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Mapping with the Amah Mutsun Tribal Band:
Supporting Indigenous ecological stewardship and cultural relationships with land using
spatial data science.

By

Annalise Taylor

A dissertation submitted in partial satisfaction of the
requirements for the degree of
Doctor of Philosophy
in
Environmental Science, Policy, and Management
in the
Graduate Division
of the
University of California, Berkeley

Committee in charge:

Professor Maggi Kelly, Chair
Professor Iryna Dronova
Professor Van Butsic

Spring 2024

Mapping with the Amah Mutsun Tribal Band: Supporting Indigenous ecological stewardship and cultural relationships with land using spatial data science

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Abstract

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Annalise Taylor

Doctor of Philosophy in Environmental Science, Policy, and Management

University of California, Berkeley

Professor Maggi Kelly, Chair

The reciprocal relationships between Indigenous people and ecosystems are crucial for both the health and cultural sovereignty of Indigenous communities and the health of many ecosystems that depend on this stewardship for survival. Indigenous communities in California are working to restore these relationships with their homelands and leading efforts to address the causes and impacts of climate change and environmental destruction. In tandem, ecologists are increasingly recognizing the importance of ecological restoration and stewardship. However, the study of Indigenous ecological stewardship – a dynamic cultural, social, and environmental process that is situated in the unique place where it is continually regenerated – is complex and requires tribal involvement and leadership. This is especially true at the intersection of ecology and spatial data science, where the complicated history of spatial technologies requires scientists to co-design culturally relevant methods that respect Indigenous data sovereignty and acknowledge the power of maps to cause harm. In this dissertation, I explore how non-Native ecologists such as myself might transform the ways that we study ecological stewardship and leverage spatial data science through mutual partnership with an Indigenous community: the Amah Mutsun Tribal Band.

The Amah Mutsun Tribal Band (hereafter AMTB or the Tribe) is an Indigenous community with homelands along the Central Coast of California. Across five years, Alexii Sigona (Amah Mutsun tribal member and PhD candidate at UC Berkeley) and I have built a research partnership with the Tribe through interviews with tribal members, events with the broader community, and field visits with Amah Mutsun stewards. Our conversations with tribal members through these interactions revealed two exciting research priorities within the community. First, we heard a desire to reconnect with, steward, and gather culturally important plants. Second, many tribal members discussed their goal of bringing more cultural fire back onto the landscape.

My dissertation therefore explores two interrelated objectives: first, to apply spatial data science to the study of Amah Mutsun cultural plants and cultural fire, and second, to examine how a mutual partnership with the AMTB could generate ecological research that was both culturally relevant and affirming. In each of these chapters, I use a different suite of datasets and leading-edge spatial data science methods to explore our co-designed research questions.

Chapter 1 discusses important historical context for this research, introduces the AMTB, and considers how ecological and spatial research intersects with community members' interests and goals. In Chapter 2, I draw on machine learning models and climate data to predict the habitat of culturally important plants and prioritize potential areas for tribal gathering and stewardship. Chapter 3 takes us to a coastal grassland within Año Nuevo State Reserve to study the effects of different fire regimes through interdisciplinary methods including remote sensing, interviews with tribal members, and a vegetation survey. This analysis shows how culturally important plants as well as invasive species are responding to repeated low severity burning, which will guide the Tribe's cultural fire restoration work. In Chapter 4, I return to the same site to develop and evaluate methods for the remote sensing of fire recovery in grasslands from two types of fire – low severity intentional burning and high severity wildfire – using a temporally dense time series of high resolution Sentinel-2 imagery. These methods can be used to monitor and evaluate the impacts of intentional burning (both cultural fire and prescribed fire) in grasslands globally. In Chapter 5, I conclude with my major findings as well as broader reflections on my research partnership with the Amah Mutsun Tribal Band, and what lessons my experience might hold for other non-Native scientists.

Reparative partnerships between environmental scientists and Indigenous communities are essential due both to past harms perpetuated by environmental science and the urgency of climate change. If conducted with care, research that centers Indigenous communities and stewardship practices stands to significantly strengthen global environmental efforts and generate greater ecocultural benefits for Indigenous communities.

Table of Contents

Acknowledgements.....	ii
Dedication.....	iv
Chapter 1: Introduction to Indigenous stewardship, spatial data science, and the Amah Mutsun Tribal Band.....	1
Chapter 2: Modeling spatial distributions of Amah Mutsun priority cultural plants to support Indigenous cultural revitalization.....	5
Chapter 3: Centering Amah Mutsun voices in the analysis of a culturally important, fire-managed coastal grassland.....	26
Chapter 4: Using Sentinel-2 imagery to measure spatiotemporal changes and recovery across three adjacent grasslands with different fire histories.....	54
Chapter 5: Conclusions and reflections on collaborative research with the Amah Mutsun Tribal Band.....	81
References.....	85
Appendices.....	95
Appendix S2.....	95
Appendix S3.....	97

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This work is dedicated to the Amah Mutsun community, whose resilience and compassion are transforming the world for the better.

Chapter 1

Introduction to Indigenous stewardship, spatial data science, and the Amah Mutsun Tribal Band

Indigenous Peoples have been shaping the Earth's ecosystems for millennia, stewarding landscapes through practices such as burning, gathering, and planting (Anderson, 2013; Cuthrell et al., 2016). This stewardship represents a reciprocal relationship, wherein the health and cultural sovereignty of Indigenous communities depends on these ecosystems, and these ecosystems benefit from or depend on these stewardship activities (Baumflek et al., 2015; Kimmerer, 2011; Lake et al., 2017; Lopez, 2013). This reciprocal relationship has been restricted by both the immediate effects of Euro-American colonization – such as the displacement and genocide of Indigenous Peoples – and its ongoing legacies (Martinez et al., 2023). In spite of these many obstacles, Indigenous communities in California are working to restore reciprocal relationships with their homelands and leading efforts to mitigate climate change and restore native ecosystems (Goode et al., 2022; Martinez et al., 2023).

In parallel, ecologists are increasingly recognizing the importance of ecological restoration and stewardship for addressing the causes and impacts of climate change (Brown & Mitchell, 1998). However, the ecological and environmental sciences have a long history of demeaning Indigenous Peoples and perpetuating ecological ideals of 'untouched' or 'pristine' ecosystems that erase the legacy and importance of active Indigenous ecological stewardship (Fletcher et al., 2021). These preservationist ideals have led not only to the cultural erasure of Indigenous stewardship practices, but also ecological degradation (Fletcher et al., 2021). Therefore, research that reckons with this history and works to remedy the exclusion of Indigenous perspectives from the environmental sciences is essential. However, the depth of relationships and cultural sensitivity that are necessary for this type of research mean that examples of this are still rare, and more work is needed to comprehensively develop this field.

In particular, the study of Indigenous ecological stewardship is complex and requires tribal involvement and leadership. Indigenous stewardship can be understood as a cultural, social, and environmental process that is dynamic and situated in the unique place where it is continually regenerated, and will therefore vary greatly between different Native communities (Goode et al., 2022; Martinez et al., 2023; Whyte, 2013). In spite of the asymmetrical power relations between Western-trained scientists and Indigenous communities, Indigenous scholars and cultural leaders have worked to discuss, study, and uphold the environmental, social, and cultural importance of ecological stewardship practices. Unfortunately, despite recent movement away from preservationist ideas in the environmental sciences, much of the current research on the impacts of stewardship practices ignores the cultural importance of these ecosystems and marginalizes Indigenous knowledge systems (Martinez et al., 2023). Therefore, research seeking to repair Indigenous erasure and study stewardship practices must be conducted collaboratively and equitably with an Indigenous community. Briefly, some components of equitable research partnerships involve co-designing research questions

with community stakeholders, using methods that respect and uphold the sovereignty and privacy rights of tribes, and being accountable to community partners after a research project is published (Bharadwaj, 2014; Smith, 2021). Non-Native researchers in particular must bring awareness of their positionality and the historical and contemporary contexts relevant to their Native partners, and this is especially true in the field of mapping.

Mapping, remote sensing, and spatial analysis are powerful interrelated spatial technologies that have been used for decades in environmental research and management (Goodchild, 2003). Recent developments in digital spatial data availability, technological advances in computing and the cloud, and the increased possibilities for collaboration have changed the spatial technology landscape (Palomino, 2018). All of the interrelated advances in spatial data, methods, and tools are collectively called “spatial data science” and such approaches have emerged as a cornerstone of the ecological and environmental sciences (Palomino, 2018). For example, analyses of remotely sensed, climate, and other spatial data can be used to track changes in land use (Wang et al., 2022), measure ecosystem recovery from disturbance (Frolking et al., 2009), and predict climate-mediated shifts in species’ distributions (Guisan & Thuiller, 2005). Despite their innumerable beneficial applications to the environmental sciences, spatial technologies have a complicated history and their use in the study of Indigenous ecological stewardship must be designed with care. Many spatial technologies have origins in the military-industrial complex, and maps have long been used to perpetuate colonization, land seizure, and racial segregation (i.e. red-lining), perpetuating harms similar to those in the broader environmental sciences (Aaronson et al., 2021; Brealey, 1995). Therefore, the use of spatial data science in collaboration with Indigenous communities requires scientists to co-design culturally relevant methods with their community partners that respect Indigenous data sovereignty and acknowledge the power of maps to cause harm (Walter et al., 2021).

In this dissertation, I explore how non-Native ecologists such as myself might transform the ways that we leverage spatial data science through mutual partnership with an Indigenous community. Inspired by the work of Native scholars, organizers, and peers in the environmental movement, I came to UC Berkeley with the aim of partnering with an Indigenous community to research their questions related to ecology and spatial data science.

My journey to partner with an Indigenous community in my dissertation research was a multi-year effort that involved many people and organizations briefly outlined here. I began with the help of Alexii Sigona, a PhD candidate in ESPM and a member of the Amah Mutsun Tribal Band, who led the establishment of our research partnership with his tribe. The Amah Mutsun Tribal Band (hereafter AMTB or the Tribe) is an Indigenous community with homelands along the Central Coast of California, centered at the Pajaro River. As a non-federally recognized tribe, the AMTB has limited political rights within their traditional homelands. Therefore, the Tribe is increasingly partnering with researchers, land-owning agencies, and conservation organizations to create opportunities for Amah Mutsun people to steward and connect with their homelands as a means of healing both ecosystems and people. Much of this reconnection and

restoration work is led by the Amah Mutsun Land Trust (AMLT). AMLT leads a Native Stewardship Corps program that employs Amah Mutsun tribal members to work full-time on various stewardship projects related to research, restoration, and education (www.amahmutsunlandtrust.org). Along with members of the Amah Mutsun Tribal Council, the Native stewards and other AMLT staff represented some of my closest research partners. Prior to defining my research projects, I spent two years building relationships with Amah Mutsun community members, assisting with tribally-led mapping projects, and defining our shared research interests. Together, Alexii and I conducted twelve interviews with tribal leaders, elders, and cultural practitioners regarding their relationships to ecological stewardship practices and Amah Mutsun culture. Alexii and I also joined the Native Stewardship Corps for a number of outings to learn about their relationships with land and cultural plants in a more contextualized and experiential setting over the course of many years.

Our conversations with tribal members through these interviews, field visits, and community events revealed two exciting research priorities within the community. First, we heard a desire to reconnect with, steward, and gather culturally important plants. Second, interviewees – and Native Stewards in particular – discussed their goal of bringing more cultural fire back onto the landscape. We developed a number of ideas for how spatial data science could make critical contributions to both of these broader efforts. In the case of restoring relationships with culturally important plants (such as those used in foods, medicines, ceremonies, and other materials), maps can answer key questions regarding the location of a plant's habitat (Evangelista et al., 2018; Guisan & Zimmermann, 2000). Spatial analyses can also reveal where cultural plants might be most easily accessible, or where vegetation health or density is expected to be highest. In the case of cultural fire, analysis of remotely sensed data can help to study the impacts of fires on vegetation at variable spatial and temporal scales. For example, satellite imagery is used to track vegetation recovery from fire, or to estimate wildfire risk based on the amount of vegetation fuels on a landscape (Szpakowski & Jensen, 2019). Spatial analyses can also be used to prioritize areas where the restoration of cultural fire would be most beneficial based on a myriad of intersecting factors.

Spatial analyses such as these complement but do not replace in-person relationships with cultural plants and cultural fire. For example, direct relationships with cultural plants are still necessary to determine if a given area is suitable for gathering and stewardship, which may be determined by factors such as plant abundance and plant quality (e.g. if the shoots of a plant are growing straight enough for use in basketry) (Dent et al., 2023; Marks-Block et al., 2019). In the case of cultural fire, the Amah Mutsun (like other Native tribes throughout California) pull from millenia of place-based knowledge of when, where, and how to apply fire on the landscape that should not be overshadowed by spatial analyses (Martinez et al., 2023). In addition, spatial data science does not offer solutions to the logistical and policy constraints that currently shape the Tribe's ability to practice cultural burning (Clark et al., 2021).

My dissertation therefore explores two interrelated objectives: first, to apply spatial data science to the study of Amah Mutsun cultural plants and cultural fire, and second, to examine how a mutual partnership with the AMTB could generate ecological

research that was both culturally relevant and affirming. This interdisciplinary and community-embedded approach fills a critical need in the ecological and spatial sciences for research that centers the goals and cultural priorities of an Indigenous community. In each of these chapters, I use a different suite of datasets and leading-edge spatial data science methods to explore our co-designed research questions.

In Chapter 2, I explore how Indigenous communities can leverage spatial models and community science datasets to map potential gathering areas and reconnect with culturally important plants throughout their homelands. Methodological advances in this paper include using an ensemble of five different machine learning models to improve prediction accuracy, and statistical methods that account for strong spatial biases in community-collected iNaturalist plant location data. I also explore how spatial scientists partnering with tribes can honor past and ongoing harms in this field by not publishing spatial results that were deemed confidential by the Tribe's leadership.

In Chapter 3, I study the effects of different fire regimes in a coastal grassland through an interdisciplinary lens. I show how interviews with tribal members can enrich our understanding of culturally significant ecosystems, and pair this with a culturally relevant biodiversity survey and remote sensing analysis of fire severity. I explore how using these three methods in parallel builds a much richer understanding of fire in these grasslands. In combining traditional biodiversity survey and remote sensing methods with these interviews, I also examine how commonly used Western scientific methods may succeed or fall short in terms of capturing an ecosystem of high cultural significance. Lastly, I discuss the processes of collaboration inherent in community engagement and highlight which phases of our research partnership with the Tribe involved the highest levels of collaboration, and which aspects were more consultative (David-Chavez & Gavin, 2018).

In Chapter 4, I develop and evaluate methods for the remote sensing of fire recovery in grasslands from two types of fire: low severity intentional burning and high severity wildfire. These methods leverage a temporally dense time series of high resolution Sentinel-2 satellite imagery to track how three grasslands' phenological signatures differ before and after two fire events. Importantly, I show how to summarize complex changes in seasonality over both space and time, and how to test for recovery relative to an undisturbed reference site. My approach addresses a growing need to study the effects of small, intentional burns in low-biomass ecosystems such as grasslands, which are an essential part of cultural fire restoration.

In Chapter 5, I summarize the central outcomes that emerged from this research and my broader partnership with the Tribe. I also discuss some possible future work that would continue to advance this field. The insights gathered through this research support the revitalization of Amah Mutsun stewardship practices and the broader movement for equitable and collaborative research with Indigenous communities.

Chapter 2

Modeling spatial distributions of Amah Mutsun priority cultural plants to support Indigenous cultural revitalization

This chapter has been previously published and is reproduced here with kind permission of all co-authors.

Taylor, A., Sigona, A., & Kelly, M. (2023). Modeling spatial distributions of Amah Mutsun priority cultural plants to support Indigenous cultural revitalization. *Ecosphere*, 14(1), <https://doi.org/10.1002/ecs2.4374>.

Abstract

Along the Central Coast of California, USA, native plant biodiversity has depended on various forms of Indigenous stewardship such as burning, tilling, and gathering. Simultaneously, the Amah Mutsun Tribal Band (the Tribe) depends on these native ecosystems for cultural survivance. However, much of the knowledge related to the location and caretaking of cultural plants has become dormant in the community due to the immediate and ongoing effects of Euro-American colonization. We identified potential gathering areas by modeling the spatial distributions of ten culturally important plants throughout the Tribe's stewardship area. We utilized community science datasets with an ensemble modeling approach that combined the results of five machine learning models to predict not only the distribution of each species, but also the relative certainty of those predictions spatially. Our results revealed that 265.2 km² (2.1 %) of the Tribe's stewardship area is predicted habitat for seven or more of these cultural plants, and that the Tribe had potential access to approximately a third of these high priority areas. Our findings will directly inform the Tribe's cultural revitalization and ecological stewardship programs. We show how geospatial models can support the revitalization of an Indigenous culture by renewing relationships with cultural plants.

2.1 Introduction

Indigenous Peoples throughout California, USA have been shaping the region's ecosystems for millennia, stewarding landscapes through practices including burning, tilling, gathering, and planting (Anderson, 2013; Cuthrell et al., 2016). These reciprocal relationships between people and ecosystems are crucial for both the health and cultural sovereignty of Indigenous communities and the many ecosystems that depend on human stewardship (Baumflek et al., 2015; Kimmerer, 2011; Lake et al., 2017; Lopez, 2013). This "mutual caretaking between people and place" (Diver et al., 2019) has been restricted by both the immediate effects of Euro-American colonization (i.e. displacement and genocide) and its ongoing legacies (i.e. proprietization of land and systemic oppression of Indigenous Peoples) (Sanchez et al., 2021). Despite these challenges, Indigenous communities in California are working to restore relationships with their

homelands. In tandem, ecologists are increasingly recognizing the importance of active restoration and stewardship of native ecosystems, creating new opportunities for collaboration between tribes and land managers (Lightfoot et al., 2021).

For many people within the Amah Mutsun Tribal Band (hereafter AMTB or the Tribe), ecological restoration of their stewardship area along California's Central Coast (Figure 2.1) is a key goal of cultural revitalization efforts and is seen as a spiritual and moral obligation (Lopez, 2013). Past research with and by the Tribe has highlighted the importance of Amah Mutsun stewardship for maintaining healthy populations of native plants, and particularly those dependent on disturbance (Anderson, 2013; Cuthrell, 2013). Amah Mutsun foodways, ceremonies, and medicines depend on relationships with the diverse plant and animal species found in native ecosystems (Cuthrell, 2013; Lopez, 2013). As a non-federally recognized tribe, AMTB is not guaranteed property rights within their traditional homelands. Therefore, the Tribe is increasingly partnering with researchers, land-owning agencies, and conservation organizations to create opportunities for Amah Mutsun people to steward, gather, and restore their plant relatives as a means of healing both plants and people (Lightfoot et al., 2021). However, reinstating Amah Mutsun stewardship in many of these parks depends not only on formal access agreements, but also on the revitalization of dormant ethnobotanical knowledge related to the uses, stewardship, and location of cultural plants within the community. Baumflek et al. (2015) assert that access to gathering areas enables both retention and intergenerational transmission of knowledge about plant use and ecology. Therefore, a critical next step is to build the Tribe's knowledge of the locations of cultural plants – defined here as plants that are used for food, medicine, ceremonies, basketry, and other materials – within their stewardship area. This region's particular history of colonization has meant that precise definitions of tribal political boundaries are often contentious and difficult to determine; our study therefore takes place within the Tribe's stewardship area, defined as the lands and waters that they are working to restore and steward.

Species distribution models (SDMs) are frequently used to predict the actual or potential locations of a species (Guisan & Zimmermann, 2000). These models use a variety of statistical approaches to build a relationship between environmental or climatic variables and known presence locations of that species (Elith et al., 2006; Li & Wang, 2013). Previous work has used a single SDM to map the habitat of one or two ethnobotanical species (Baumflek et al., 2015; Gorman et al., 2008). By expanding both the number of models used and the number of species mapped, SDMs can create a more accurate and comprehensive picture of areas that are likely to contain multiple ethnobotanical species. Known locations of the target species are an integral input to an SDM; while a field survey of multiple species is not commonly feasible, large community science databases such as iNaturalist now enable modeling of multiple species across large areas using methods that account for their spatial biases (Di Cecco et al., 2021). Additionally, although any SDM has certain limitations and biases, an ensemble modeling approach minimizes the biases of any one model (Eisen et al., 2018).

While geospatial tools and data are useful, they have been used to exploit, extract, and reduce Indigenous ways of knowing (Baumflek et al., 2015; Brown & Kytta, 2018; Reid & Sieber, 2020). Therefore, this research began with two years of discussions

with the AMTB Tribal Council, the tribally held Amah Mutsun Land Trust, and associated researchers about our mutual research goals. Lead author Taylor is a non-Native scientist trained in the ecological and geospatial sciences; co-author Sigona is an interdisciplinary social scientist and an Amah Mutsun tribal member. Taylor and Sigona conducted twelve in-depth interviews with tribal elders and cultural practitioners regarding their relationships to land, culture, and the environment. Interviewees were identified in partnership with AMTB leadership and included tribal members with experience stewarding lands for cultural purposes. These semi-structured interviews and our participation in tribal events helped us to build relationships with a broader group of Amah Mutsun community members. This study was designed from the priorities expressed in those interviews – principally the restoration of ethnobotanical knowledge and reconnection with specific basketry and food plants – and represents one piece of our ongoing collaboration.

This study aims to support the Tribe's larger goal of restoring relationships between tribal members and culturally important plants. Currently, the Tribe has potential access to more than 1,000 km² of land within their stewardship area, with varying opportunities for gathering or stewardship of cultural plants. A complete field survey of these lands is not monetarily or physically feasible; therefore, we developed an ensemble distribution modeling method to identify and prioritize potential gathering areas with the ultimate goal of restoring ethnobotanical knowledge. Our three objectives were to:

1. Model the distribution of ten cultural plants within the Amah Mutsun stewardship area,
2. Identify areas where multiple cultural plants are likely to be found, and
3. Evaluate which of these possible gathering locations are most accessible to the Tribe.

Our results will directly inform the Tribe's restoration and gathering programs and guide recommendations for agencies in their stewardship area. We recognize that the Amah Mutsun community relates to these plants as relatives. Due to the sensitive nature of these culturally important species, some of our spatial results are not public and are visible only to members of the Amah Mutsun community. With the permission of the Amah Mutsun Tribal Council, we have included our complete results for one of the ten priority plants: California black oak (*Quercus kelloggii*). California black oaks are generally found in foothills or lower elevation mountains and their acorns are a preferred source for Mutsun acorn foods. We have also shared spatial results for the wavy-leafed soap plant (*Chlorogalum pomeridianum*), which can be prepared as food or used as a soap. For the eight other cultural species and the final results regarding potential gathering areas, we have included summarized results that do not indicate spatial locations.

2.2 Methods

2.2.1 Model Area and Study Area

All models (described below) were run within the maximum rectangular extent of the Amah Mutsun stewardship area (the ‘model area’) and our final results were restricted to the actual boundaries of the stewardship area (the ‘study area’) (Figure 2.1). The study area includes regions of San Mateo, Santa Clara, Santa Cruz, San Benito, and Monterey counties within the Central Coast of California. This region is characterized by a Mediterranean climate with cool wet winters and warm dry summers and is subject to frequent periods of drought. Inland areas have greater temperature variations throughout the year (hotter summer temperatures and colder winter temperatures) as compared to coastal areas.

2.2.2 Observation Data

Species observation data included a combination of three confidential datasets and one public dataset. AMTB collected presence locations for twenty culturally significant species on preserves managed by the Midpeninsula Regional Open Space District located within San Mateo and Santa Clara counties from 2014 to 2019. We also incorporated plant observation data from the University of California Santa Cruz Younger Lagoon Reserve plant restoration team collected from 2014 to 2021 within Santa Cruz County, and from archeological surveys conducted in collaboration with the Tribe from 2014 to 2020 (Apodaca & Lightfoot, 2020; Younger Lagoon Reserve, 2020).

We combined these three confidential datasets with research-grade species observation data from the iNaturalist API using the `pyinaturalist` Python package for fifteen of the Tribe’s cultural priority species within the model area (iNaturalist, 2021). We used the coarsest resolution of our predictor variables (30 arc seconds, or approximately 740m by 920m) to spatially filter the observation data using the Point to Raster and Raster to Point tools in ArcGIS Pro (Version 2.9), which excluded duplicate points if they fell within the same pixel footprint. We then selected the ten species with at least 100 observations. These ten plants are *Artemisia douglasiana*, *Calandrinia menziesii*, *Chlorogalum pomeridianum*, *Clinopodium douglasii*, *Corylus cornuta* ssp. *californica*, *Quercus kelloggii*, *Rubus parviflorus*, *Rubus ursinus*, *Sambucus nigra* ssp. *caerulea*, and *Vaccinium ovatum*. The ArcPy Python package was used to prepare each species’ observation dataset for input into the models (Version 2.9).

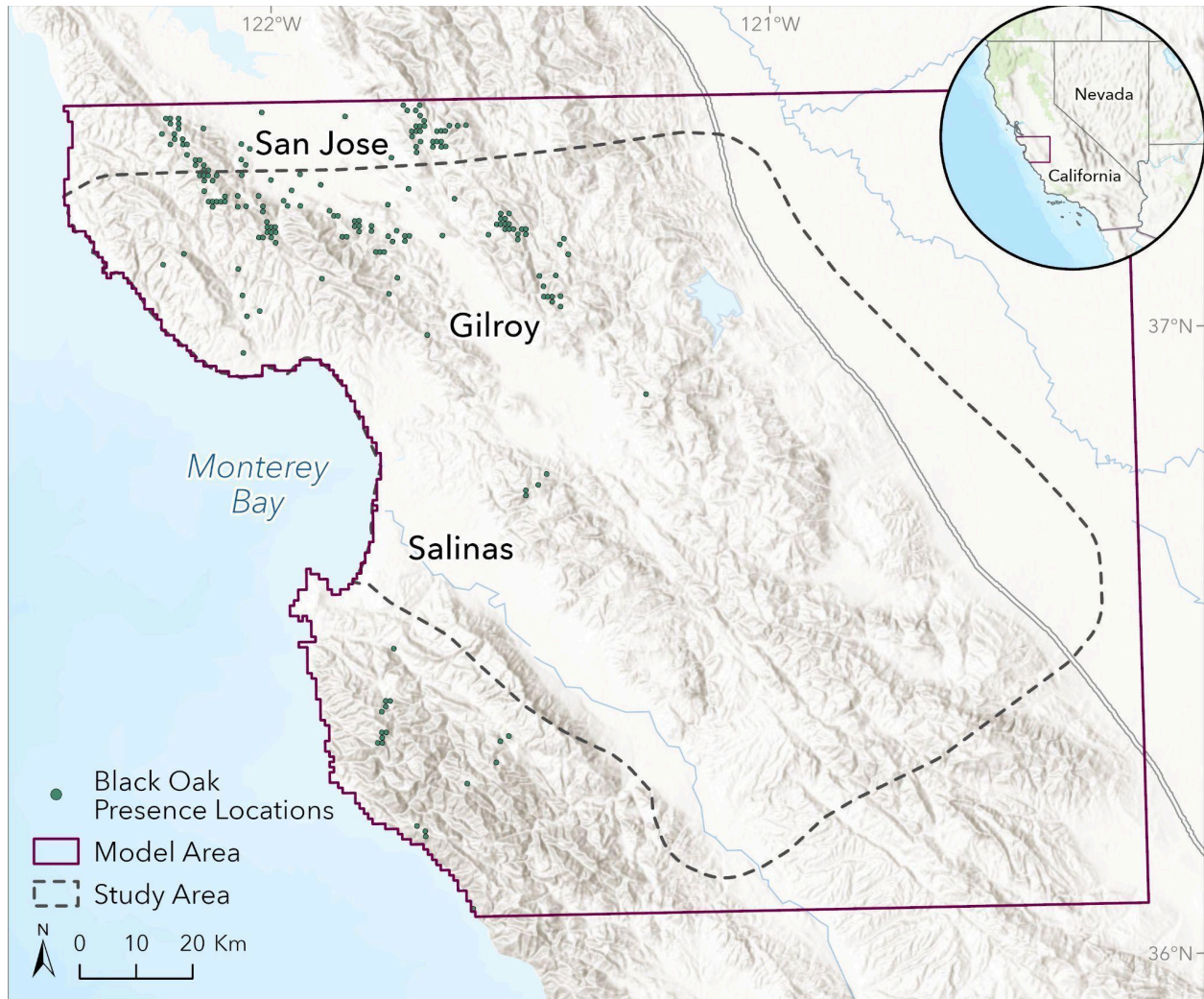


Figure 2.1. Model area, study area, and spatially filtered presence locations of California black oak (*Quercus kelloggii*) used with the model runs. The model area represents the area over which the models were run. Our final results were restricted to the study area, i.e. the boundaries of the Amah Mutsun stewardship area. The inset map in the upper right shows the location of the model area within California, USA.

2.2.3 Background Points

We used presence-only observation data that were collected opportunistically in some cases and systematically in others. While this is a common approach in SDMs, uneven sampling effort and lack of recorded absence locations can lead to results that are spatially biased toward more accessible areas (Phillips et al., 2009). When the environmental ranges captured by observation data are biased, SDMs ultimately predict sampling effort rather than the habitat of a given species. To reduce this sampling bias and improve our models' predictive capacity, we used the target group background point selection method in which background points are generated from observation data for a broader set of species (Jarnevich et al., 2015; Phillips et al., 2009). We used the 145,000

most recent research-grade observation locations for all plant species within the model area from iNaturalist.org as our target group (iNaturalist, 2021). We then spatially filtered and restricted this to 8,000 background points to maximize model speed and performance (Phillips & Dudík, 2008).

The target group sampling method was compared to another background point generation method which randomly places 8,000 background points within a 95% Kernel Density Estimate (KDE) of the presence location area. We compared the performance of these two background point generation methods using the average AUC value across all models and cross validation runs for California black oak.

We also used the target group background points to assess the level of environmental bias in our sampling effort. To do this, we ran the 8,000 background points through our species distribution models as input presence locations; high AUC values (larger than 0.70) would indicate that the sampling effort had a high environmental bias (Phillips et al., 2009).

2.2.4 Predictor Data

Environmental and climate datasets were standardized across the model area using ArcGIS Pro (Version 2.9). WorldClim bioclimatic data are biologically meaningful climatic variables representing historical averages from 1970-2000 (Fick & Hijmans, 2017). These variables include annual metrics, seasonal metrics, and climatic extremes at 30 arc seconds spatial resolution (pixels are approximately 740m by 920m within the study area). All 19 bioclimatic variables were used as potential model inputs (Table 2.1). Additionally, aspect, slope, and curvature (which indicates if a surface is concave, convex, or flat) were calculated from a $\frac{1}{3}$ arc second (approximately 10m spatial resolution) digital elevation model provided by the US Geological Survey (USGS, 2020). Elevation was also included as a predictor.

To capture the potential impact of past fires, we used CAL FIRE's fire perimeter data from 1911 to 2020 which includes both prescribed fires and wildfires larger than 10 acres (CAL FIRE & USFS, 2021). The fire perimeters were converted to raster data with 30 m spatial resolution; if two or more fires overlapped in a given cell, the year of the more recent fire was used. Fire years were then converted to a raster representing years since the most recent fire, with areas with no recorded fire since 1911 conservatively assigned a value of 110 years. This process was conducted for prescribed fires and wildfires separately due to their differing impacts on vegetation.

The topographic and fire raster data were reprojected when necessary and resampled to match the spatial resolution, footprints, and projection of the bioclimatic variables. Modeling was conducted in the WGS84 geographic coordinate system (EPSG: 4326), a requirement of the modeling software. Table 2.1 lists all the predictor datasets and their sources.

Table 2.1. Environmental and topographic datasets input as potential predictors and their sources. Original spatial resolution of WorldClim data was 30 arc seconds; all other datasets were 30 m (or 1.2 arc seconds) spatial resolution.

Variable	Source
Annual Mean Temperature	WorldClim 2.0
Mean Diurnal Range	WorldClim 2.0
Isothermality	WorldClim 2.0
Temperature Seasonality	WorldClim 2.0
Max Temperature of Warmest Month	WorldClim 2.0
Min Temperature of Coldest Month	WorldClim 2.0
Temperature Annual Range	WorldClim 2.0
Mean Temperature of Wettest Quarter	WorldClim 2.0
Mean Temperature of Driest Quarter	WorldClim 2.0
Mean Temperature of Warmest Quarter	WorldClim 2.0
Mean Temperature of Coldest Quarter	WorldClim 2.0
Annual Precipitation	WorldClim 2.0
Precipitation of Wettest Month	WorldClim 2.0
Precipitation of Driest Month	WorldClim 2.0
Precipitation Seasonality	WorldClim 2.0
Precipitation of Wettest Quarter	WorldClim 2.0
Precipitation of Driest Quarter	WorldClim 2.0
Precipitation of Warmest Quarter	WorldClim 2.0
Precipitation of Coldest Quarter	WorldClim 2.0
Elevation	USGS DEM
Curvature	USGS DEM
Aspect	USGS DEM
Slope	USGS DEM
Years since Wildfire	CalFire, USFS
Years since Prescribed Fire	CalFire, USFS

2.2.5 Ensemble Modeling

For each of the ten species, location data and predictor data were input into five different SDM algorithms using the VisTrails Software for Assisted Habitat Modeling (SAHM, Version 2.2.2) (Morissette et al., 2013). The five models used were boosted regression trees (BRT), random forest (RF), Maxent, multivariate adaptive regression splines (MARS), and a generalized linear model (GLM) with the default parameterization built into SAHM. The five selected models provided a mix of widely used regression and machine learning models (Elith et al., 2006). The five models were run for each of the ten species using the

following workflow (Figure 2.2). First, we removed collinear variables based on a combined correlation coefficient, calculated as the maximum value of the Pearson, Spearman, and Kendall correlation coefficients. Collinear variables were removed stepwise starting with the variable with the greatest percentage of deviance explained (based on a univariate generalized additive model) and removing all of the variables that were highly correlated with it (correlation coefficient ≥ 0.75) until no highly correlated variable pairs remained. Finally, any variable with a percentage of deviance explained value of less than 1.0% was removed and each of the five models were run. This process was repeated independently for each species.

The resulting presence probability surfaces were converted to binary presence and absence classifications using the threshold at which the model's sensitivity equaled its specificity. We then evaluated the accuracy of each model using the mean AUC value, or area under the receiver operating characteristic curve, of ten-fold cross validation runs. The AUC value is the probability that the model will rank a randomly chosen presence observation higher than a randomly chosen absence observation (Swets, 1988). We assessed how the mean AUC value of the cross validation runs varied across plant functional types (trees, shrubs, annuals, and perennials). Each model was also evaluated via the percentage of correctly classified presences, the variable importance plot, variable response curves, and Multivariate Environmental Similarity Surface (MESS) maps which indicate areas where a model is extrapolating into environmental conditions that were not represented in the training data (Elith et al., 2010).

For each species, the results of the five models were combined using the binary presence and absence classification maps. Any individual model for which the mean AUC value of the cross validation runs was lower than 0.70 was excluded from the ensemble output. The remaining binary classifications were then added together to create an ensemble output indicating the total number of included models (0 to 5) predicting the species' presence within a given cell. To identify areas where multiple cultural species were likely to be present, we created binary species rasters from the ensemble output rasters. For each species, any pixels with at least three models (a majority) predicting that species' presence were set to 1 and all other pixels were set to 0. These binary species rasters were then summed to create a raster indicating the number of cultural species possibly present at that location (0 to 10). This predicted species count map was used in subsequent analyses to identify potential gathering areas. Figure 2.2 summarizes this workflow.

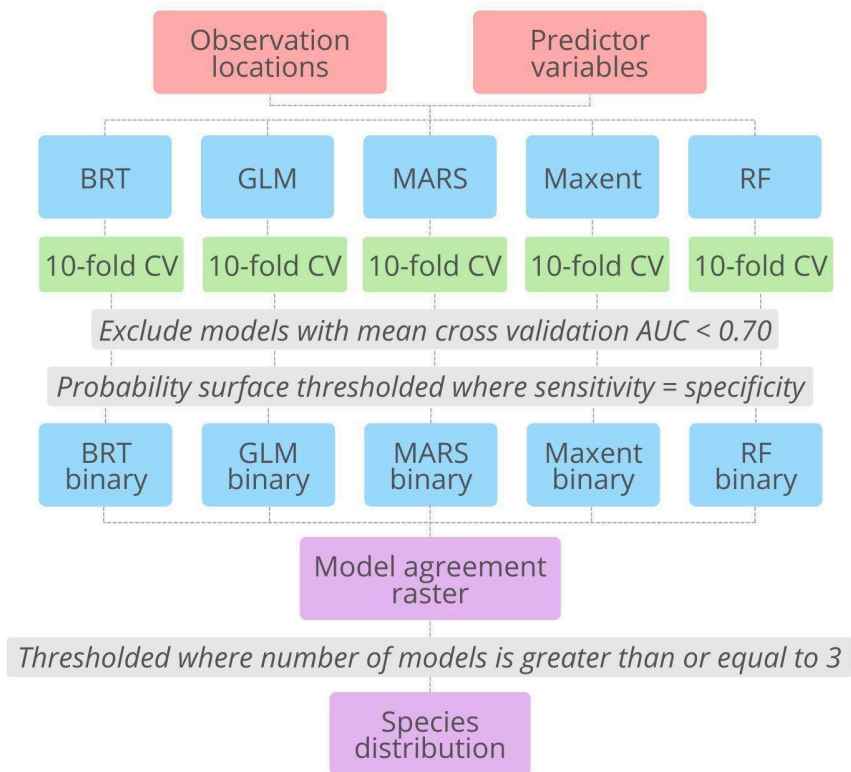


Figure 2.2. Diagram of the workflow conducted for each species. Red blocks represent input datasets, blue blocks represent model runs (cross validation testing runs are shown in green), gray blocks represent threshold decisions made by the authors, and purple blocks represent model outputs. Models included boosted regression trees (BRT), a generalized linear model (GLM), multivariate adaptive regression spline (MARS), Maxent, and random forest (RF).

2.2.6 Accessibility Analysis

The Tribe has some formal access agreements with landowners, such as park agencies and conservation organizations, within their stewardship area. More common are informal discussions in which these land-owning entities are open to possible access agreements, but no formal agreement yet exists. Based on discussions with AMTB leadership and co-author knowledge, we compiled areas where the Tribe has existing or potential gathering agreements from county parcel data and the California Protected Areas Database (Greeninfo, 2021). To calculate summary statistics and prioritize potential gathering areas, the final predicted species count raster was clipped to the potential access areas.

2.3 Results

Detailed results for California black oak, spatial results for wavy-leafed soap plant, and non-spatial results for the remaining eight species with sensitivity concerns are included here.

2.3.1 Observation Data

There were 401 research-grade iNaturalist observations of California black oak in the study area and no observations from the three other data sources. 183 points were input into the models after excluding duplicates within each pixel footprint (Figure 2.1). For the remaining nine species, the number of total observations ranged from 231 to 1,686 and the number of spatially filtered observations ranged from 109 to 686 (Table S2.1).

2.3.2 Background Points

The target group background point method improved the California black oak models' performance over the randomized KDE method as measured by the mean testing AUC value; we therefore used the target group background point method for our final analysis of all ten species. The AUC values of the background point models (i.e. target group background points input as observation data) ranged from 0.515 to 0.694 (mean = 0.651), which indicated low environmental bias in the observation datasets used (an AUC value of 0.50 indicates no predictive capability) (Botella et al., 2020; Phillips et al., 2009). Despite low environmental bias, the target group background points were distributed much more densely in the western half of the model area (Figure S2.1).

2.3.3 Ensemble Modeling: California Black Oak

Each species was run with a different subset of the 25 potential predictor variables after stepwise exclusion of collinear variables. In the case of California black oak, the models were ultimately run with nine predictor variables: isothermality (mean diurnal range divided by the annual range in temperature), minimum temperature of coldest month, precipitation of wettest month, years since prescribed burn, annual mean temperature, slope, precipitation seasonality, elevation, and aspect (Table 2.2). For four of the five models (GLM, MARS, Maxent, RF), the three most important variables were isothermality, minimum temperature of the coldest month, and precipitation of the wettest month (Table 2.2). For the BRT model, the only two input variables selected were isothermality and precipitation of the wettest month (Table 2.2). Figures 2.3 and 2.4 display the California black oak binary presence and absence classification maps individually and combined, respectively.

All five models indicated high predictive capability in the training and cross validation test runs, ranging from 0.853 (GLM) to 0.918 (BRT) in the training runs and 0.847 (GLM) to 0.869 (Maxent) in the testing runs (Table 2.3). The difference in AUC and the percent of presences correctly classified between the training and evaluation runs was small, indicating model consistency (Table 2.3, Table S2.2).

Table 2.2. Mean variable importance (%) across all eleven runs (training and 10-fold cross validation) of each model for California black oak (*Quercus kelloggii*). The selected variables are listed in order of total mean importance across all five models.

Variable	Variable Importance (%)					Mean
	BRT	GLM	MARS	Maxent	RF	
Isothermality (Bio 3)	21.17	21.48	24.12	25.54	12.09	20.88
Min Temperature of Coldest Month (Bio 6)	–	5.20	13.55	7.90	3.99	7.66
Precipitation of Wettest Month (Bio 13)	12.29	5.08	5.19	10.80	4.82	7.63
Precipitation Seasonality (Bio 15)	–	4.21	2.61	0.55	2.31	2.42
Annual Mean Temperature (Bio 1)	–	–	4.72	1.28	0.83	2.27
Slope	–	–	1.36	1.63	1.35	1.45
Elevation	–	–	0.63	0.69	1.61	0.98
Aspect	–	–	0.42	0.27	0.51	0.40
Years since Prescribed Fire	–	–	0.00	0.04	0.04	0.03

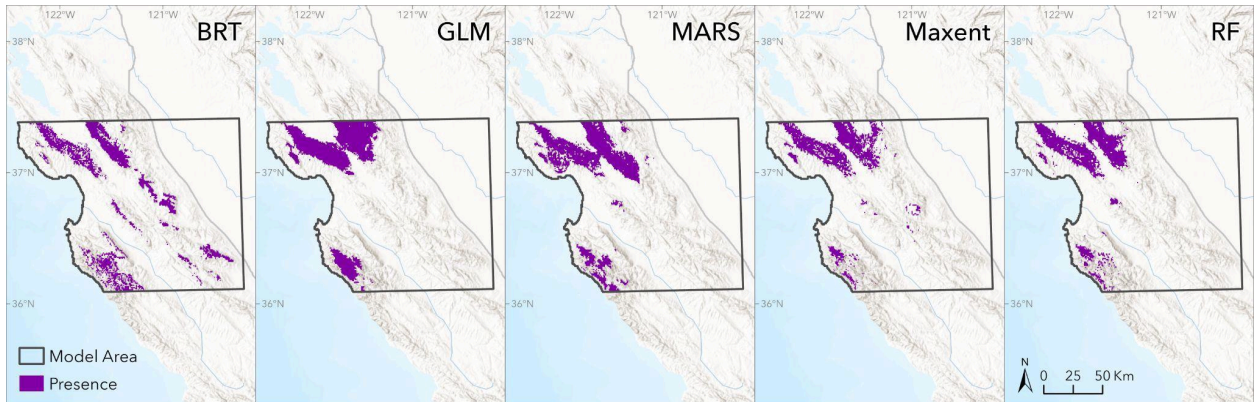


Figure 2.3. California black oak (*Quercus kelloggii*) presence classification results for each of the five species distribution models: boosted regression trees (BRT), generalized linear model (GLM), multivariate adaptive regression spline (MARS), Maxent, and random forest (RF).

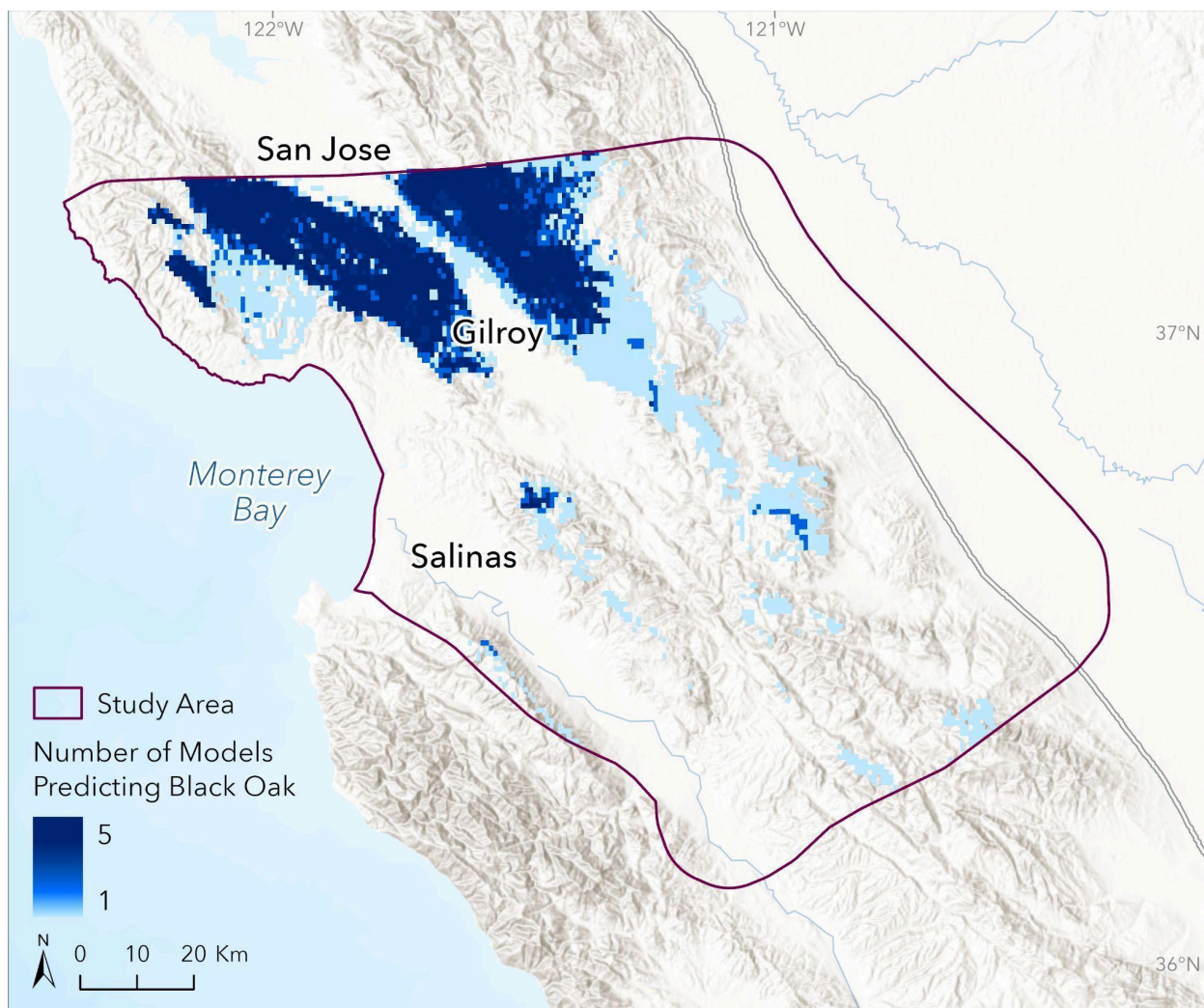


Figure 2.4. Number of models (1 to 5) predicting California black oak (*Quercus kelloggii*) presence within the study area. All five models met the criteria for inclusion, that is the mean area under the receiver operating characteristic curve (AUC) value of the cross validation runs was greater than 0.70.

Table 2.3. Area under the receiver operating characteristic curve (AUC) values for the five California black oak (*Quercus kelloggii*) models for the training run and the average AUC value of the 10-fold cross validation runs. The difference indicates the change in the AUC value in the cross validation runs as compared to the training run, which can be used to evaluate model consistency.

Type of Model Run	AUC Values					
	BRT	GLM	MARS	Maxent	RF	Mean
Training	0.918	0.853	0.865	0.868	0.894	0.880
Cross Validation (mean)	0.860	0.847	0.854	0.869	0.858	0.858
Difference	-0.058	-0.007	-0.011	0.001	-0.036	-0.022

2.3.4 Ensemble Modeling: All Species

The predictive capacity of this ensemble model approach varied across the ten cultural species studied here (Table 2.4). Of the 50 individual models run, 47 models (94%) met our criteria for inclusion in the ensemble output. The three models that were excluded from our final results due to low predictive capacity used the GLM (2) and MARS (1) methods. Twenty-nine models (58%) had an AUC value greater than or equal to 0.80. Wavy-leafed soap plant had the highest mean AUC values in testing and training runs (Table 2.4). Figure 2.5 shows the combined presence classifications for this species.

Of the five types of models run, RF most frequently resulted in the highest testing AUC value and GLM in the lowest testing AUC value (Table 2.4). Across all ten cultural species, RF, Maxent, and BRT models had greater predictive capacity than the GLM and MARS models (Table 2.4). While we did not have a large enough sample size to statistically compare how AUC values varied across plant functional types, trees (0.858; n = 1) and shrubs (0.830; n = 5) had higher AUC values on average than perennial (0.817; n = 3) and annual plants (0.697; n = 1). The MESS maps showed only minimal extrapolation (35 pixels) in the eastern edge of the model area across all ten species, indicating that the available environment within the study area was well sampled.

Table 2.4. Mean area under the receiver operating characteristic curve (AUC) values for the training and 10-fold cross validation testing runs of the five models for each of the ten cultural species. The column labeled ‘Met Ensemble Criteria’ indicates the number of models (of the five) for which the mean testing AUC was greater than 0.70 and was therefore included in that species’ final model agreement raster. The table is sorted by the mean cross validation testing AUC value.

Species	Mean AUC Value		Met Ensemble Criteria	Highest AUC Method	Lowest AUC Method
	Training	CV Testing			
<i>Chlorogalum pomeridianum</i>	0.939	0.905	5	RF	GLM
<i>Corylus cornuta ssp. californica</i>	0.919	0.894	5	RF	GLM
<i>Vaccinium ovatum</i>	0.903	0.885	5	Maxent	GLM
<i>Quercus kelloggii</i>	0.880	0.858	5	RF	GLM
<i>Rubus parviflorus</i>	0.875	0.854	5	Maxent	MARS
<i>Clinopodium douglasii</i>	0.851	0.821	5	RF	GLM
<i>Rubus ursinus</i>	0.798	0.776	5	Maxent	GLM
<i>Sambucus nigra ssp. caerulea</i>	0.779	0.743	5	BRT	GLM
<i>Artemisia douglasiana</i>	0.767	0.725	4	BRT	GLM
<i>Calandrinia menziesii</i>	0.744	0.697	3	RF	GLM

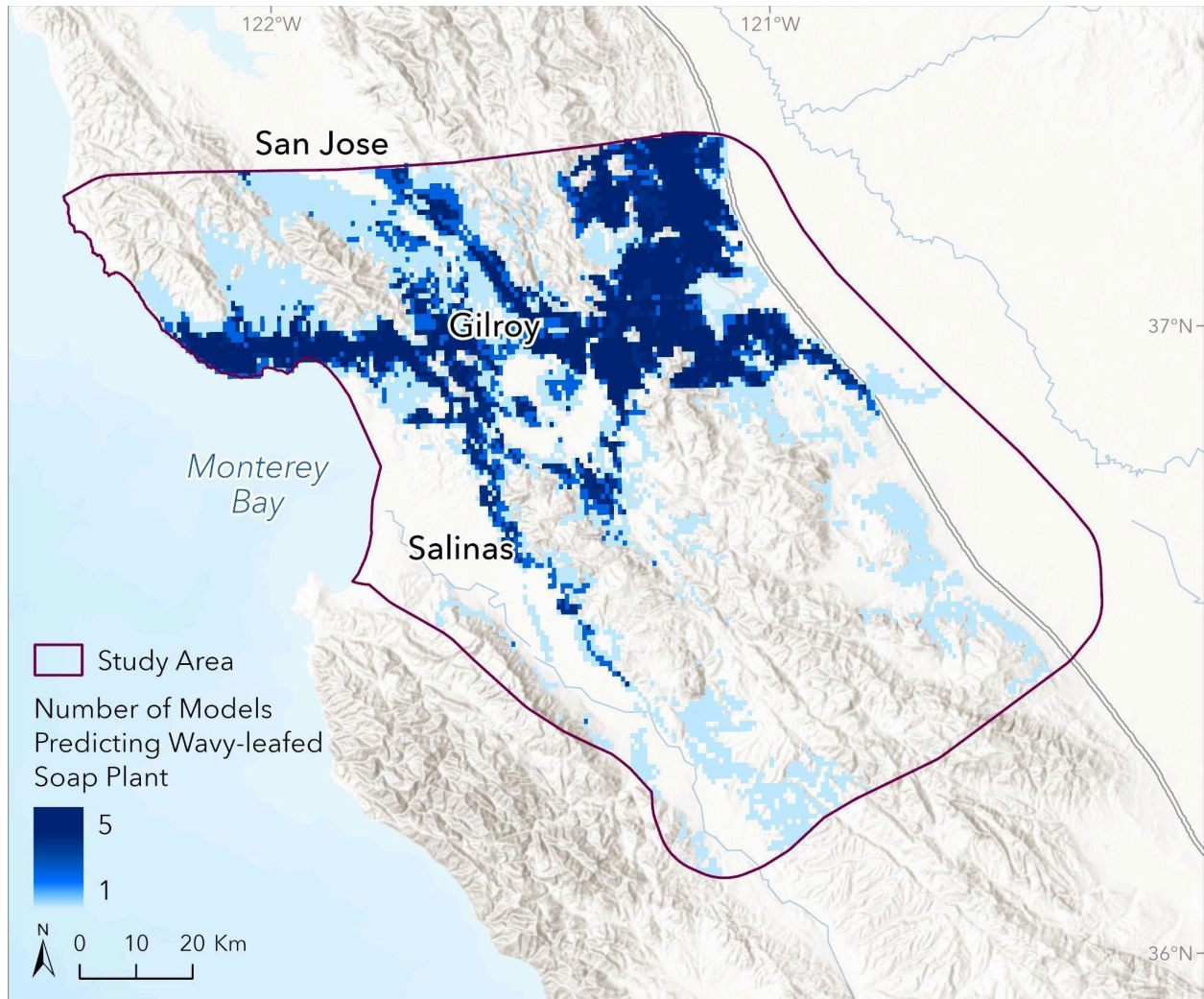


Figure 2.5. Number of models (1 to 5) predicting wavy-leaved soap plant (*Chlorogalum pomeridianum*) presence within the study area. All five models met the criteria for inclusion, that is the mean area under the receiver operating characteristic curve (AUC) value of the cross validation runs was greater than 0.70).

2.3.5 Accessibility Analysis

Areas with potential access by the Tribe made up 8.81% of the study area. The majority of these areas were accessible on a possible case-by-case basis, meaning that access was not guaranteed and that a tribal member would need to request it and potentially coordinate a date and time. In total, 3.50% (39.87 km²) required a request for access and gathering, 13.48% (153.75 km²) allowed some form of access but prohibited gathering, and 83.03% (947.11 km²) were indicated as potential but not guaranteed gathering access.

To prioritize within this large area, potential gathering places were defined as places where two or more cultural species were predicted to be present based on the predicted species count map. Within the study area, 2,501.5 km² or 19.33% of the area contained potential gathering places. Within the subset of lands where the Tribe may

have some form of access, 609.35 km² or 53.63% contained potential gathering places. Places where seven or more cultural plants were predicted to be present totaled 265.2 km² (2.1%) of the study area; 75.85 km² (28.6%) or these high priority areas fall within areas where the Tribe has some form of access. Tables 2.5 and 2.6 show the area (in km²) breakdown by the predicted number of species present within these two areas (study area and potential access areas) respectively.

Table 2.5. Area (km²) of potential gathering areas within the study area, based on the number of species predicted by ensemble distribution modeling.

Predicted Species Count	Area (km ²)	Percentage
0	8,254.4	63.77%
1	2,188.2	16.90%
2	889.7	6.87%
3	424.0	3.28%
4	428.0	3.31%
5	293.5	2.27%
6	201.2	1.55%
7	170.7	1.32%
8	78.2	0.60%
9	16.3	0.13%
Total	129,44.1	100.00%

Table 2.6. Area (km²) of potential gathering areas, based on the number of species predicted by ensemble distribution modeling, within the areas where the Amah Mutsun Tribal Band may have some form of land access.

Predicted Species Count	Area (km ²)	Percentage
0	247.41	21.77%
1	279.47	24.60%
2	245.21	21.58%
3	87.13	7.67%
4	81.73	7.19%
5	74.48	6.56%
6	44.94	3.96%
7	41.75	3.67%
8	25.24	2.22%
9	8.86	0.78%
Total	1136.23	100.00%

2.4 Discussion

Using private and public observation data for ten priority plant species and 25 predictor variables, we used an ensemble modeling approach to predict the potential distributions of each plant throughout the Amah Mutsun stewardship area. We then highlighted areas likely to contain multiple species of interest and analyzed how these predicted distributions overlapped with areas where the Tribe has various forms of access. Predicted distribution maps for each of the modeled species also highlighted the best areas to gather specific plants. Our methodology was designed using best practices in the fields of geospatial modeling and Indigenous environmental sciences in a number of key ways. In the realm of geospatial modeling, we employed an ensemble model approach and utilized target group presences as background points to reduce model bias. Based on best practices in the field of Indigenous environmental sciences, we built our research partnership on the principles of free, prior, and informed consent from the Amah Mutsun Tribal Council. In addition, we conducted interviews with community members and built relationships with tribal leadership over several years prior to beginning this study, which allowed us to design culturally relevant research.

We found that 2.1% of the Amah Mutsun stewardship area was potential habitat for seven or more of the cultural plant species included in our analysis; the Tribe had some form of access to approximately a third of these high priority areas. This subset represents the highest priority for future investigation as potential gathering areas because access agreements or partnerships are already in place. For the remaining high priority areas, the Tribe may use these maps to strategically reach out to other land-owning agencies or individuals as their gathering program expands.

2.4.1 Model Accuracy

We found these models to be highly predictive of species locations. Of the 50 models run in this study, the majority (94%) had a mean AUC value greater than or equal to 0.70 in the cross validation runs. There are a number of metrics and factors to consider when evaluating the predictive power of SDMs. First, in the case of presence-only species distribution modeling, the maximum achievable AUC value is less than 1, with widely distributed species having a lower maximum achievable AUC value (Wiley et al., 2003). It is therefore not advisable to compare AUC values across species without knowledge of the relative differences in their coverage within the study area (Wiley et al., 2003). AUC values are valuable for comparing different models and parameterizations with respect to each species individually. Across all ten species, RF and then Maxent models most frequently had the highest predictivity while GLM most frequently had the lowest predictivity (Table 2.4). This may be because GLMs generally do not capture complex ecological responses as well as the other methods used here (Elith et al., 2006). In the case of California black oak, the GLM and MARS models predicted a more widespread distribution relative to the other three modeling methods and had the two lowest percentages of correctly classified presences (Figure 2.3; Table S2.2). Across all ten species, we found that the remaining three models (RF, BRT, and Maxent) had the highest

predictivity and may be more suitable for presence-only species distribution modeling (Table 2.4).

We also evaluated how well the relative importance of each predictor variable lined up with our expectations for each species. In the case of California black oak, isothermality and precipitation of the wettest month were retained by all five models and had the first and third highest mean variable importance (Table 2.2). Across the five models, California black oak habitat was more likely to be predicted in wetter areas and at higher elevations where temperatures are more variable throughout the year, which fits our expectations for the species.

Our methods were novel in that we included years since the most recent wildfire and years since the most recent prescribed fire as potential predictors. One of these factors was selected as an input into at least one of the five models for all but one of the ten species (*Rubus ursinus*), and for 13 (prescribed fire) and 27 (wildfire) of the 50 total models. However, their mean variable importance tended to be low, as in the case of California black oak (Table 2.2). This does not necessarily indicate that fire or other forms of disturbance are not predictive of plant distribution, but rather show that it is difficult to incorporate a temporally and spatially dynamic process into a static model. Policies of fire suppression and widespread urban development have meant that both wildfire and prescribed fire are rare within the study area, and this low occurrence makes it difficult to accurately evaluate the importance of fire in predicting plant habitat.

Our methods appeared to better predict the distribution of trees and shrubs as compared to annual and perennial plants, which may be due in part to variation in life history strategies. For example, many annual plants depend on disturbance for survival and only two of the 25 potential predictors (years since prescribed fire and wildfire) reflected a form of disturbance. Our results are promising and justify future work to explore metrics of disturbance frequency in addition to disturbance presence, which may better predict species that are adapted to certain disturbance regimes.

Our ensemble results lined up well with our expected distribution for each of the ten species. Of the ten species included in our analysis, the five most widely distributed species (according to the authors' ecological knowledge and CalFlora's estimated range maps within the study area) had the five lowest AUC values (CalFlora, 2021). This aligns with previous work that showed that the maximum achievable AUC value is lower for widely distributed species (Wiley et al., 2003). The MESS maps indicated very little extrapolation across all 50 models. However, our models systematically under-predicted plant distributions in the eastern and southern portions of the study area, which is likely driven by two interrelated factors. First, the sampling effort of our observation data was biased towards the western and northern quadrants of the study area where there are more public parks and trails (Figure S2.1). Second, the inland areas in the south and east portions of the study area experience a different climate characterized by greater temperature extremes. Therefore, while it may be the case that some of these plants do not grow farther inland, it may also be that our input data do not accurately reflect how plants are distributed in this inland biome. A critical next step will be to collect field observations from these under-sampled areas to iteratively improve these models.

2.4.2 Limitations

Our methods work to mitigate the potential biases of species distribution models in several ways. First, we used a target group background point selection method to account for potential environmental bias in the sampling effort of our observation data. Second, we used an ensemble modeling approach that used majority agreement to assign any pixel as predicted habitat and excluded individual models with lower predictive capacity. Third, we excluded species for which the number of observations was below 100. Fourth, we pre-processed our inputs to reduce pseudo-oversampling of observation data and ran each model using an uncorrelated and relevant subset of predictor datasets. We also chose to include two types of fire history (both wildfires and prescribed fire) as predictor variables in our model given the unique relationships between many Amah Mutsun cultural plants and fire.

Despite these mitigation efforts, it is important to acknowledge the assumptions and limitations that are inherent to SDMs. Specifically, SDMs assume that the presence locations for each species are a representative sample of its habitat, that the chosen predictor variables accurately capture the habitat constraints on each species, and that the spatial resolution of the models can capture each species' habitat (Jarnevich et al., 2015). In particular, while the bioclimatic variables are an extremely useful resource for distribution modeling, they reduced the spatial resolution of our analysis 25-fold. At this coarser resolution, our topographic predictor inputs did not reveal important microhabitats such as small ridges and valleys that may be important indicators of each plant's habitat.

In addition, we used presence-only models that leverage background points (as opposed to absence points) to model the environmental niche of each species. The iNaturalist observation data incorporated here is often collected opportunistically and we found that the sampling effort was biased towards popular or accessible areas (Figure S2.1). We used the target group background point method to reduce the potential bias of our models resulting from this sampling bias and found that it increased the predictive capability of our models, which aligns with previous studies (Botella et al., 2020; Phillips et al., 2009). We found that the iNaturalist data was skewed not only toward accessible areas but also toward certain taxa, and that observations of native grasses were particularly sparse. Many native grass species are important cultural plants for the Tribe but were ultimately excluded from our analysis due to an insufficient number of unique observation locations. Accurate identification of grass species is difficult and often requires specialized knowledge of grass anatomy which may be less common among iNaturalist users. Lastly, these models identify areas where a cultural species is likely to be present, but do not indicate where each species is likely to be most abundant. The implications of this are discussed in more detail in the next section.

While we acknowledge the limitations of our data and models, these predicted distributions are a valuable step towards rebuilding the Tribe's relationships with cultural plants. Our results will be used to direct valuable resources towards the highest priority areas and are not considered definitive species maps. Our ensemble modeling approach also allows us to map regions of more or less certainty, either by assessing how many

models predicted presence in a given area, or by viewing the MESS maps to determine if any models were extrapolating into a given area.

2.4.3 Applications and Future Work

The primary next step will be to prioritize a subset of the areas identified as potential gathering areas for further investigation in the field. There are several existing factors that the Tribe may wish to use in this prioritization, including proximity to known Amah Mutsun sacred and cultural landscapes, ease of access (proximity to trails, parking lots, and tribal members' homes), and ADA accessibility. A possible next step may be to create detailed maps showing these factors in relation to the potential gathering areas. Once refined, these potential gathering areas could become part of an interactive mapping tool (restricted to the Amah Mutsun community) that supports wider access to ethnobotanical resources, an expressed tribal priority.

In addition to directly supporting the Tribe's gathering program, this analysis can be used to protect culturally and ecologically sensitive areas. Specifically, these maps empower the Tribe to request changes in the management of these priority areas to exclude the use of pesticides and herbicides, or to conduct mowing and burning to the times of year best suited to sensitive species. In addition, there are multiple potential gathering areas in places where the Tribe does not yet have access or gathering rights; these maps can therefore be used to begin new partnerships, both with public agencies and private landowners.

Future work to analyze phenological patterns within the priority areas identified here could further refine the Tribe's stewardship programs. Stewardship and gathering of cultural plants requires knowledge of both the location and phenology of each plant; the phenology determines not only when a plant may be ripe or ready to gather, but also the appropriate times for other stewardship activities such as cultural burning, mowing, or sowing of seeds. Given that the ideal timing of gathering or other stewardship activities may vary year to year and along environmental gradients, remote sensing methods that efficiently capture phenological signatures over large spatial and temporal scales can augment existing place-based knowledge held by tribal members.

The Tribe still faces many barriers in rebuilding relationships with cultural plants. In the absence of Indigenous stewardship and reciprocal relationships, many of these plants will not produce materials of an abundance or quality high enough for cultural use or consumption. For example, California black oak acorns can be infested with acorn weevil in the absence of cultural burning (Anderson, 2013). Previous work with the Karuk and Yurok tribes also highlighted how California hazelnut (*Corylus cornuta* ssp. *californica*) required thinning or burning to produce basketry-quality shoots (Marks-Block et al., 2019). In areas where a cultural plant is present but not abundant enough for tribal members to gather it, additional stewardship or restoration may be necessary before gathering is possible. The minimum plant abundance necessary for gathering will vary by species and will likely be determined in partnership between the Tribe and relevant landowner. Second, while these maps serve as a guide for prioritizing new access partnerships, they do not do all the work of outreach, communication, and relationship

building that is required to build and maintain those partnerships. Finally, there are challenges when balancing confidentiality and ease of use. Given the sensitive nature of the potential gathering area maps, it is critical that they be kept within the Amah Mutsun community. However, if they are kept so confidential that most community members cannot use them, they lose their purpose. An integral next step in our work will be to incorporate our results into an accessible platform that can be kept internal to the Amah Mutsun community.

2.5 Conclusions

This work is a novel example of how geospatial modeling can be utilized by an Indigenous community to rebuild relationships with cultural plants across large areas of their homelands and directly contribute to land access and cultural revitalization. Our analysis paints a picture of the most accessible places for the restoration of relationships with native plants, which will help to direct limited time and resources to priority areas. The technical methods we developed represent cutting edge modeling techniques and incorporate best practices in species distribution modeling. We compared five commonly used species distribution models and found that Random Forest and Maxent models performed best across ten plant species in a presence-only modeling context. We also included past prescribed fire and wildfire as metrics of disturbance on the landscape and showed their relevance for predicting plant habitat, which we hope will spark more work in this area. Furthermore, our methodology leverages publicly available data and an open-source program (SAHM), enabling us to quickly scale up this analysis to include dozens of cultural plants at no cost. These methods are easily replicable and can be adopted by other Indigenous communities in their diverse efforts to reconnect with land. Finally, this work is an example of a partnership between spatial scientists and an Indigenous community in which the results of the study are directly applied towards cultural revitalization. We modeled a framework for integrating culturally sensitive information into geospatial research while respecting its confidentiality and the sovereignty of that Indigenous community.

2.6 Acknowledgements

We are deeply grateful to the Amah Mutsun Tribal Band and Amah Mutsun Land Trust for their partnership. Interview participants from the Amah Mutsun community generously shared both their time and stories with us; these interviews inspired this research and continue to guide its future applications. The Amah Mutsun Tribal Council and Tribal Chairman Valentin Lopez devoted their time to refine which results could be shared and which to keep internal to the Tribe; we are grateful for their partnership and trust. We thank the citizen scientists who contributed plant observations to the iNaturalist database. The Kelly Lab at UC Berkeley provided feedback that improved our research methods and manuscript and Shane Feirer from the University of California Statewide Program in Informatics and GIS (IGIS) provided support with SAHM software. The interviews described here were approved by the IRB office at the University of California,

Berkeley (#2020-01-12905). We thank two anonymous reviewers whose suggestions greatly improved the manuscript.

Data Availability

The maps showing the modeled locations of the eight sensitive species are available to qualified researchers through the Tribal Council of the Amah Mutsun Tribal Band by contacting info@amahmutsun.org. The raw data, derived data, and code supporting this research (Taylor et al., 2023) that are not sensitive are available in Figshare: doi.org/10.6084/m9.figshare.20469156.v1.

Chapter 3

Centering Amah Mutsun voices in the analysis of a culturally important, fire-managed coastal grassland

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Abstract

Indigenous communities throughout California, USA are increasingly advocating for and practicing cultural fire stewardship, leading to a host of social, cultural, and ecological benefits. Simultaneously, state agencies are recognizing the importance of controlled burning and cultural fire as a means of reducing the risk of severe wildfire while benefiting fire-adapted ecosystems. However, much of the current research on the impacts of controlled burning ignores the cultural importance of these ecosystems and risks further marginalizing Indigenous knowledge systems. Our work adds a critical Indigenous perspective to the study of controlled burning in California's unique coastal grasslands, one of the most biodiverse and endangered ecosystems in the country. In this study, we partnered with the Amah Mutsun Tribal Band to investigate how the abundance and occurrence of shrubs, cultural plants, and invasive plants differed among three adjacent coastal grasslands with varying fire histories. These three sites are emblematic of the state's diverging approaches to grassland management: fire suppression, fire suppression followed by wildfire, and an exceedingly rare example of a grassland that has been repeatedly burned approximately every two years for more than 30 years. We found that *Danthonia californica* was significantly more abundant on the burned sites and that all included shrub species (*Baccharis pilularis*, *Frangula californica*, and *Rubus ursinus*) were significantly more abundant on the site with no recorded fire, results that have important implications for future cultural revitalization efforts and the loss of coastal grasslands to shrub encroachment. In addition to conducting a culturally relevant vegetation survey, we used Sentinel-2 satellite imagery to compare the relative severities of the two most recent fire events within the study area. Critically, we used interviews with Amah Mutsun tribal members to contextualize the results of our vegetation survey and remote sensing analysis, and to investigate how cultural burning contrasts from typical Western fire management approaches in this region. Our study is a novel example of how interviews, field data, and satellite imagery can be combined to gain a deeper ecological and cultural understanding of fire in California's endangered coastal grasslands.

3.1 Introduction

Indigenous communities throughout North America are leading efforts to expand the practice and research of cultural fire stewardship, broadly defined as the lighting of small, intentional burns that renew cultural and ecological resources on the landscape (Cagle, 2019; Goode et al., 2022; Lake et al., 2017). Interdisciplinary research led by or conducted in partnership with Indigenous scholars has revealed a holistic view of the cultural, social, and ecological benefits of cultural fire, including intergenerational knowledge sharing, experiential learning, community healing, reduction of fuel loads and wildfire risk, and benefits to the interconnected plants and animals present in these ecosystems (Adlam et al., 2022; Clark et al., 2021; Long et al., 2021). Cultural fire is also a critical practice supporting food sovereignty, as it is necessary to enhance the quality and abundance of many food, medicine, and basketry plants (Marks-Block et al., 2019; Norgaard, 2014; Sowerwine et al., 2019). Euro-American colonization has greatly restricted cultural fire practices both directly (i.e., policies of fire suppression) and indirectly (i.e. displacement and genocide of Indigenous Peoples) over at least the past century (Colenbaugh & Hagan, 2023; Martinez et al., 2023; Stephens & Ruth, 2005). Due to its profound importance, Indigenous communities throughout California, USA are increasingly advocating for and practicing cultural burning despite well-documented political and bureaucratic barriers (Clark et al., 2021; Marks-Block & Tripp, 2021; Norgaard, 2014).

There is increasing agreement within the Western (also referred to as ‘mainstream’ or ‘dominant’) scientific community and state political leadership regarding the benefits of both Indigenous fire stewardship (also called cultural fire or cultural burning) and controlled burning (also called prescribed burning) as a means of reducing fuel loads and risk of severe wildfire on a landscape, as well as benefiting some of California’s fire-adapted ecosystems (Anderson, 2006; Forest Management Task Force, 2021; Kolden, 2019). However, many studies investigate controlled burning primarily within the context of reducing wildfire risk and some incorrectly conflate cultural and controlled burning, thereby reducing or eliminating what is a highly variable and dynamic cultural relationship to fire for many Indigenous communities (Christianson et al., 2022; Goode et al., 2022; Kimmerer & Lake, 2001; Lake, 2013; Martinez et al., 2023). Therefore, more research is needed to understand how state-led approaches to fire management may coincide with and differ from cultural fire.

In addition, Indigenous cultural practitioners and Western scientists may hold diverging perspectives about how best to define cultural fire and how to measure its impacts (Christianson et al., 2022; Goode et al., 2022). Despite often being reduced to a set of management practices or a base of environmental knowledge, Indigenous stewardship is a cultural, social, and environmental process that is dynamic and situated in the unique place where it is continually regenerated (Goode et al., 2022; Martinez et al., 2023; Whyte, 2013). In contrast to this long term, place-based approach, Western scientific methods often attempt to evaluate an ecosystem quantitatively using universal metrics (e.g. plant abundance, diversity indices) over relatively short periods of time (Klein et al., 2022). Given the asymmetrical power relations between Western-trained scientists

and Indigenous communities, researching cultural fire using Western methods alone risks marginalizing and misinterpreting Indigenous knowledge systems, and ignores evidence that the experiential and observational approaches found in these knowledge systems can be more relevant or useful to land managers (Lyver et al., 2018; Martinez et al., 2023; Mason et al., 2012; Ray et al., 2012). Therefore, fire management research that centers Indigenous voices in the analysis and interpretation of results helps to contextualize and enrich the analytical approaches common to quantitative ecology (Buell et al., 2020; Lake et al., 2017; Long et al., 2020; Ray et al., 2012). This study aims to demonstrate and test such an approach through our partnership with the Amah Mutsun Tribal Band, hereafter referred to as the AMTB or the Tribe.

Along California's Central Coast, the AMTB is one of the many Indigenous communities working to reintegrate cultural fire practices as a means of restoring ecosystems, revitalizing culture, and healing their community (Lopez, 2013). Many of the Tribe's efforts to restore cultural fire to date have targeted coastal grasslands, one of the state's most biologically diverse and increasingly endangered ecosystems (Ford & Hayes, 2007). An estimated 99% of the state's grassland ecosystems have been lost to development, agriculture, introduction of invasive species, and fire suppression as a result of Euro-American colonization (Bartolome et al., 2007; Cuthrell et al., 2016; Ford & Hayes, 2007; Noss & Peters, 1995). Many facets of Amah Mutsun culture – including Mutsun ceremonies, foodways, and medicines – rely on the native plant and animal diversity found in these grasslands (Cuthrell, 2013; Lopez, 2013). Just as the Tribe relies on these ecosystems for cultural revitalization, these ecosystems in turn rely on periodic disturbance for their continued renewal and survival (Anderson, 2013; Cuthrell, 2013). In the places where coastal grasslands have been spared from development or have recovered from agricultural use, policies of fire suppression and the exclusion of Indigenous fire stewardship have resulted in grassland habitat loss due to the steady encroachment of shrubs and trees (Cuthrell, 2013; Ford & Hayes, 2007; Gibson, 2009). The AMTB uses cultural burning to impede this woody plant encroachment and support the proliferation of culturally important grassland species, among many other goals. The cultural significance of these grassland species is broad and interconnected; many are used directly in foods, medicines, ceremonies, and basketry. For example, *Achillea millefolium* (common yarrow) is used in various medicines and the berries of *Rubus ursinus* (Pacific blackberry) are used in different Mutsun foods.

Grassland conversion to woody plant communities has many impacts in addition to the loss of endangered habitat and culturally important biodiversity. First, in the event of a wildfire, shrub-dominant areas are more likely to burn at high intensity than grasslands, therefore posing a greater risk to nearby communities (Russell & McBride, 2003). Second, woody plant conversion of grasslands has been shown to reduce soil moisture and streamflow, which negatively impacts the drought resilience of a watershed (Hibbert, 1983; Pitt et al., 1978). Therefore, by not facilitating more cultural burning, California is losing not only its grassland habitat, but also the many ecosystem services that grasslands provide in the form of drought and wildfire resilience. The reintroduction of fire in these grasslands may also favor some fire-adapted native grass species over their invasive competitors, although this effect varies based on many factors (Ditomaso et

al., 2006; Reiner, 2007; Roy et al., 2014). Despite widespread interest in this management strategy (frequent, low-severity burning) in California’s fire-adapted grasslands, there are exceedingly few places within the Central Coast and the state as a whole where Indigenous communities and management agencies can research it in practice. Fortunately, Año Nuevo State Reserve – an area stewarded in part by the Tribe and the focus of this research – offers us the vanishingly rare opportunity to study a frequently burned grassland.

Within the reserve, a coastal grassland known as Cascade Field has been burned in a manner similar to the frequency and severity of Indigenous fire stewardship practices for over 30 years. Specifically, the California Department of Parks and Recreation (hereafter shortened to State Parks) has conducted controlled burns at Cascade Field in the late fall every two to three years from 1991 to the present in an effort to control invasive species and support native grasses; the controlled burn studied here occurred in November 2020 (T. Hyland, personal communication, March 27, 2023). The coastal grassland immediately adjacent to this site burned at high severity in the CZU wildfire in August 2020 (“CZU” refers to the CAL FIRE district in which the fire occurred). This area therefore allows us to compare sites that have experienced two very different types of fire, as well as a third adjacent site with no recorded fire in at least 100 years (Figure 3.1). Tim Hyland, a Natural Resource Program Manager at State Parks, estimates that this is one of the most consistently burned coastal grasslands in California, and one of the most diverse grassland ecosystems within the parks system (T. Hyland, personal communication, March 27, 2023).

This unique study area provides a natural comparison between three types of management that are emblematic of California’s current approaches to land management: fire suppression, fire suppression followed by high severity wildfire, and frequent low severity controlled burning. In addition, the area is home to a multi-year land management partnership between an Indigenous community (the AMTB) and a state agency (State Parks), a style of partnership that has proliferated in recent decades and therefore deserves greater attention. The management program at Año Nuevo State Reserve is run by State Parks and differs from traditional Mutsun stewardship practices. However, due to the suppression of Indigenous fire stewardship over many centuries in California, there are no other areas to our knowledge that have been burned with a frequency or severity similar to that of Indigenous cultural burning practices within the Tribe’s stewardship area. This area is therefore a unique and important opportunity to study the results of repeated burning in coastal grasslands over many decades (Long et al., 2021). Additionally, the tribally led Amah Mutsun Land Trust (AMLT), which leads many of the Tribe’s stewardship efforts, participated in the controlled burn at Cascade Field in 2020. For these reasons, this area was a research priority for the Tribe.

This study was designed and conducted collaboratively with partners from the Tribe and AMLT to compare the ethnobotanical diversity of three adjacent coastal grasslands with varying fire histories. Specifically, we conducted a systematic survey to study how the abundance and occurrence of key cultural, shrub, and invasive plant species varied across the three sites. In addition, we used multispectral imagery from the Sentinel-2 satellites to compare the severities of the two most recent fires. Finally, we

used the results from our interviews with Amah Mutsun tribal members to contextualize and evaluate this fire management program more broadly. This work is part of a four year research partnership between lead author Taylor (non-Native) and co-author Sigona (Amah Mutsun) with the AMTB. The conceptualization and design of this study were directly informed by these interviews as well as informal discussions with tribal members and other researchers partnering with the Tribe, which are discussed in more depth in the Methods section. We recognize that the Amah Mutsun community relates to these plants as relatives and views cultural fire as sacred. Our work aims to disrupt current power dynamics within the land management and conservation spaces by centering the voices of Amah Mutsun tribal members and the importance of cultural plants, while de-centering Western analytical methods as the “objective arbiter[s] of truth” (Klein et al., 2022). In combining traditional biodiversity survey and remote sensing methods with these interviews, we aim to understand how commonly used Western scientific methods may succeed or fall short in terms of capturing an ecosystem of high cultural significance.

In addition to integrating social and ecological methods, our study fills a number of gaps in the current literature. First, our work adds a critical Indigenous perspective to ongoing discussions in the research community about the impacts of cultural fire on California’s unique coastal grasslands, one of the most endangered ecosystems in the country (Stromberg et al., 2001). In addition, there is still a dearth of research regarding the impacts of fire (i.e. wildfire, controlled burning, or cultural fire) in non-forest ecosystems in California, despite non-forest ecosystems comprising more than half the state (Brodie & Palmer, 2020; Calhoun et al., 2022). Finally, critical gaps in our understanding of this management strategy (frequent, low severity controlled burning) remain, and this site represents one of the only places in the state where it is possible to study it. Investigating how a history of repeated controlled burns has impacted ethnobotanical biodiversity, shrub conversion, and plant invasions at this site will inform current restoration efforts led both by the AMTB and State Parks, and is an integral step towards the larger scale reintroduction of cultural burning throughout the state. Our study integrates interviews, vegetation data collected in the field, and remote sensing analysis to address the following questions:

1. **Approaches to Fire Management:** How do Amah Mutsun tribal members describe cultural fire? What are the intentions behind it and how do they differ from Western fire management goals?
2. **Fire and Vegetation:** How does the occurrence and abundance of cultural, shrub, and invasive species vary between adjacent coastal grasslands with different fire histories?
3. **Fire Severity:** How does the severity of the controlled burn differ from that of the wildfire?

3.2 Methods

3.2.1 Study Area

The study area consists of a contiguous coastal grassland ecosystem within Año Nuevo State Reserve in San Mateo County, California (Figure 3.1). There are three adjacent areas with differing fire histories: an area that burned in the CZU wildfire complex in August and September 2020, an area (Cascade Field) that has been burned in controlled fires in the fall months every two to three years since 1991, and an area that has not experienced fire of any kind for at least 100 years (Figure 3.1). These three sites are referred to as the wildfire, controlled burn, and no fire sites respectively. The controlled burn site was burned in November 2020 in partnership with AMLT's Native Stewardship Corps, a group of Amah Mutsun tribal members who work full time on various stewardship projects related to research, conservation, and education. To delineate the boundaries of our study area, we used a highway (State Route 1) to the east and a trail along the bluff to the west. CAL FIRE's official fire perimeters were used to approximate the two fire sites (CAL FIRE & USFS, 2022). To control for soil differences between the three areas, we used the Soil Survey Geographic database (SSURGO) to exclude any areas with clay soils, dune soils, or steeper grades, leaving only loamy, sandy loam, and loamy sand types with similar grades (Figure S3.1) (NRCS, 2022). Because we expected that riparian drainages within the study area would have a different species assemblage, we used San Mateo County's elevation dataset (1 m spatial resolution) to exclude ravines and large drainages based on slope (San Mateo County, 2017). These steps were conducted in ArcGIS Pro (Version 3.1.2) in the NAD83 (2011) UTM zone 10N projection (EPSG: 6339).

After these exclusions, the sites were 0.23, 0.46, and 0.35 km² for the no fire, controlled burn, and wildfire sites respectively. We then defined an 80m by 80m grid on which to place the survey plots. This grid size was chosen to allow for a minimum of 41 plots to be placed within the smallest site (no fire), which was greater than the estimated number of plots necessary to produce a statistically powerful ANOVA analysis. Within the two larger sites (wildfire and controlled burn), 41 and 42 plots were randomly selected from the total plots available (56 and 69, respectively) using Python (Version 3.1)



Figure 3.1. Map of the study area showing the no fire (a), controlled burn (b), and wildfire (c) sites from northwest to southeast. Surveyed plots (n=124) are shown as white circles and were randomly selected from an 80m by 80m grid overlaid on the study area. The location of the study area within the San Francisco Bay Area is indicated by a dark purple box within the inset map in the upper right.

3.2.2 Interviews with Amah Mutsun Tribal Members

This study is part of a multi-year research collaboration with the AMTB. Lead author Taylor is a non-Native scientist trained in the ecological and geospatial sciences; coauthor Sigona is an interdisciplinary social scientist and an Amah Mutsun tribal member. Taylor and Sigona conducted twelve semi-structured interviews with eleven tribal elders and cultural practitioners regarding their relationships to land stewardship practices and Amah Mutsun culture (UC Berkeley Institutional Review Board protocol #2020-01-12905) (Section S3.1). Interviewees were identified based on their experience stewarding lands for cultural purposes as a part of AMLT's Native Stewardship Corps, as well as elders or cultural leaders within the tribe. Many of these interviews were conducted in 2020 and 2021 using online video conferencing software (Zoom) due to risks of the COVID-19 pandemic and were 1.5 to 2.5 hours in length. Interviews were

transcribed using the same software and then manually corrected. The design and implementation of the biodiversity survey were informed both by these interviews as well as informal discussions during related fieldwork days with the Native Stewardship Corps from 2019 to 2022.

Following our biodiversity survey data collection, we identified all interview quotes related to fire (including wildfire, controlled burning, and cultural fire) and organized them into categories based on our three research objectives: 1) approaches to fire management; 2) fire and vegetation; and 3) fire severity. These quotes were used to contextualize our quantitative results and distinguish between Western and Indigenous approaches to fire management. These interviews have been de-identified for the purposes of this study.

3.2.3 Data Collection

In April 2022, we conducted a vegetation survey totaling 124 1 m² plots across the three sites. This survey consisted of two primary forms of data collection: identifying and recording the plant species present in each plot, and visually estimating the percentage of area coverage for eleven focal plant species within each plot. In doing so, we prioritized a subset of species that were deemed most ecologically and culturally critical for the more time-consuming collection of abundance data.

These eleven focal species were identified through discussions with staff and researchers at AMLT, AMTB leadership, and State Parks staff familiar with the ecosystem. We began with a list of all of the cultural species we knew to be significant to the Amah Mutsun community and removed the species that we did not expect to be present in a coastal grassland. We subsequently added in a number of invasive species of concern that were identified by our partners at State Parks. While we requested comments from members of the Native Stewardship Corps, we did not receive additional input. This final list totaled 17 species, 11 of which were ultimately present in our survey plots. These include six cultural plants – *Achillea millefolium* (common yarrow), *Chlorogalum pomeridianum* (California soap root), *Danthonia californica* (California oatgrass), *Frangula californica* (coffeeberry), *Madia sativa* (coast tarweed), and *Rubus ursinus* (Pacific blackberry) –, four invasive plants of particular importance in this area – *Briza maxima* (rattlesnake grass), *Holcus lanatus* (velvet grass), *Phalaris aquatica* (harding grass), and *Plantago lanceolata* (ribwort plantain) –, and *Baccharis pilularis* (coyote brush) (Table 3.1). *Artemisia douglasiana* (California mugwort), *Bromus sitchensis* var. *carinatus* (California brome), *Clinopodium douglasii* (yerba buena), *Elymus glaucus* (blue wild rye), *Fragaria chiloensis* (beach strawberry), and *Nassella pulchra* (purple needlegrass) were the six species that were originally included as cultural species of interest but were not found within our plots. Of these, *Artemisia douglasiana*, *Bromus sitchensis* var. *carinatus*, *E. glaucus*, *Fragaria chiloensis*, and *N. pulchra* were seen within the study area but were not found within our plots.

Table 3.1. List of the eleven focus species with scientific and common names listed. The group column includes both the life form (shrub or herbaceous) and whether it is considered an important cultural plant to the Amah Mutsun Tribal Band.

Group	Species Name	Common Name
Native Shrub	<i>Baccharis pilularis</i>	Coyote brush
Cultural Shrub	<i>Frangula californica</i>	Coffeeberry
	<i>Rubus ursinus</i>	Pacific Blackberry
Cultural Herbaceous	<i>Achillea millefolium</i>	Common yarrow
	<i>Chlorogalum pomeridianum</i>	California soap root
	<i>Danthonia californica</i>	California oatgrass
	<i>Madia sativa</i>	Coast tarweed
Invasive Herbaceous	<i>Briza maxima</i>	Rattlesnake grass
	<i>Holcus lanatus</i>	Velvet grass
	<i>Phalaris aquatica</i>	Harding grass
	<i>Plantago lanceolata</i>	Ribwort plantain

A number of invasive species are actively managed within the study area, either through herbicide treatment, manual pulling, or other techniques. These managed species include *Cortaderia jubata* (purple pampas grass), *Foeniculum vulgare* (common fennel), *Hypericum canariense* (Canary Islands St. John's wort), *Phalaris aquatica*, and *Ulex europaeus* (common gorse). Due to the importance of the *Phalaris aquatica* invasion in this area, we included it in our list of focal species. It should be noted that this species is only treated with herbicide within certain parts of the controlled burn site and not on the other two sites, an inconsistency that we discuss in more detail in the Discussion section.

The location of each plot was determined with submeter accuracy (mean = 0.58 m, median = 0.44 m) using a Bad Elf Flex GNSS receiver paired with the ESRI Field Maps phone application. A 1 m² quadrat was then placed immediately west of the located plot to designate the boundaries of the plot. There were eight instances in which the proliferation of *Toxicodendron diversilobum* (Pacific poison oak) made the planned plot location unsafe for data collection; these plots were shifted in whichever direction allowed for the minimum distance necessary to exclude the plant from the plot (14.45m on average). Seven of these eight shifted plots were located within the no fire site.

Within each plot, we recorded a list of all identifiable species present. We consider these lists to be highly representative but not complete, as there were immature grasses present across the study area that were not possible to identify to the species level even by an experienced botanist. When possible, the genus or family of the species was recorded instead. Some species were later identified via expert consultation using photos captured in the field.

In addition to species identification, we visually estimated the percent cover of the eleven focal species. We attached strings to delimit nine sub-squares within the quadrat – each representing approximately 11% of the total area – which aided in the visual

estimation of species' percent cover. Our estimates were rounded to the nearest 5%, and a minimum value of 5% was recorded if a focal species was present in a plot. These percentage values were estimated such that when a subset of the 11 focal species covered the entire plot, the estimates summed to 100% (this was the case for 9 plots of the 124, or 7% of all plots). All visual estimates were conducted by lead author Taylor to ensure consistency. Lastly, we recorded two photos of each plot (from above and at a low angle) and photographed any unknown species for later identification.

Next, we acquired Sentinel-2 satellite images prior to and following the wildfire in August and September 2020 and the controlled burn in November 2020. Sentinel-2 imagery contains 12 spectral bands ranging from 10m to 60m spatial resolution, and we utilized the level 2A imagery products which are orthorectified, geometrically corrected, and atmospherically corrected to surface reflectance values (Louis et al., 2019; Main-Knorn et al., 2017). We selected the first cloud-free image prior to and following each fire event using Google Earth Engine (Gorelick et al., 2017). For the wildfire, which burned from August 16 to September 22, 2020, the images were captured on August 2nd and September 26, 2020. For the controlled burn which occurred on November 19th, 2020, the images were captured on November 15th and November 25th, 2020 (Figure 3.2).

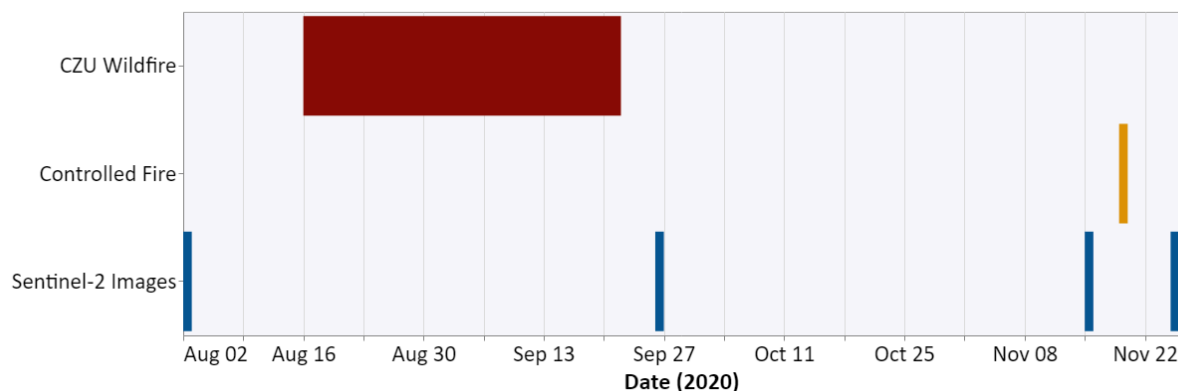


Figure 3.2. Timeline showing the dates of the two fire events and the dates of Sentinel-2 imagery captured in the fall of 2020.

3.2.4 Data Analysis

We calculated the Relativized Burn Ratio (RBR) for all four satellite images. This fire severity index was chosen to account for differences in pre-fire species composition across the two burned sites, and also due to its reliability in low biomass ecosystems such as grasslands (De Simone et al., 2020; Parks et al., 2014). RBR ($RBR = dNBR / (NBR_{prefire} + 1.001)$) uses the Normalized Burn Ratio (NBR) and difference NBR (dNBR) values to account for pre-fire differences, where $NBR = (NIR - SWIR) / (NIR + SWIR)$ and $dNBR = NBR_{prefire} - NBR_{postfire}$ (Key & Benson, 2006; Parks et al., 2014). We calculated NBR, dNBR, and RBR values in Google Earth Engine and then used ArcGIS Pro (Version 3.1.2)

to calculate the two fire severity metrics ($RBR_{\text{controlled burn}}$ and RBR_{wildfire}) for each of our plot locations.

We next compared how the abundance of the eleven focal species varied across the three sites. Given the non-normal distributions of our data, we used the Kruskal–Wallis one-way analysis of variance test to test for significant differences between the three sites (Kruskal & Wallis, 1952) and conducted pairwise comparisons using the Dunn post hoc test (Dunn, 1964). We used the *Scipy* and *Scikit_posthocs* Python packages to conduct these tests and used a probability threshold of 0.05 to determine significance (Terpilowski, 2019; Virtanen et al., 2020).

If a focal species was present in a given plot, this was counted as one occurrence. We then conducted chi-square tests for differences in focal species' occurrence across the three sites for six of the focal species for which the total number of occurrences was greater than 15: *Baccharis pilularis*, *D. californica*, *Holcus lanatus*, *Phalaris aquatica*, *Plantago lanceolata*, and *R. ursinus*. This threshold was based on the criteria commonly applied in the chi-square test in which all expected values be equal to or greater than 5 (Pearson, 1900). We applied the Bonferroni correction to all p values to account for multiple comparisons (i.e. multiplied all p values by 18, the total number of comparisons). To reveal which values contributed most to the chi-square statistic, we calculated the standardized residuals of each cell (i.e. each combination of plant occurrences and site), defined as follows using the observed (O) and expected (E) values: $(O - E) / \sqrt{E}$ (Sharpe, 2015).

3.3 Results

3.3.1 Interviews with Amah Mutsun Tribal Members

Table 3.2 contains the eleven interview quotes most directly related to our three research objectives: 1) approaches to fire management, 2) fire and vegetation, and 3) fire severity (Table 3.2). Quotes in the first category (n=4) provided insight into potential similarities and differences between Western and Amah Mutsun fire management, including how they may vary in practice, purpose, and temporal scale. These differences are discussed in more depth in section 3.4.5 of the Discussion. Quotes in the second (n=6) and third (n=1) categories contextualized the results of our vegetation survey and fire severity analysis and are therefore discussed alongside those quantitative results in sections 3.4.1, 3.4.2, 3.4.3, and 3.4.4 of the Discussion.

Our interviews were semi-structured and designed to enquire broadly about past and future Amah Mutsun stewardship practices (Section S3.1). In general, interviewees who had experience lighting cultural burns or supporting agency-led controlled burns spoke more extensively about the Tribe's relationship to fire and tended to be current or previous members of the Native Stewardship Corps.

Table 3.2. Selected quotes from interviews with Amah Mutsun Tribal Band members related to fire, organized into three categories based on our stated research questions.

Research Objective	Representative Quotes
Approaches to Fire Management	<p>Q1. “We smudge before fire, maybe say a prayer. Maybe the difference is how we start the fire...we can start the fire the traditional way with a stick [wooden drill] and a plank, these guys start the fire with torches...And we do ceremonies and smudge...it’s a big cultural difference between the firefighters and the Native American firefighters. And we’ve got more of a connection to the land. But overall, we all work together.”</p> <p>Q2. “The amount of thankfulness you pour into it and the humility you have spiritually cleanses your body. Because you’re walking away with a different perspective.”</p> <p>Q3. “And then there’s also education of the public, you know, because we see there’s not enough Amah Mutsun today to steward all the lands, but if we could teach others how to take care of the lands in the traditional ways...then that would be very important to restore the lands from issues like climate change and other devastation caused by all the invasives, and the poor management practices”</p> <p>Q4. “We’re working hard to restore the traditional ways of our ancestors in our lands...You know, the important thing is that we do it right, we do it thoughtfully, and the most important thing of all restoration is that you restore spirituality. To restore the spirituality to the land and to the people and to the rivers, and to the ocean, to the fish, the birds.”</p>
Fire and Vegetation	<p>Q5. “We’re there to restore the lands to how it used to be. Because there w[ere] doug[las] fir [trees] originally there, but now they’re just overpopulating and taking over. [Us] thinning out the trees and cutting and burning the burn piles is just opening up. Opening up for those native plants to come back, for the animals to come, and restoring the waterways and just renewing all relationships.”</p> <p>Q6. “It’s gonna be a lot of work if we try to go out there and...take the brush out with our hands. The fire can do a lot more work for us...and then next year everything will grow back, and it’ll grow back better...Native seeds need fire to come back. They’ve been dormant for so many years because they haven’t had fires.”</p> <p>Q7. “I would say it’s very important to prescribed or cultural[ly] burn. I’m learning that maybe burning annually or every two to four years is a great way to manage the land. And it’s helpful to manage the land...it opens waterways. It renews the native plants and trees and whether it’s for basketry plants or medicinal uses...I would say that fire is sacred. That’s what mother earth, it needs, it wants.”</p> <p>Q8. “Maybe do some prescribed burns...maybe bring back some nice [native] grasses from the fires and keep the invasive plant species out by burning and putting new seeds, putting our native seeds.”</p>

	<p>Q9. "It's just important that we have a place, that we have places where we can nurture those [basketry] materials. Because just like managing a fire, you have to manage the growth and the beds and the rhizomes of those plants in order for them to be healthy and usable for the baskets...If you're not taking care of the land, cutting it back, cultivating it properly, you're not gonna get the materials that you need...If we don't have the proper materials, we're not gonna be able to carry it [basketry practices] on."</p> <p>Q10. "The shift of the landscape caused this once 50 percent grass seed fire pit, that insinuated this whole area was a grassland, to now be this Douglas fir forest that's filled with woody vegetation...And within just a couple of 100 years, that grassland turned into a forest...A lot of those trees are 60 to 80 years old. So it's a very recent event. What happened was a lack of burning on this land, burning that grassland."</p>
Fire Severity	<p>Q11. "It was a wildfire so there was a lot of devastation and it wasn't a controlled or cultural burn. So there's a big difference there, of course. And it was really devastating."</p>

3.3.2 Fire Severity Analysis

In comparing the fire severity of the two fire events using the RBR index, we found that the CZU wildfire resulted in significantly higher severity than the controlled burn. The average RBR of all pixels within each site was 0.44 for the wildfire within the wildfire site, 0.20 for the controlled burn within the controlled burn site, and 0.07 for the no fire site (for the no fire site, RBR values were averaged across both fire events) (Figure 3.3). All three sites had significantly different RBR values compared to each other, as determined by the Kruskal-Wallis and Dunn tests ($F = 7930.43, p < 0.001$). Figure 3.4 shows how the distribution of RBR varied across the three sites; while the fire severity of the controlled burn was much lower than the wildfire, the variance of their distributions is similar (Figure 3.4).

In the case of the wildfire, the presence of seasonal fog and smoke from the fire itself as well as the longer duration of the fire event resulted in image capture dates that were farther apart. There was no precipitation at the site between the pre- and post-fire images. While there was some precipitation between the capture of the pre- and post-fire images in the case of the controlled burn, it occurred just one and two days prior to the burn; therefore, regrowth of vegetation between the images (taken five days before and five days after the burn) was unlikely. Visual inspection of the true color images confirmed that no visible vegetative regrowth was occurring in either post-fire image and that no other identifiable image artifacts were present.

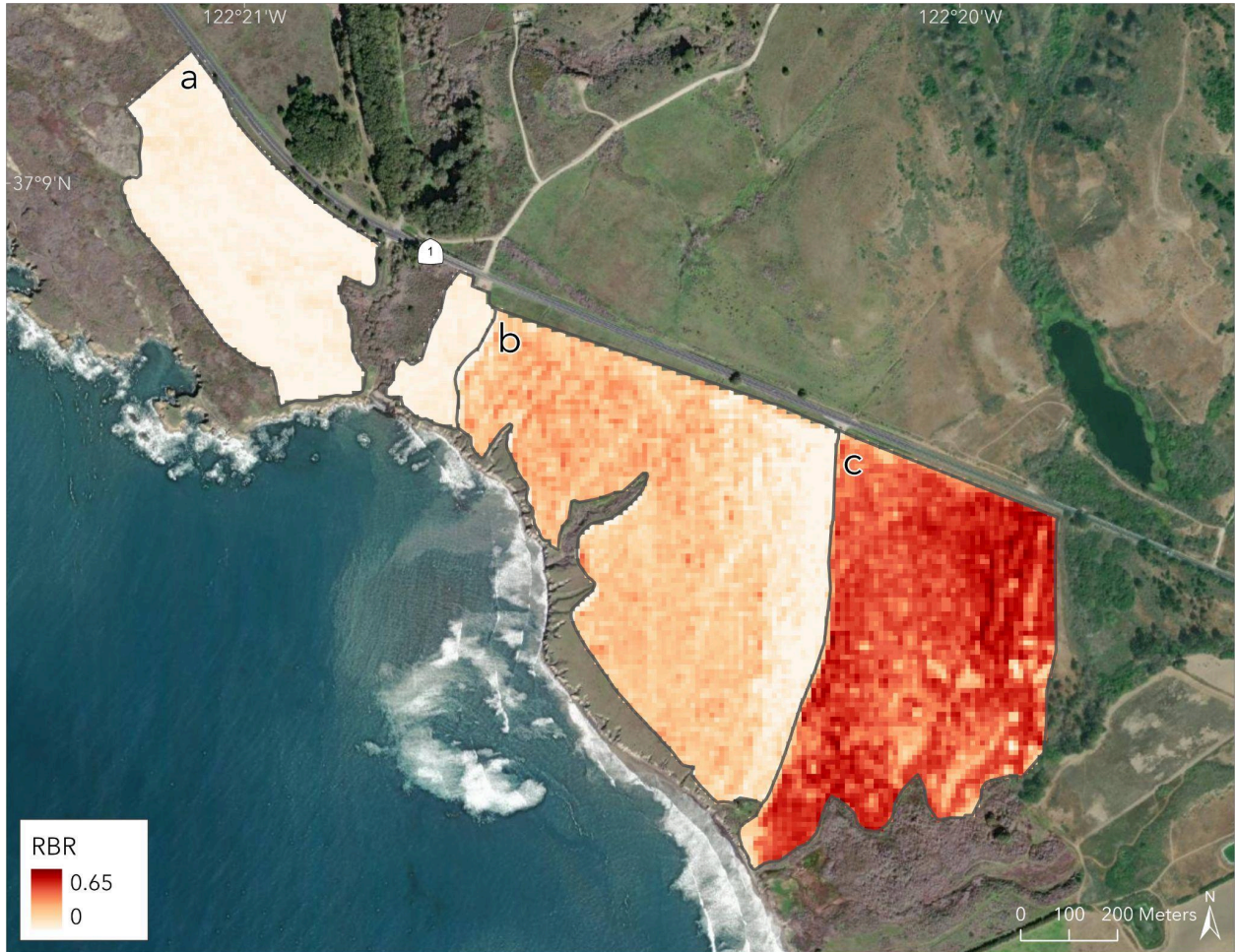


Figure 3.3. Relativized Burn Ratio (RBR) values for the two fire events as calculated from Sentinel-2 imagery across the three sites: no fire (a), controlled burn (b), and wildfire (c). The no fire site (a) contains the average RBR value of both fire events.

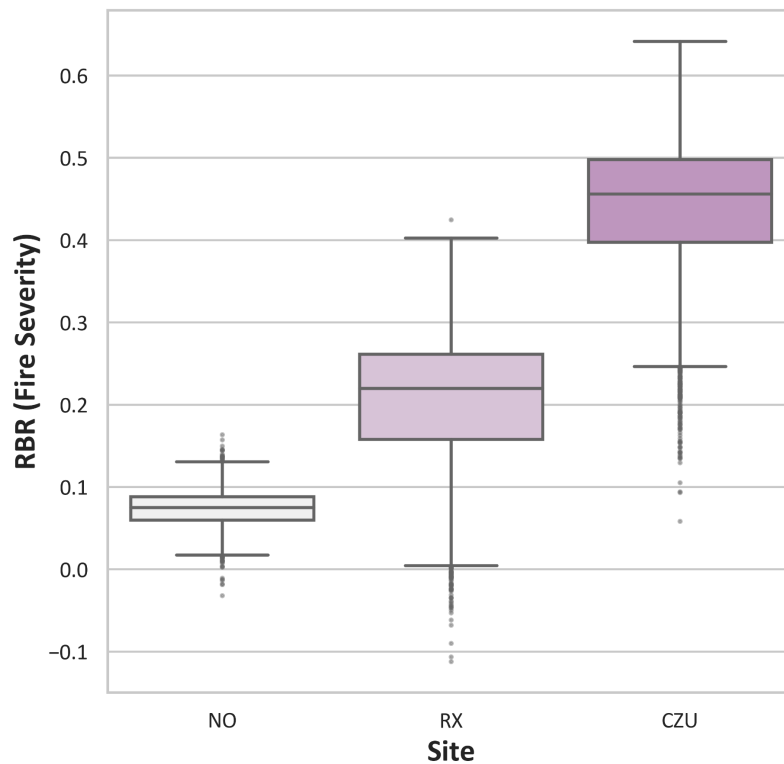


Figure 3.4. Boxplot showing the distribution of RBR values for the two fire events, as calculated from Sentinel-2 imagery, across the three sites: no fire (NO), controlled burn (RX), and wildfire (CZU). The no fire site contains the average RBR value of both fire events.

3.3.3 Abundance of Focal Species

Eight of the eleven species had significant differences in abundance across the three sites (Table 3.3). Of the three included shrub species (*Baccharis pilularis*, *Frangula californica*, and *R. ursinus*), all were significantly more abundant on the no fire site than the fire sites (Table 3.3, Figure 3.5). Of the culturally important species, *D. californica* was significantly more abundant on the fire sites than on the no fire site; we did not find significant differences in abundance for the other three cultural species (Table 3.3, Figure 3.5). The invasive species displayed different patterns: *Briza maxima* was significantly more abundant on the no fire site than on the other two sites; *Phalaris aquatica* was significantly less abundant on the controlled burn site than on the other two sites; *Plantago lanceolata* was significantly more abundant on the controlled burn site, followed by the wildfire site; and the abundance of *Holcus lanatus* was deemed significantly different across the sites by the Kruskal-Wallis test, but not deemed significant in the pairwise Dunn test (Table 3.3, Figure 3.5). Figure 3.5 shows the distribution of abundance values for four species of interest across the three sites.

Table 3.3. Mean percent cover of each focal species across the three sites: no fire (NO), controlled burn (RX), and wildfire (CZU) sites. Species with significant differences as indicated by the Kruskal-Wallis test are bolded. Significant differences between sites (as indicated by the post hoc Dunn test) are indicated with asterisks, with significantly higher mean percentage cover highlighted using increasing asterisks when applicable.

Group	Species	Mean percent cover (%)		
		NO	RX	CZU
Native Shrub	<i>Baccharis pilularis</i>	19.878*	0.952	2.317
Cultural Shrub	<i>Frangula californica</i>	3.902*	0.000	0.244
	<i>Rubus ursinus</i>	10.854*	2.500	0.976
Cultural Herbaceous	<i>Achillea millefolium</i>	0.365	0.238	0.000
	<i>Chlorogalum pomeridianum</i>	0.000	0.119	0.366
	<i>Danthonia californica</i>	1.341	11.071*	15.244*
	<i>Madia sativa</i>	0.000	0.833	0.000
Invasive Herbaceous	<i>Briza maxima</i>	1.829*	0.000	0.000
	<i>Holcus lanatus</i>	2.073	2.381	4.024
	<i>Phalaris aquatica</i>¹	22.561*	0.714	10.610*
	<i>Plantago lanceolata</i>	0.610	11.310**	4.024*

¹ Note that State Parks has been applying herbicide to *Phalaris aquatica* plants only on the controlled burn site following each controlled burn for 17 years.

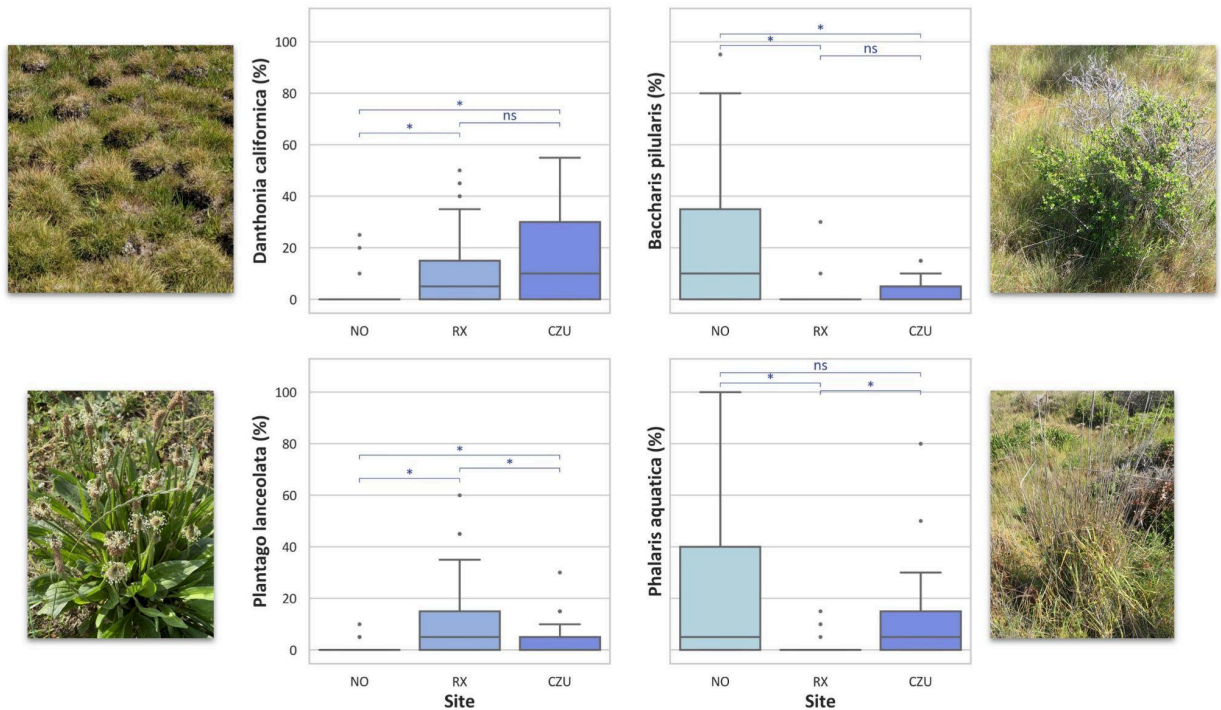


Figure 3.5. Boxplots of the percent cover (abundance) of *Danthonia californica* (California oatgrass), *Baccharis pilularis* (coyote brush), *Plantago lanceolata* (ribwort plantain), and *Phalaris aquatica* (harding grass) across the three sites: no fire (NO), controlled burn (RX), and wildfire (CZU). Asterisks indicate when a given pairwise comparison was statistically significant as determined by the post hoc Dunn test; 'ns' indicates that the pairwise comparison was not significant. Images show representative individuals for each species. *Danthonia californica* image used with permission from Mason Cole and *Plantago lanceolata* image used with permission from Petr Harant. Images of *Baccharis pilularis* and *Phalaris aquatica* were taken by Annalise Taylor.

3.3.4 Occurrence of Focal Species

Five of the six focal species tested had significant differences in occurrence across the three sites ($\chi^2 > 16.000$ and $p_{adj} < 0.01$) (Table 3.4). Of the two shrub species tested (*Baccharis pilularis* and *R. ursinus*), both occurred more frequently on the no fire site and less frequently on the controlled burn site; *R. ursinus* also occurred less frequently on the wildfire site while *Baccharis pilularis* did not (Table 3.4). The one culturally important species tested (*D. californica*) occurred more frequently on the two fire sites (Table 3.4). The three invasive species tested displayed different results. *Phalaris aquatica* occurred more frequently on the no fire site and less frequently on the controlled burn site, while *Plantago lanceolata* displayed the opposite pattern (Table 3.4). Lastly, the occurrence of *Holcus lanatus* was not significantly different across the three sites ($\chi^2 = 4.909$, $p_{adj} = 0.258$) (Table 3.4).

Table 3.4. Standardized residuals from the chi-square test of each plant-site combination, defined as $(O - E) / \sqrt{E}$, with O being the actual number of observations and E being the expected number of observations based on the null hypothesis. Standardized residuals with an absolute value greater than 2 generally indicate a lack of fit of the null hypothesis in that cell and are bolded (Sharpe 2015). The actual number of observations (occurrences) for each species on each site are listed in parentheses following the standardized residual value. Species names for which the chi-square test was significant are bolded.

Group	Species	Standardized Residuals (Occurrences)		
		NO	RX	CZU
Native Shrub	<i>Baccharis pilularis</i>	3.322 (24)	-2.942 (2)	-0.380 (11)
Cultural Shrub	<i>Rubus ursinus</i>	4.389 (25)	-2.347 (3)	-2.041 (4)
Cultural Herbaceous	<i>Danthonia californica</i>	-3.348 (3)	1.551 (23)	1.796 (24)
Invasive Herbaceous	<i>Holcus lanatus</i>	-0.905 (8)	-0.905 (8)	1.809 (17)
	<i>Phalaris aquatica</i>	2.121 (27)	-3.536 (3)	1.414 (24)
	<i>Plantago lanceolata</i>	-3.153 (4)	2.668 (28)	0.485 (19)

3.4 Discussion

Through a multi-year collaboration with the AMTB, we designed and implemented a biodiversity survey at one of the most frequently burned grasslands in California and two adjacent sites with contrasting fire histories. This survey generated a detailed snapshot of ethnobotanical biodiversity, shrub encroachment, and plant invasions within an extraordinary natural experiment. In comparing species-level occurrence and abundance data across these three sites, we have expanded our knowledge of how individual cultural, native, and invasive species may respond differently to fire regimes of varying frequency and severity. This fine-scale analysis of plant species' association with different types of fire holds critical implications for coastal grasslands throughout California, which are one of the most endangered ecosystems in the country (Noss & Peters, 1995). Further, our interviews with tribal members revealed important insights that are directly applicable to the increasing number of collaborations between Indigenous communities and state agencies throughout the country. Our quantitative and qualitative findings will directly inform the Tribe's current work to restore a number of coastal grassland ecosystems in this region.

Methodologically, our research aimed to model more culturally relevant methods for studying biodiversity and stewardship in culturally important ecosystems and joins a growing body of literature that incorporates Indigenous voices and knowledge to inform and drive ecological conservation (Long et al., 2020; Marks-Block et al., 2019; Mucioki et al., 2022; Sowerwine et al., 2019; Taylor et al., 2023). By integrating vegetation data collected in the field and remote sensing analysis with our interviews with Amah Mutsun tribal members, we show how to contextualize applied ecological research within a broader cultural and social landscape. The perspectives of tribal members and the place-based context they offered were used to evaluate not only the results of our quantitative analysis, but also the broader outcomes of the controlled burning program at

Cascade Field. We first discuss the results of our fire severity and biodiversity survey analysis within the context of related quotes from tribal members. Next, we discuss potential differences between Amah Mutsun and Western fire management. Finally, we discuss the limitations of our study and draw conclusions about the future of fire stewardship partnerships and their implications for California's grasslands.

3.4.1 Fire Severity

While fire severity was not specifically addressed in the interviews, interviewees universally distinguished controlled and cultural fires from wildfires, with the latter causing devastation and risk to human and non-human life (Table 3.2, Q11). Many interviewees specifically mentioned the CZU wildfire as it directly impacted the Native Stewardship Corps' operations and led to a forced evacuation.

Our remotely sensed metric of fire severity (RBR) similarly revealed that the controlled burn resulted in significantly lower fire severity than the CZU wildfire across the study area (Figures 3.3 and 3.4). This finding fits with our expectation, as one of the main factors distinguishing controlled or cultural fire from wildfire is a lower resulting severity. Given that fire severity is defined by the extent of vegetation change and soil impacts as a result of a fire, most fire severity indices are influenced by pre-fire species composition (Keeley, 2009). However, we utilized the RBR index as it had been shown to better account for differences in pre-fire species composition in low biomass ecosystems (De Simone et al., 2020; Miller & Thode, 2007). We found that RBR effectively distinguished not only the two types of fire, but also revealed marked variability within the controlled burn site (Figures 3.3 and 3.4). Given that we would expect the severity of these controlled burns to vary year to year due to differences in fuels, weather conditions, or burning strategy, this analysis also serves as a baseline to compare these biennial controlled burns to one another. RBR and other indices that relativize the impacts of a fire to the pre-fire vegetation condition therefore offer considerable advantages over dominant vegetation indices such as dNBR in grasslands and when analyzing lower severity fires such as controlled or cultural burns.

3.4.2 Shrub Species

One of the themes that emerged in the interviews was the importance of fire for reducing the encroachment of shrubs and other woody vegetation. Many interview participants discussed how cultural fire keeps grasslands open and prevents shrub and woodland conversion of coastal grasslands (Table 3.2: Q5, Q6, Q7, Q10). This ecological succession – grasslands converting to coyote brush scrub and then ultimately to woodlands – is common along the Central Coast of California (Ford & Hayes, 2007). As one tribal member explained: “A lot of those trees are 60 to 80 years old. So it's a very recent event. What happened was a lack of burning” (Table 3.2: Q10). This quote, which references Douglas fir conversion of a nearby grassland, highlights how quickly this ecosystem conversion can take place in the absence of fire stewardship or other disturbances.

This concept was borne out by the results of our biodiversity survey, which showed that the shrub species were significantly less abundant on the two fire sites as compared to the site without fire (Table 3.3, Figure 3.5). The frequency of the controlled burns conducted at Cascade Field (roughly every two to three years) approximates that of traditional burning practices within this disturbance-adapted ecosystem (Anderson, 2006). Given how quickly shrub establishment can occur, it is this frequency that prevents the establishment and growth of many shrub species (McBride & Heady, 1968; Williams et al., 1987). The shrubs most commonly found in this area – *Baccharis pilularis* (coyote brush), *Frangula californica* (coffeeberry), *R. ursinus* (Pacific blackberry), and *T. diversilobum* (Pacific poison oak) – are fire tolerant and adapted to resprout and recover quickly from a single fire event (Ford & Hayes, 2007; Keeley, 1987; McBride & Heady, 1968; Stewart, 1978). Therefore, controlled burning programs with a longer interval between fires may enable shrubs to establish, and subsequent burns may only temporarily top-kill these species; this may be particularly true for *Baccharis pilularis* (McBride & Heady, 1968). We observed many top-killed *Baccharis pilularis* plants on the wildfire site that were already beginning to resprout approximately 20 months following the fire, which aligns with previous research on this shrub (Ford & Hayes, 2007). Given that dead plant matter was not included in our percent cover observations, our abundance comparison shows the wildfire and controlled burn sites to be comparable with regard to shrub abundance (Table 3.3, Figure 3.5). However, our occurrence comparison shows that the wildfire site had significantly more established *Baccharis pilularis* individuals than the controlled burn site and is therefore likely to continue converting from a coastal grassland to a coastal shrub ecosystem without further disturbance or management intervention (Table 3.4).

In practice, conducting controlled or cultural burning consistently enough to prevent the establishment of shrubs is challenging, due to a host of barriers such as obtaining permits and insurance (Clark et al., 2021; Marks-Block & Tripp, 2021). Much of the success of the burning program at this site can be attributed to favorable abiotic conditions, including a predictable wind pattern, lack of nearby habitation that could be impacted by smoke or fire risk, and existing fire breaks (the ocean and the highway) bounding two sides of the site (T. Hyland, personal communication, March 27, 2023). The markedly lower abundance and occurrence of shrub species at the controlled burn site suggests that this type of fire management – however difficult it may be to implement under less favorable conditions – successfully prevents the conversion of endangered coastal grasslands to shrub-dominant ecosystems.

3.4.3 Cultural Species

Many interviewees discussed the power of cultural fire to support the growth of native plants and specifically the cultural keystone plants used for food, medicine, and basketry (Table 3.2: Q5, Q6, Q7, Q9). Learning about, gathering, and using cultural plants was a strongly expressed priority of many interviewees. Given this connection, restoring cultural fire practices is seen not only as a direct form of cultural revitalization, but also as a key foundation for other cultural practices such as basketry, ceremonies, and traditional

medicines (Table 3.2: Q9). This cyclical link between cultural fire and the renewal of food, medicine, and basketry plants and therefore other cultural practices has been emphasized by members of many other Indigenous communities in California (Goode et al., 2022; Marks-Block et al., 2019; Sowerwine et al., 2019).

In our statistical analysis, we found this fire-plant connection to be especially true for *D. californica* (California oatgrass), an important cultural plant and formerly dominant perennial bunchgrass (Reiner, 2007). *D. californica* was significantly more abundant and occurred more frequently on the sites with fire (Figure 3.5, Table 3.3, and Table 3.4). Given that past research of the effect of fire on *D. californica* has been fairly inconclusive, this is an important finding that suggests it is fire tolerant and may even benefit from fire under certain conditions (Reiner, 2007). However, considering that our study is an observational one, more experimental research is necessary to determine the nature of this relationship. The cultural shrub species *Frangula californica* and *R. ursinus* were both significantly more abundant on the no fire site, which we would expect given that one objective of repeated and frequent controlled burning is to reduce shrub establishment and growth (Figure 3.5, Table 3.3, and Table 3.4). Three other important cultural species found within our plots did not show significant differences between the three sites, likely due to low occurrence within our plots. These were *Achillea millefolium* (common yarrow), *Chlorogalum pomeridianum* (California soap root), and *M. sativa* (coast tarweed) which only had 3, 2, and 1 observations respectively. The former was observed across all three sites, while the latter two were only observed (both within plots and otherwise) on the sites with fire. While many geophytes such as *Chlorogalum pomeridianum* are stimulated by fire, the absence of other Indigenous stewardship practices associated with its gathering (such as replanting smaller bulblets and aerating the soil) may partially explain why its populations are relatively small at this site despite the recent fires (Anderson and Lake 2016). Although these populations are relatively less abundant than the other cultural species we found, their presence at this site is nonetheless highly significant to the Tribe. In addition, we observed a number of other cultural keystone species that were not observed in our plots, including *Artemisia douglasiana* (California mugwort), *Bromus sitchensis* var. *carinatus* (California brome), *Fragaria chiloensis* (beach strawberry), and *N. pulchra* (purple needlegrass). **This is one of the ways in which a typical biodiversity study design that is optimized to reduce spatial bias may obscure information about the landscape that is important to tribal members and other land managers.** We therefore recommend that researchers work closely with cultural practitioners and tribal members familiar with the area to design methods that are more likely to capture more culturally important plant populations, either by adapting survey methods or by developing an additional protocol that records them opportunistically alongside any standardized data collection protocols. This latter approach places Indigenous and non-Indigenous methods in parallel, rather than compelling tribes to fit their knowledge systems within existing Western ecological paradigms (Buell et al., 2020).

Importantly, the presence of cultural species does not indicate that an area is suitable for gathering of food and medicine plants (Mucioki et al., 2022; Taylor et al., 2023). There are many other ways to view a plant community from an Amah Mutsun

perspective, including (but not limited to) the quality of the plant materials, whether or not an individual permit is required to gather plants, and the ability to connect spiritually with a place without the scrutiny of recreational users. These aspects were not evaluated as a part of this study but are important considerations for gathering of cultural plants. Accessibility is another decisive factor, and the lower abundance of shrubs, *T. diversilobum* (Pacific poison oak, which causes painful skin rashes), and *Phalaris aquatica* (harding grass, which grows in dense patches and up to 1.5 m in height) at the controlled burn site makes it easier and safer to navigate than the other two sites. Lastly, the herbicide application occurring on the controlled burn site likely precludes gathering of cultural foods, medicines, and materials, given potential health implications and cultural beliefs (Dent et al., 2023). This issue is discussed in more detail in the following sections.

3.4.4 Invasive Species

Interviewees frequently discussed the threat of invasive species and cited cultural fire and other Indigenous stewardship practices as a means of controlling these invasions (Table 3.2: Q3, Q6, Q8). One interviewee implied that burning alone may not be enough to control these invasive species, explaining the need to plant or spread native seeds in the burned area following the fire (Table 3.2: Q8). This is supported by an experimental study in western Oregon that found that “burning without sowing large quantities of native seed could be counterproductive” as the soil seed banks of previously invaded grasslands tend to be dominated by invasive species (Maret & Wilson, 2005).

Similarly, our survey results presented a more mixed picture for invasive species. The analysis of some of the invasive species included in our biodiversity study was confounded by State Parks’ historical and ongoing management of invasive species through hand removal and herbicide treatments. Of the invasive plants not directly targeted by current or past management, our findings indicated that controlled fire and wildfire may favor some, such as *Plantago lanceolata* (ribwort plantain), and deter others, such as *Briza maxima* (rattlesnake grass), which is supported by the literature (McMahon, 1991; Mojzes & Kalapos, 2014) (Figure 3.5, Table 3.3, and Table 3.4). *Plantago lanceolata* is common in highly disturbed areas and controlled burning is typically an ineffective means of control (DiTomaso et al., 2013). Given that its seeds may survive in the seed bank for up to 20 years, it may be that this plant will continue to reestablish after each controlled burn without other management interventions (DiTomaso et al., 2013). However, given that its ecological impacts are considered more minor than *Phalaris aquatica* for example, and State Parks’ constraints on time and resources, this outcome may be acceptable to some land managers. While our interviews with Amah Mutsun tribal members did not discuss this type of tradeoff, future work with the Tribe could investigate how community members approach fire stewardship in the context of highly invaded grassland ecosystems.

There are a number of invasive plants that are the target of active control efforts across one or all of the three sites in our study: *Cortaderia jubata* (purple pampas grass), *Foeniculum vulgare* (common fennel), *Hypericum canariense* (Canary Islands St. John's

wort), *Phalaris aquatica*, and *U. europaeus* (common gorse). Within our plots, none of these species were observed except for *Phalaris aquatica*, implying that these control efforts, which include hand removal and herbicide application, have been largely successful. In particular, historic photos show widespread invasions of *U. europaeus*, which was present within the study area during our survey in only isolated patches. *Phalaris aquatica* is a particularly important invasive species in coastal grasslands statewide, as it tends to establish in thick monocultures that choke out native plants and is exceedingly difficult to remove. For at least the past 17 years, State Parks has been applying herbicide to *Phalaris aquatica* plants on the controlled burn site following each burn (T. Hyland, personal communication, March 27, 2023). Our findings indicate that this approach has been fairly successful: *Phalaris aquatica* was significantly less abundant and had significantly fewer occurrences at the controlled burn site than in the surrounding sites (Figure 3.5, Table 3.3, and Table 3.4). However, the treatment of *Phalaris aquatica* and subsequent burning is possibly leaving an ecological gap for other ruderal species to populate, which could be contributing to the dominance of *Plantago lanceolata* at the controlled burn site. While these interventions appear to be very effective in controlling *Phalaris aquatica*, the use of herbicides is discussed below as a difference between Amah Mutsun stewardship and Western land management practices.

3.4.5 Differences between Amah Mutsun and Western Fire Management

Our interviews with Amah Mutsun tribal members revealed key differences between Amah Mutsun and Western techniques for ecosystem stewardship with fire.

The practice of Amah Mutsun cultural fire differs from Western fire management in the gratitude, humility, and sacredness that comes from a deep and ancestral connection to the land being burned (Table 3.2: Q1, Q2, Q7). The critical importance of this spiritual connection has been highlighted by cultural practitioners from many other California tribes, including the North Fork Mono, Yurok, and Karuk Tribes among many others (Cagle, 2019; Goode et al., 2022; Klein et al., 2022). Many interviewees distinguished Mutsun cultural fire practices from controlled burning, while simultaneously acknowledging the value of partnerships with non-Native land managers and agency partners. One interviewee expressed hope that these traditional stewardship practices could be adopted by more land managers (Table 3.2: Q3).

The purposes of Amah Mutsun cultural fire were defined broadly by interviewees and went beyond fuel reduction and wildfire mitigation, which are commonly emphasized in Western fire management in California (Long et al., 2021; Martinez et al., 2023). While multiple interviewees cited the importance of reducing fuel loads on the landscape to reduce risk of severe wildfire, this was only one of many goals offered. Interviewees discussed the importance of opening up grassland landscapes (e.g. preventing woody plant succession), restoring spiritual connections within the land, restoring waterways, supporting native plant germination, and encouraging proper growth of medicine and basketry plants (Table 3.2: Q4 to Q10). While many of these impacts are well-documented, these goals are often not prioritized by Western management agencies (Martinez et al., 2023).

Finally, the interviews revealed the long temporal scale of tribal members' perspectives with respect to fire. While there is widespread acknowledgement that colonization has caused environmental devastation within Mutsun homelands, many interviewees expressed a long temporal view of the landscape as a source of hope for its restoration. From a Western point of reference, two centuries encompass almost the entire colonial period in California. Notably, tribal members tended to frame the environmental changes wrought by colonization as relatively recent phenomena. Q10 discusses the suppression of cultural fire and subsequent build up of fuels and conversion of grasslands to woodlands as beginning only in the last few centuries, a "very recent event." This finding aligns with other works in underscoring the temporal depth of Indigenous environmental perspectives and place-based knowledge (Goode et al., 2022; Long et al., 2020).

In addition to these broad categories, our study revealed other potential contrasts between Amah Mutsun and Western fire management. While it is impossible to distill a singular Mutsun worldview of this ecosystem, we can highlight how it broadly differs from a Western land management perspective. As institutions, Western management agencies can be siloed and focused on narrow performance metrics or targets, such as the eradication of an invasive species or reduction of wildfire risk (Long et al., 2020). For example, while an agency might be focused on a single goal (i.e. eradicate a certain invasive plant species), a Mutsun steward might instead be considering how to best support a web of native species of all kinds (e.g. animals, insects, fungi, people), in addition to the health of the soils and waters of this area.

As mentioned above, State Parks is using periodic application of the herbicide glyphosate to remove *Phalaris aquatica* from the controlled burn area. Glyphosate is widely used in grassland restoration to remove invasive species with the aim of enabling native species to reestablish in an area. However, recent work has found that it negatively impacted soil microbes and mycorrhizal fungi, may decrease non-target plant health and nutrition, and may even increase non-native forb cover (Bueno de Mesquita et al., 2023; Kanissery et al., 2019; Stover et al., 2017). It is not known how the lower frequency of glyphosate application at the controlled burn site (approximately every other year) and prior controlled burning may reduce these adverse effects. Testing of glyphosate accumulation in soil, surface water, and cultural plants may be necessary to better determine the impacts of this treatment. The application of herbicides and pesticides in culturally important ecosystems can either restrict tribal members' ability to gather plants or expose them to potentially harmful chemicals. Given their close relationship with cultural plants and risk of exposure, Indigenous weavers throughout California are among the strongest advocates for the cessation of herbicide and pesticide use on public lands (Dent et al., 2023). Ultimately, when any single management outcome is prioritized (e.g. eradication of one plant), there may be unintended side effects that might be of crucial importance to an Indigenous community (e.g. subsequent dominance of a different invasive plant, inability to gather cultural plants due to herbicide or pesticide contamination, potential impacts on water quality or animals) (Dent et al., 2023). Therefore, land managers that aim to partner with Indigenous communities should initiate a conversation about potentially controversial management

techniques such as herbicide application or the use of heavy machinery so as not to contradict the community's broader goals or intentions.

Lastly, Western management agencies may define success using quantitative or standardized metrics that can unintentionally contradict some goals of Indigenous communities. For example, biodiversity studies tend to value greater species richness and evenness, as evidenced by the widespread use of diversity indices such as the Shannon and Simpson indices. However, from the perspective of gathering, a relatively large population of even only one cultural plant is highly valuable to the Tribe, and denser patches can actually facilitate gathering and stewardship (Marks-Block et al., 2019). Therefore, important gathering areas may in fact have low species richness and low species evenness. This is especially true with respect to culturally important grasses, as gathering grass seed is more practical in an area in which the target species is fairly dominant. **Our work joins other recent research in demonstrating that if land managers and ecologists use only Western metrics of biodiversity and a limited temporal scale to evaluate the results of controlled or cultural burning programs, we are likely to overlook essential parts of the ecosystem and cultural landscape** (Goode et al., 2022; Lake, 2013; Martinez et al., 2023; Mason et al., 2012; Ray et al., 2012).

3.4.6 Limitations of this Study

There are several limitations to this study. It is important to note that our work evaluates a novel combination of repeated controlled burning with herbicide treatment and hand removal of invasive plants rather than a Mutsun cultural fire stewardship regime. Second, our survey results represent only a snapshot in time and therefore do not capture plant species that do not emerge or bloom every year, or do so at other times of the year. Interannual climate variations also impact the emergence of many grassland species. Future work might partner with cultural practitioners within the AMTB to implement a multi-year monitoring approach with surveys conducted at different times during the spring and summer to capture information about more plant species, such as culturally important geophytes. Third, we moved a few plot locations based on the proliferation of *T. diversilobum* (Pacific poison oak) so as to reduce unsafe exposure to the plant's oil compounds, so our data are systematically biased against this species and any other plants typically associated with it. However, by logging which plots were shifted, we found that the vast majority of the poison oak is growing on the no fire site, which corroborates our finding that the occurrence of shrubs is higher on the no fire site. Fourth, as is common with studies that incorporate stochastic events such as wildfire, this is not a controlled experiment and there is no systematic survey data available across all three sites prior to the fires. Therefore, we are not able to extrapolate causal mechanisms or analyze the direct effects of these fires. Fifth, we used 5% as the minimum percent cover value if a focal species was present in a plot which in some cases overestimated the abundance of species with very low (1-2%) cover. Lastly, the methods of this study do not capture a holistic view of this area. For example, we focused solely on plant species, which excludes other organisms (e.g. animals, insects, fungi) and other metrics of environmental health (e.g. water, soil, and air conditions).

3.4.7 Amah Mutsun Community Participation

As a means of increasing transparency and accountability, we used the framework developed by David-Chavez and Gavin (2018) to evaluate the levels of Amah Mutsun community participation in our research. Specifically, parts of our research process are best classified as collegial (“community members and researchers work together, community members have primary authority over the research process”) or collaborative (“community members and researchers work together, researchers have primary authority over the research process”), while we consider other parts of the process to be consultative (“community members asked for opinions and consulted, decisions made by researchers”) (David-Chavez & Gavin, 2018). The design stage of our research contained more aspects of collegial or collaborative participation. Prior to defining our research, we spent two years building relationships and trust with Amah Mutsun community members, assisting with tribally led mapping projects, and defining mutual research interests. Given that the Tribe did not have a formal process for approving research, we presented our project and obtained consent from the AMTB Tribal Council before beginning our interviews. All interview participants were paid an honorarium and sent a gift box with culturally relevant foods and medicines. Authors Taylor and Sigona also joined the Native Stewardship Corps for a number of outings into various ecosystems to learn about their relationships with land and cultural plants in a more contextualized and experiential setting over the past four years. Staff at AMLT initially expressed interest in this project as an interesting case study that could be used to inform the Tribe’s other fire and restoration work, and the biodiversity survey was then designed to answer culturally relevant research questions. As the survey began, Taylor joined the Native Stewardship Corps at the study site to learn more about the most important plants, which guided the designation of our focal species.

While we aimed to conduct a genuinely collaborative study, there were several parts of the implementation and analysis stages of our research that are better classified as consultative, which aligns with trends that David-Chavez and Gavin (2018) found in a larger review. For example, tribal members and partners were often consulted via email messages to confirm data collection protocols, which garnered few responses. In addition, much of our interaction with the Amah Mutsun community was limited to the AMTB Tribal Council and Native Stewardship Corps, which make up a small subset of the community. In particular, the COVID-19 pandemic limited our opportunities to organize or attend in-person events with a broader proportion of the community. Future work with the Tribe could be more deeply collaborative by involving more tribal members in the implementation of the research; one option would be to host outings to explore or document biodiversity at all three sites in partnership with the Native Stewardship Corps or with interested tribal practitioners and compensate them for their time. Furthermore, the results of our work need to be communicated within the context of the Tribe’s existing restoration plans and incorporated to ensure that this work benefits the community. To support more truly collaborative research, more grant-awarding agencies could fund and recommend best practices such as community events or honoraria for study participants. In addition, more studies that discuss their approach to collaboration

with Indigenous communities and acknowledge shortcomings will help to improve the field of community-engaged research (David-Chavez & Gavin, 2018).

3.5 Conclusions

This site is a vanishingly rare example of a long-term, biennially burned coastal grassland and, although it is not directly managed by the Amah Mutsun Tribal Band, it offers important corollaries to their cultural fire practices. The CZU wildfire complex that burned through the area only two months prior to a recent controlled burn facilitated a unique comparison of how these two types of fire histories – as well as a third site with no recorded fire – may be impacting shrubs, cultural plants, and invasive plants on the landscape. This observational study offers critical insight into the plant communities and ethnobotanical diversity present two years after these fires, and should be repeated periodically to reveal how the species assemblages of these areas diverge or converge over time. Our study design and interpretation were developed within a multi-year partnership with the AMTB through both interviews and site visits with community members conducted over many years. Our results revealed that this burning program may benefit certain cultural plants (including *D. californica*) and reduce grassland conversion to a shrub-dominated ecosystem, while use of herbicides may inhibit gathering of cultural plants. By incorporating Amah Mutsun voices and perspectives, our study also revealed how the biodiversity metrics typically employed by Western-trained ecologists may contradict some of the community's diverse goals and aims. Our findings, while specific to this region and the Amah Mutsun community, are widely applicable to similar research and management partnerships with Indigenous communities globally.

While expanding the practice of controlled burning would likely aid in conserving California's coastal grasslands, greater support for cultural burning and Indigenous stewardship specifically would strengthen these conservation efforts and generate greater ecocultural benefits for Indigenous communities. When and where Indigenous communities have more opportunity to resume their stewardship practices, they can accelerate the restoration of these fire-adapted ecosystems. This would have positive implications not only for the biodiversity and perseverance of California's grasslands, but would also increase the drought resilience of certain watersheds, reduce the risk of severe wildfire, and contribute to the revitalization of cultural practices that are essential to many Indigenous communities.

3.6 Acknowledgements

We are profoundly grateful to our partners at the Amah Mutsun Tribal Band and Amah Mutsun Land Trust for their trust and support. In particular, we appreciate the time and stories of our interview participants and the members of the AMLT Native Stewardship Corps, who allowed us to join for various site visits and generously shared their perspectives. The Amah Mutsun Tribal Council and Tribal Chairman Valentin Lopez graciously offered their time to approve and guide this study throughout the research process. Thank you also to our wonderful collaborators: Dr. Robert Cuthrell and Rick

Flores provided a deep knowledge of the study area, Amah Mutsun cultural plants, and hands-on help with plant identification; Tim Hyland provided critical context regarding the study site that contributed heavily to our objectives and methods; and Dr. Van Butsic provided statistical support. A special thank you to the people who supported the vegetation survey and provided feedback on the manuscript: Dr. Carol Rhodes, Dr. Madelynn Taylor, and Dr. Chippie Kislik. We thank two anonymous reviewers whose suggestions greatly improved the manuscript. Figures were created in Python using the seaborn, altair, and matplotlib packages.

Data Availability

Public datasets utilized in this study included California fire perimeter data from CAL FIRE (<https://gis.data.ca.gov/datasets/CALFIRE-Forestry::california-fire-perimeters-all-1/about>) and San Mateo County elevation data (<https://data-smcmaps.opendata.arcgis.com/datasets/6ce67725cf44432fb7d579534e2fa544/about>). NRCS soil survey data were downloaded from the Web Soil Survey tool (<https://websoilsurvey.nrcs.usda.gov/>). Data collected in the field and spatial data analyzed for this publication are archived in a public repository on Figshare: <https://doi.org/10.6084/m9.figshare.23915913>. Scripts used to analyze data are archived in a public repository on Github: https://github.com/annietaylor/grassland_fire.

Chapter 4

Using Sentinel-2 imagery to measure spatiotemporal changes and recovery across three adjacent grasslands with different fire histories

Abstract

Grasslands are highly biodiverse ecosystems that hold deep cultural significance for many Indigenous communities in California, USA. Indigenous fire stewardship of grasslands involves frequent, low severity burning and is a long-held stewardship practice that supports grassland ecosystem health. As a result of Indigenous communities' advocacy and increasing evidence of the ecological importance of fire, the California state legislature has invested in the restoration of intentional burning (the practice of deliberately lighting low severity fires, which includes both cultural and prescribed fire) in an effort to reduce the occurrence and severity of wildfires. Recognizing both the growing need to monitor the impacts of these smaller, low severity fires and the relative lack of remote sensing studies that study fire in grasslands, in this paper we propose methods that leverage Sentinel-2 imagery to reveal important inter- and intra-annual variation in grasslands before and after fires. Specifically, we analyzed and explored the value of three methodological approaches: 1) the complete time series of the Normalized Burn Ratio (NBR), 2) annual summary metrics (mean, fifth percentile, and amplitude of NBR), and 3) maps depicting spatial patterns in these annual NBR metrics before and after fire. We also used a classification of pre-fire vegetation to stratify these analyses by three dominant vegetation cover types (grasses, shrubs, and trees). We applied these methods to a unique study area in which three adjacent grassland sites had diverging fire histories and showed how grassland recovery from a low severity intentional burn and a high severity wildfire differed both from each other and from a reference site with no recent fire. On the low severity intentional burn site, our results showed that annual NBR metrics recovered to pre-fire values within one year, and that regular intentional burning on the site was promoting greater annual growth of both grass and shrub species even in the third growing season following a burn. In addition, we found that annual productivity of individual shrubs appeared to increase more than that of grasses in the years following the intentional burn. In the case of the high severity wildfire, our metrics indicated that this grassland had not returned to its pre-fire phenological signals in at least three years after the fire, indicating that it may be undergoing a longer recovery or an ecological shift. These proposed methods address a growing need to study the effects of small, intentional burns in low-biomass ecosystems such as grasslands, which are an essential part of cultural fire restoration.

4.1 Introduction

Indigenous communities throughout California, USA have long cultural histories of practicing fire stewardship in diverse ecosystems (Martinez et al., 2023). This practice of fire stewardship (often referred to as cultural burning) varies across the state and

commonly aims to restore culturally important ecosystems, improve food and basketry materials, open waterways, and reduce the risk and severity of wildfire, among other objectives (Adlam et al., 2022; Goode et al., 2022; Lake et al., 2017; Long et al., 2021). The significance of cultural burning has gained attention as wildfires have become increasingly more severe and frequent across California in just the past decade, a deadly pattern that is expected to continue (Goss et al., 2020). This upward trend in wildfire severity and frequency is caused by a confluence of factors, including anthropogenic climate change and sociopolitical changes instituted during the European colonization of California in the 1700s that prohibited the practice of cultural burning and decimated Indigenous nations (Goss et al., 2020; Martinez et al., 2023). Nonetheless, many Indigenous communities have persisted in preserving the knowledge and practice of cultural fire; however, many continue to meet significant barriers to cultural burning, such as difficulties obtaining the required permits, equipment, and certifications (Clark et al., 2021; Marks-Block & Tripp, 2021; Martinez et al., 2023). In the absence of this deliberate application of frequent, low severity fire, many of California’s disturbance-dependent ecosystems have declined and fuel loads have accumulated to dangerous levels (Lightfoot & Lopez, 2013; Long et al., 2021; Martinez et al., 2023).

As a result of Indigenous communities’ advocacy and increasing evidence of the ecological importance of fire, the California state legislature has invested millions of dollars into the restoration of cultural burning and prescribed fire in an effort to reduce the occurrence and severity of wildfires (Forest Management Task Force, 2021). Prescribed fire – also referred to as controlled burning – is the practice of lighting low severity fires to reduce fuel loads and support the growth of fire-adapted plants. Cultural burning practices, which vary between Indigenous communities, tend to be distinct from typical state-led controlled burning practices in a number of ways. In addition to the variety of ecological and cultural purposes described above, cultural burning is a spiritual practice deeply rooted in generations of place-based knowledge (Marks-Block & Tripp, 2021). While there are other important differences in the purposes and practices of controlled burning and cultural burning that we do not discuss in depth here, we use the term “intentional burn” to refer to the broader category of deliberately set, low severity fires that encompasses both of these categories.

Given the size of this investment and the sea change in fire management policy, research that analyzes the impact of these intentional burns is critical. In particular, post-fire studies help to determine if these intentional burns are meeting their stated goals, which may include a reduction in certain wildfire fuels, recovery of important native plants, or hydrological restoration. While field-based surveys provide valuable and direct observations of these effects, the extent of fire restoration in California demands a suite of methods that are more scalable, affordable, and efficient. Remote sensing – or more specifically the analysis of satellite imagery – enables the study of ecosystem health and function over large areas and long periods and is therefore critical in measuring how fire impacts different ecosystems.

Many remote sensing analyses of fire impacts on vegetation focus primarily on wildfires (rather than intentional burns) and evaluate only a limited number of points in time. Common methodologies use a pre- and post-fire image to calculate wildfire

severity, or use single images captured many years after the wildfire to measure the extent of vegetation recovery (Szpakowski & Jensen, 2019). Many of these methods are specifically tailored to conifer-dominated forest ecosystems, and therefore best capture mortality of high-biomass vegetation or recoveries that endure many years (Calhoun et al., 2022; Szpakowski & Jensen, 2019). There are fewer remote sensing methods developed for the study of other types of fire – in particular, lower severity fire such as intentional burns – and for the study of fire in non-forest ecosystems, such as grasslands and shrublands (Calhoun et al., 2022).

The study of how different types of fire impact grasslands is of particular importance. Grasslands are simultaneously one of California's most biodiverse and most threatened ecosystems and are home to many plant and animal species that are significant to Indigenous communities across the state (Noss & Peters, 1995; Taylor et al., in press). California's grassland ecosystems are dependent on frequent, low severity fires for renewal and to prevent the encroachment of shrub and tree species (Ford & Hayes, 2007; Reiner, 2007). Specifically, low severity fires increase soil nutrient availability and stimulate germination and seed production in many native perennial grasses (Reiner, 2007). Conversely, high severity fires (such as wildfires) and the complete suppression of fire have both been shown to reduce nutrient availability and may favor non-native annual grasses over native perennial grasses (Reiner, 2007). However, because grasses regrow much faster and exhibit greater seasonal variation than trees, annually derived metrics of vegetation recovery (which work well for tracking the impacts of fires on forests) may not capture meaningful metrics of recovery in grasslands.

Many remote sensing studies use annually derived vegetation index (VI) values (e.g. an annual mean or median) to track disturbance recovery over many years (Szpakowski & Jensen, 2019). For fast-changing grasslands, these annually integrated VI values may fail to capture important ecological changes that could be captured by measures of intra-annual VI variation. Given the importance of seasonal variation and recent increases in computational capacity, remote sensing studies of disturbance are increasingly calculating VI-derived phenological curves from dense time series of satellite imagery. These VI-derived phenological curves yield detailed metrics that describe these intra-annual changes in growth and senescence (Dronova & Taddeo, 2022). Examples of these phenological metrics include the timing of the start and end of the growing season, the rate of growth or senescence, and the amplitude of the annual growth curve, among many others (Dronova & Taddeo, 2022). Computation of these phenological metrics typically relies on imagery with high temporal resolution, such as imagery from the MODIS satellites (Descals et al., 2021; Di Mauro et al., 2014). Though useful over large areas, MODIS imagery has a 1 km spatial resolution, which makes it infeasible to reliably study phenological phenomena occurring at smaller scales and more generally introduces greater uncertainty in phenological interpretation of spatially heterogeneous ecosystems (Helman, 2018). From 2019 to 2022, 91.44% of the intentional burns in California were smaller than 1 km² and have therefore not been the subject of many phenological studies, despite the post-fire recovery of these ecosystems having immense ecological and societal importance (CAL FIRE, 2023). Therefore, in order to study phenological changes caused by these smaller intentional burns, we need to

develop methodologies that utilize imagery with higher spatial resolution and adequate temporal resolution.

To address this, our study used Sentinel-2 satellite imagery, which has a considerably higher spatial resolution than MODIS imagery (10m to 60m) and a temporal resolution of 5 days. Combined with its appropriate spectral sensitivity, Sentinel-2 imagery enables phenological analysis of smaller areas, and is therefore more applicable to the study of intentional burning. However, its lower temporal resolution means that Sentinel-2 derived metrics of phenological *timing* (such as the timing of the start, peak, and end of season) are often delayed (Gómez-Giráldez et al., 2020; Zhou et al., 2019). Therefore, we propose a methodology that focuses instead on the shape of the VI-derived phenological curve. Specifically, we analyze five years of Sentinel-2 imagery and summarize annual trends using the VI mean, fifth percentile, and amplitude values over time and space.

To test our proposed methodology, we chose a unique contiguous grassland along the Central Coast of California with three diverging fire histories: one site that has undergone low severity controlled burns every two to three years, a second site that experienced a high severity wildfire, and a third adjacent site with no recorded fire in over 100 years (Figure 4.1a). These sites also represent a natural comparison between three emblematic land management approaches in California: frequent intentional burning, fire suppression followed by high severity wildfire, and fire suppression, respectively. Given the logistical challenges associated with researching fire, few studies have examined sites with a history of repeated intentional burns. Fewer still are able to compare a repeatedly burned grassland to a grassland burned by a wildfire, or to study the recovery of those sites over many years.

These three sites had different proportions of grass, shrub, and tree cover prior to both fire events, which we expected to respond differently to the low and high severity fires. We therefore stratified our analysis based on these vegetation cover types to further interrogate the ecological impacts of the fires. We predicted that the grasses and shrubs on the controlled burn site would benefit from the influx of nutrients and sunlight provided by the low severity fire, leading to a temporary increase in productivity (Reiner, 2007). In the case of the wildfire, we predicted that the shrubs and trees would experience an immediate decline in productivity in the year following the fire due to direct mortality, with these plants either converting to grass or, in the case of shrubs, resprouting in subsequent years (Ford & Hayes, 2007; Fuhlendorf et al., 2011). We expected productivity to fluctuate on the no fire site due to climatic variation during the study period, but to a much lesser degree than on the sites that experienced fires. While we expected a temporary shock from both fire events, we aimed to investigate whether the wildfire site would appear more phenologically similar to the controlled burn site after three years, or return to a signal more closely resembling the site with no fire.

Recognizing the growing need to monitor the impacts of smaller, low severity fires and the aforementioned gaps in current methodologies, we propose methods that leverage a dense time series of high spatial resolution imagery to reveal important inter- and intra-annual variation in grasslands before and after two fires. Specifically, we propose three different spatiotemporal analyses that illuminate changes in three key

metrics derived from Sentinel-2 imagery. We test these methods in a unique study area in which adjacent grasslands have diverging fire histories to show how recovery from a low severity controlled burn and a high severity wildfire differ from each other and from an adjacent reference site with no recent fire. These methods are intended to be readily scalable and broadly applicable in monitoring the impacts of both high and low severity fires in grasslands and other low-biomass ecosystems.

4.2 Methods

4.2.1 Study Area

The study area is a coastal grassland located within Año Nuevo State Reserve in San Mateo County, California (Figure 4.1a). Within this area, there are adjacent sites with three different fire histories: an area that has undergone state-led controlled burns every two to three years since 1991 (and most recently in fall of 2017, 2020, and 2023), an area that burned in the CZU wildfire complex in August and September 2020, and an area that has not experienced fire of any kind for over 100 years (Figure 4.1a). We refer to these three sites as the controlled burn, wildfire, and no fire sites respectively. The CZU wildfire burned at very high severity within the study area and caused significant vegetation mortality (Taylor et al., in press). A field survey conducted in April 2022 revealed extensive mortality of trees and shrubs as a result of the wildfire, with many shrubs just beginning to resprout (Taylor et al., in press). The controlled burn that is the focus of this study was conducted in November 2020 and burned at low severity (Taylor et al., in press).

We describe the process of defining our study area boundaries in Taylor et al. (in press). Briefly, CAL FIRE's official fire perimeters were used to delineate the controlled burn and wildfire sites, and the highway (State Route 1) and a bluff trail defined the eastern and western borders of each site respectively (CAL FIRE & USFS, 2022). We used the Soil Survey Geographic database (commonly known as SSURGO) to limit soil type differences between the three areas and San Mateo County's elevation dataset (1 m spatial resolution) to exclude ravines and large drainages based on slope (NRCS, 2022; San Mateo County, 2017). At the end of this process, the sites were 0.46, 0.35, and 0.23 km² for the controlled burn, wildfire, and no fire sites respectively (Figure 4.1a).

4.2.2 Satellite Imagery Preprocessing

Using the Google Earth Engine (GEE) Python API and the *geemap* Python package, we acquired and processed Sentinel-2 multispectral satellite images capturing the study area every 5 days from 2018 to 2023 (Gorelick et al., 2017; Wu, 2020). We utilized the Level-2A imagery products in GEE which are atmospherically corrected, orthorectified, geometrically corrected, and harmonized across processing adjustments implemented in 2022 (European Space Agency, 2021). This dataset was available from December 31, 2018 up to present day in our study area.

We initially filtered out all Sentinel-2 images with an image-wide cloudy pixel percentage of 93% or greater. Next, we used the Sentinel-2 cloud probability dataset in

GEE to remove pixels that had more than a 15% probability of containing clouds. We then removed any remaining images for which the coverage of the study area was negligible after filtering out cloudy pixels. After this cloud-filtering process, our analysis included 263 images in total.

This imagery contains 12 spectral bands ranging from 10m to 60m spatial resolution. We used the near-infrared (NIR, 10m) and shortwave-infrared-2 (SWIR2, 20m) bands to calculate the Normalized Burn Ratio or NBR as follows: $NBR = (NIR - SWIR2) / (NIR + SWIR2)$. NBR was developed to identify burned areas, which reflect lower NBR values than vegetated areas (Key & Benson, 2006). Conversely, photosynthetically active vegetation with a higher moisture content will reflect a higher NBR value (Hislop et al., 2018). We chose NBR because in addition to being sensitive to photosynthetic activity and vegetation moisture content, and it is less likely to saturate when compared with other vegetation indices such as the Normalized Difference Vegetation Index (Hislop et al., 2018; Key & Benson, 2006; Parks et al., 2014). For each pixel, we calculated the average NBR value across all available images within a 30-day time frame before and after each image (i.e. a 30-day moving average) to control for noise in the overall signal. Based on the 5-day temporal revisit time and gaps in the data caused by clouds, each of these 30-day averages was calculated from 1 to 6 images. We expected variation in the NBR signal based on changes in vegetation health (caused by year-to-year changes in precipitation as well as the fires) as well as seasonal changes (i.e. higher NBR values during the growing season when vegetation is most photosynthetically active).

4.2.3 Pre-fire Vegetation Classification

We expected our results to vary based on the primary pre-fire vegetation cover type within each Sentinel-2 pixel, and therefore created a land cover classification distinguishing grasses, shrubs, and trees – the three cover types most dominant within the study area. Using ArcGIS Pro (Version 3.2.0), we first classified an image captured by the National Agriculture Imagery Program (NAIP) on May 27th, 2020, which contained four spectral bands (red, green, blue and near-infrared) at 60 cm spatial resolution. We manually delineated training samples of the three cover classes based on the NAIP image and pre-fire Google Earth imagery and then ran a supervised, pixel-based support vector machine classification with 500 samples per class. The accuracy of the classification was evaluated using a separate set of manually delineated testing samples. The final classified map is shown in Figure 4.1b.

All Sentinel-2 pixels contained completely within our study area ($n = 9,793$) were converted to polygons of the same boundaries and size ($100m^2$). We then calculated the percentage of each vegetation cover class within each pixel-based polygon using both ArcGIS Pro and the *geopandas* package in Python (Van den Bossche et al., 2023).

We next compared how the percent cover of these vegetation types varied across the three sites. Given the non-normal distributions of our data, we used the Kruskal–Wallis one-way analysis of variance test to test for significant differences between the three sites (Kruskal & Wallis, 1952) and conducted pairwise comparisons using the Dunn post hoc test (Dunn, 1964). We used the *scipy* and *scikit_posthocs* Python

packages to conduct these tests and applied the Bonferroni correction to all p-values to account for multiple comparisons (i.e. multiplied all p values by 9, the total number of comparisons), then used a probability threshold of 0.05 to determine significance (Terpilowski, 2019; Virtanen et al., 2020).

If a given cover class made up 60% or more of the polygon, it was considered a dominant cover type (Figure 4.1c). Only pixels with a dominant cover type were included in the vegetation-stratified analysis (n = 9,248). The classification and analysis were conducted in the WGS 1984 UTM Zone 10N projection (EPSG 32610).

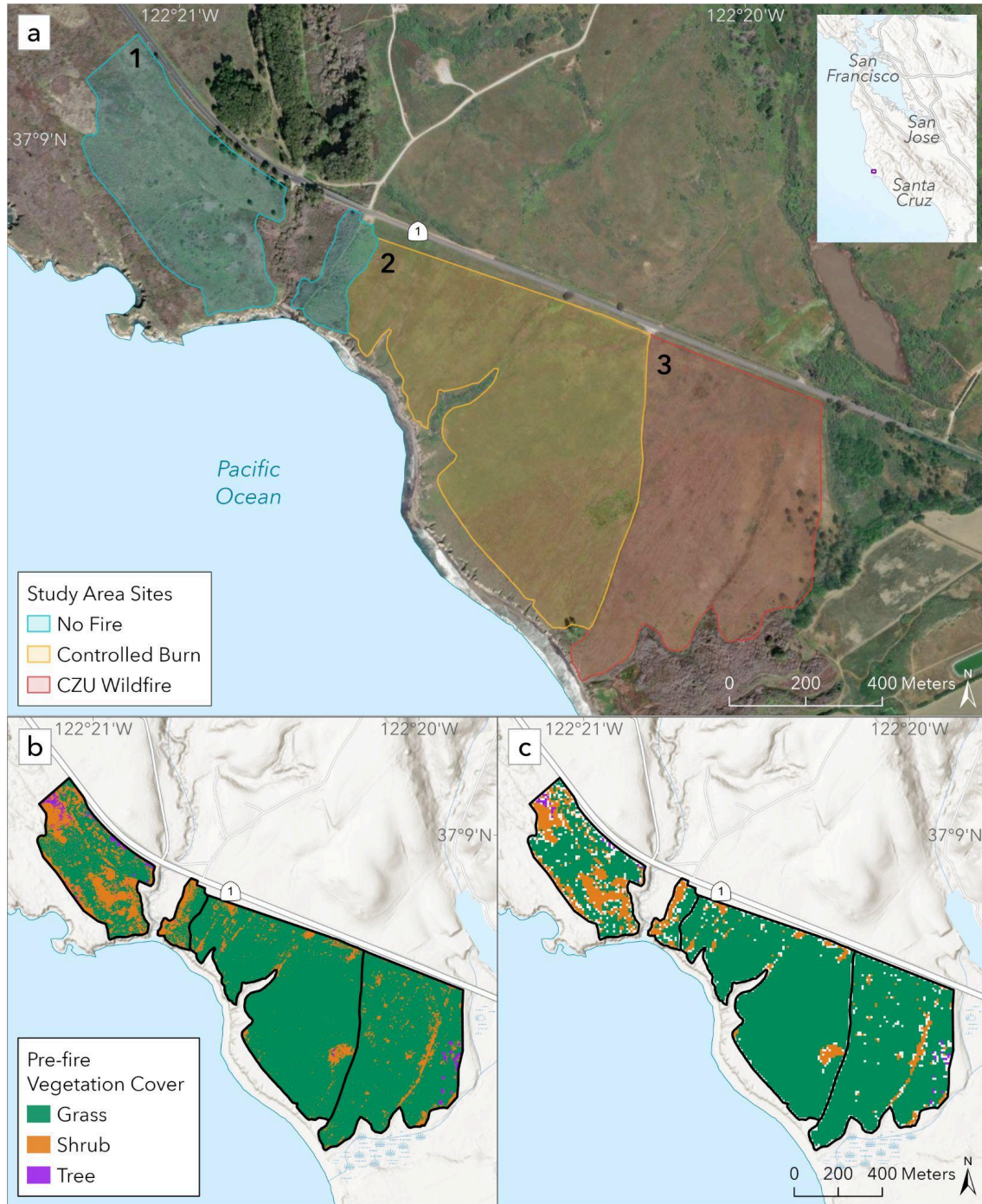


Figure 4.1. Map (a) shows the study area with the no fire (1), controlled burn (2), and wildfire (3) sites located from northwest to southeast. The location of the study area within the San Francisco Bay Area, California, USA is indicated by a dark purple box within the inset map in the upper right. Map (b) shows the results of the pre-fire vegetation cover classification of the 5/27/2020 NAIP image (60cm spatial resolution) within the study area, and map (c) shows the dominant vegetation cover class within each Sentinel-2 pixel of those located completely within the study area and with a single vegetation cover totaling 60% or greater. Pixels with no dominant vegetation cover (i.e. with no single vegetation cover class totaling 60% or more within the pixel) are not shown on this map and were excluded from the vegetation-stratified analyses.

4.2.4 Spatiotemporal Analysis

The full time series showing the mean 30-day moving average NBR was calculated for each site and for each site-vegetation pair (i.e. shrub-dominated areas on the controlled burn site). The processed Sentinel-2 images were then split into their corresponding water years, defined in California as October 1st of the previous year to September 30th of the given year. For example, water year (WY) 2022 ran from October 1, 2021 to September 30, 2022. There were two main exceptions to this rule in our analysis. First, WY 2019 begins on December 31, 2018 due to a lack of surface reflectance imagery available in GEE within our study area prior to that date. Second, WY 2020 had no usable images in August due to the smoke from the CZU wildfire and other clouds, and we excluded four clear images captured in September in order to standardize our analysis; this ensured that WY 2020 represented only pre-fire data for both fire events. We originally tested all of our analyses with those four September images included to test the magnitude of impact that their exclusion would have on our results and found a negligible effect.

We then summarized over each of these water years at the pixel level across our study area. Using the original (not the 30-day moving average) NBR values, we calculated the mean, 5th percentile, and 95th percentile values for each water year and for each pixel. The 5th and 95th percentile values were used in place of the annual minimum and maximum values in order to exclude potential outlier values caused by noise. We then calculated the amplitude as the difference between the 95th and 5th percentile values for each pixel and water year.

To summarize trends across the three sites, we took a random sample of 200 points from each site and calculated the mean for each metric (mean, fifth percentile value, and amplitude) and water year. To account for pre-fire differences between each of the fire sites and the no fire site used as our reference, we also calculated a pairwise offset for each of these metrics and for each site similar to Di Mauro et al. 2014. This pairwise offset was defined as the average difference between the pre-fire (WYs 2019 and 2020) values on each fire site and the no fire site. This average difference was calculated separately for each fire site and then added to all of the sampled values within that fire site across all five water years. This allowed us to not only compare the absolute values of these metrics across the sites (using the original values), but also how the metric values on each fire site varied *relative to the no fire site* (pairwise offset values).

We next tested whether the pairwise offset values on the fire sites differed significantly from the no fire site in the two post-fire years (WYs 2022 and 2023). Given the non-normal distributions of our data, we used the Mann Whitney U test to test for significant differences between each fire site's pairwise offset values and the no fire site (Mann & Whitney, 1947). We used the *scipy* Python package to conduct this test and applied the Bonferroni correction to all p-values to account for multiple comparisons (i.e. multiplied all p values by 12, the total number of comparisons), then used a probability threshold of 0.05 to determine significance (Virtanen et al., 2020).

Finally, we calculated the mean for each metric (mean, fifth percentile, and amplitude) and water year on each site stratified by the dominant vegetation type in the

sampled pixels. In this case, it was not always possible to sample 200 points from each vegetation-site pair. In the case of grass cover, 200 grass-dominated pixels were randomly selected across all three sites. For shrub-dominated pixels, 200 were randomly selected from the no fire site, whereas all 168 and 139 shrub-dominated pixels were selected from the controlled burn and wildfire sites respectively. All 27 and 19 tree-dominated pixels were selected from the no fire and wildfire sites respectively, and the controlled burn site had no tree-dominated pixels.

4.3 Results

4.3.1 Vegetation Classification

The vegetation cover classification of the 2020 NAIP image had an accuracy of 98.40% when compared with an independent set of testing samples (Figure 4.1b). The no fire site was classified as 42.90% shrub, 3.61% tree, and 53.49% grass cover. The controlled burn site was classified as 7.39% shrub, 0.15% tree, and 92.46% grass cover. The wildfire site was classified as 42.90% shrub, 3.61% tree, and 53.49% grass cover.

Of the 9,248 Sentinel-2 pixels located completely within the study area with a vegetation cover totaling 60% or greater, 88.72% (8,205) were dominated by grass cover, 10.78% (997) by shrub cover, and 0.50% (46) by tree cover (Figure 4.1c). There were no tree-dominant pixels on the controlled burn site (Figure 4.1c).

The Sentinel-2 pixels within each of the sites differed significantly in terms of mean pre-fire grass, shrub, and tree cover ($F > 900$, $p_{\text{adj}} < 0.001$, $n = 9,793$ for all three Kruskal-Wallis tests). The pixels within the controlled burn site had the highest mean cover of grass (93.14%), followed by the wildfire site (90.02%), and then the no fire site (55.43%); all sites were significantly different from each other in terms of grass cover ($p_{\text{adj}} < 0.001$). The no fire site had the highest mean cover of shrubs (41.31%), followed by the wildfire site (9.03%), and then the controlled burn site (6.70%); all sites were significantly different from each other in terms of shrub cover ($p_{\text{adj}} < 0.001$). The no fire site had the highest mean cover of trees (3.26%), followed by the wildfire site (0.94%), and then the controlled burn site (0.16%); the no fire site was significantly different from each of the fire sites in terms of tree cover ($p_{\text{adj}} < 0.001$), but the two fire sites were not significantly different from one another ($p_{\text{adj}} = 1.00$).

4.3.2 Full Time Series

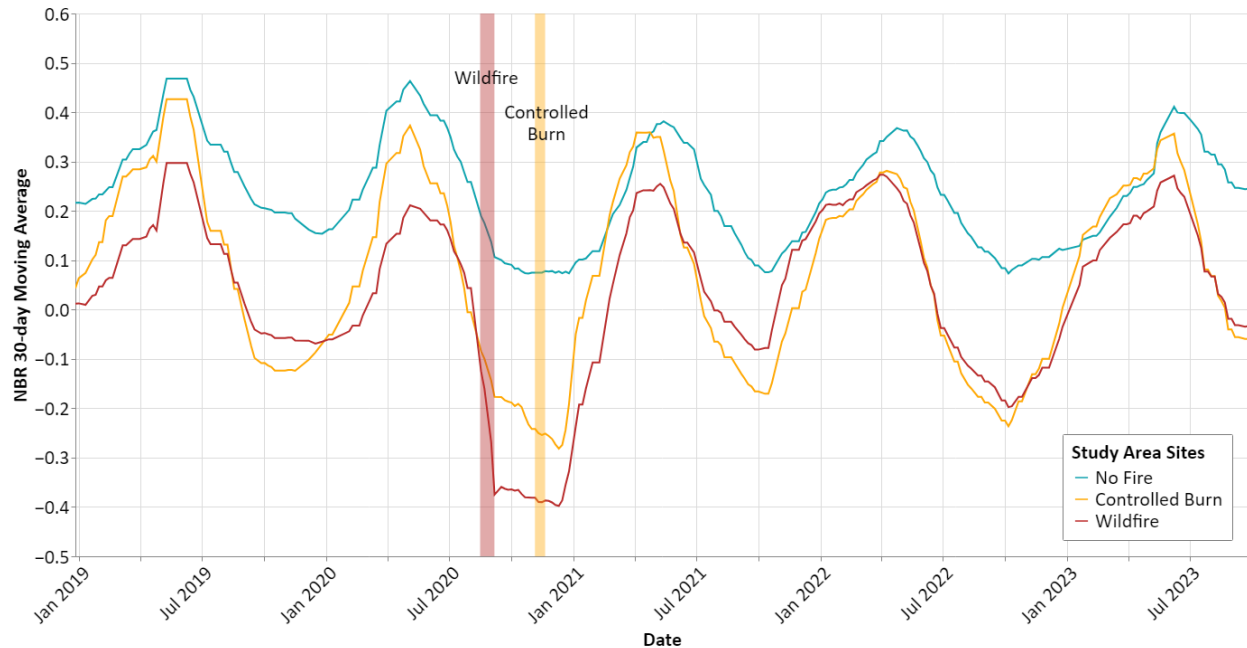


Figure 4.2. Thirty-day moving average of the mean NBR values across each study area site during the study period (December 31, 2018 to September 30, 2023). The timing of the wildfire and controlled burn events are shown as labeled vertical bars shaded in red and orange respectively.

Figure 4.2 shows how the 30-day moving average of NBR values on each site changed over time, which helped to reveal general trends in the green-up (i.e. seasonal growth) and senescence of vegetation before and after the two fire events. The no fire site generally had a shallower phenological curve (i.e. smaller amplitude) and higher NBR values on average throughout the year. The controlled burn site had a greater amplitude in its annual phenological curve than either site prior to the fire events, and had a lower minimum value than the other two sites in all years except the year immediately following the wildfire event. The controlled burn's phenological curve appeared to recover to pre-fire patterns in the year immediately following the controlled burn. The dip in NBR following the two fire events was much greater for the wildfire than for the controlled burn. The wildfire site had the lowest maximum value of the three sites in all years except the second growing season following the fire events (WY 2022). In general, the amplitude of the wildfire site's phenological curve was similar to the no fire site prior to the wildfire, and less than that on the controlled burn site and larger than that on the no fire site following the wildfire. Both sites appeared to recover to a maximum NBR similar to the pre-fire values in the growing season immediately following the fire events (WY 2021).

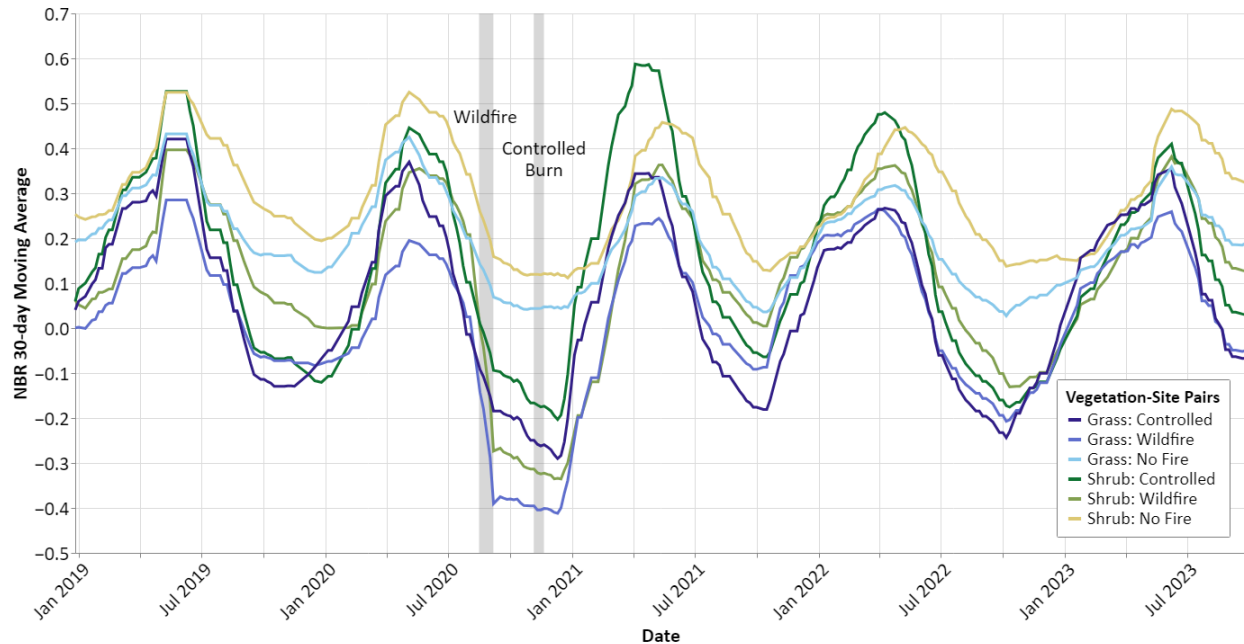


Figure 4.3. Thirty-day moving average of the mean NBR values within the Sentinel-2 pixels dominated by grasses, shrubs, and trees within each study area site across the study period (December 31, 2018 to September 30, 2023). The wildfire site experienced significant vegetation mortality and vegetation type changes during and after the fire; therefore, the vegetation categories should not be interpreted as remaining constant in the period following the fire. The timing of the wildfire and controlled burn events are shown as labeled vertical bars shaded in gray. Tree-dominated pixels were excluded from this figure due to small sample size and to facilitate legibility.

Figure 4.3 shows how the 30-day moving average of NBR values changed over time within the pixels dominated by grasses and shrubs on all three sites. In comparing the shrub-dominated pixels across all three sites, we found that the amplitude of the phenological curve was greatest on the controlled burn site. Notably, the shrub-dominated pixels on the controlled burn site had a higher maximum NBR and earlier green-up in the two water years following the burn as compared to the no fire and wildfire sites. In comparing the grass-dominated pixels, the no fire site and controlled burn site exhibited similar phenological patterns during the growing season, with the dry season minimum being consistently much lower on the controlled burn site. The amplitude of both the grass- and shrub-dominated pixels on the wildfire site increased dramatically following the wildfire and more closely resembled the shape of the controlled burn phenological curves.

4.3.3 Annual Metrics

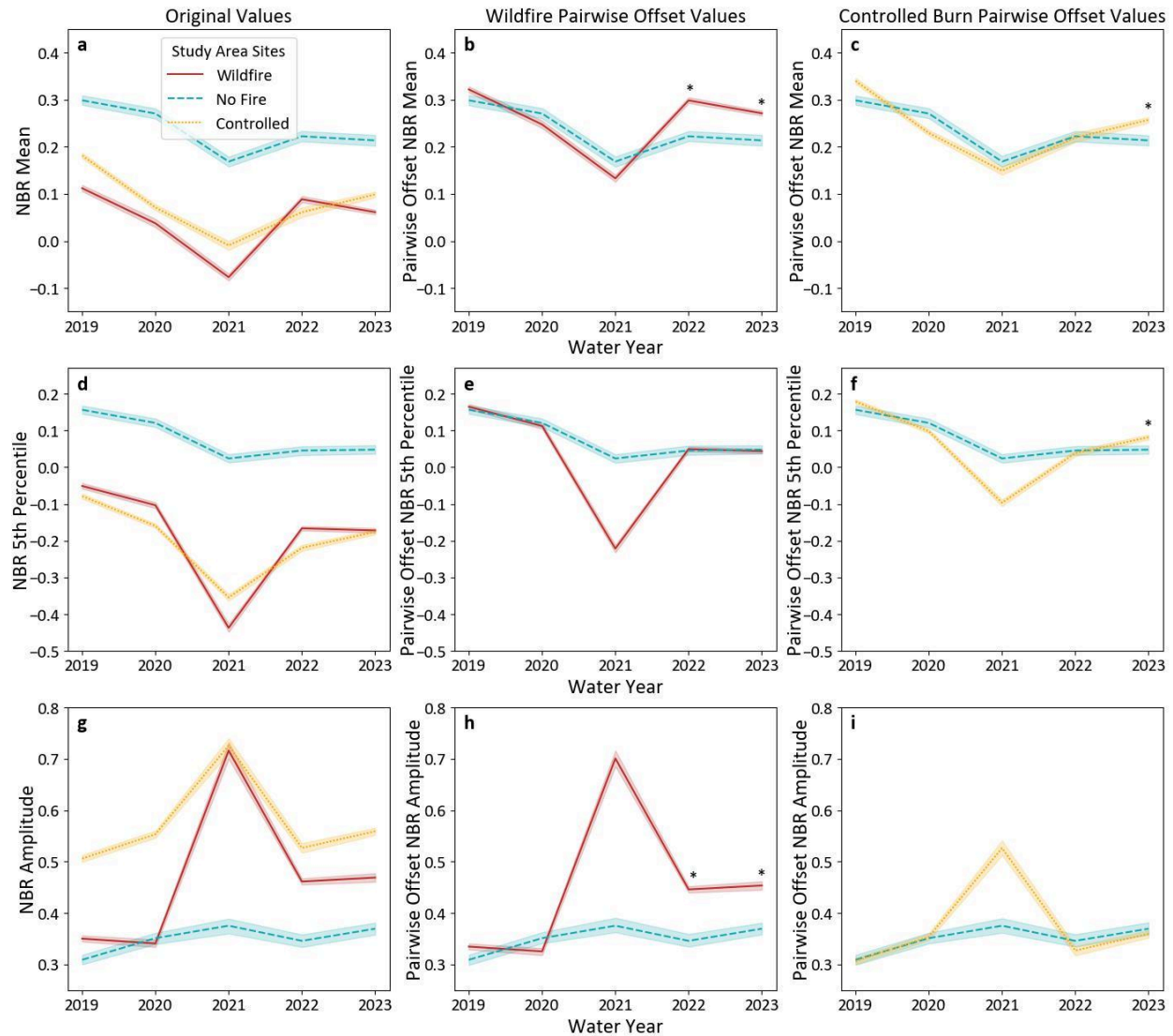


Figure 4.4. Mean metric values (NBR mean, fifth percentile, and amplitude) from 200 randomly sampled pixels on each of the three sites across the five water years of the study period. The first column (a, d, g) shows the original NBR values; the second column (b, e, h) shows pairwise offset values (i.e. the average difference between the pre-fire WY 2019 and 2020 values on each fire site and the no fire site) for the wildfire site; and the third column (c, f, i) shows pairwise offset values for the controlled burn site. The pairwise offset values illustrate relative differences between the fire sites and no fire site following the fires, which were statistically tested in WYs 2022 and 2023. Asterisks (*) above pairwise offset values in WYs 2022 and 2023 indicate that the means of the two sites were significantly different using the Mann U Whitney test ($p_{adj} < 0.05$). The shaded bounds surrounding each line represent the 95% confidence interval of each sample.

The first column of Figure 4.4 (a, d, and g) shows how each of these phenological metrics varied over five water years on each of the three sites. The second column (Figure 4.4b, e, h) shows the *relative differences* between the wildfire site and the no fire site by

applying a pairwise offset that accounts for average pre-fire differences between it and the no fire site. In other words, the average difference between the wildfire and no fire site's metric values in WYs 2019 and 2020 was subtracted from the wildfire site's original metric values. The third column (Figure 4.4c, f, i) similarly shows the relative differences between the metric values on the controlled burn and no fire sites. The pairwise offset panels allowed us to more directly compare the relative changes in each of these metrics between the reference no fire site and the sites with fire events, which helped to account for climate changes over the study period. Testing the difference between these relative values in WYs 2022 and 2023 (Figure 4.4b, c, e, f, h, i) also helped to measure recovery of these metrics while taking annual climate differences into account.

In general, all three sites experienced a decrease in mean and fifth percentile NBR in WY 2021 (to varying degrees) and slight increases in the following water years (Figure 4.4a, d). The temporal patterns of the NBR amplitude were more variable (Figure 4.4g). Amplitude gradually increased over the study period on the no fire site, and was much lower than the two fire sites. On both the sites with fire, the amplitude increased greatly in the year of the fire, with the wildfire site's amplitude values staying significantly higher than its pre-fire values by the end of the study period and the controlled burn site's amplitude values returning to the range of its pre-fire values – and in line with the trend on the no fire site – after only one year (Figure 4.4g, h, i). When comparing the original amplitude values on each site, the controlled burn site had a substantially higher amplitude than both sites in the two pre-fire and two post-fire years (WYs 2019, 2020, 2022, and 2023) (Figure 4.4g). In contrast, the amplitude on the wildfire and no fire sites were fairly comparable in the two pre-fire years.

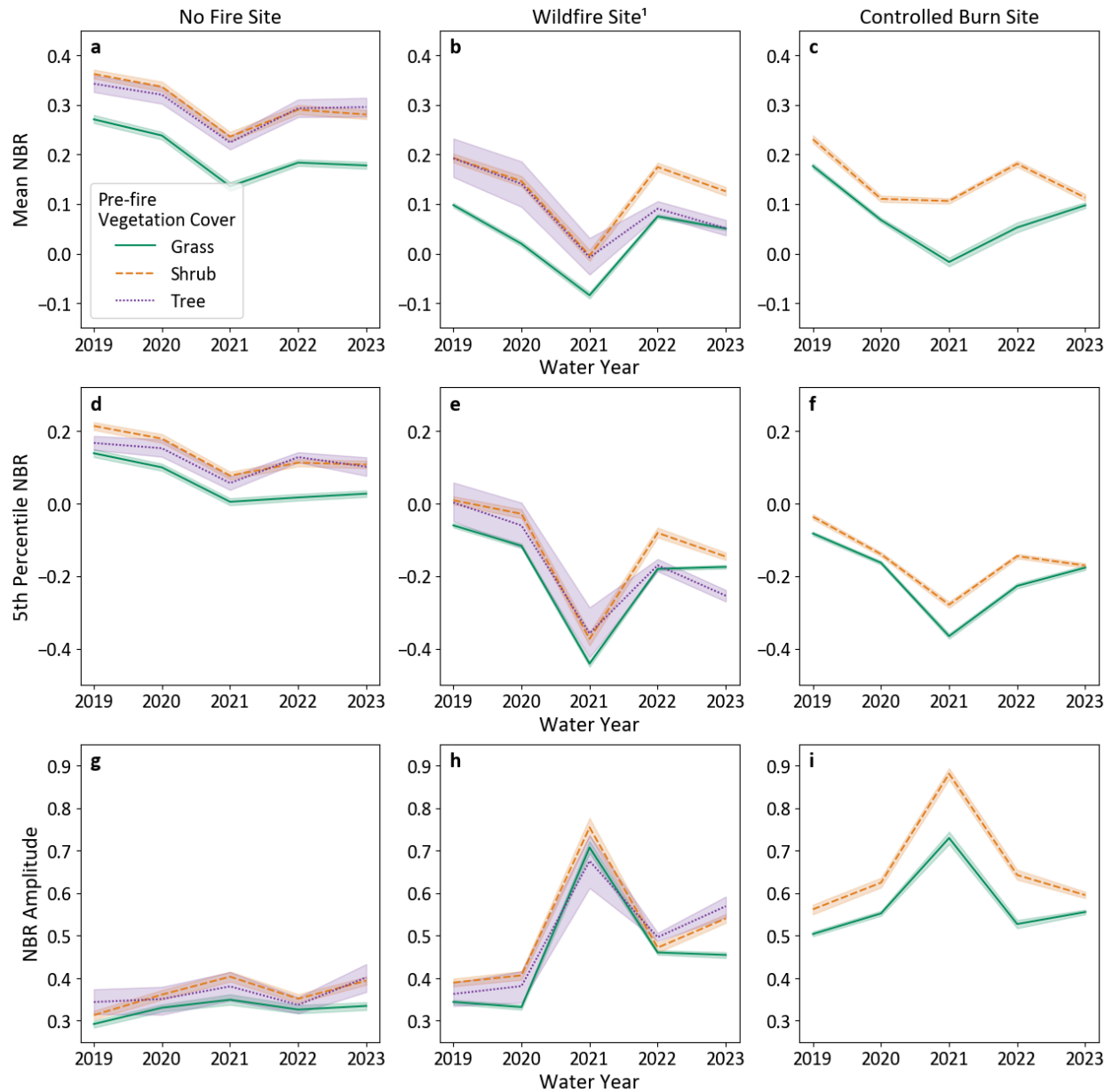


Figure 4.5. Average metrics (NBR mean, fifth percentile, and amplitude) from sampled pixels dominated by each pre-fire vegetation type (grass, shrub, and tree) across the five water years of the study period. The columns correspond to the no fire, wildfire, and controlled burn sites from left to right. The shaded band surrounding each line represents the 95% confidence interval of that sample. A note on variation in sample sizes: 200 pixels were randomly sampled from each site-vegetation cover pair except in the following four cases: All 168 and 139 shrub-dominated pixels were selected from the controlled burn and wildfire sites respectively and all 27 and 19 tree-dominated pixels were selected from the no fire and wildfire sites respectively. ¹The wildfire site experienced significant vegetation mortality and vegetation type changes during and after the fire; therefore, the pre-fire vegetation categories should not be interpreted as remaining steady in the years during and after the fire.

Figure 4.5 shows how each metric varied over the study period stratified by the pre-fire vegetation type that dominated that pixel (i.e. cover of 60% or greater). The low sample size for the tree-dominated pixels (only 27 on the no fire site and 19 on the wildfire site) means that these results were only exploratory and should not be interpreted with certainty. Across all sites and water years, the mean and fifth percentile NBR values of tree- and shrub-dominated pixels were higher than that of the grass-dominated pixels on average (the one exception is tree-dominated pixels two years after the wildfire, which is discussed below) (Figure 4.5a-f). Unlike on the no fire and wildfire sites, shrub-dominated pixels on the controlled burn site did not have a lower mean NBR during the first growing season after the fire (WY 2020) (Figure 4.5c).

The NBR amplitude of all vegetation types varied very little on the no fire site (Figure 4.5g). The NBR amplitude was comparable for all vegetation types on the wildfire site for most of the study period, but diverged two years following the wildfire – pixels that were dominated by shrub and tree cover prior to the fire experienced an increase in amplitude relative to pixels that were dominated by grasses prior to the fire (Figure 4.5h). Lastly, the grass- and shrub-dominated pixels on the controlled burn site exhibited similar trends, with the latter having a higher average NBR amplitude across all five water years (Figure 4.5i).

4.3.4 Spatial Variation

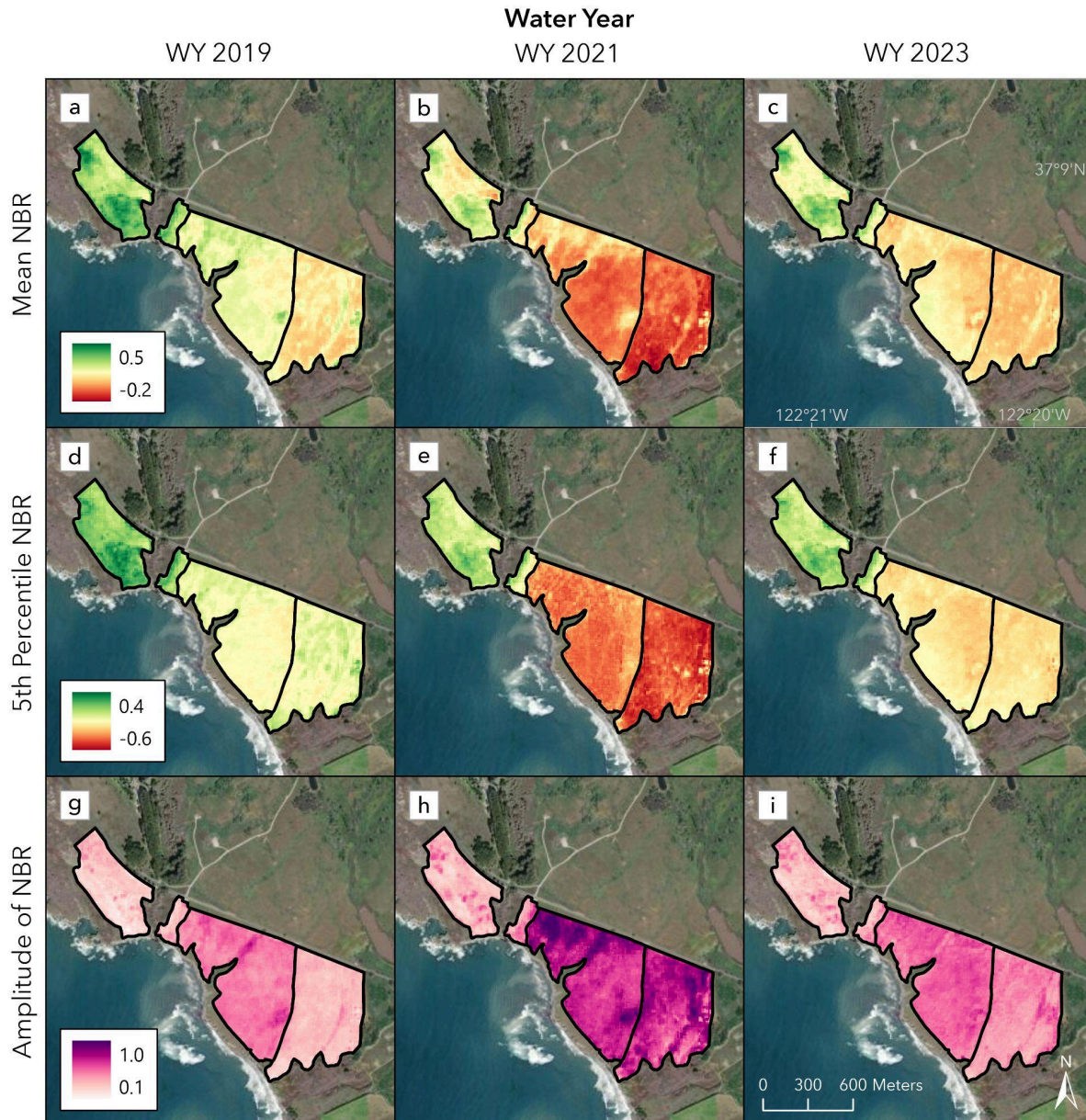


Figure 4.6. Spatial variation in the mean, fifth percentile, and amplitude of NBR across the study area sites for three water years: two years prior to the fire events (WY 2019), the year of the fire events (WY 2021), and two years after the fire events (WY 2023).

Figure 4.6 shows how each of these phenological metrics varied over space and time across the three sites. Many of the temporal patterns exhibited in Figure 4.4 are also shown here, for example that the mean and fifth percentile NBR decreased on the fire sites in the water year that included the fire events (WY 2021), and two years later (WY 2023) these values appeared close to but slightly lower than pre-fire values (Figure 4.6a-f). The amplitude was much greater on the sites with fire in the water year of those

fires (WY 2021), which captured the first post-fire growing season (Figure 4.6g-i). Two years following the fire events, the amplitude of the fire sites was elevated compared to the no fire site, and relative to their pre-fire values, the wildfire site's amplitude was higher while the controlled burn site's amplitude was similar. The amplitude on the wildfire site appeared to be more spatially variable following the wildfire (WY 2021 and 2023) than before the fire (WY 2019). Spatially, the areas with higher mean NBR on the fire sites tended to have higher amplitude values across all three water years, indicating that there may be some environmental factor influencing vegetation productivity in these particular areas (Figure 4.6a-c, g-i). Mean and fifth percentile NBR were higher in all three years on the no fire site, and all three metrics appeared to be highest where shrubs and trees were dominant within that site.

4.4 Discussion

We used Sentinel-2 imagery to track phenological indicators of post-fire recovery in adjacent coastal grasslands with varying fire histories: one site burned in a low severity controlled burn, one site burned in a high severity wildfire, and one site with no recent fire (Figure 4.1a). The methods developed in this paper aimed to monitor post-fire recovery at a temporal resolution relevant to grasslands and at a spatial resolution small enough to capture intentional burns.

In interpreting the results, it is necessary to note that the three sites experienced different disturbance regimes prior to the study period. Both the no fire site and the wildfire site experienced no fires of any kind for more than 100 years prior to the study period, whereas the controlled burn site had been burned at low severity in the fall every two to three years since 1991, and most recently in 2017, 2020, and 2023. Only the 2020 controlled burn was directly included in this study. However, the baseline years included in this study (WYs 2019 and 2020) represented the second and third growing seasons following the fall 2017 controlled burn. While we focused on the effects of the 2020 controlled burn, it is important to keep in mind that the vegetation and seasonality on that site were also influenced by these prior fires.

To characterize differences in pre-fire vegetation cover across the three sites, we conducted a vegetation classification based on pre-fire imagery captured in May 2020 (WY 2020) and drew on vegetation survey data collected across all three sites in April 2022 as part of related research (Taylor et al., in press). Both of these sources revealed that these three sites had different vegetation composition communities: broadly, the controlled burn site was dominated by grass with sparsely distributed shrubs, while the no fire and wildfire sites had higher shrub cover as well as evergreen trees encroaching along the edges. These differences are likely related in part to their distinct historical and current fire regimes (Figure 4.1a) (Taylor et al., in press).

We expected the inter- and intra-annual NBR signal to vary based on many factors. First, NBR can be an indicator of vegetation health, as photosynthetically active vegetation with a higher moisture content will reflect a higher NBR value (Hislop et al., 2018). We expected this to vary between years based on climatic differences (e.g. how much precipitation falls and when in the year it falls), nutrient availability, and disturbance.

The no fire site served as a reference to account for relative differences in NBR metrics within and between years that are likely due to climatic variation, as that site experienced no known disturbances during the study period.

Second, vegetation will exhibit higher NBR values when it is photosynthetically most active (during its growing season), and lower values when it is dormant or less photosynthetically active. Therefore, we expected the NBR signal to vary differently for the grasses, shrubs, and trees present within the study area based on differences in their seasonal growth patterns. In general, the growing season of these grasses begins in December or January – soon after California’s wet season begins – and lasts through May or June, senescing during the dry season (Reever Morghan et al., 2007). Shrubs in this area begin their growing season in January, but differ from grasses in that they stay photosynthetically active through the dry season, flowering from August to December (Smither-Kopperl, 2016). The coniferous trees common in this area are evergreen and therefore exhibit less seasonal variation than the shrubs or grasses, but they do grow new shoots in the spring months. Given these expected differences in seasonal signals and that the three sites had differences in their pre-fire vegetation communities, we first conducted each analysis to compare the three sites, then additionally stratified them by these three types of vegetation cover.

4.4.1 Full Time Series

The full time series revealed complex patterns of disturbance and recovery in these grasslands as well as differences in phenological timing between the sites (Figure 4.2) and vegetation-site pairs (Figure 4.3). First, the full NBR time series revealed important changes in pre- and post-fire seasonality across the three sites (Figure 4.2). There was less intra-annual variation in NBR on the no fire site, which we would expect given its lack of disturbance and higher abundance of shrubs and trees compared to the other two sites. The average NBR was consistently higher on the no fire site except for two periods in which the average NBR on the controlled burn site surpassed it: 1) in the green-up period immediately following the controlled burn (WY 2021), and 2) in the green-up period two years after the controlled burn (WY 2023). One plausible explanation for this considerable change in NBR relative to the reference site could be that the controlled burn resulted in decreased competition for water and light, as well as an influx of available nutrients that enabled the grasses and shrubs on that site to grow earlier and at a faster rate than the other two sites (Stavi, 2019). While we did see a post-fire increase in the average NBR on the wildfire site, it was still consistently lower than that of the controlled burn site, which agrees with other research showing that higher severity fire may not benefit grassland productivity as it can cause soil erosion, soil hydrophobicity, nutrient depletion, and mortality of belowground biomass (Neary & Leonard, 2020; Stavi, 2019). Importantly, our findings also suggest that the expected benefits of the controlled burn (e.g. increased access to nutrients, water, and sunlight) were still distinguishable up to two years after the burn.

Across all years, the vegetation on the no fire site appeared to senesce at a similar point in time as the fire sites but at a slower rate and to a lesser degree,

suggesting that vegetation on that site experienced less seasonal change (Figure 4.2). This similarity in senescence timing aligns with other research showing that senescence in grasslands is primarily driven by changes in day length (Serrano-Bueno et al., 2021). The wildfire site exhibited less seasonal change than the controlled burn site prior to the wildfire, but more closely matched the shape of the controlled burn site's growth curve after the wildfire (Figure 4.2). This suggests that this disturbance immediately increased the seasonal variation in that grassland, and that some of that increase persisted even two years after the wildfire.

Next, we stratified the full NBR time series by vegetation type to analyze differences in pre- and post-fire seasonality across the vegetation-site pairs (Figure 4.3). This vegetation stratification step allowed us to test various comparisons, for example whether shrubs responded differently to fires of different severities, and whether grasses and shrubs responded differently to the same fire. Figure 4.3 shows that the pattern of earlier and faster green-up on the controlled burn site following the controlled burn was largely driven by the shrub-dominated pixels, both in the green-up period immediately following the burn (WY 2021) and two years later (WY 2023). This indicates that shrub-dominated areas responded more favorably to this low severity fire than grass-dominated areas, which may be due to differences in direct mortality resulting from the fire (i.e. shrubs did not experience mortality of aboveground biomass to the same extent as grasses in the controlled burn). Grass-dominated areas appeared to respond similarly to both types of fire, which suggests that the wildfire did not burn at high enough severity to cause lasting damage to the soil or grasses (Neary & Leonard, 2020; Stavi, 2019).

When comparing the response of shrubs to these two types of fire, we see that the shrub-dominated areas on the controlled burn site exhibited earlier green-up and a higher magnitude of green-up than the pre-fire values when compared to the wildfire site, while the shrub-dominated areas on the wildfire site appeared to be phenologically similar pre- and post-fire. This suggests that while shrub productivity may be increased following low severity fire, it may not be significantly impacted by high severity fire (or at least not within a three year post-fire period). One possible explanation is that the negative NBR signal from shrub mortality following the wildfire was balanced by the regrowth of grasses and resprouting of fire-adapted shrubs (Ford & Hayes, 2007; Taylor et al., in press). It is important to note that while low severity fire appeared to increase the productivity of individual shrubs, we do not suggest that it increases the abundance of shrubs. In fact, the frequent, low severity burns conducted at the controlled burn site likely reduce the establishment and encroachment of more shrubs and other woody vegetation, which is one of goals of this style of fire management (Ford & Hayes, 2007; Taylor et al., in press).

4.4.2 Annual Metrics

While the full time series are vital in understanding differences in intra-annual patterns between the sites (Figure 4.2) and vegetation-site pairs (Figure 4.3), it can be difficult to distinguish longer-term patterns occurring across multiple water years. To summarize and

facilitate interpretation of these complex time series, we focused on three key annual metrics: mean, fifth percentile, and amplitude (Figures 4.4 and 4.5). Each of these three metrics summarized ecologically important information about the growth patterns on each site (Figure 4.4) or vegetation-site pair (Figure 4.5). Briefly, annual mean values of VIs such as NBR are commonly used to track changes in overall vegetation condition and are correlated with annual gross primary productivity (Eastman et al., 2013). The fifth percentile NBR value is useful in tracking disturbance (the minimum values of NBR are designed to track damage from fire) and discerning the extent of senescence during the dry season, which can help to distinguish shrub- or tree-dominated areas from grass-dominated ones (Figure 4.3) (Key & Benson, 2006). Finally, the amplitude of the NBR curve (here defined as the 5th percentile value subtracted from the 95th percentile value) is an efficient measure of both seasonality and annual gross primary productivity, as it is directly correlated to the area under the annual phenological curve (Paruelo & Lauenroth, 1998).

Changes in these three annual metrics revealed important differences across the three sites (Figure 4.4). First, it is important to note that changes in the NBR signal on the no fire site are likely due primarily to year-to-year differences in climate. California experienced lower than average precipitation in WYs 2020 and 2021, and we saw a general trend of decreasing mean and fifth percentile NBR over the study period on the no fire site (Figure 4.4). Therefore, when measuring this ecosystem's resilience, it is best not to test whether these metrics recovered to pre-fire values because climatic differences between these years may have resulted in a gradual decline. For that reason, we employed a pairwise-offset method to facilitate analysis of changes in each metric relative to the reference (no fire site), thereby accounting for climatic differences between years (similar to Di Mauro et al. 2014). These pairwise offset charts (Figure 4.4, columns 2 and 3) highlighted how these metrics changed on the fire sites relative to the no fire site, which experienced the same climatic changes between water years but no disturbance.

While their overall trajectories are similar, there were clear differences in the magnitude of response to disturbance between the controlled burn and wildfire sites (Figure 4.4). Specifically, the wildfire site exhibited a greater relative decline in fifth percentile NBR during the year of the fire and a much greater relative increase in NBR amplitude following the fire. Interestingly, our relative comparison between the controlled burn site and the reference site indicated that the annual NBR metrics recovered to pre-fire values within one water year following the low severity burn, and was potentially more productive than the no fire site in WY 2023 (Figure 4.4c, f, i). This aligns with our expectations that grasslands recover quickly and benefit from low severity fire, and that high severity fire may lead to larger ecological shocks (Reiner, 2007).

The amplitude of the phenological curve is fairly under-utilized compared to other annual metrics and our results showed it to be important in the analysis of grassland disturbance and recovery. The controlled burn site had a considerably higher amplitude than either the wildfire or no fire site across all years (Figure 4.4g), indicating that this site is more seasonally variable. As predicted based on their similar pre-fire disturbance regimes, the amplitude on the wildfire site was very comparable to the no fire site for the

two pre-fire years of our study (Figure 4.4g). The wildfire site's amplitude increased dramatically in the year of the wildfire and while it decreased in the years since, it remained significantly higher than the no fire site in WY 2023 (Figure 4.4g, h). Therefore, it will be important to study whether the amplitude and seasonality on the wildfire site either diverges permanently from the no fire site, or if it eventually converges back in the absence of repeated disturbance.

Next, we analyzed changes in these three annual metrics across the eight vegetation-site pairs (Figure 4.5). While the separation of vegetation types was imperfect – Sentinel-2 pixels cover an approximate area of 100m² and therefore almost always included a mix of vegetation types – our analysis revealed important differences between the phenological signals of grass-, tree-, and shrub-dominated pixels both before and after the fire events. As we hypothesized, the mean and fifth percentile NBR values were higher for the shrub- and tree-dominated pixels than for the grass-dominated pixels on all three sites. On the no fire site, the difference between average mean and fifth percentile NBR values of these two groups of vegetation stayed consistent across all five water years (Figure 4.5a, d). This indicated that the signals on the reference site were acting as we expected, with all vegetation types experiencing slight differences each year due to variations in climate.

Vegetation changes over the course of the study (WYs 2019 to 2023) were not observed on the no fire and controlled burn sites (Taylor et al., in press). However, it was more difficult to interpret the post-fire signals on the basis of vegetation on the wildfire site – the CZU wildfire burned at very high severity and caused significant vegetation changes. Specifically, we found that the majority of shrubs on that site were top-killed by the wildfire (meaning they exhibited partial or total mortality of aboveground biomass) and had just begun to resprout in April 2022 (Taylor et al., in press). In this case, a decline in fifth percentile NBR in the following years could be due to seasonally variable grasses replacing these dead shrubs, rather than a decline in vegetation health. Therefore, in the case of high severity fire, it is important to field-verify whether a change in VI values is due to shifts in vegetation cover or changes in vegetation health.

On the controlled burn site, the shrub-dominated areas exhibited greater mean NBR values for two growing seasons post-fire, confirming our earlier finding that shrub-dominated areas appeared to benefit from this low severity fire (Figure 4.5c). The grass-dominated areas on the controlled burn site exhibited a decline in mean and fifth percentile NBR in the year of the fire but appeared to recover in one or two years relative to pre-fire values on that site and corresponding values on the no fire site, which is consistent with other literature showing that these grasses are highly resilient to low severity fire (Figure 4.5c, f) (Reiner, 2007). The trajectories on the wildfire site appeared to be similar again to the controlled burn site but greater in magnitude, with the exception of shrubs: the mean NBR of shrub-dominated areas on the wildfire site sharply declined in the year of the wildfire, whereas those on the controlled burn site exhibited no decline in the year of that fire (Figure 4.5b, c). This is likely due to the fact that the high severity wildfire top-killed many shrubs on that site, while the low severity controlled burn resulted in minimal canopy mortality of shrubs (Taylor et al., in press). However, the mean NBR of shrub-dominated areas on the wildfire site quickly rebounded in WYs 2022 and

2023, which ran contrary to our expectation that the signal of shrub re-sprouting would occur over three or four years based on other studies that have measured rates of resprouting in coyote brush (*Baccharis pilularis*), the dominant shrub within the wildfire site (Ford & Hayes, 2007; Fuhlendorf et al., 2011). Therefore, it is likely that this signal of fast recovery is due to grass regrowing beneath top-killed shrubs, and the same is true for trees (Taylor et al., in press).

The amplitude of the NBR curve varied significantly between the three sites and between vegetation types (Figure 4.5g-i). On the no fire site, the amplitude of NBR was relatively constant between water years and for all three vegetation types (Figure 4.5g). It was surprising that the amplitude of the grass- and shrub-dominated areas on the no fire site – and wildfire site prior to the fire – were much lower than the controlled burn site (Figure 4.5g-i). The lower seasonality and lower annual growth on those sites could be due to greater competition for light, water, and nutrients in the absence of fire or other disturbances, and potentially the build-up of dead biomass. It is also possible that the observed differences in amplitude on the three sites can be explained partially by differences in species composition, given that the amplitude on the wildfire site increased in all post-fire water years, and likely experienced at least temporary shifts in vegetation composition due to canopy and total mortality of shrubs and trees. However, given that the amplitude of shrub-dominated areas was higher than that of grass-dominated areas across all water years and sites (Figure 4.5g-i), it is more likely that increased amplitude values post-fire were due not to shrub mortality but rather to higher annual productivity following the fire caused by a release from competition for light, nutrients, and water (Reiner, 2007). Given the relatively lower amplitude on the wildfire site two years post-fire, our findings suggest that the regular controlled burning on the site (roughly every three years) is promoting greater annual growth of both grass and shrub species even in the third growing season following a burn, and to a greater extent than infrequent high severity fire. This fits with our expectation, as many of the plants in California's coastal grasslands are adapted to this disturbance regime (Reiner, 2007).

4.4.3 Spatial Variation

In addition to these temporal variations, all three metrics displayed varying degrees of spatial heterogeneity across the study period that likely correspond to spatial variation in abiotic conditions, fire severity, and other factors (Figure 4.6). Across both fire sites, we found that the areas with higher mean and fifth percentile NBR values across all years corresponded with depressions and drainages where we would expect water to gather based on the area's topography. Interestingly, the NBR amplitude also appeared to follow this pattern. This suggests that the areas likely to have higher soil moisture farther into the dry season are more productive. The increase in spatial variation of NBR amplitude on the wildfire site following the wildfire is an interesting result that may be explained by variation in fire severity resulting in differences in the availability of nutrients, light, and water (Neary & Leonard, 2020; Stavi, 2019). Investigating the spatial variation in these

temporal changes is a necessary step as it checks for additional factors that may be contributing to the signals in the full time series and the annual NBR metrics.

4.4.4 Methodological Strengths

This is a strategic approach to remote sensing of fire recovery in grasslands that analyzes intra- and inter-annual changes over the spatial and temporal dimensions. Unlike in forests where intra-annual changes may be less significant, the health of a grassland may be signaled by changes in the timing and magnitude of green-up and senescence (Dronova & Taddeo, 2022). While all of our results revealed important details about the ecosystem's response to fire, we found that the full time series stratified by vegetation type (Figure 4.3) was valuable for discerning overall patterns. Our methods overcome some of the key barriers that make full time series charts like this one less accessible to scientists and land managers. Performed on a local computer, preparing and analyzing a dense time series like this one would require a potentially prohibitive amount of computational power and storage space. Our analysis instead uses the GEE Python API, which stores and analyzes all of the imagery on external servers, enabling the analysis of hundreds of images on a small laptop. Another important barrier to full time series analysis is the exclusion of clouds and noisy images, which we do using an automated algorithm that is directly transferable to other areas. Finally, by calculating the 30-day moving average as we do here, scientists and land managers are able to study these important temporal patterns without relying on a perfect cloud filtering algorithm.

Annual temporal summaries helped make these dense datasets more readily legible and understandable. Furthermore, the pairwise offsets comparing relative changes on the fire sites to the no fire site (Figure 4.4) allowed us to investigate post-fire recovery time while accounting for climatic variation, similar to other works that used temporal changes in mean VI values to measure rates of recovery (Di Mauro et al., 2014). This analysis of post-fire recovery time may help managers to determine the appropriate return interval for intentional burning, which is relatively understudied in California's grasslands (Calhoun et al., 2022; Ford & Hayes, 2007). In the case of the controlled burn site, our findings suggest that the ecological benefits of this intentional burning (e.g. increased vegetation productivity due to greater access to water, nutrients, and sunlight) may last for at least three growing seasons following the burn. In this ecosystem, the optimal return interval of intentional burning may be instead driven by the desire to reduce encroachment of shrubs and trees, which if given more than three growing seasons to establish may be difficult to kill with low severity fire (Ford & Hayes, 2007; Hopkinson et al., 2020).

Depending on the application, maps showing variation in each of these metrics over space (such as Figure 4.6) may reveal critical spatial patterns that are meaningful for land managers. We would expect this spatial evaluation to be most important on sites with variable soil types, microclimates, or other abiotic factors. Taken together, our three methodological approaches – analyzing the full time series, summarizing it through annual metrics, and evaluating spatial variation – successfully condensed complex spatiotemporal data to reveal ecologically relevant information.

The methods we propose here are designed to be accessible, transferable, and computationally lightweight. First, we utilized free data and open source software whenever possible. The geemap package is open source, and Sentinel-2 imagery, which is reliably orthorectified and atmospherically corrected, is free to use. The main exception to this is the GEE Python API, which is not open source but is free to researchers and nonprofit organizations. Second, in contrast to many phenological studies of disturbance, we designed methods that do not rely on curve-fitting models. While curve-fitting models can be very useful in summarizing phenological patterns, they typically rely on user-inputted assumptions that are tailored to the seasonal patterns of a given study area or ecosystem, making methods that rely on them less broadly applicable or replicable (Helman, 2018; Misra et al., 2020). We instead make use of parameters related to the shape of the phenological curve, namely the mean, fifth percentile, and amplitude, which are efficient to calculate, do not require user-inputted assumptions, and are not negatively affected by the temporal lag caused by the coarser temporal resolution of Sentinel-2 imagery (Eastman et al., 2013; Gómez-Giráldez et al., 2020; Zhou et al., 2019).

4.4.5 Limitations and Future Work

Our study had two important limitations. First, in choosing to use the Sentinel-2 surface reflectance imagery available through the GEE Python API, we limited our study period to its first available image date of December 31, 2018. This meant that the first water year included in our study period (WY 2019) is missing images from October, November, and most of December. This omission could have falsely inflated the mean and fifth percentile NBR values in that year, as those months tended to have the lowest NBR values across the other water years (Figure 4.2). This may partially explain why WY 2019 has the highest mean and fifth percentile NBR values and lowest NBR amplitude values (Figure 4.4). However, this difference was small and the value of using atmospherically corrected imagery outweighed this small drawback. Future work could take advantage of the full Sentinel-2 imagery archive to study relative changes in VIs extending as far back as 2015, either using the top-of-atmosphere imagery available in GEE or by conducting the analysis outside of GEE. This longer time series would also enable comparison of the impacts of an earlier controlled burn at the site (2017) to the two more recent burns (2020 and 2023).

Second, our study utilized field data from only one post-fire growing season, which was not sufficient to thoroughly validate our remotely sensed findings. As discussed previously, fluctuations in NBR can be the result of changes in vegetation health, density, or type (e.g. shrubs converting to grasses after a high severity fire), and data collected in the field can help to differentiate among these possible causes. In particular, field monitoring may be especially useful in the case of high severity wildfire, when vegetation type conversions are more common. Research that conducts multiple vegetation surveys over many years is now needed to validate which of these metrics is most helpful in capturing important vegetation changes, and if amplitude or other metrics can reliably differentiate between more specific vegetation types (i.e. annual and perennial grasses). However, the stochastic nature of wildfire means that pre-fire field

data are not always available to scientists and land managers. Therefore, methods such as ours that do not rely on comprehensive field data may offer the only pre-fire view available.

More research is now needed to test how these methods perform for other intentional burns in other grasslands worldwide, and to compare how these methods perform in forest ecosystems as well. In addition, comparative analysis across multiple fires would help to identify the most informative pre- and post-fire time frames for such assessments, such as the minimum time needed to reliably determine differences between sites or to declare recovery of the ecosystem parameters targeted by managers. As mentioned previously, longer term studies of intentional burn recovery could also help to better illuminate the optimal fire return interval in different grasslands. Finally, these methods represent only one piece of evaluating intentional burning in grasslands. In particular, some of the goals of intentional burns – such as supporting growth of certain native grasses or removal of invasive species – are not easily captured with satellite imagery analysis.

4.5 Conclusions

As California continues to invest unprecedented amounts into intentional burning across its many ecosystems, methods that track the impacts of smaller fires on low-biomass ecosystems such as grasslands are needed. Many existing methods were developed for high-biomass and less seasonally variable ecosystems (such as forests) and for larger, more severe fires, and therefore use imagery with coarser spatial resolutions. The methods proposed here leverage satellite imagery with a higher spatial resolution (Sentinel-2) to more accurately capture the impacts of intentional burns, which tend to be smaller in size. We also leverage the temporal resolution of Sentinel-2 imagery (5-days) to reveal critical phenological patterns in grassland disturbance and recovery and compare grassland response to low severity and high severity fire. Our results revealed that this grassland recovered from the low severity intentional burn within one year, and that the benefits of this burn lasted at least three years after the fire. In addition, we found that shrub productivity and growth appeared to increase more than that of grasses in the years following the low severity intentional burn. In the case of the high severity wildfire, our metrics indicated that this grassland had not returned to its pre-fire values in at least three years after the fire, indicating that it may be undergoing a longer recovery or larger shift. These methods are readily transferable to other grasslands and are an important step towards efficiently measuring the impacts of intentional burning across the state.

4.6 Acknowledgements

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regarding the study site that informed our objectives and methods. We would also like to thank our partners at the Amah Mutsun Tribal Band and Amah Mutsun Land Trust for their constant support and partnership over many years that informed and guided this research. Figures were created in Python using the altair and matplotlib packages.

Data Availability

Public datasets utilized in this study included California fire perimeter data from CAL FIRE (<https://gis.data.ca.gov/datasets/CALFIRE-Forestry::california-fire-perimeters-all-1/about>) and San Mateo County elevation data (<https://data-smcmaps.opendata.arcgis.com/datasets/6ce67725cf44432fb7d579534e2fa544/about>). NRCS soil survey data were downloaded from the Web Soil Survey tool (<https://websoilsurvey.nrcs.usda.gov/>). Scripts used to analyze Sentinel-2 data are archived in a public repository on Github: https://github.com/annietaylor/RS_grassland_fire.

Chapter 5

Conclusions and reflections on collaborative research with the Amah Mutsun Tribal Band

Traditional stewardship activities such as burning, tilling, gathering, and planting are part of a body of Indigenous practices that support the health and cultural sovereignty of Indigenous communities as well as the many ecosystems that depend on disturbance and management. Understanding such practices and implementing them more widely is crucial to mitigating and adapting to the impacts of climate change, and spatial data science is central to these efforts. My work in this dissertation demonstrates how leading-edge spatial data and methods can be used to support Indigenous ecological stewardship through a research partnership with the Amah Mutsun Tribal Band (hereafter AMTB or the Tribe), an Indigenous community in the Central Coast of California working to steward ecosystems and restore their cultural connections to these lands and waters. Together with my partners at AMTB and the Amah Mutsun Land Trust (AMLT), I have conducted a suite of research projects that relate to two Tribal priorities: culturally important plants and the practices of cultural fire. These three studies contribute both to the Tribe's broader stewardship goals and to the field of community-driven ecological research.

In Chapter 2, I showed that species distribution models built upon community-collected plant locations and climate data could be used to map potential hotspots for the stewardship and gathering of culturally important plants. I found that these models performed best for woody vegetation (shrubs and trees) and for specialist species. In addition, I showed how to test for and reduce spatial bias in the community-collected plant location data, and found that three types of machine learning models performed best in this context. One remaining challenge in this work is that the climate data used to predict plant habitat is still fairly coarse, which means that the resulting distribution maps may not be detailed enough to meaningfully narrow down the Tribe's efforts to gather plants or validate these results in the field. Another limitation is the lack of research-grade observations of grass species found in the iNaturalist database. This is due to a number of factors, foremost among them that identifying grasses to the species level is a highly specialized skill, and that users are more likely to take photos and observations of charismatic plants (e.g. plants with larger leaves or flowers). This data gap is significant to tribes because grasses are a very culturally important group of plants. Guided by the principles of Indigenous data sovereignty, I showed how to publish this work without sharing maps and results that were deemed confidential by the Amah Mutsun Tribal Council.

In Chapter 3, I illustrated how interviews, field data, and remotely sensed satellite imagery could be combined to create a deeper ecological and cultural understanding of fire in California's endangered coastal grasslands. I studied how the abundance of culturally important plants, invasive grasses, and shrubs varied across three grasslands with different fire histories: repeated controlled burning, wildfire, and no recorded fire. My results showed that an important native perennial grass (*Danthonia californica*, or

California oatgrass) may be adapted to repeated low severity fire, and that this repeated burning is preventing shrub conversion of this grassland. Importantly, our interviews revealed how State Parks' periodic use of herbicides at the site likely precludes the area's use for gathering of cultural plants. Placing quantitative results within the context of interviews and conversations with Amah Mutsun tribal members, my colleagues and I learned how typical biodiversity metrics and methods that prioritize species diversity and evenness may fail to capture culturally significant information.

Lastly, in Chapter 4 I demonstrated how advances in remote sensing methodologies could better capture the impacts of intentional burns on grasslands, which present the two-fold challenge of being small in size and recovering over short periods of time. I developed methods that overcome these challenges by using higher resolution satellite imagery (Sentinel-2) and tested these methods within the same three grassland sites analyzed in Chapter 3. These methods offered a detailed view of vegetation changes across both space and time, and summarized annual changes in phenological metrics most relevant to this fast-changing ecosystem. I found that the amplitude of the annual growth curve (as measured by a vegetation index) was an efficient and revealing complement to more commonly used metrics, and that stratifying the analysis by vegetation type enabled a more detailed ecological interpretation of the results. Ultimately, this analysis suggested that the ecological benefits of the intentional burn persisted for at least three years after the fire.

These spatial analyses are an important yet only partial contribution towards the Tribe's diverse efforts to restore ecosystems and strengthen their cultural connections with land. For example, the maps of potential gathering areas that I developed in Chapter 2 identify the best places to begin the difficult work of field validation and development of partnerships with the respective land management agencies. There are many other factors that will determine whether or not an area is suitable for tribal stewardship and gathering, including accessibility, safety (e.g. herbicide use), and plant health and abundance, among many others. In the case of the intentional burning program that I analyzed in Chapters 3 and 4, my spatial analyses demonstrated the value of intentional burning, but did not do the hard work of advocating for funding and tribal participation in or leadership of future burns. Spatial data scientists partnering with tribal communities may keep these limitations in mind as they design culturally relevant research.

A central piece of my dissertation work is the importance of equitable and culturally relevant research partnerships with Indigenous communities. In pursuit of that aim, I want to share the valuable advice I have received from my partners at the AMTB and AMLT – and Alexii Sigona in particular – over the past five years. The first is to begin a partnership with an offer of time, skills, or both, and to aim to make yourself immediately useful to the community in the ways that key collaborators express are needed. For example, I spent two years supporting or leading mapping projects that staff at AMLT told me were needed before later introducing my own ideas and gaining approval for specific projects. This was crucial because in many ways, my research partnership was a burden for the Tribe – various people had to take time to answer my questions, consider various approvals, and ready me to support the work that they were already doing. This initial work also helped me to engage with the community's projects

directly before forming my ideas, which ensured that my research ideas were shaped by the Tribe from the outset.

The next piece of advice I received from Alexii and other partners during this research was to direct my requests for support towards members of the community who were paid to partner with me whenever this was possible or appropriate. For example, Alexii and I often fielded as many of our questions as possible through the staff members at AMLT, given that elected members of the Amah Mutsun Tribal Council were not compensated for their work reviewing our research ideas. When we did request review and approval from the Tribal Council, we did so only after several rounds of improving and refining our proposals with AMLT staff members. When asking for feedback or requesting direction from community leaders, it is also helpful to bring multiple options to begin the discussion, rather than presenting open-ended questions that may unintentionally give another task to overburdened community advocates. I learned this lesson in a Tribal Council meeting while asking for guidance on how to share my results with the broader Amah Mutsun community – one of the council members politely asked me to return with three concrete options for them to consider. These teachings helped me to understand our collaboration as a delicate balance between seeking community ideas and feedback (and not imposing a path forward) while also ensuring that my efforts to contribute did not further burden the community I strived to support.

The final piece of advice I have come away with is that humility is a crucial piece of trust-building with community partners. It was important to learn that my research was not an urgent priority in the midst of the Tribe's pressing and integral work to support tribal members. Therefore, I tried to strike a balance between offering my knowledge and skills while also acknowledging that my work was one small piece of a broader picture. For example, while I brought knowledge of spatial data science and mapping, I needed to learn from tribal members how the Tribe might want to apply my skills, including how my maps might best portray Amah Mutsun places and non-human relatives. In addition, while it is not part of my dissertation, my work with the Tribe required me to learn how California organizes its archaeological data, and how to leverage this data to support cultural site monitoring. I also created confidential maps of Mutsun sacred sites and developed a map for the campaign to protect Juristac, a sacred landscape within the Tribe's homelands (www.protectjuristac.org). My partners at AMTB and AMLT helped me to find ways that my skills could support their wide array of projects aimed at supporting the Amah Mutsun community and their homelands.

To advance the field of community-engaged research, it is critical that scientists explicitly discuss their approach to collaboration with Indigenous communities and acknowledge inevitable shortcomings. While Alexii and I aimed to create a genuinely equitable research partnership, I feel that my research was most collaborative in the first years of research design and initial implementation, and became less so in the later analysis stages. Future work with the Tribe could be more deeply collaborative by involving more tribal members in the fieldwork and data analysis phases of the research. Furthermore, the results of our work need to be explicitly incorporated into the Tribe's existing restoration plans to ensure that this work benefits the community.

My research has also left me with take-aways regarding the strengths and limitations of spatial data science approaches in general, and remote sensing in particular. Satellite imagery is an extremely valuable source of data in cases where data collected in the field is lacking. In the case of one of our study sites, there was a completely unique, multi-decadal fire management program underway with very little field data capturing how this grassland had transformed over time. In Chapter 4, I showed how a dense time series of high spatial resolution satellite imagery enabled us to analyze these changes over many years. As stochastic events like wildfires cannot be predicted and planned for, satellite imagery gives us the ability to compare pre- and post-disturbance conditions with relative ease. However, vegetation indices can be difficult to interpret with certainty without field-based knowledge of an ecosystem. At the core of this limitation is that fluctuations in satellite-derived vegetation indices can indicate changes in vegetation health as well as changes in vegetation density or abundance. In conducting place-based research with the AMTB, satellite imagery presents a paradox: on the one hand, it provides a detailed, multidimensional view of an ecosystem. On the other hand, remote sensing methods are just that – remote – and without proper care, researchers can reach conclusions about places they have never visited or experienced. I look forward to following the many Indigenous scholars and practitioners who are re-imagining how to Indigenize and decolonize the field of spatial data science.

I envision many future directions for this research. First, as the Tribe conducts more cultural burns and ecological restoration projects, there is a need to collect field data to measure how these practices are impacting culturally important plants. In particular, data gathered before and after these actions will help to interrogate causal relationships. Second, I would like to train interested tribal members in the use of geospatial tools so that the Tribe's spatial data science projects can originate from and be fundamentally shaped by the community. Lastly, I will continue to learn from other examples of tribes who partner with environmental researchers and conservation groups. While we developed methods and approaches that are applicable to other ecosystems and other Indigenous communities, it is important not to extrapolate our results beyond their cultural context within the AMTB. We need to continue charting road maps for these kinds of partnerships and writing about our successes and failures so that more of these crucial partnerships can flourish.

Reparative partnerships between environmental scientists and Indigenous communities are essential due both to past harms perpetuated by environmental science and the urgency of climate change. Greater support for Indigenous stewardship practices stands to significantly strengthen global environmental efforts and generate greater ecocultural benefits for Indigenous communities. When and where Indigenous communities have more opportunities to practice their stewardship practices, they can accelerate the restoration of biodiverse ecosystems, reduce the risk of severe climate events such as wildfires, and contribute to the revitalization of essential cultural practices.

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Appendices

Appendix S2.

Supporting Materials for Chapter 2: Modeling spatial distributions of Amah Mutsun priority cultural plants to support Indigenous cultural revitalization.

Table S2.1. Number of observations before and after spatial filtering for each of the ten included cultural species. Observation data were combined from research-grade iNaturalist observations and three local datasets.

Species	Number of Observations	
	Total	Filtered
<i>Artemisia douglasiana</i>	777	415
<i>Calandrinia menziesii</i>	753	403
<i>Chlorogalum pomeridianum</i>	1379	586
<i>Clinopodium douglasii</i>	505	294
<i>Corylus cornuta ssp. californica</i>	231	109
<i>Quercus kelloggii</i>	401	183
<i>Rubus parviflorus</i>	898	395
<i>Rubus ursinus</i>	1686	686
<i>Sambucus nigra ssp. caerulea</i>	1021	515
<i>Vaccinium ovatum</i>	829	281

Table S2.2. Percent of input presence locations correctly classified as presence locations (PCC) for the five California black oak (*Quercus kelloggii*) models for the training run and the average of the 10-fold cross validation runs. The difference indicates the change in the PCC value in the cross validation runs as compared to the training run.

Type of Model Run	Percent Correctly Classified (%)					
	BRT	GLM	MARS	Maxent	RF	Mean
Training	83.91	77.00	77.58	80.48	81.56	80.10
Cross Validation (mean)	86.04	76.72	78.58	89.48	80.87	82.34
Difference	2.14	-0.28	1.00	8.99	-0.68	2.23

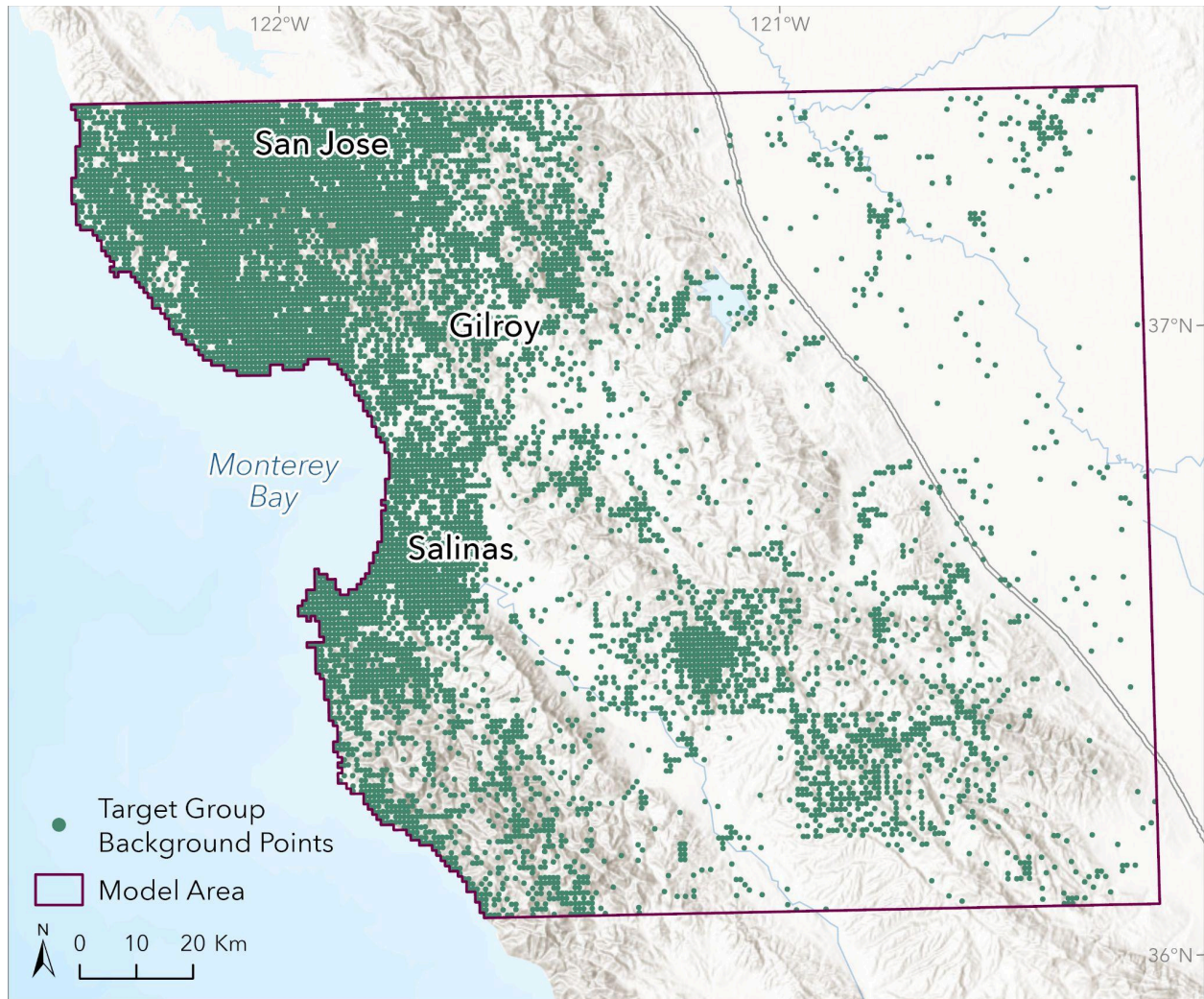


Figure S2.1. Location of target group background points input into each model as pseudo-absences. These points were extracted from the 145,000 most recent research-grade iNaturalist observations for all plant species in the model area and then spatially filtered down to 8,000 points.

Appendix S3.

Supporting Materials for Chapter 3: Centering Amah Mutsun voices in the analysis of a culturally important, fire-managed coastal grassland.

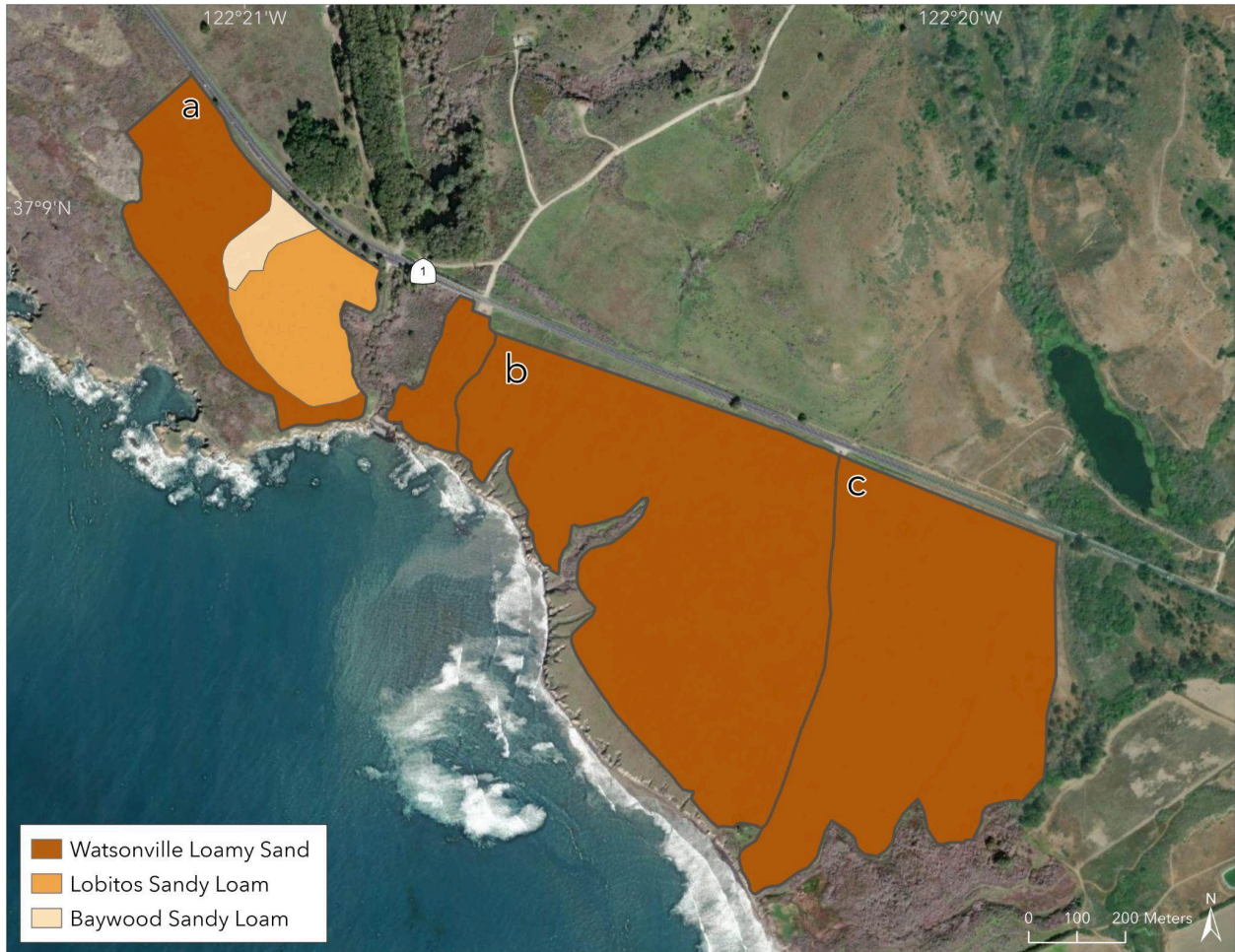


Figure S3.1. Map of the USDA's soil survey data (SSURGO) primary soil types across the no fire (a), controlled burn (b), and wildfire (c) sites, from northwest to southeast.

Section S3.1.

Questions used to guide semi-structured interviews with Amah Mutsun tribal members, as approved under UC Berkeley research protocol #2020-01-12905.

- What is your name, where do you live, and what Amah Mutsun lineage do you descend from?
- When did you start learning about your identity as an Amah Mutsun person?
- What is your relationship like with Amah Mutsun traditional territory?
- Before European contact, how did Amah Mutsun people interact with their environment?
- How did the Spanish Missions affect the Amah Mutsun community?
- Do you gather any plants for food or medicine, or have you in the past?
- Do you think it is easy or difficult for you to access cultural resources such as food or medicine plants?
- What are the barriers that limit your relationship with Amah Mutsun traditional territory?
- Today, how do Amah Mutsun people take care of their land?
- How do you perceive fire in the environment?
- Do you think it is important for Indigenous communities to be involved in environmental management of traditional territory?
- Do you think it is important for living members to practice Amah Mutsun cultural ways?
- Do you believe that future generations of tribal members will be able to practice Amah Mutsun culture?
- Is there anything that has not been brought up that you would like to include?