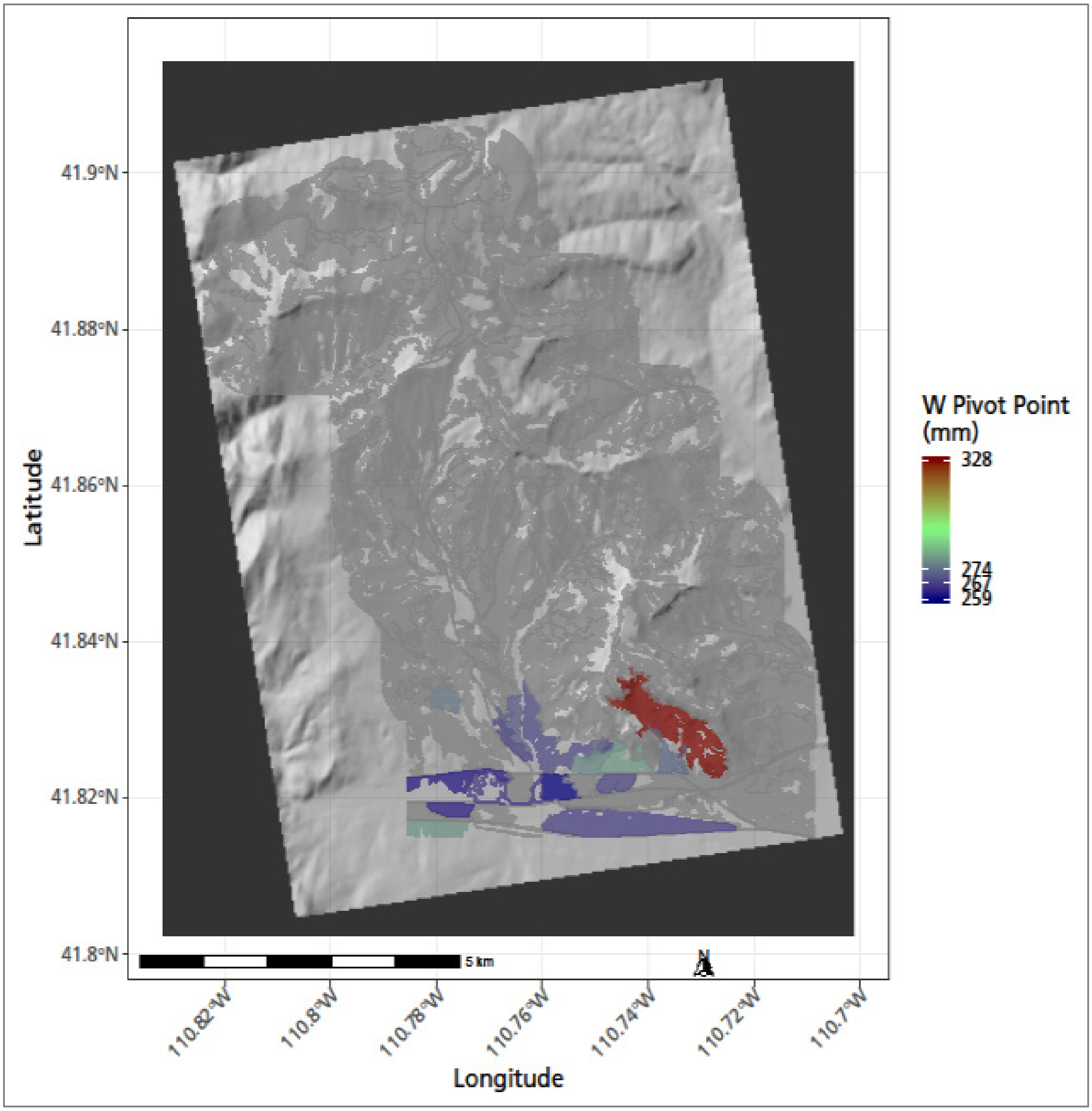

Figure 40. A map showing the locations of polygons where water was significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.
NPS

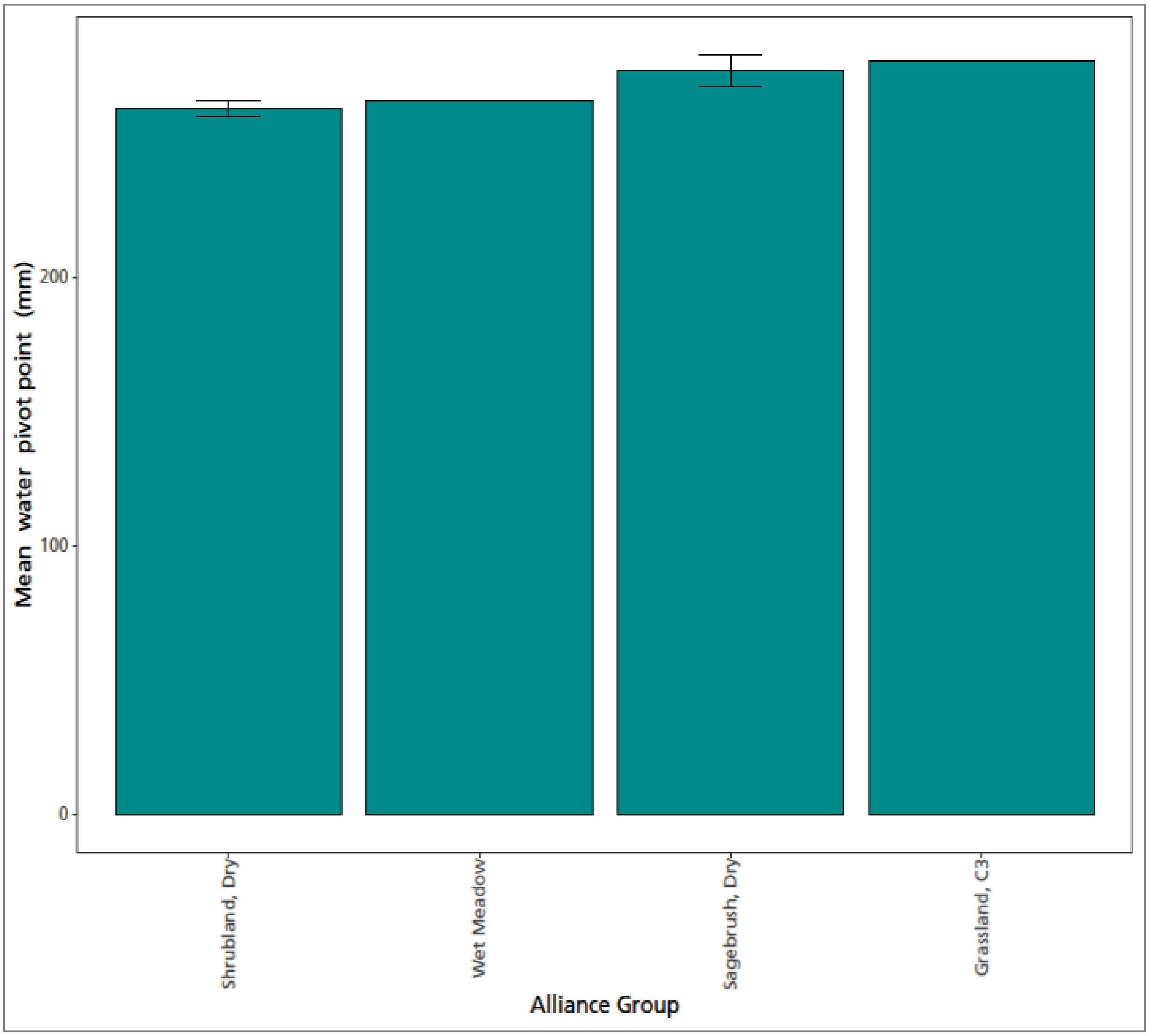

Figure 41. Pivot points for polygons where water was significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.
NPS

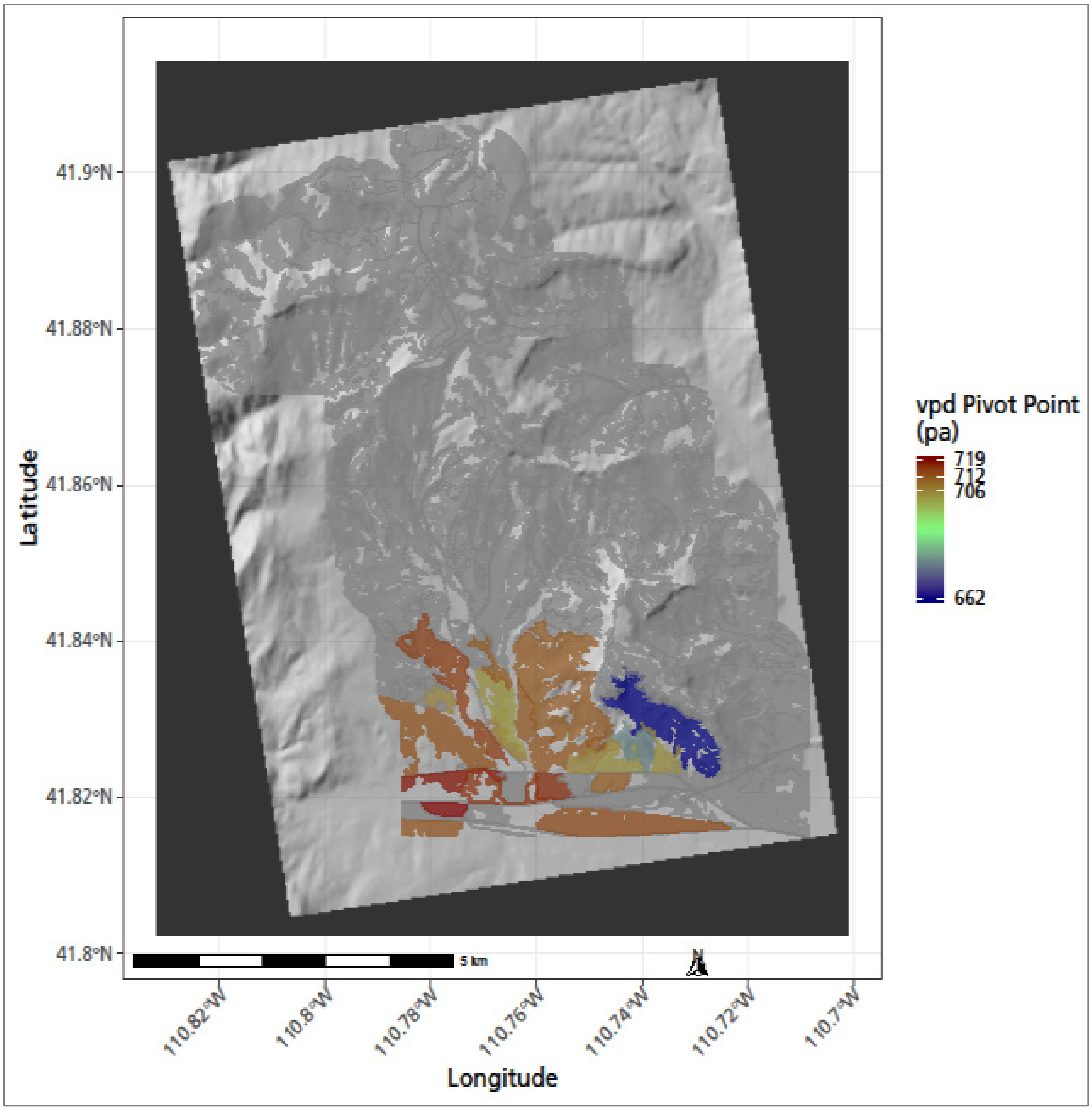

Figure 42. A map showing the locations of polygons where vapor pressure deficit was significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year. *NPS*

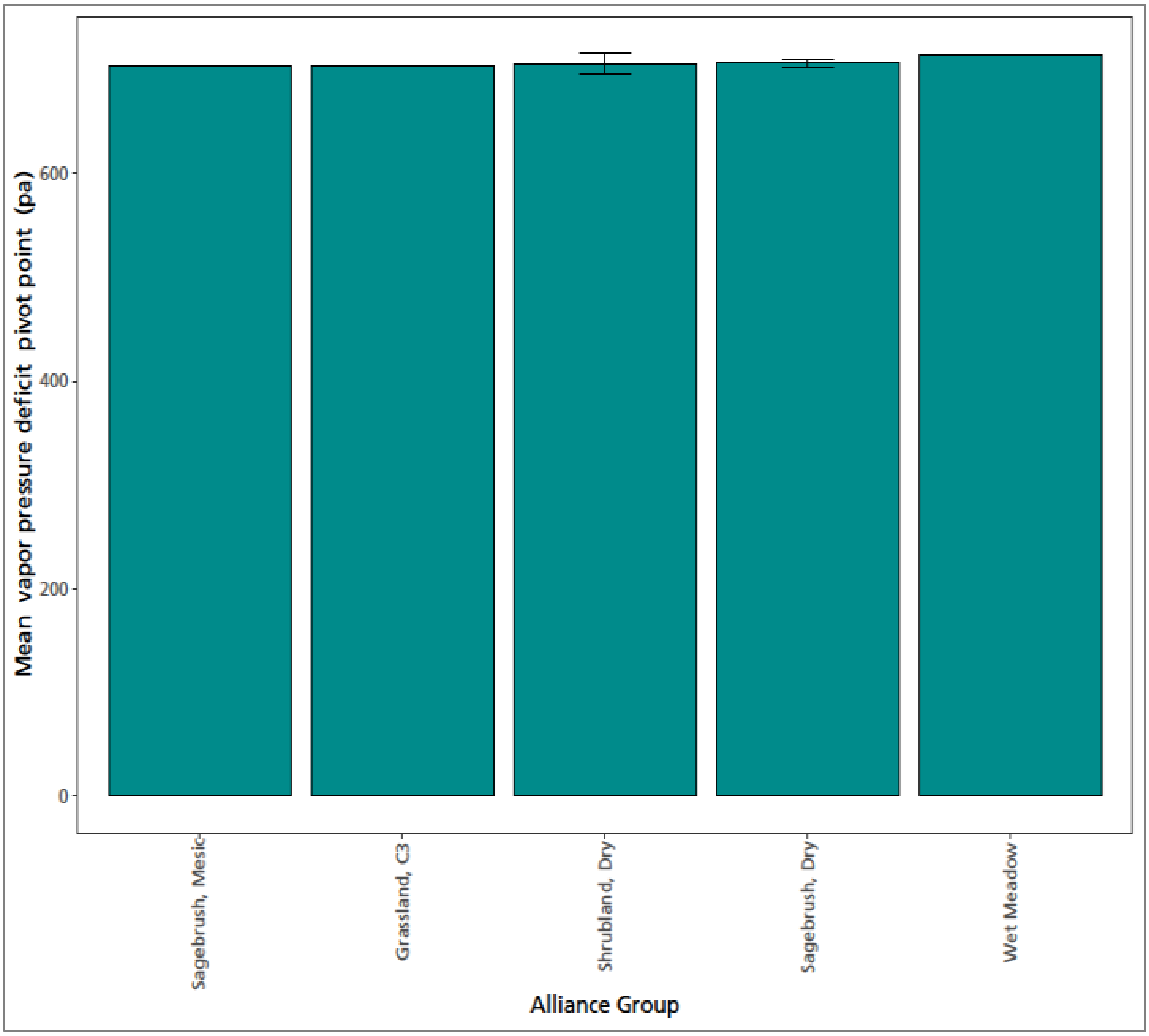

Figure 43. Pivot points for polygons where vapor pressure deficit was significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.
NPS

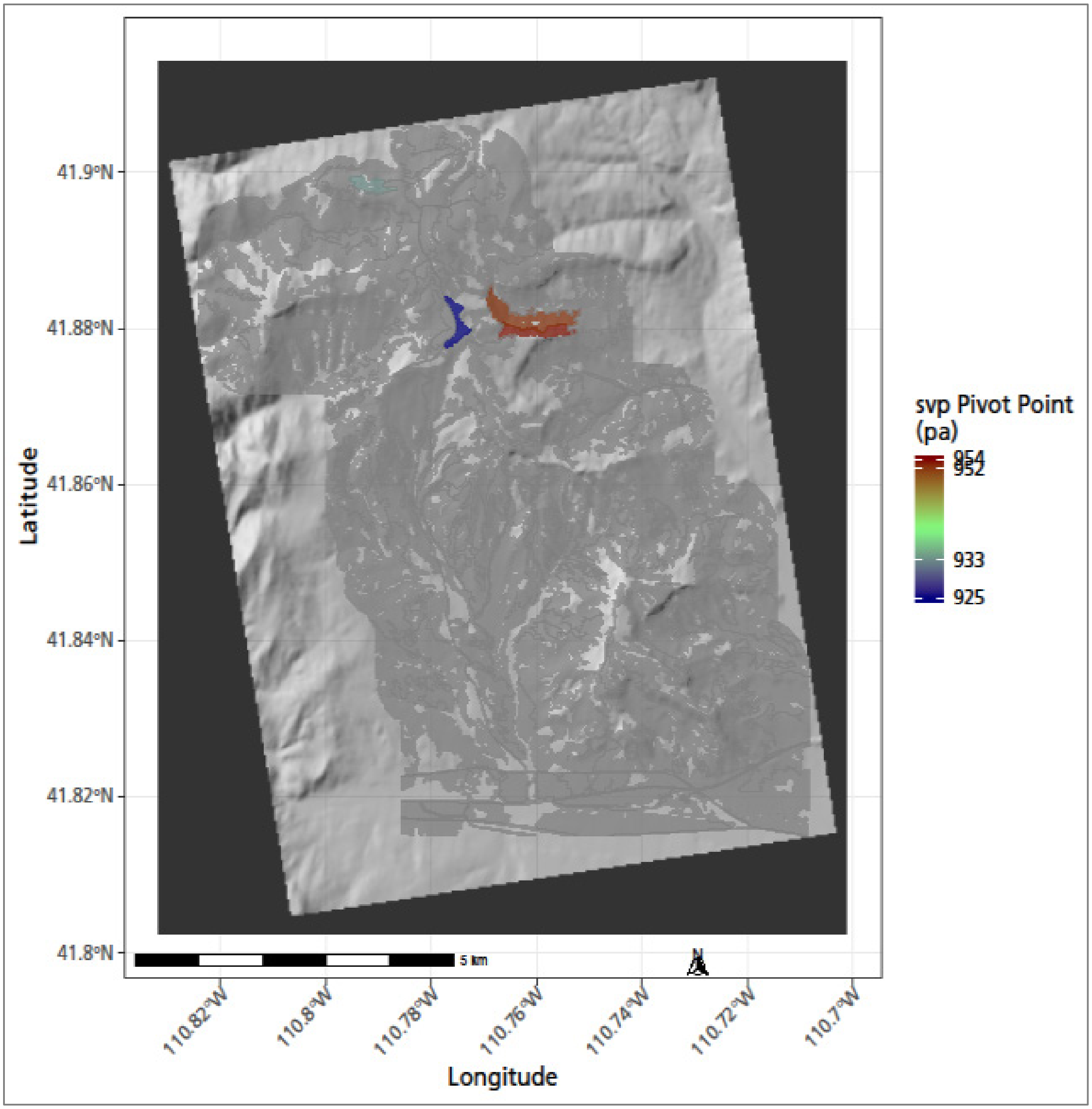

Figure 44. A map showing the locations of polygons where saturation vapor pressure was significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year. *NPS*

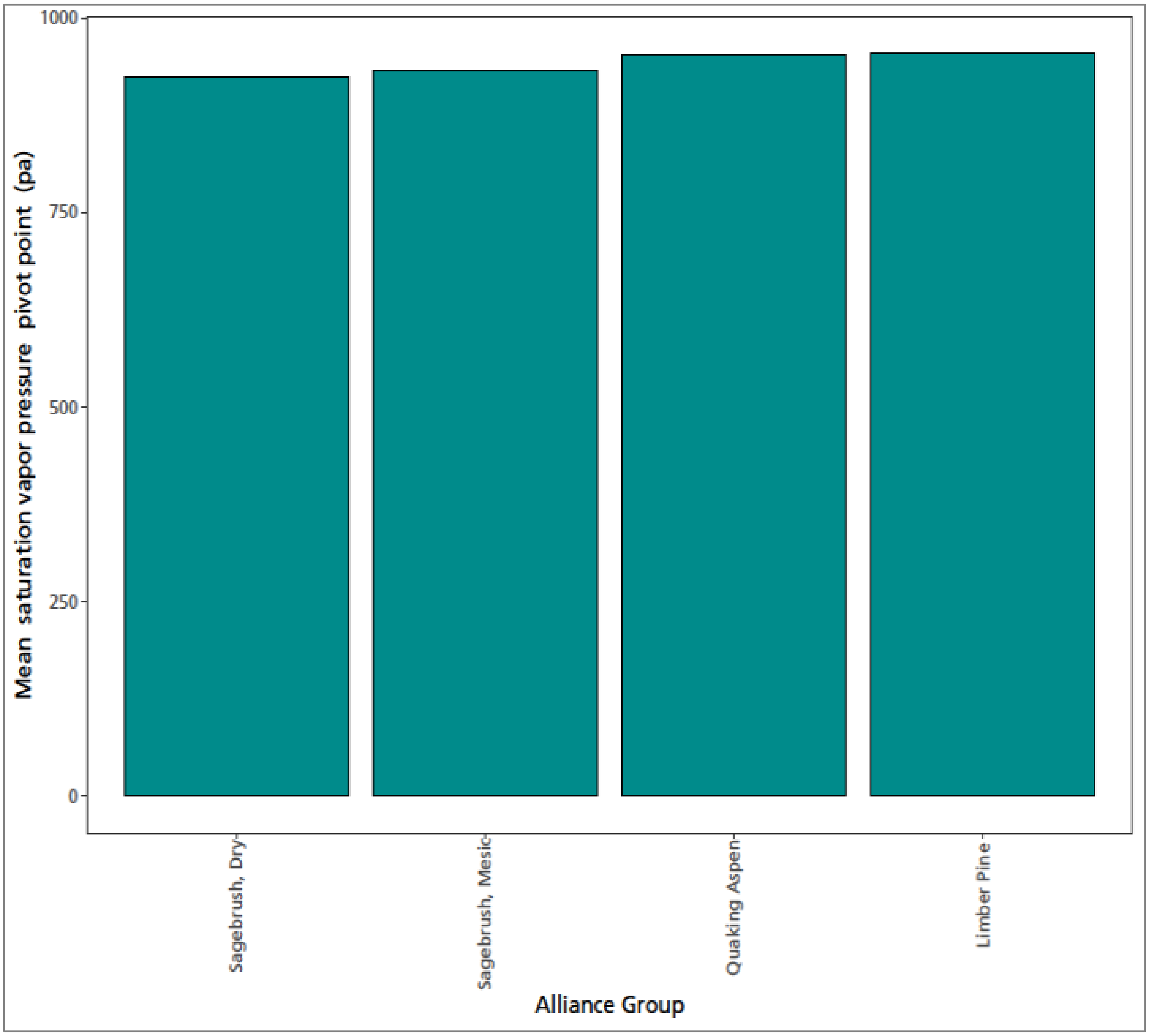

Figure 45. Pivot points for polygons where saturation vapor pressure was significantly related to interannual variation in production (p-value < 0.05). Climate data summarized by water year.
NPS

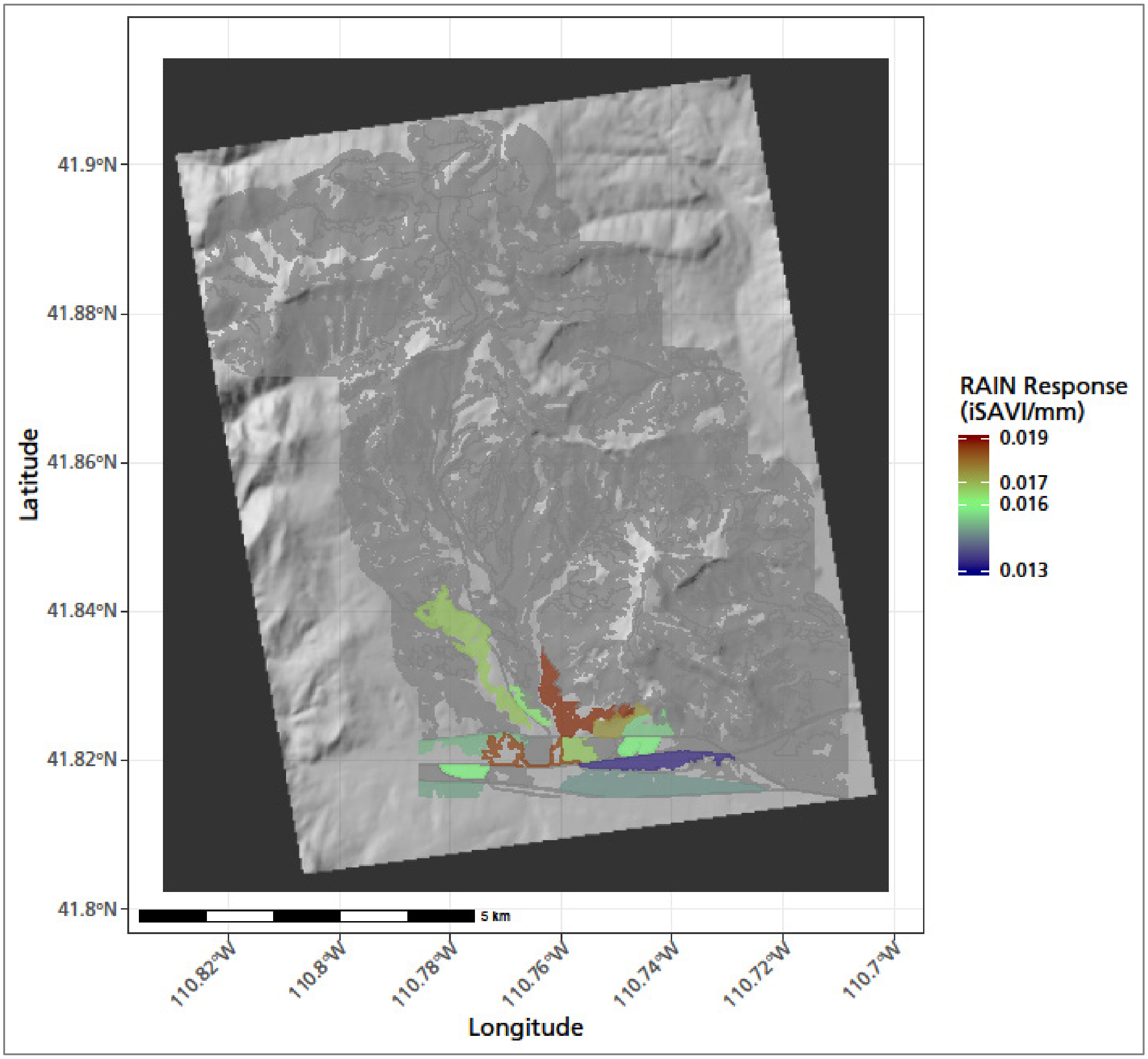

Figure 46. Sensitivity of growing season vegetation production to rain, where the relationship was significant (p-value < 0.05). Climate data summarized by water year.

NPS

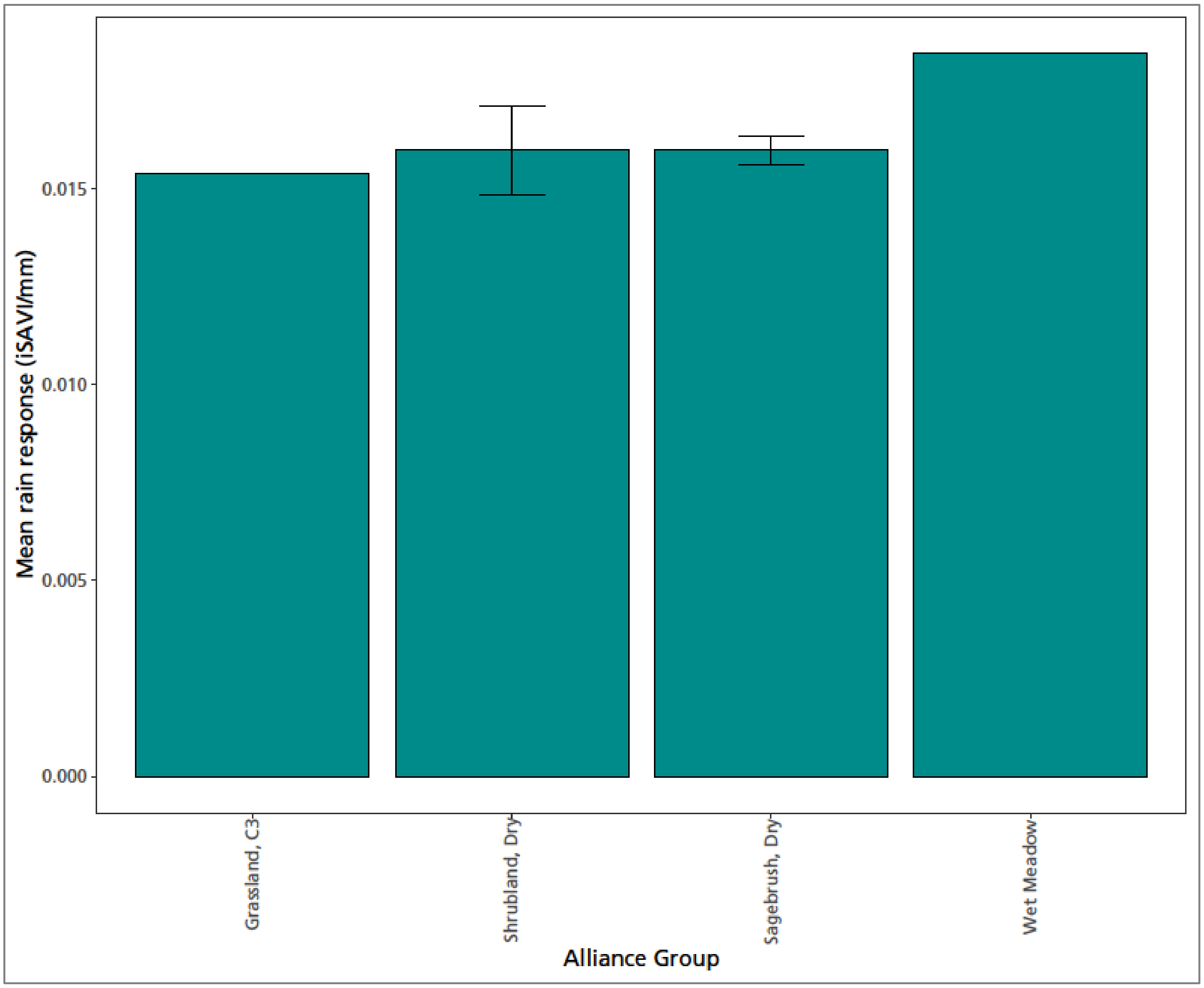

Figure 47. Sensitivity of growing season vegetation production to rain in polygons, where the relationship was significant (p-value < 0.05). Climate data summarized by water year.

NPS

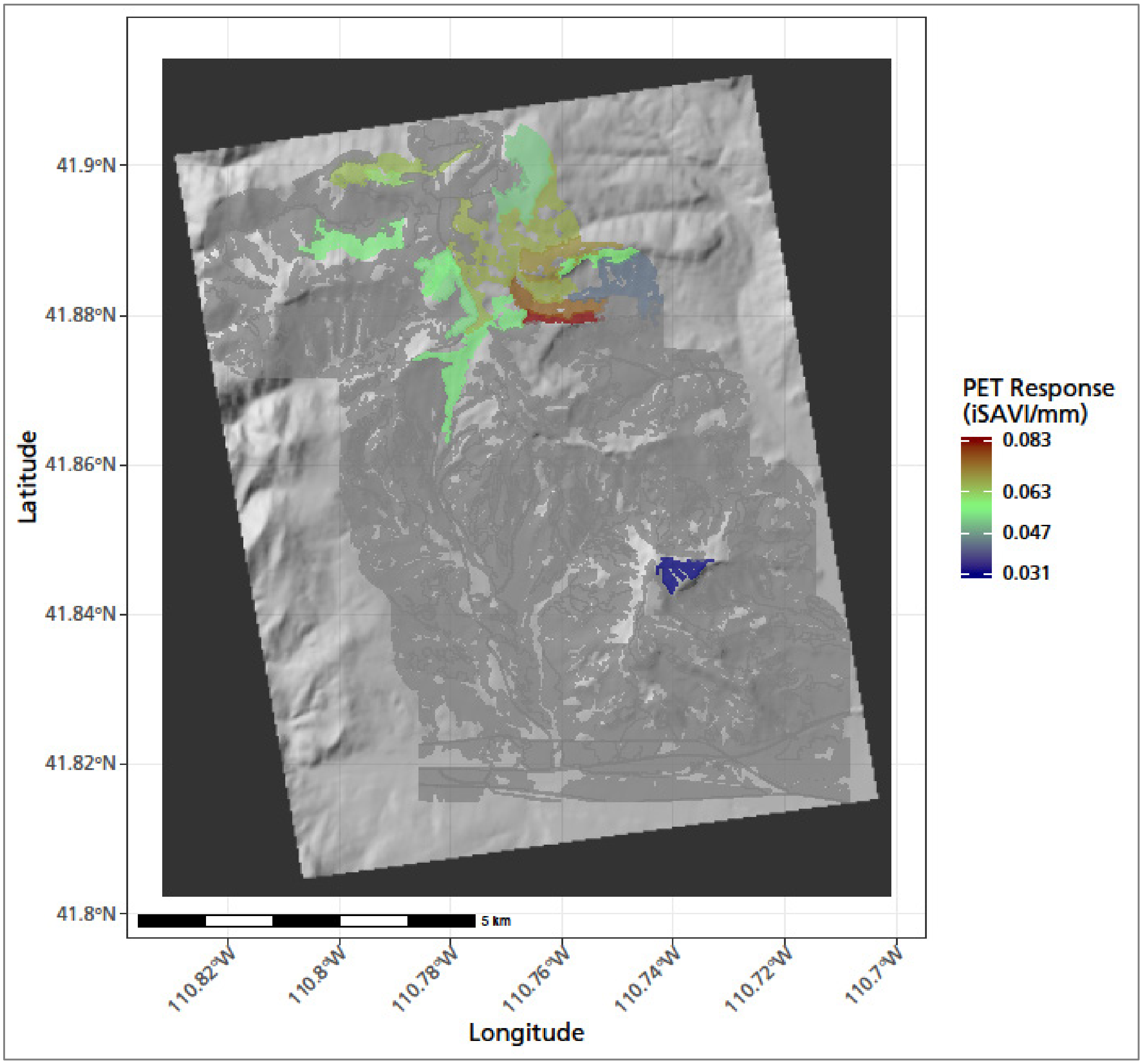

Figure 48. A map showing the sensitivity of growing season vegetation production to potential evapotranspiration in polygons, where the relationship was significant (p-value < 0.05). Climate data summarized by water year.

NPS

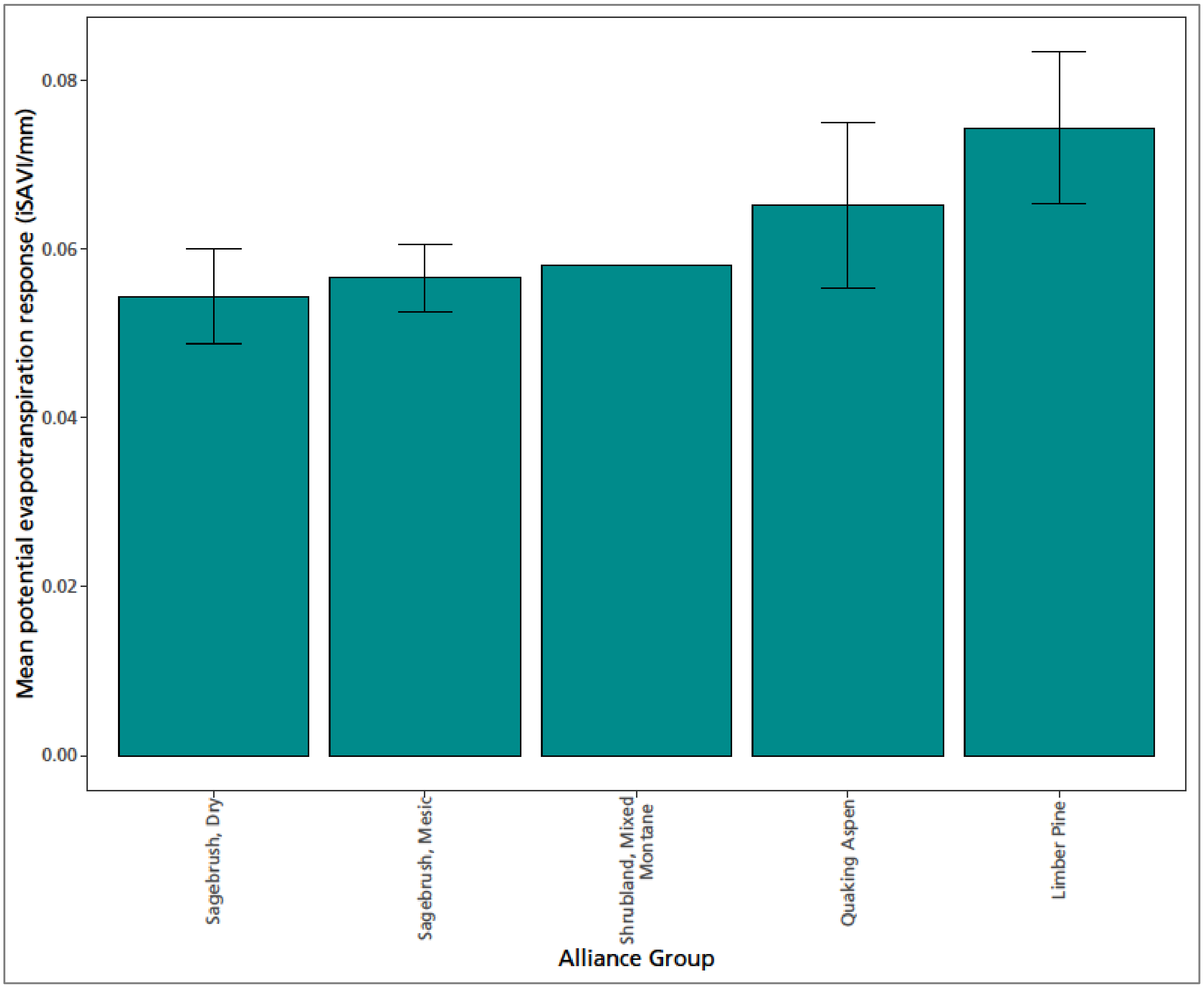

Figure 49. Sensitivity of growing season vegetation production to potential evapotranspiration in polygons, where the relationship was significant (p-value < 0.05). Climate data summarized by water year.

NPS

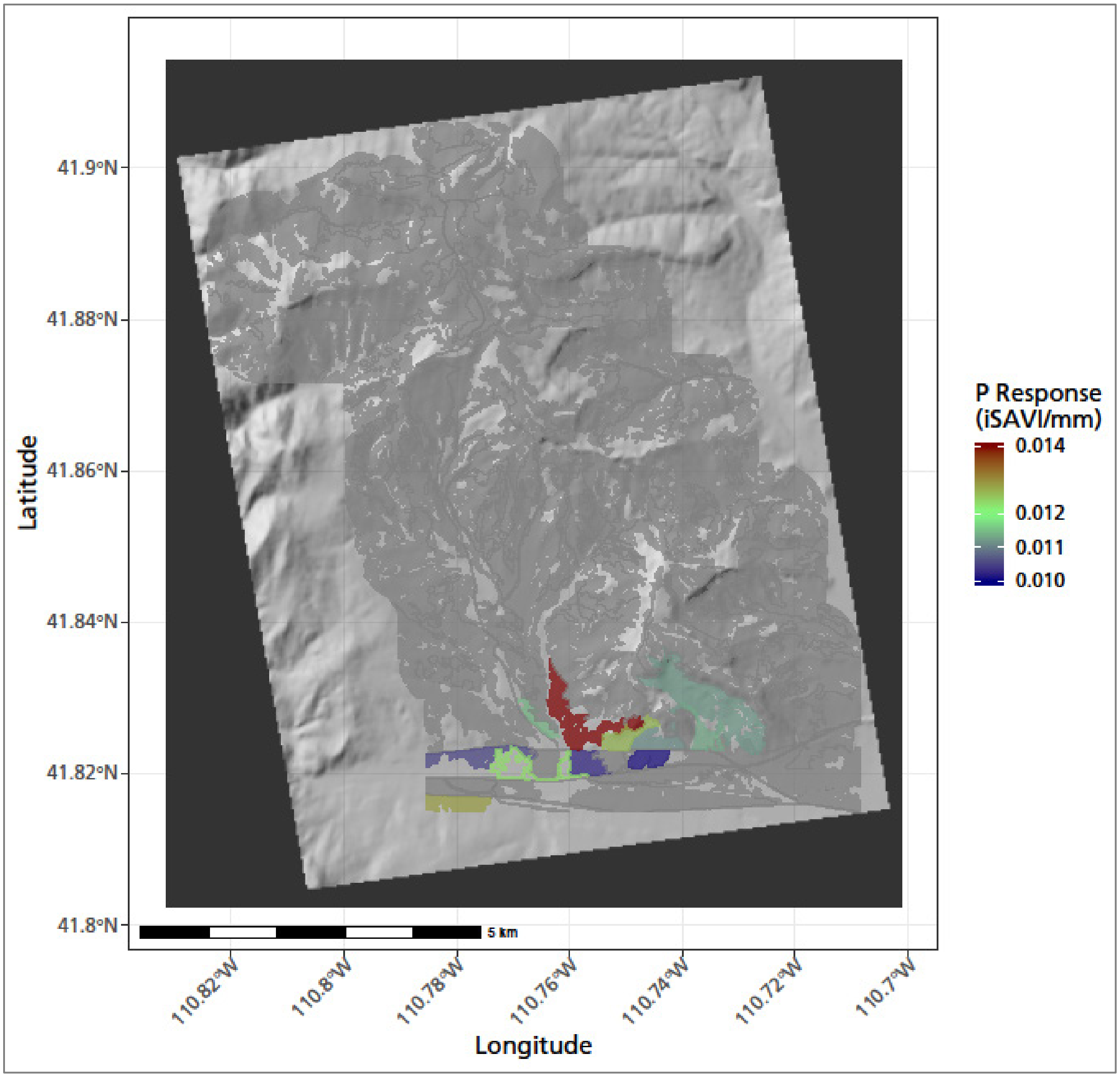

Figure 50. A map showing the sensitivity of growing season vegetation production to precipitation in polygons where the relationship was significant (p-value < 0.05). Climate data summarized by water year. *NPS*

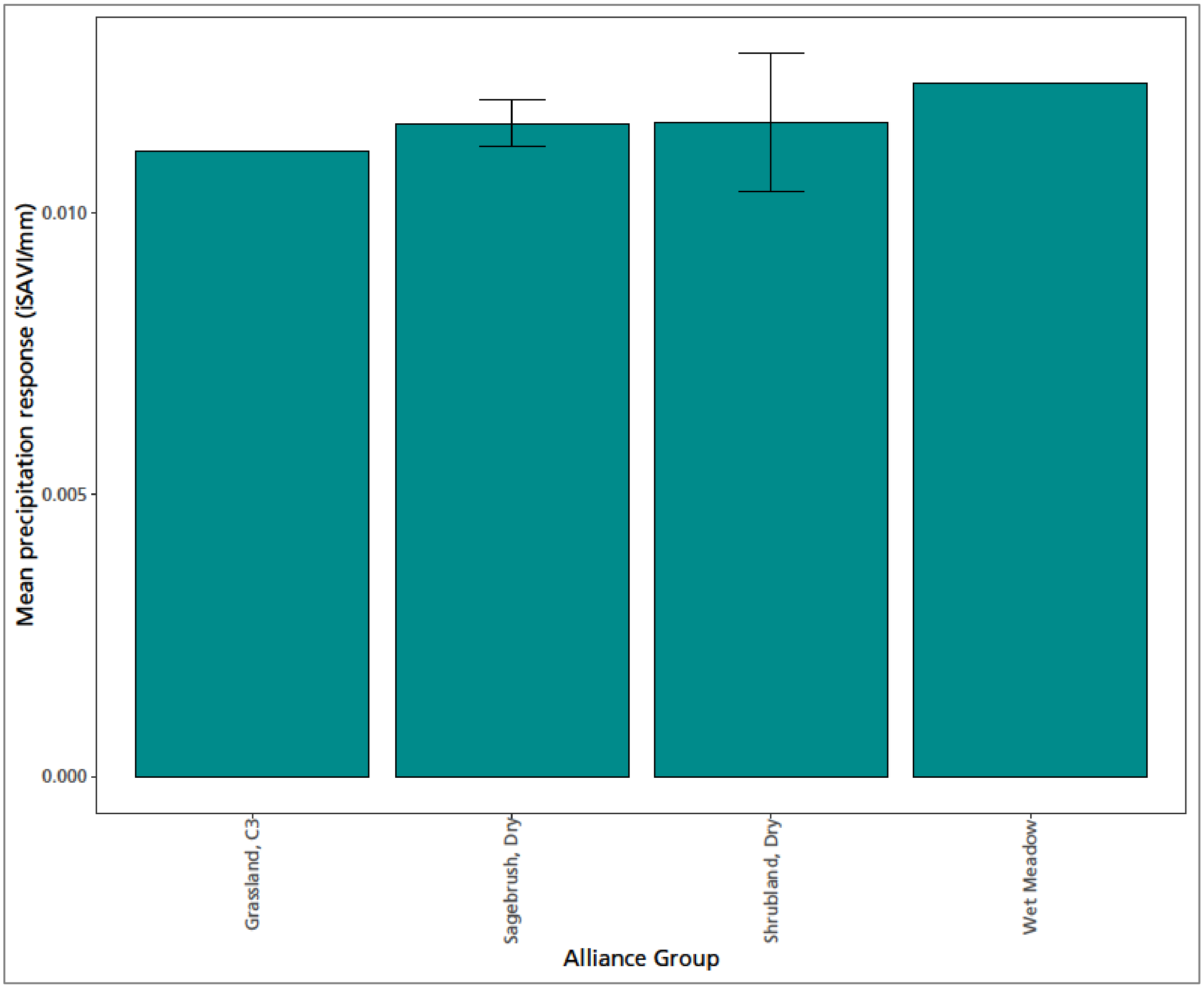

Figure 51. Sensitivity of growing season vegetation production to precipitation where the relationship was significant (p-value < 0.05). Climate data summarized by water year.

NPS

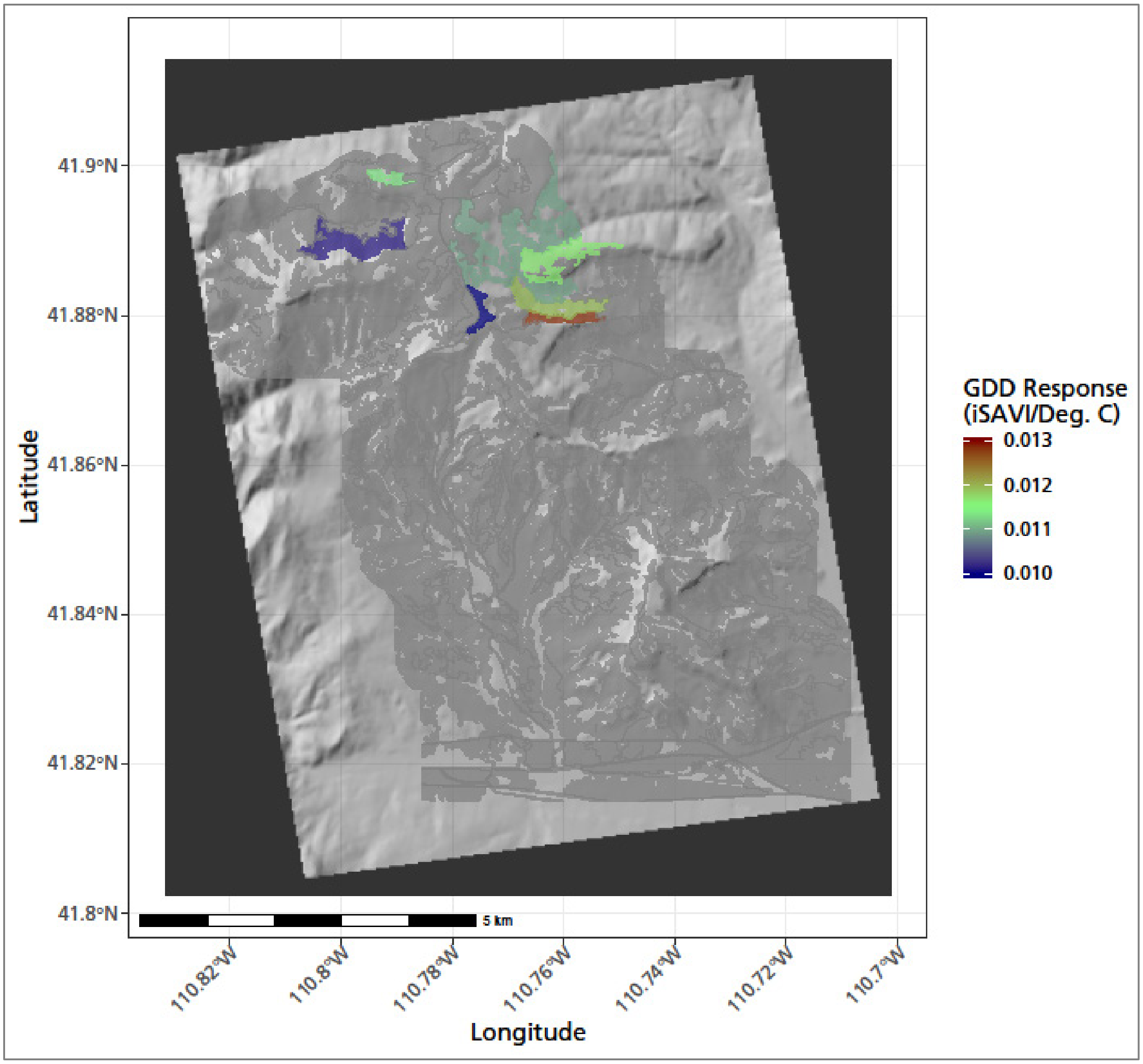

Figure 52. A map showing the sensitivity of growing season vegetation production to growing degree days in polygons, where the relationship was significant (p-value < 0.05). Climate data summarized by water year.

NPS

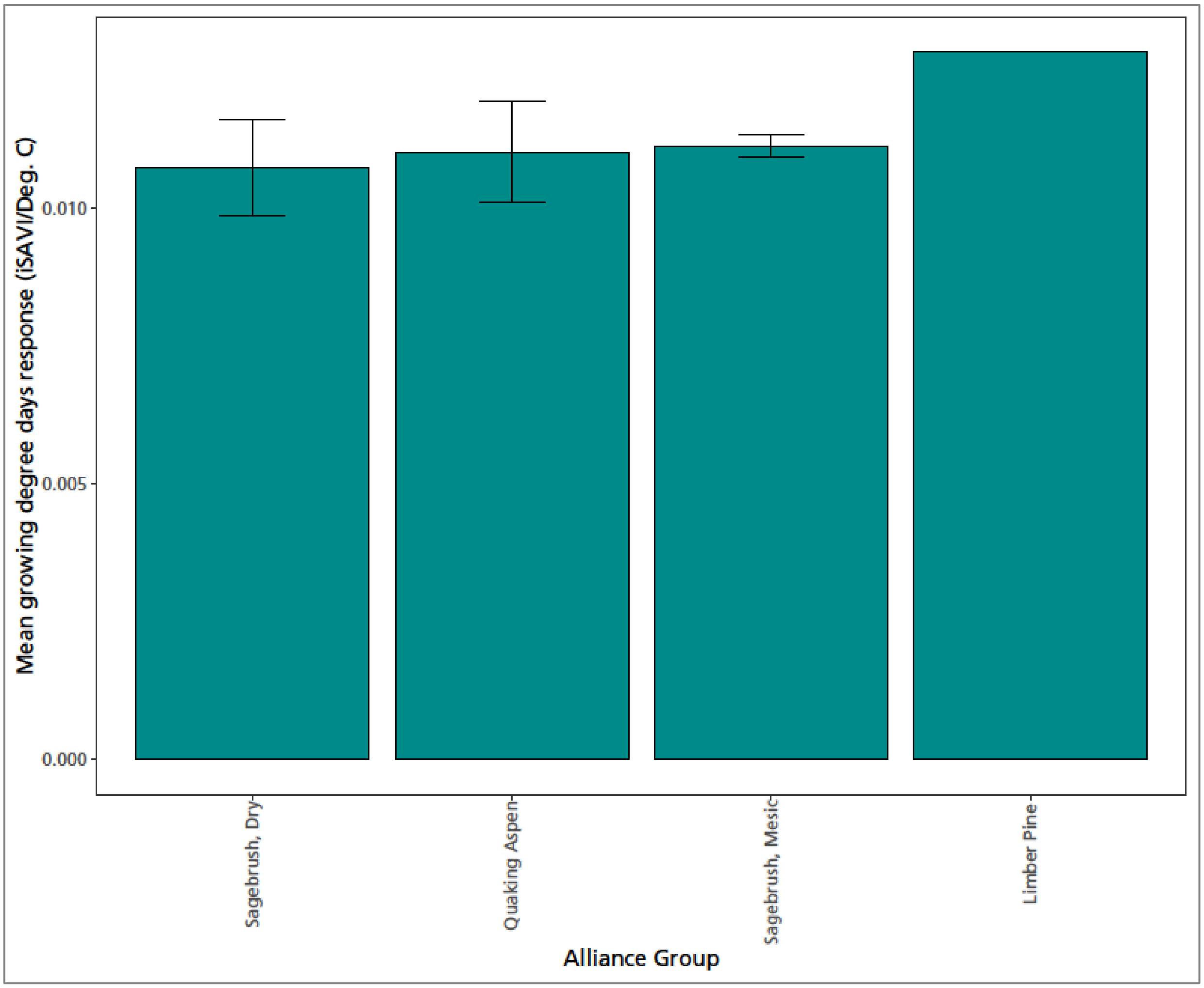

Figure 53. Sensitivity of growing season vegetation production to growing degree days where the relationship was significant (p-value < 0.05). Climate data summarized by water year.
NPS

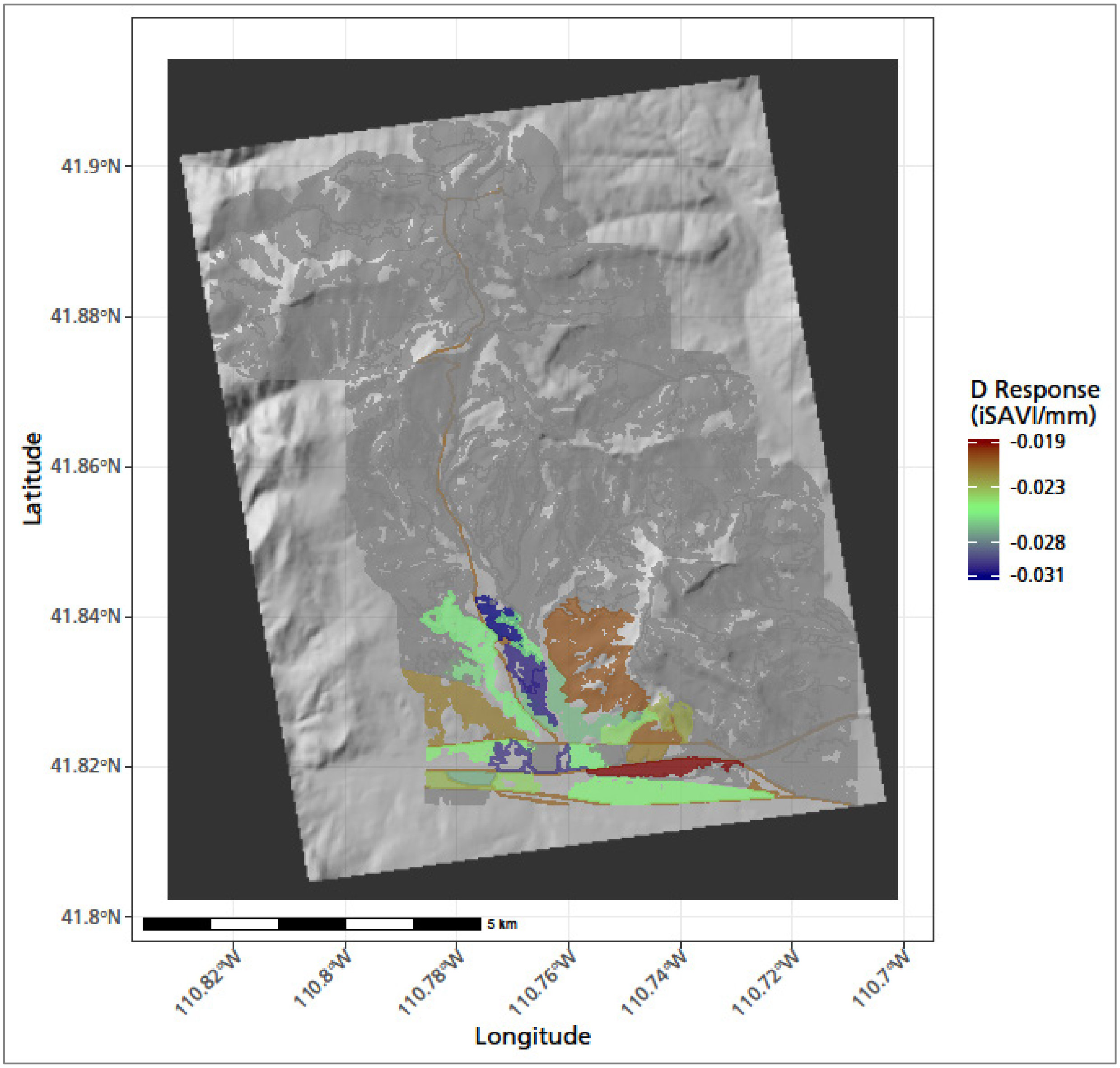

Figure 54. Sensitivity of growing season vegetation production to water deficit, where the relationship was significant (p-value < 0.05). Climate data summarized by water year.
NPS

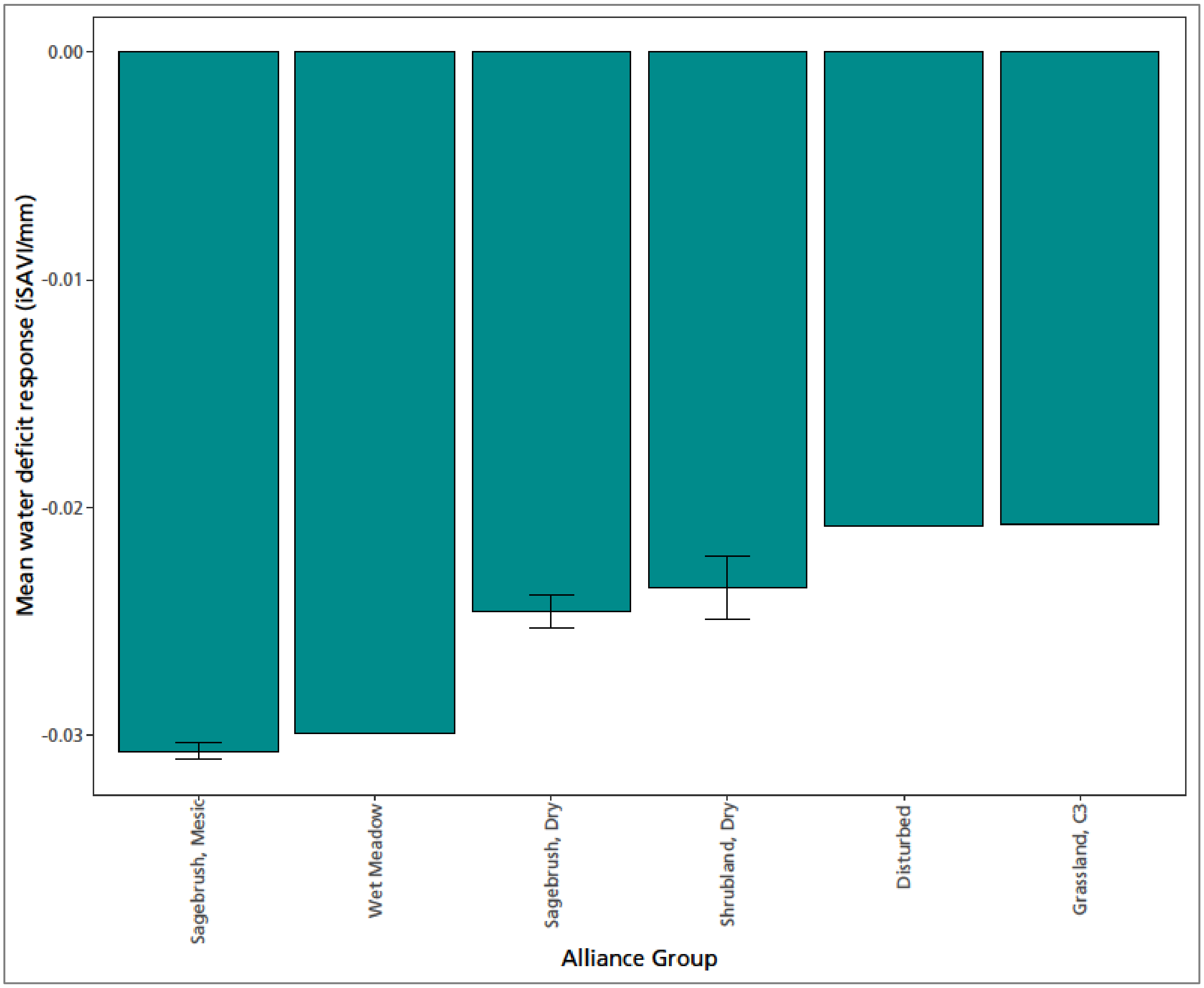

Figure 55. Sensitivity of growing season vegetation production to water deficit where the relationship was significant (p-value < 0.05). Climate data summarized by water year.

NPS

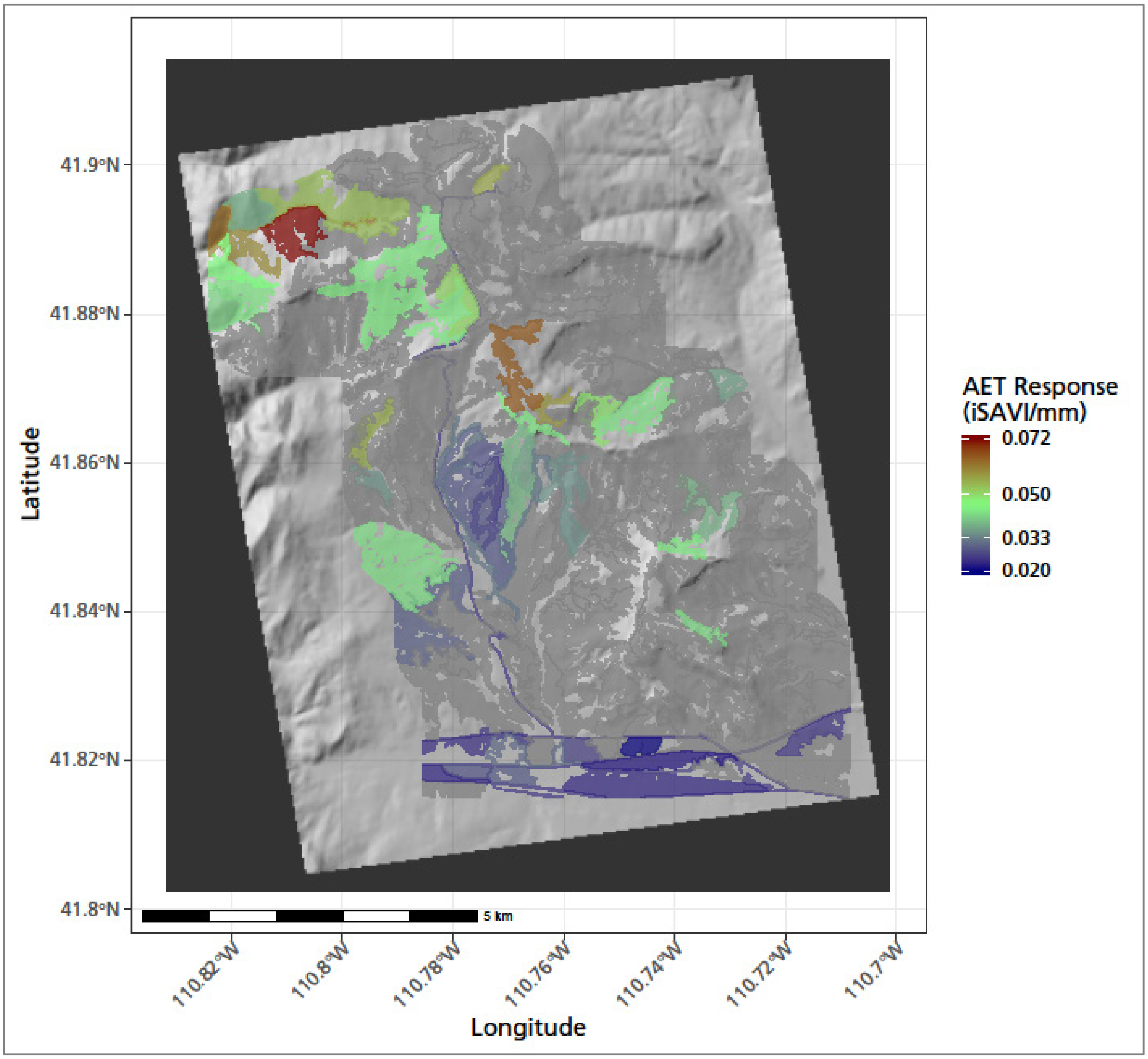

Figure 56. Sensitivity of growing season vegetation production to actual evapotranspiration, where the relationship was significant (p-value < 0.05). Climate data summarized by water year.

NPS

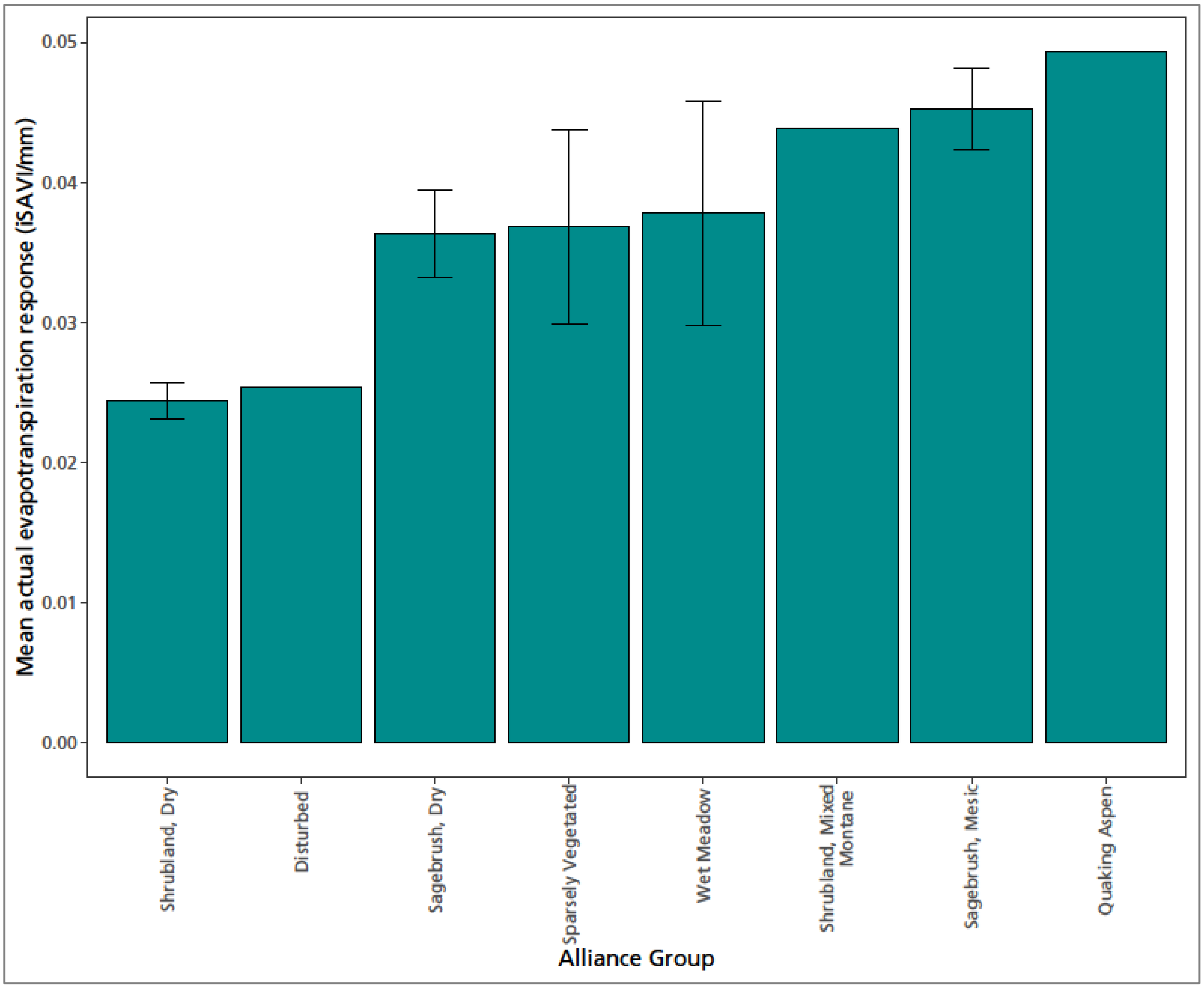

Figure 57. Sensitivity of growing season vegetation production to actual evapotranspiration, where the relationship was significant (p-value < 0.05). Climate data summarized by water year.

NPS

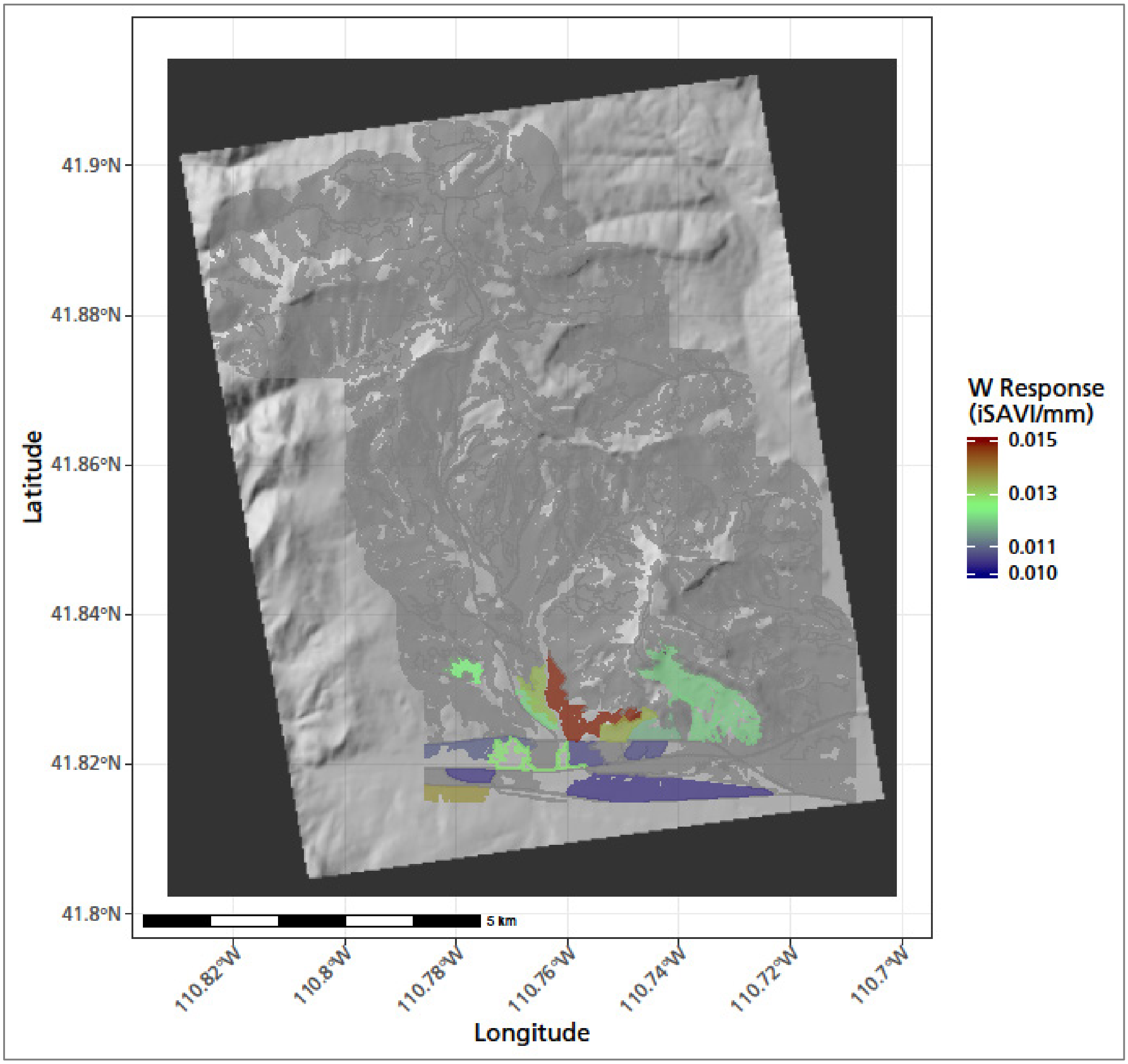

Figure 58. Sensitivity of growing season vegetation production to water, where the relationship was significant (p-value < 0.05). Climate data summarized by water year.
NPS

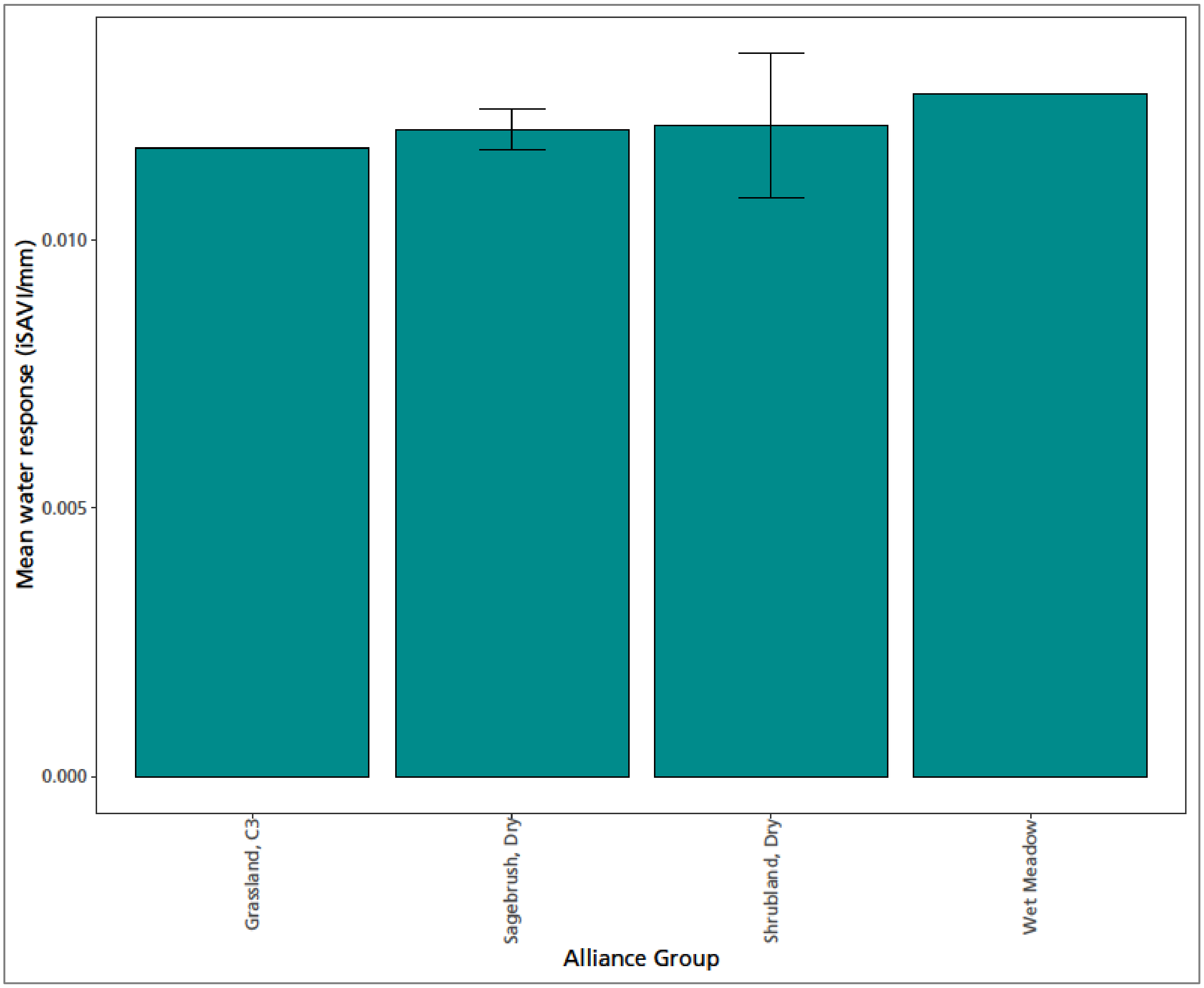

Figure 59. Sensitivity of growing season vegetation production to water, where the relationship was significant (p-value < 0.05). Climate data summarized by water year.
NPS

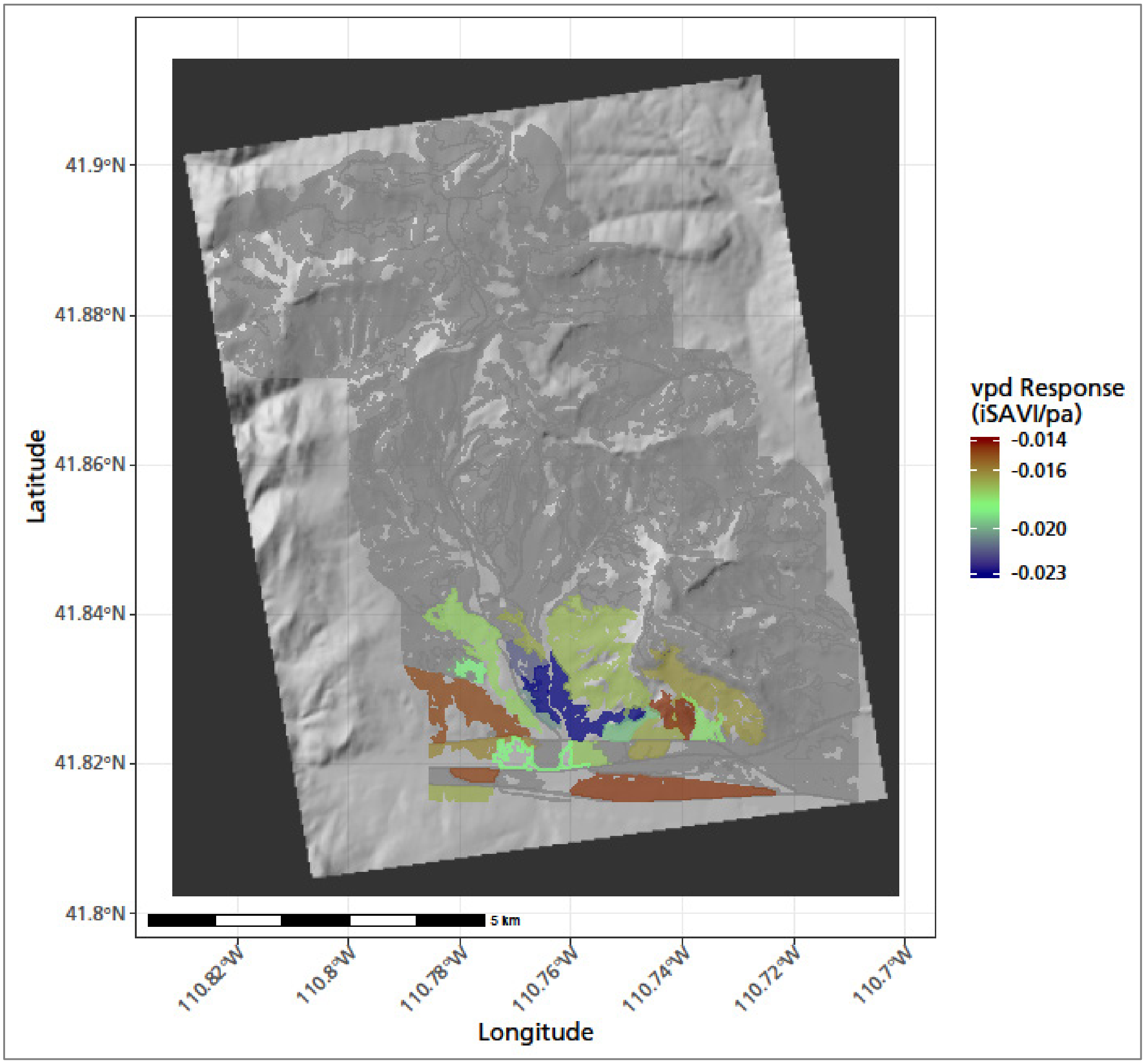

Figure 60. A map showing the sensitivity of growing season vegetation production to vapor pressure deficit in polygons where the relationship was significant (p-value < 0.05). Climate data summarized by water year.

NPS

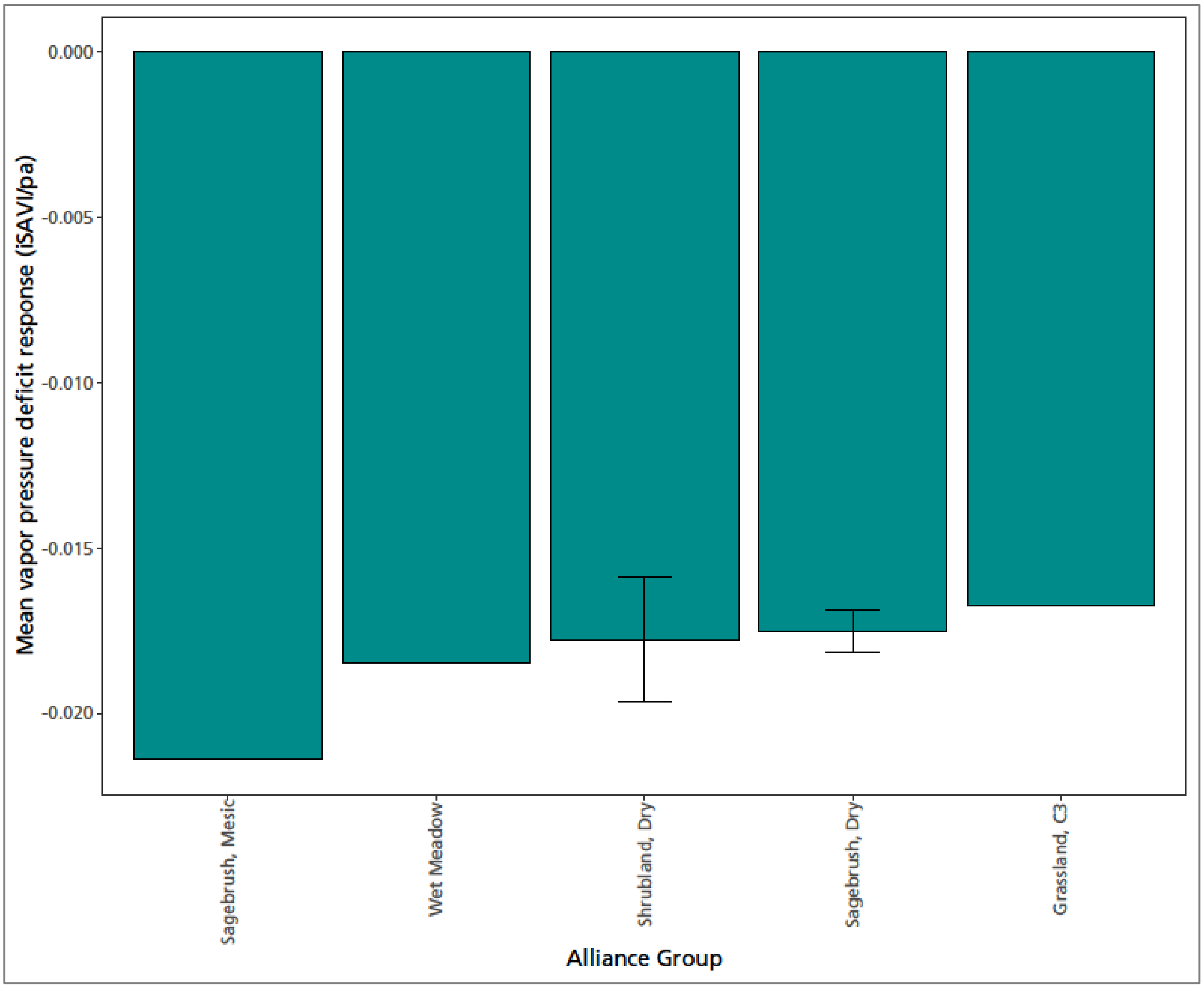

Figure 61. Sensitivity of growing season vegetation production to vapor pressure deficit where the relationship was significant (p-value < 0.05). Climate data summarized by water year.
NPS

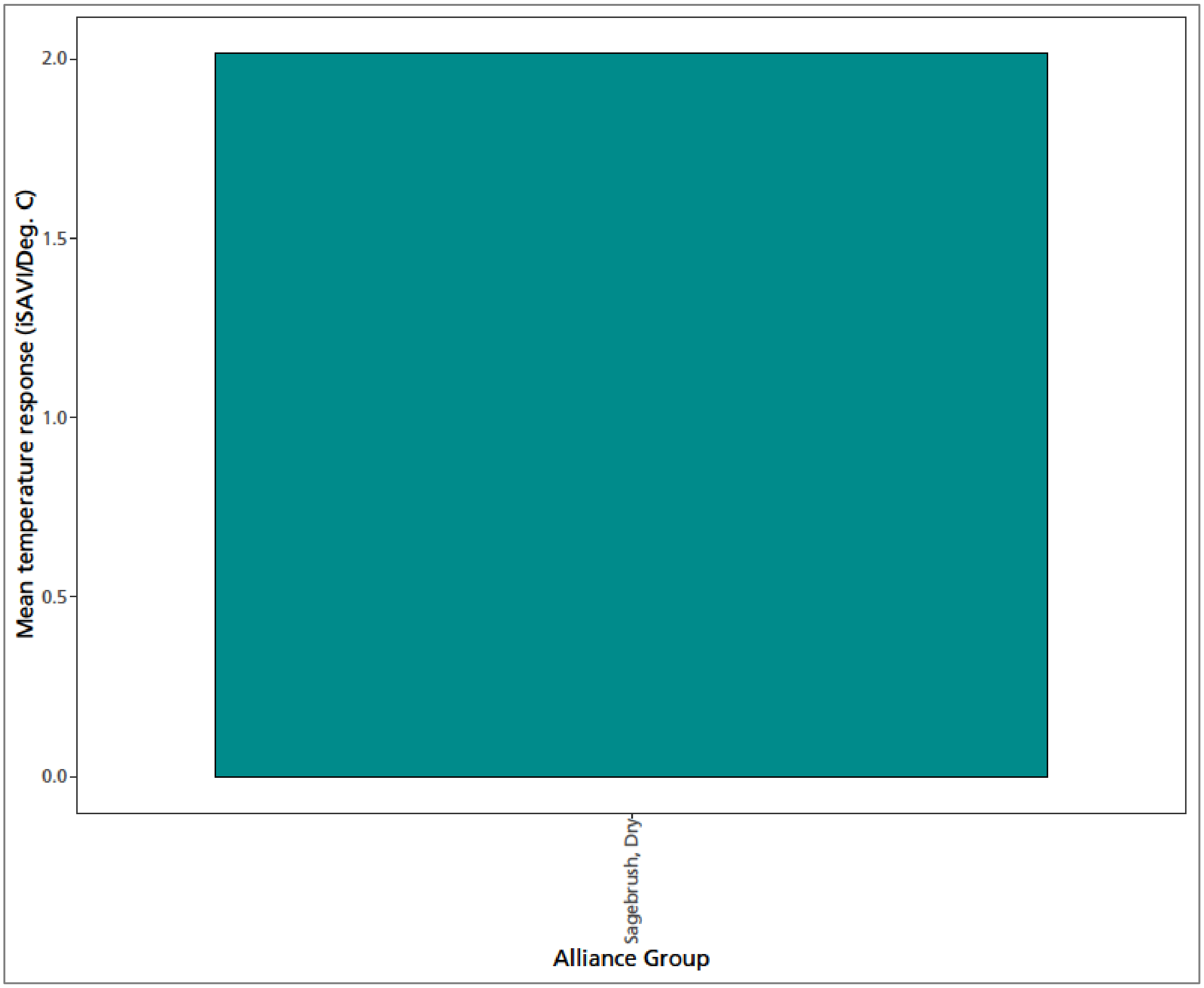

Figure 62. Sensitivity of growing season vegetation production to temperature where the relationship was significant (p-value < 0.05). Climate data summarized by water year.
NPS

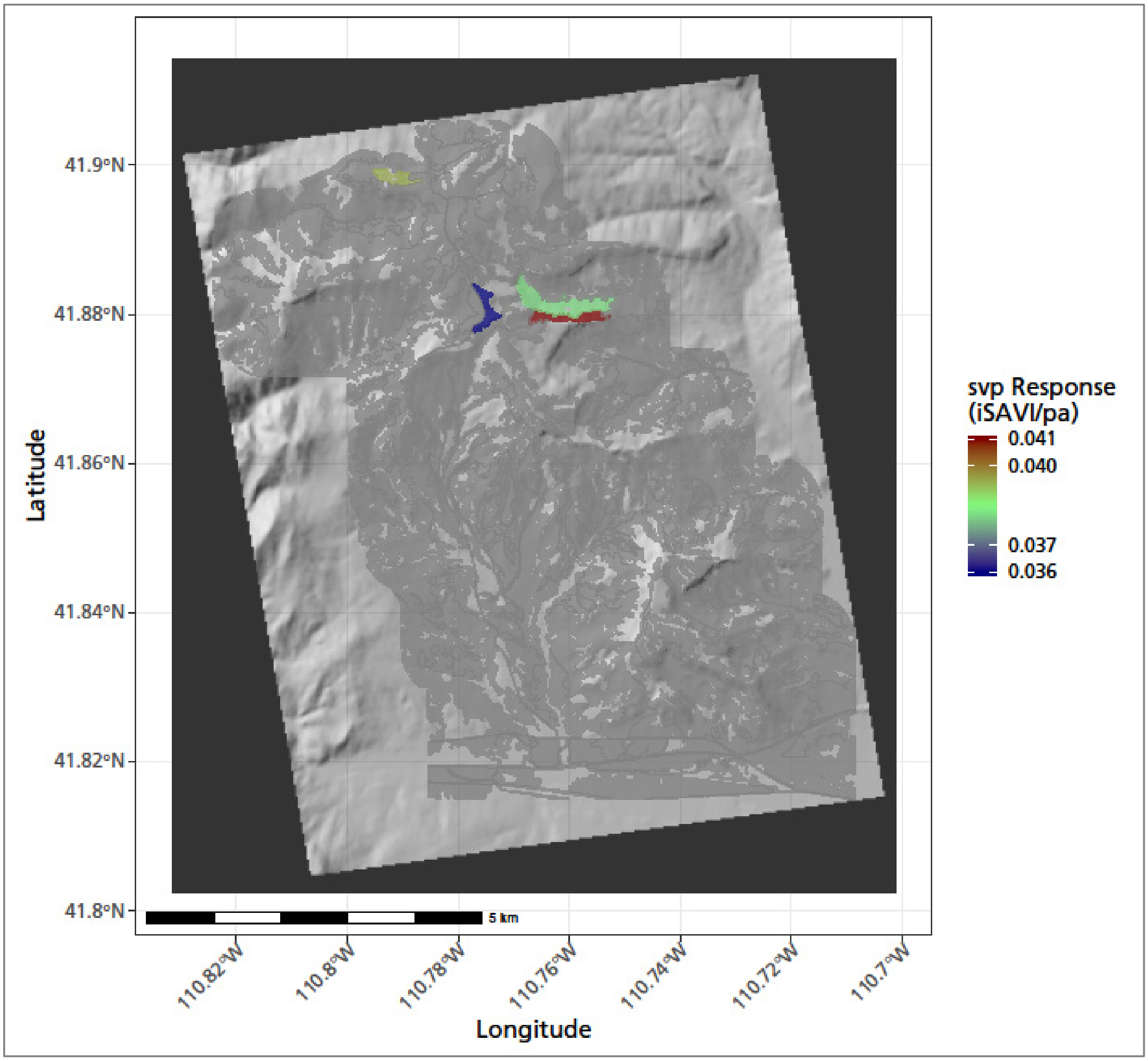

Figure 63. A map showing the sensitivity of growing season vegetation production to saturation vapor pressure in polygons where the relationship was significant (p-value < 0.05). Climate data summarized by water year.

NPS

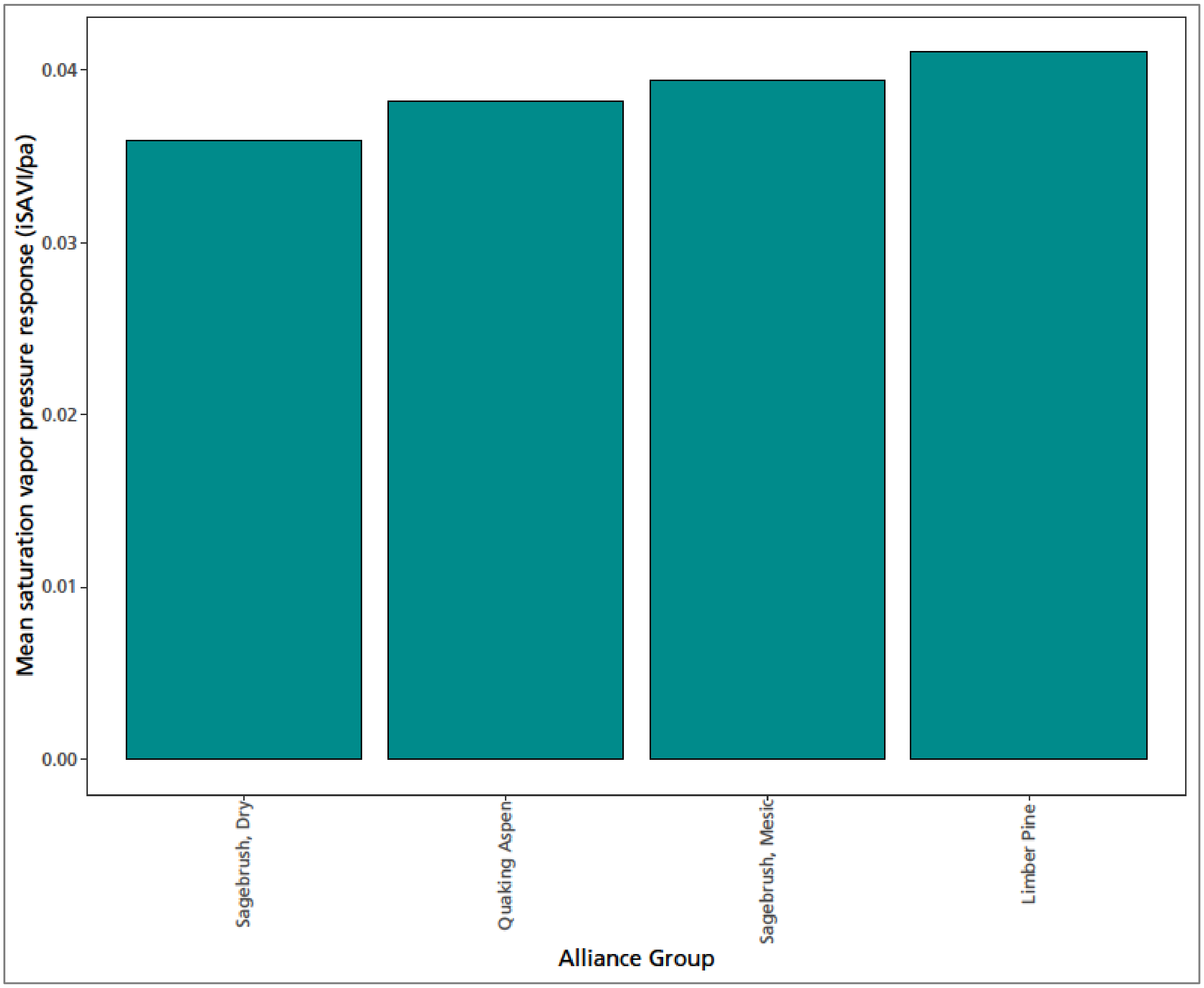

Figure 64. Sensitivity of growing season vegetation production to saturation vapor pressure in polygons, where the relationship was significant (p-value < 0.05). Climate data summarized by water year.
NPS

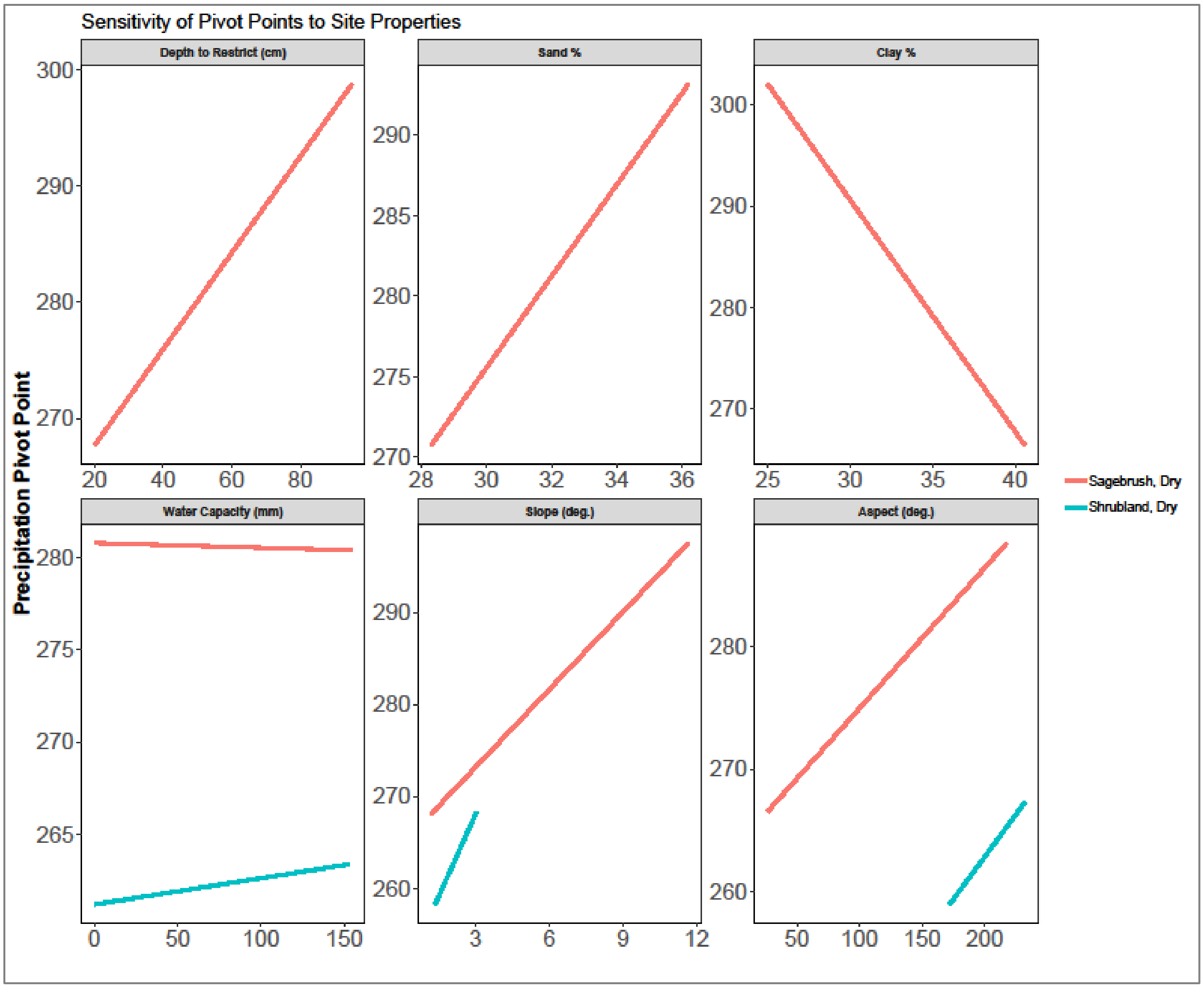

Figure 65. Variation in precipitation pivot points as related to soil and site characteristics. Steeper slopes indicate greater sensitivity of pivot points to site properties. These site properties are important modifiers of climate because they control water retention and distribution in the soil profile and, in the case of site slope and aspect, because they affect the heat load on vegetation.

NPS

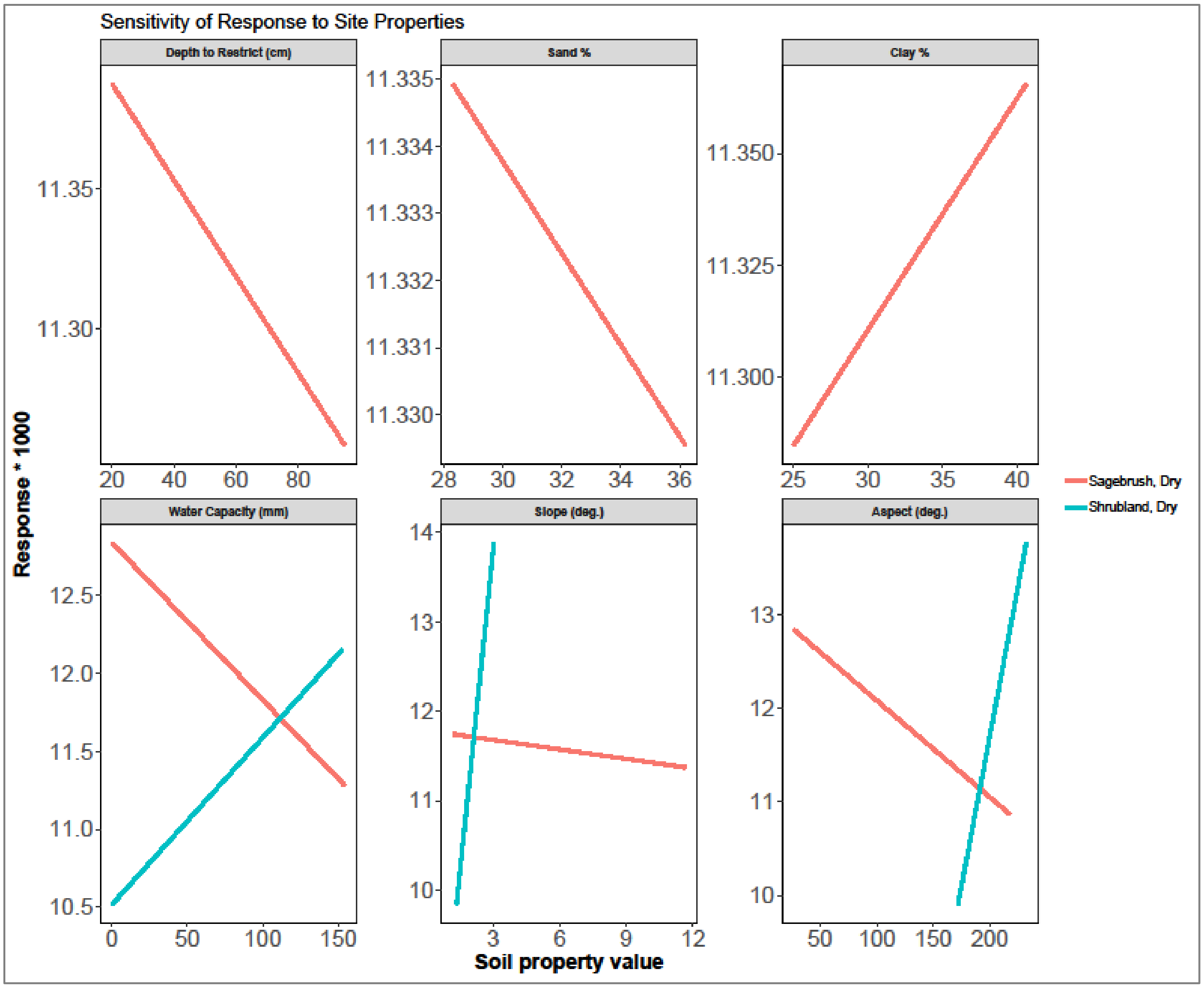

Figure 66. Variation in responses to precipitation as related to soil and site characteristics. Steeper slopes indicate greater sensitivity of responses to site properties. These site properties are important modifiers of climate because they control water retention and distribution in the soil profile and, in the case of site slope and aspect, because they affect the heat load on vegetation.

NPS

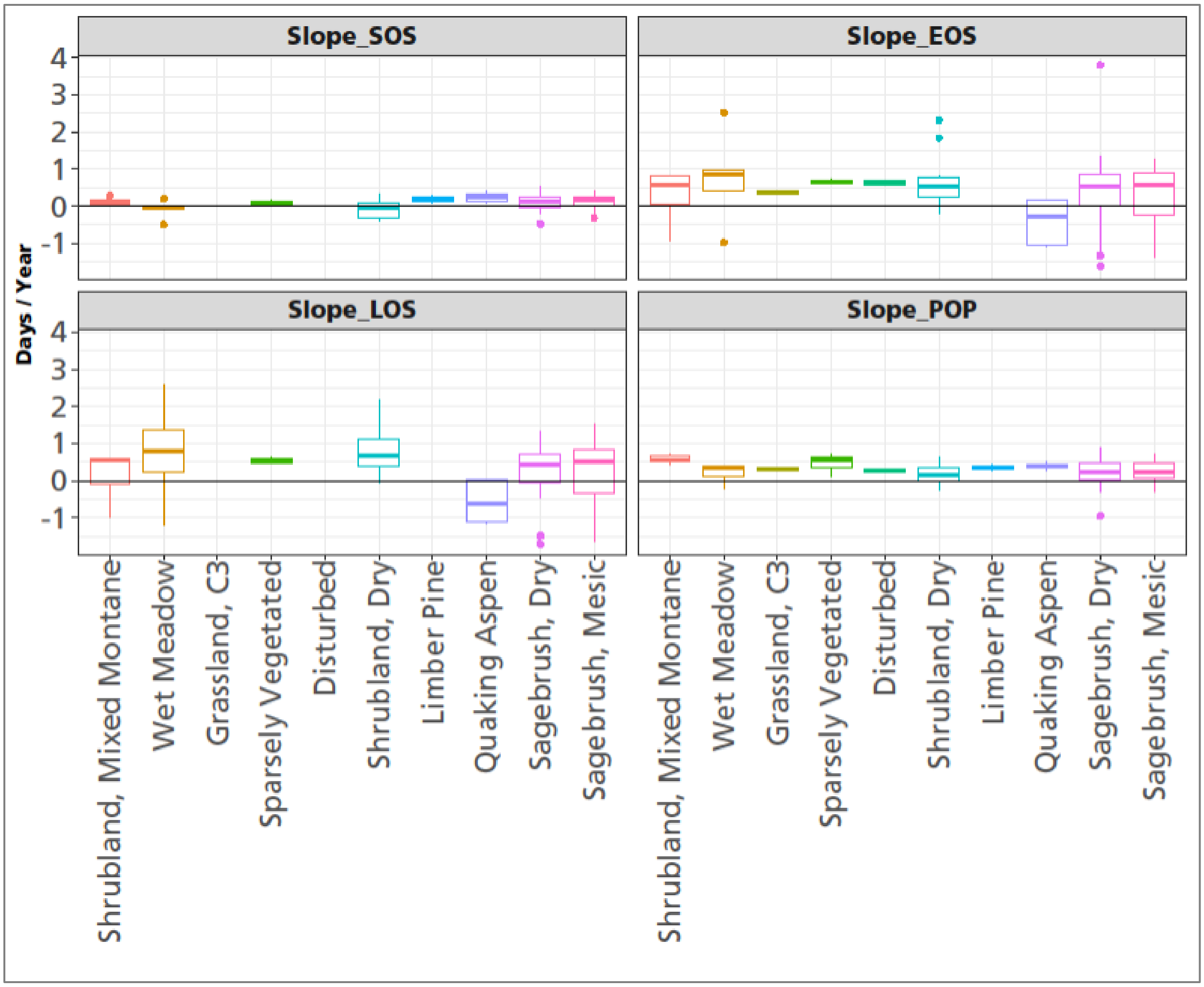

Figure 67. Direction and magnitude of change rate in land surface phenology metrics determined as ± days per year for the start of season date (Slope SOS), end of season date (Slope EOS), length of season (Slope LOS), and timing of peak SAVI (Slope POP). Slope refers to the slope of linear regression of phenology metric versus year for the period 2000–2019.

NPS

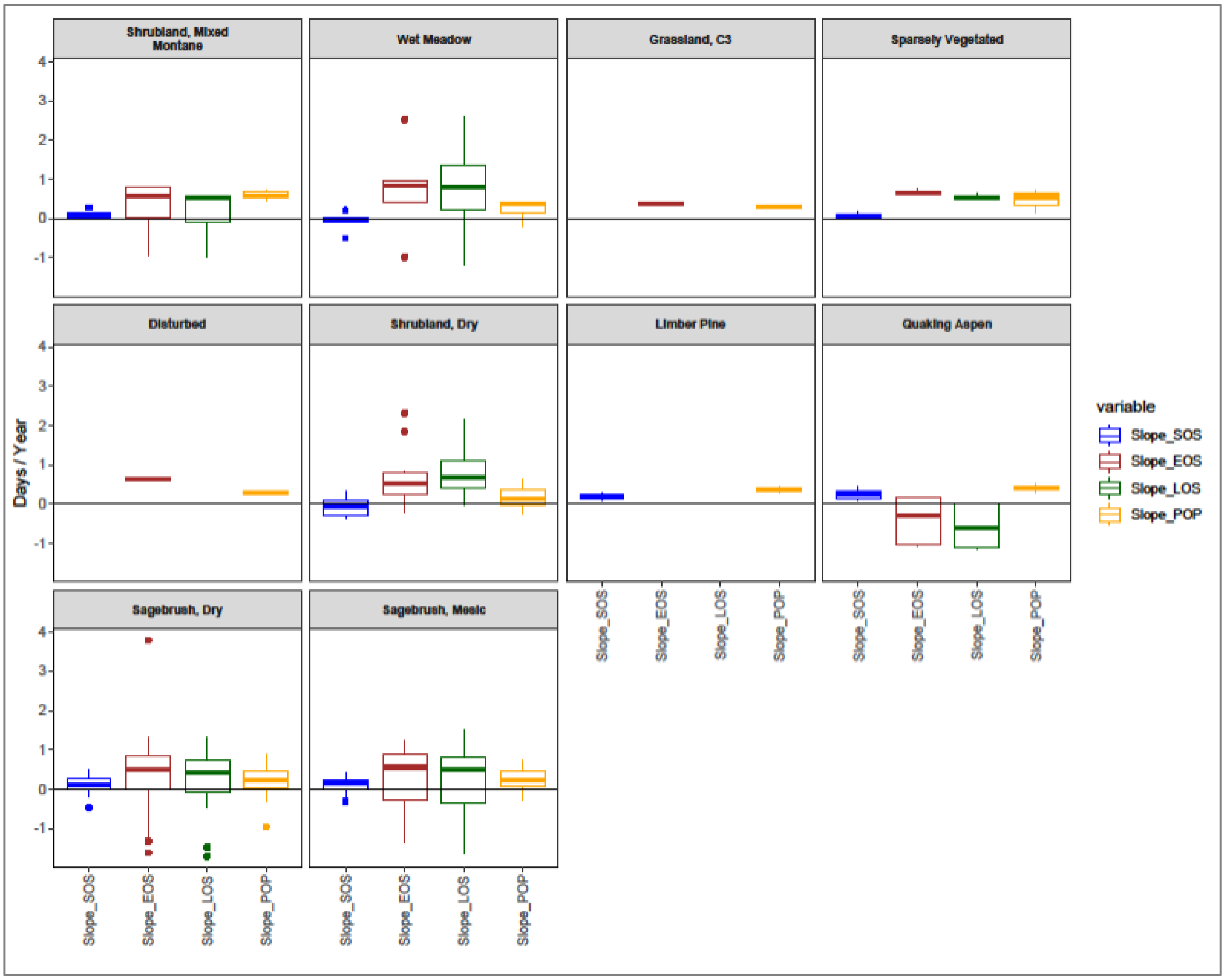

Figure 68. Direction and magnitude of change rate in land surface phenology metrics by alliance group, determined as ± days per year for start of season date (Slope SOS), end of season date (Slope EOS), length of season (Slope LOS), and timing of peak SAVI (Slope POP). Slope refers to the slope of linear regression of phenology metric versus year for the period 2000–2019.

NPS

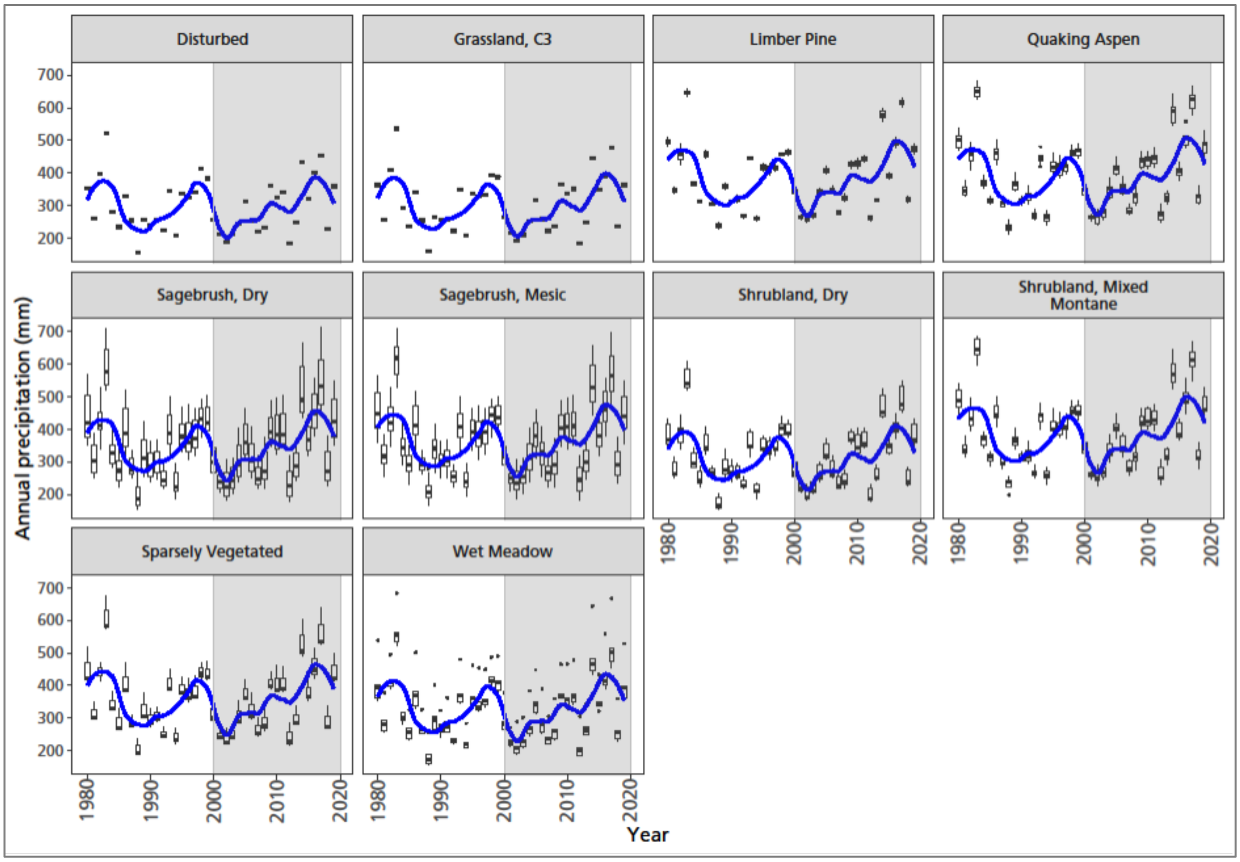

Figure 69. Cumulative annual precipitation over time (1980 to 2019) in vegetation alliance groups. Box plots demonstrate the range of variation within alliance groups by year. The blue line is a loess smooth with a 25 percent span to illustrate multi-year patterns. Gray shaded area includes the period investigated for relationships between production and climate when satellite imagery and climate data were both available.

NPS

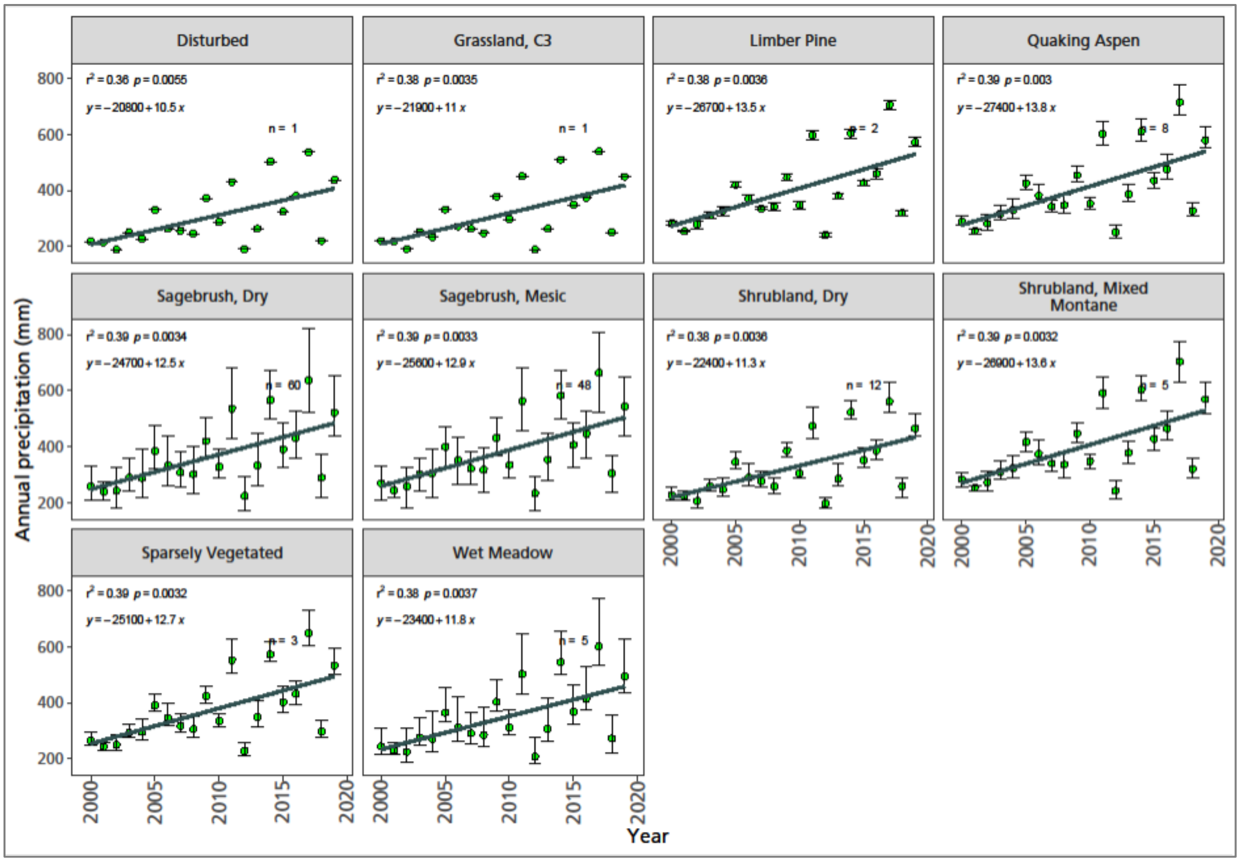

Figure 70. Cumulative annual precipitation from 2000 to 2019 across vegetation alliance groups. Each panel shows a linear trend line with standard error bars. These trends correspond to the gray shaded time period in the preceding figure.

NPS

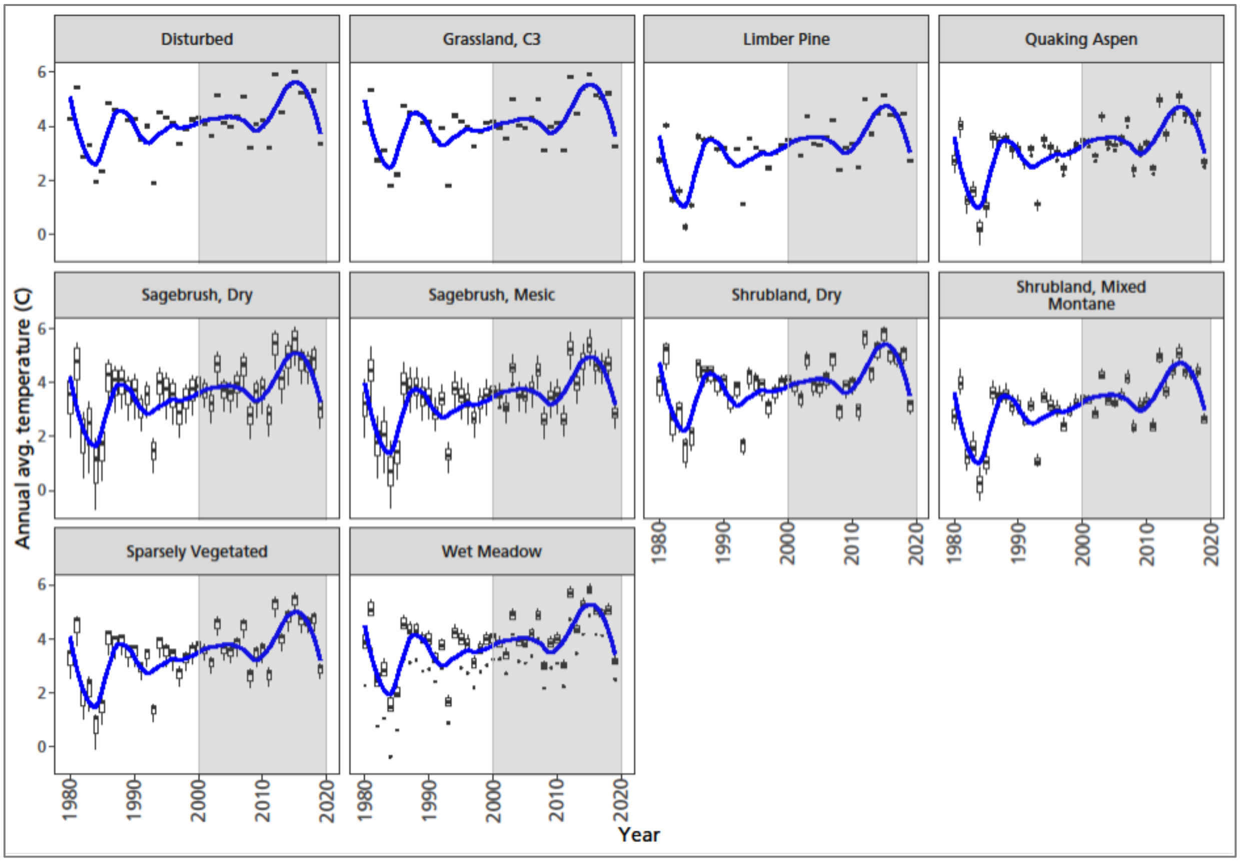

Figure 71. Annual average temperature over time (1980 to 2019) in vegetation alliance groups. Box plots demonstrate the range of variation within alliance groups by year. The blue line is a loess smooth with a 25 percent span to illustrate multi-year patterns. Gray shaded area includes the period investigated for relationships between production and climate when satellite imagery and climate data were both available.

NPS

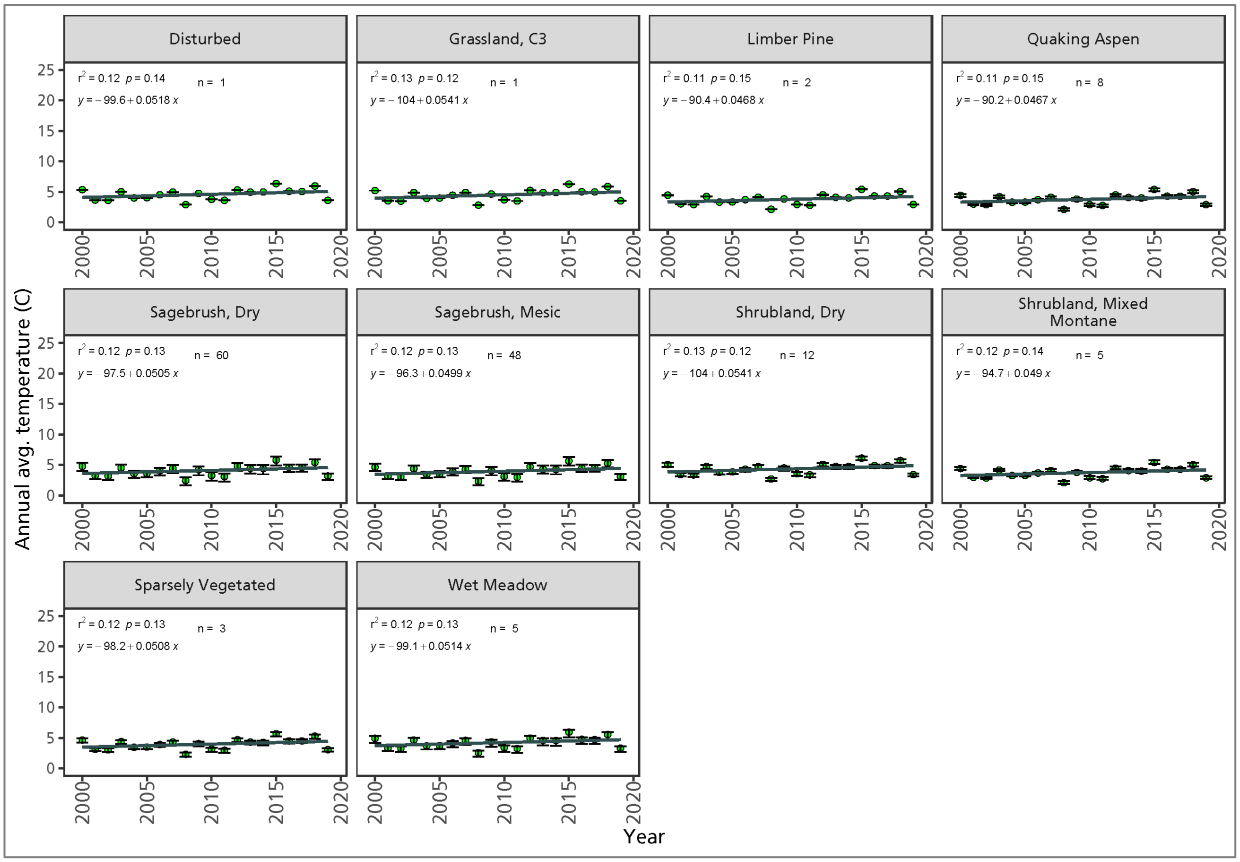

Figure 72. Annual average temperature over time (2000 to 2019) in vegetation alliance groups. The trend over time is shown for the period in gray in the previous figure. Error bars are standard error.

NPS

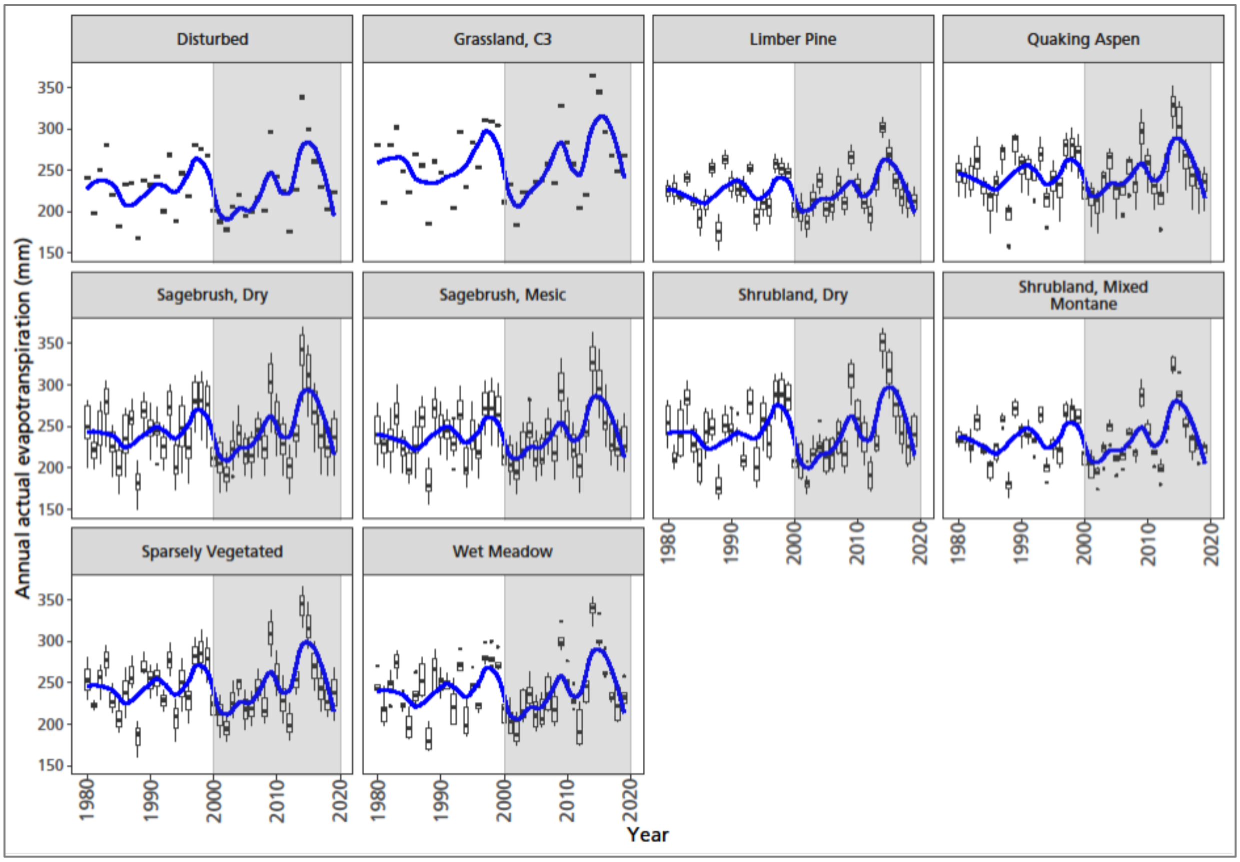

Figure 73. Cumulative annual actual evapotranspiration over time (1980 to 2019) in vegetation alliance groups. Box plots demonstrate the range of variation within alliance groups by year. The blue line is a loess smooth with a 25 percent span to illustrate multi-year patterns. Gray shaded area includes the period investigated for relationships between production and climate when satellite imagery and climate data were both available.

NPS

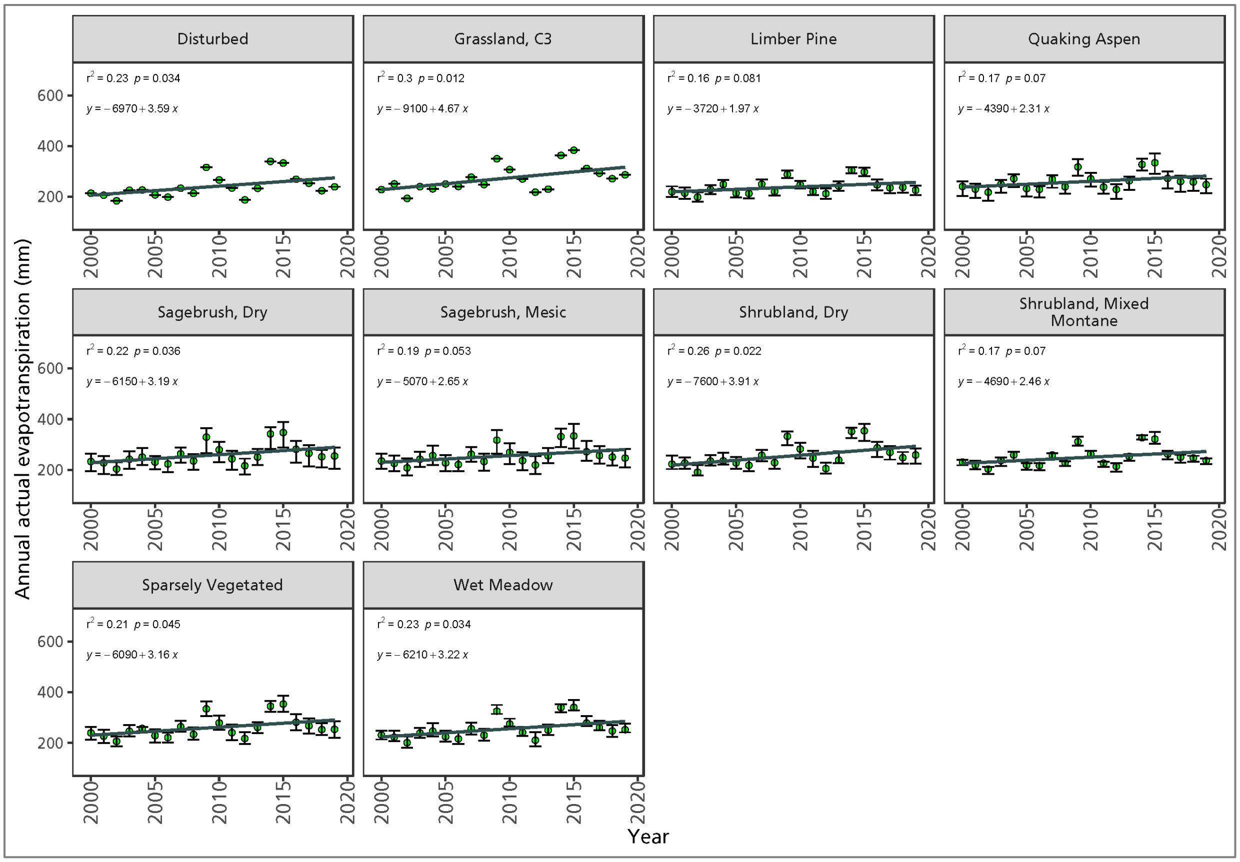

Figure 74. Cumulative annual actual evapotranspiration over time (2000 to 2019) in vegetation alliance groups. The trend over time is shown for the period in gray in the previous figure. Error bars are standard error.

NPS

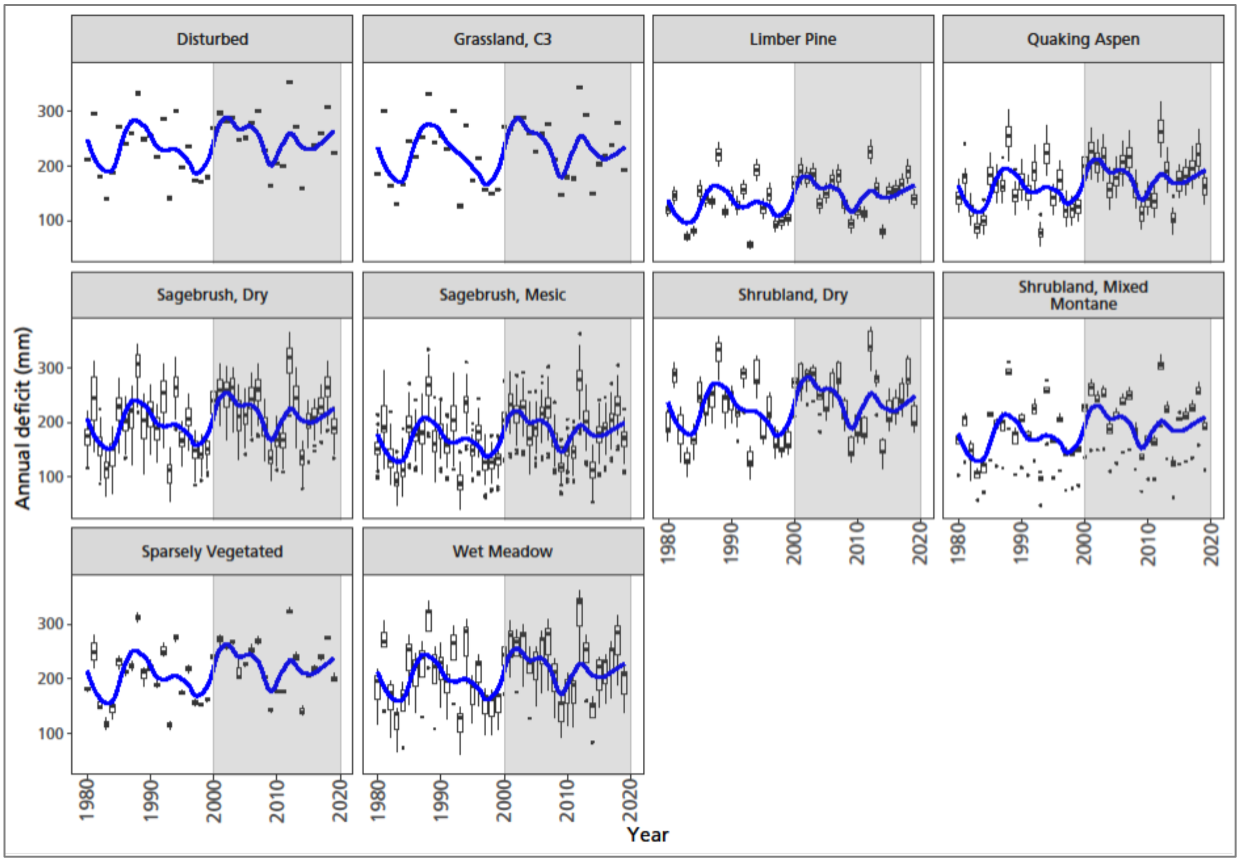

Figure 75. Cumulative annual water deficit over time (1980 to 2019) in vegetation alliance groups. Box plots demonstrate the range of variation within alliance groups by year. The blue line is a loess smooth with a 25 percent span to illustrate multi-year patterns. Gray shaded area includes the period investigated for relationships between production and climate when satellite imagery and climate data were both available.

NPS

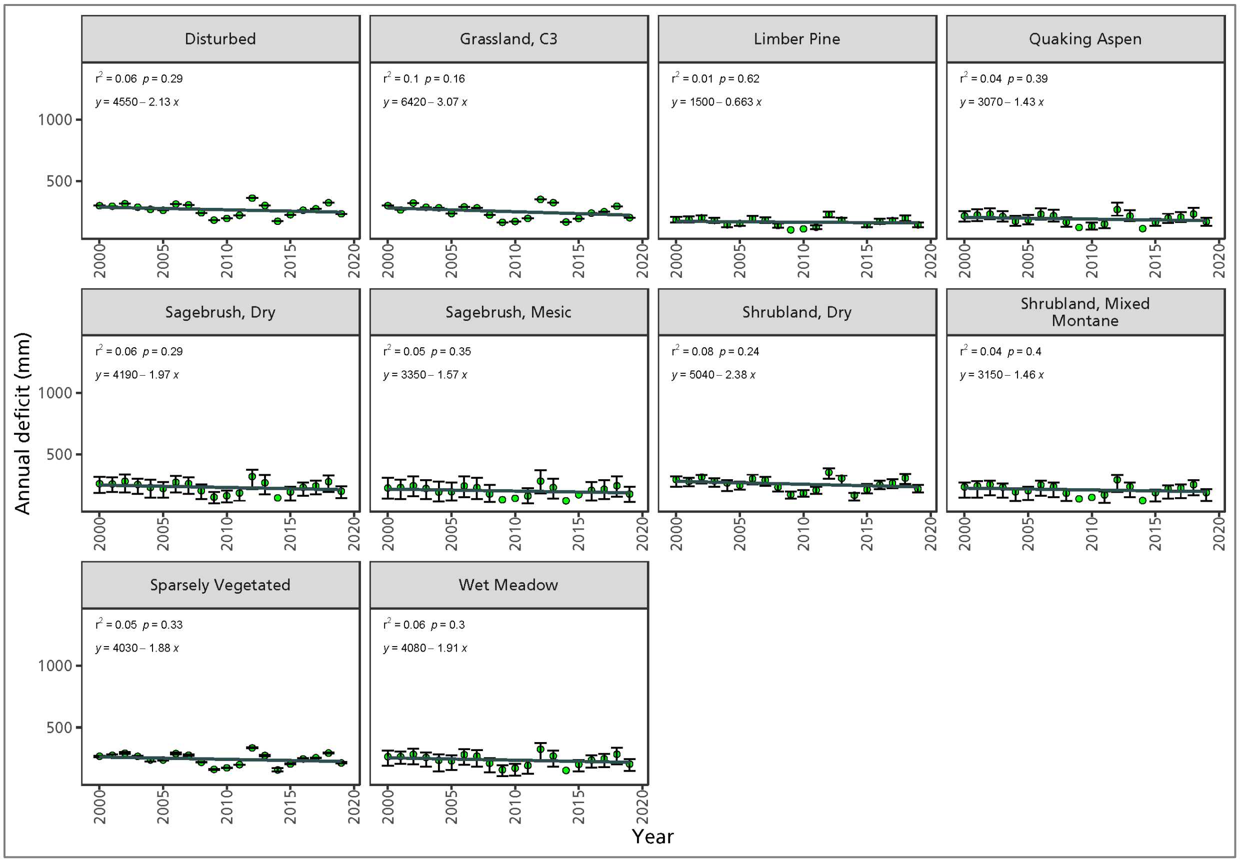

Figure 76. Cumulative annual water deficit over time (2000 to 2019) in vegetation alliance groups. The trend over time is shown for the period in gray in the previous figure. Error bars are standard error. *NPS*

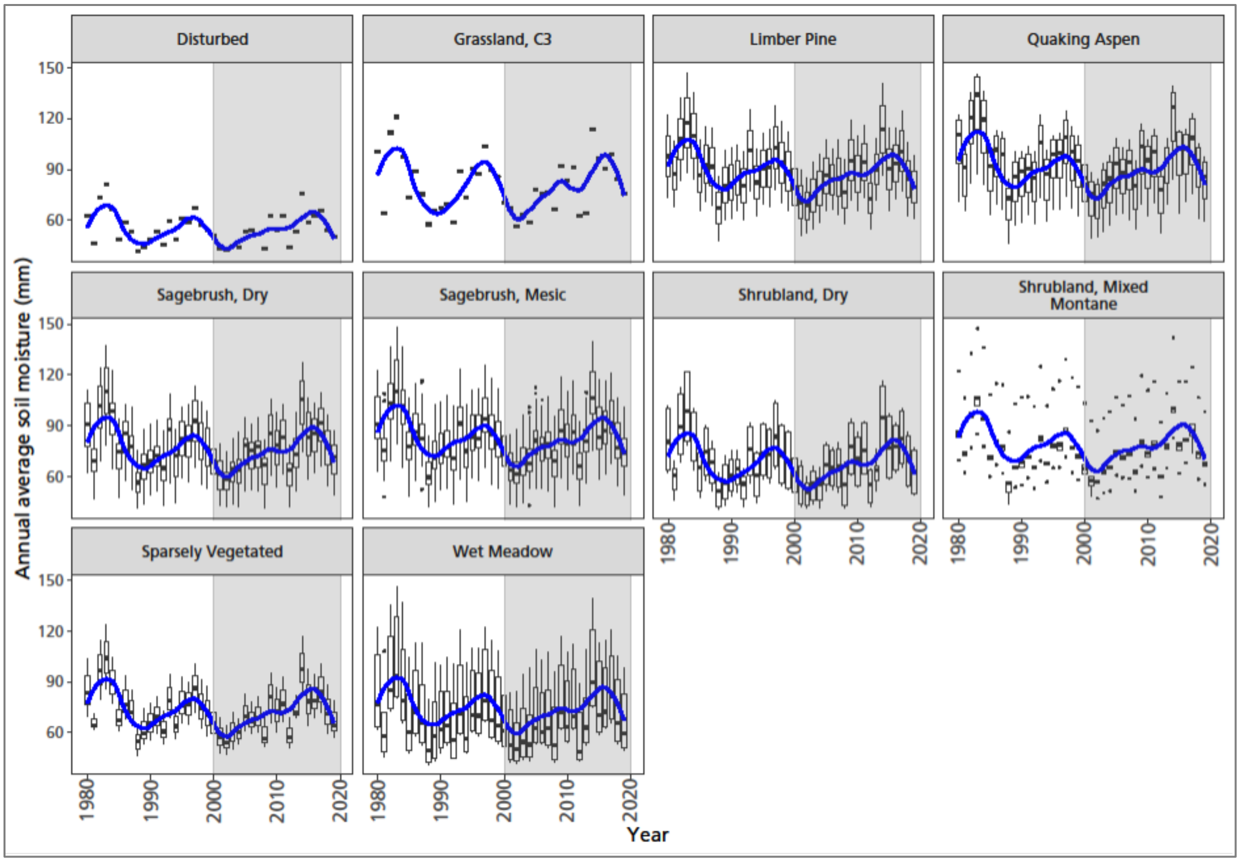

Figure 77. Annual average soil moisture over time (1980 to 2019) in vegetation alliance groups. Box plots demonstrate the range of variation within alliance groups by year. The blue line is a loess smooth with a 25 percent span to illustrate multi-year patterns. Gray shaded area includes the period investigated for relationships between production and climate when satellite imagery and climate data were both available.

NPS

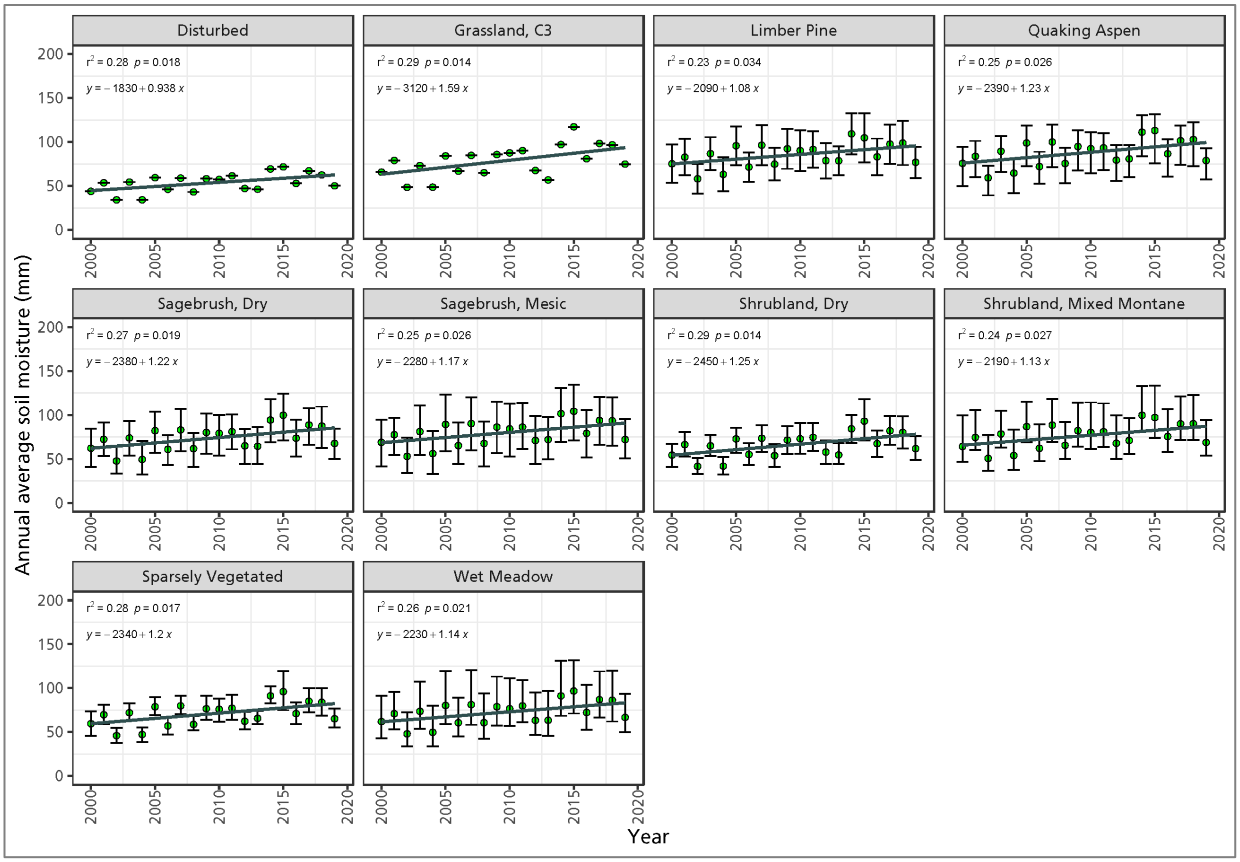

Figure 78. Annual average soil moisture over time (2000 to 2019) in vegetation alliance groups. The trend over time is shown for the period in gray in the previous figure. Error bars are standard error. *NPS*

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