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California's Dynamic Landscape:
Monitoring Ecological Response to Human Impact and Drought Using Satellite Imagery

A dissertation submitted in partial satisfaction of the
requirements for the degree Doctor of Philosophy
in Geography

by

Katherine Sarah Willis

2016

ABSTRACT OF THE DISSERTATION

California's Dynamic Landscape:

Monitoring Ecological Response to Human Impact

and Drought Using Satellite Imagery

by

Katherine Sarah Willis

Doctor of Philosophy in Geography

University of California, Los Angeles, 2016

Professor Thomas Welch Gillespie, Co-chair

Professor Glen Michael MacDonald, Co-chair

Space-borne remote sensing is a rapidly evolving field and is exceptionally useful for monitoring landscape dynamics. The increasing impact of humans on natural ecosystems via land use change and climate change make ecological monitoring vital to environmental health. Human population levels are causing rapid changes in land cover and development, which in turn puts increasing stress on the natural landscape. Anthropogenic greenhouse gas emissions have accelerated climate change causing varied unexpected changes to vegetation. The effects of increased frequency and intensity of drought in the western United States is an example of this which can be monitored using satellite imagery.

This dissertation assesses how these human-induced threats are driving landscape changes and the application of remote sensing to assess the ecological impacts. To address these objectives, remote sensing is applied to natural resource monitoring for effective conservation-based land management (Chapter 2). These methods are then applied to various research, including monitoring ecological status of southern California National Parks (Chapter 3), assessment of the effects of drought on southern California native plants (Chapter 4) and on browning over California vegetation zones (Chapter 5). The remote sensing-based analyses utilize several best practice methods such as supervised classification and time series statistics to examine landscape changes throughout California. Outputs include a standardized protocol to determine future ecological conservation management actions, status reports on current and historical land use, publically available spatial datasets, and assessment of the California landscape and native species in response to 20th Century drought conditions.

The dissertation of Katherine Sarah Willis is approved.

Gregory Stewart Okin

Philip W Rundel

Thomas Welch Gillespie, committee co-chair

Glen Michael MacDonald, committee co-chair

University of California, Los Angeles

2016

This dissertation is dedicated to my parents.

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VITA

EDUCATION

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Willis, K. S., Gillespie, T. W., Okin, G. S., MacDonald, G. M. (in prep) Response of native southern California vegetation to drought using MODIS-derived time series. Global Change Biology.

Willis, K. S., Gillespie, T. W., Ostermann-Kelm, S., Federico, F., Lee, L., MacDonald, G. M. (in prep) Monitoring Landscape Dynamics using MODIS in the Mediterranean Coast Network of Southern California. Environmental Management.

MacDonald, G. M., **Willis, K. S.**, Williams, A. P. (in prep) Has California Browned? Geography of Vegetation Sensitivity to 21st Century Drought in California. Environmental Research Letters.

Willis, K. S., Beilman, D., Booth, R. K., Amesbury, M., Holmquist, J., MacDonald, G. M. (2015) Peatland paleohydrology in southern West Siberian Lowlands: Comparison of multiple testate amoebae transfer functions, sites, and Sphagnum δ13C values. The Holocene. 1-12.

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Willis, K. S., S. Ostermann-Kelm, L. Lee, T. W. Gillespie, F. Federico, and G. M. MacDonald. Protocol for Monitoring Landscape Dynamics in the Mediterranean Coast Inventory and Monitoring Network of Southern California. Natural Resource Report NPS MEDN NRR 2013. National Park Service, Fort Collins, Colorado. In Review.

SELECTED GRANTS, FELLOWSHIPS, AND AWARDS

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American Geophysical Union, Ecological Society of America, American Association of Geographers, California Geographical Society

CHAPTER 1

1. Introduction

1.1 Background

Landscape conservation is vital to maintaining biodiversity and protecting earth's natural resources, and its effectiveness can only be assessed through systematic monitoring. An extremely effective monitoring tool for ecologically sensitive regions is remote sensing, an efficient, unbiased, quantitative method that is applicable at the landscape scale. However, there is often a gap between the rapidly evolving field of remote sensing science and the real world needs of conservation resource managers. Managers and ground monitoring personnel do not always have remote sensing training or access to the imagery or analytic software necessary to develop and maintain a landscape monitoring database. For example, the National Park Service maintains an 'Inventory and Monitoring Program' to quantify ecological status and changing trends within their Parks; an exemplar application of remote sensing and GIS (Fancy et al., 2009). However, this Program does not have direct access to remote sensing software and often relies on contracting this work to academic groups (Kennedy et al., 2010; Townsend et al., 2006; Willis et al., In Review).

California is a prime area to remotely assess ecological well-being since large swaths of land are protected for environmental reasons and there are multiple environmental stressors on the landscape, such as a large human population and climate change. California is not only a world-leading economic force and important to the US economy, but it is also rich in biodiversity and vital ecologically (Hayhoe et al., 2004).

Human population in California makes up about 12% of the US population (Diffenbaugh et al., 2015) and is rising at a 0.9% crude growth rate (State of California Department of Finance, 2014). This means that more land is constantly developed for residential and business purposes, which degrades natural landscapes. This increases environmental degradation, puts species at risk, and can adversely affect biodiversity and natural resources. Increased human population also introduces invasive plant and animal species, an issue that is widely prevalent throughout southern California (Donlan et al., 2003). Invasive species fragment natural habitats, alter trophic structures and disturbance regimes, can decrease natural resources, and are even further exacerbated by land use and climate change (Reaser et al., 2007).

Climate change may also act as a stressor to California landscapes and affects ecological health. The presence of drought is defined by a deficiency in precipitation and an increase in demand, due to water consumption and/or increased water loss which can be amplified by temperature (Cook et al., 2015; Diffenbaugh et al., 2015; Mann and Gleick, 2015). Any future periods of decreased precipitation are thus likely to become periods of drought due to climate change and predictions of increased temperatures in California (Diffenbaugh et al., 2015; Mann and Gleick, 2015). The present California drought, currently in its fourth consecutive year, is an example of these future scenarios to come and has received a great deal of media attention as of late (Figure 1.1). For example, the Los Angeles Times has even created its own "California Drought" section due to the severity.

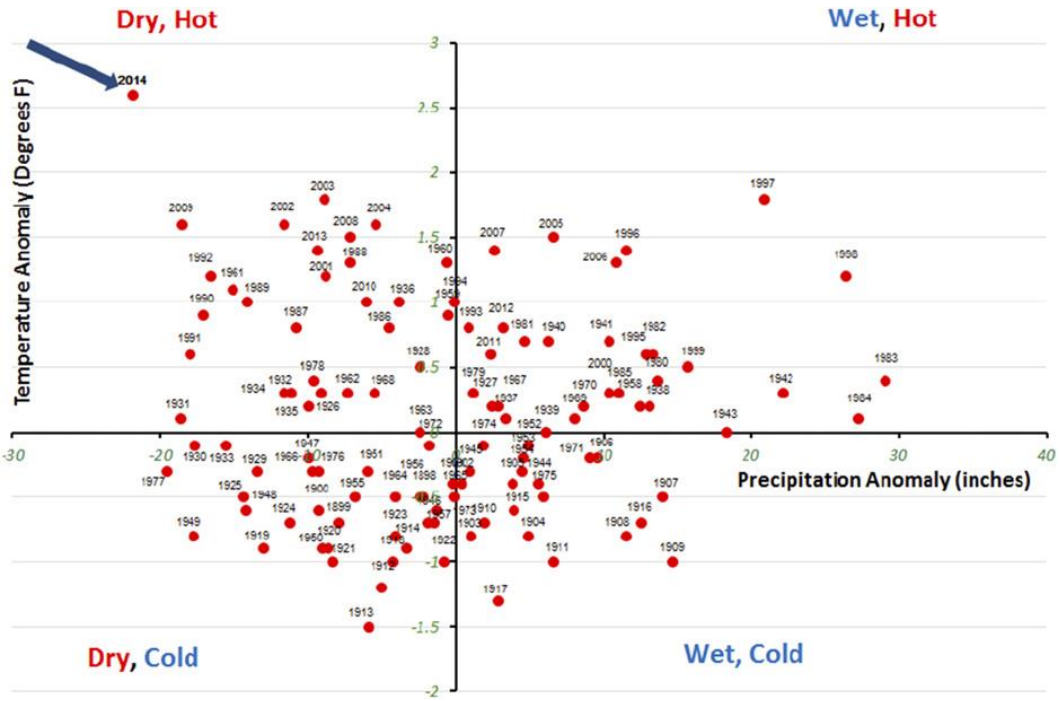

Figure 1.1 California temperature (°F) and precipitation (inches) anomalies from January 1895 to November 2014, plotted as 3 year anomalies relative to 1901–2000 mean. (Data from the National Climatic Data Center nClimDiv dataset, figure from Mann & Gleick, 2015).

The predicted changes in California's climatic regime will result in variable landscape changes, such as a noteworthy decline in snowpack, vegetation type distribution, and plant seasonality and health. For example, models predict the loss of 75-90% of alpine forests by the end of the century (Hayhoe et al., 2004). This has consequences for the human population and economy in terms of its drinking water, fisheries, and agricultural output (Mao et al., 2015). For instance, 77% of California's water goes to the agricultural sector, which in turn provides almost half of the fruits, nuts, and vegetables in the US food supply (Diffenbaugh et al., 2015; United States Department of Agriculture, 2015).

This dissertation aims to quantify the effects of increased pressure introduced by human population and climate change on the natural California landscape. First, the best practice remote sensing approaches for conservation monitoring strategies are identified. These methods

are then applied to monitor National Park land cover change in coastal Southern California and to assess the impacts of current drought on local native vegetation and state-wide ecological health.

1.2 Dissertation Structure

This dissertation uses remote sensing methodologies to aid conservation management, with a focus on human impacts to southern California ecology in protected areas and adjacent parcels. Chapters 2-5 are written as peer-reviewed publications in scientific journal (Chapters 2, 4, 5) or government report (Chapter 3) format. The extent of human impact to the southern California landscape is assessed in several contexts: the direct impacts of land use change and introduced species, as well as the indirect impacts of climate change under the context of the following scientific questions:

1. *How do human-induced threats (climate change, land use change, and invasive species) affect southern California ecosystems?*
2. *How can we use remote sensing to better understand these threats?*

This first chapter is an introduction and background to give context and clarification to the studies. The second chapter provides a review of current remote sensing methods utilized by the United States to monitor changes in protected areas. It provides recommendations of best-practice methods and data for applied change detection monitoring. The third chapter is a government report applying these techniques to monitor landscape dynamics in southern California National Parks. Land cover and vegetation changes are assessed spatially and temporally from 1986-present. Shifts between native to nonnative vegetation and developed land are identified, and areas of focus for further ecological monitoring are recommended. The

fourth chapter analyzes the response of local native plant communities to monthly drought according to a 2000-2014 time series. Chaparral- and coastal sage scrub-dominated ecosystem responses are contrasted across southern California counties. The fifth chapter addresses the whether the impacts of the recent drought are related to vegetation type or geographic region. It also assesses the spatial variability of browning over California's vegetation zones during 20th Century droughts and examines possible mechanisms for differential geographic/vegetation responses. This dissertation highlights the importance of remote sensing to ecological monitoring by demonstrating its application to various landscape dynamics.

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CHAPTER 2

2. Space-borne remote sensing for monitoring ecological change in United States protected areas

A version of: Willis, K. S. (2015) Remote sensing change detection for ecological monitoring in United States protected areas. Biological Conservation. 182, 233-242.

2.1 Abstract

Remote sensing allows for cost- and time-efficient monitoring of landscapes vital to conservation of natural resources, ecosystems, and biodiversity. This review synthesizes and recommends best practice methods utilized by land management groups to monitor chief ecological change indicators currently monitored in United States protected areas. Methods in remote sensing change detection are rapidly improving in a manner which coincides with the needs of conservation-based management. Key components in any monitoring process include choice of appropriate study area, scale, data, and key indicator or proxy to represent the ecological phenomenon at hand. The indicators frequently monitored via change detection include: land use/land cover, disturbance, and phenology. Landsat products are the most common remote sensing data used for monitoring land use/land cover and disturbance, due to their continuous data accessibility free of cost since 1972 at a 30-meter spatial resolution. Data from the Moderate Resolution Imaging Spectrometer (MODIS) are recommended for monitoring changes in phenology due to its 1-2 day return interval at any given location. Careful validation of results is stressed, either by combination of remotely sensed datasets with high resolution imagery or *in situ* data, in order to increase accuracy and to better align the remotely sensed data to the scale of the on-the-ground processes. Above all, collaborations between ecologists, land managers, conservation groups, and scientists are emphasized as vital for successful integration of remote sensing-based monitoring of changes in protected areas.

2.2 Introduction

In recent years there has been a rapid evolution of satellites, sensors, and techniques to monitor and model terrestrial protected areas, especially in the United States. This has been most evident in the number of scientific articles that utilize remote sensing to assess landscape change, biodiversity, and natural resources in individual protected areas at a global, regional, and local scale (Gross et al., 2009, 2012; Remote sensing of protected lands, 2012). Monitoring ecological processes is essential to understanding and protecting the natural environs and to preserving biodiversity. However, there is a general lack of communication between remote sensing scientists and monitoring practices, which has the potential to continue over time (Wiens, 2002). Several groups have bridged this gap and are currently utilizing remote sensing to monitor protected areas for ecological purposes (Fancy et al., 2009; Kennedy et al., 2009). This paper provides a review of initiatives which have been designed to effectively manage changes in protected areas using remote sensing methods.

2.3 Theory

2.3.1 What is a protected area?

The definition of a protected area (PA) adopted in this paper is "a clearly defined geographical space, recognized, dedicated, and managed, through legal [or other effective] means, to achieve the long-term conservation of nature with associated ecosystem services and cultural values" defined by the World Commission on Protected Areas (Dudley, 2008). For the purpose of this paper this definition includes landscapes in the United States managed by conservation groups in the public sector, government, and private organizations. We address the

use of space borne remotely sensed data (i.e. not including flyovers, photography, or *in situ* cameras) for conservation purposes.

Conservation is defined in this context as "the management of human use of the biosphere in order for it to yield the greatest sustainable benefit to current generations while maintaining its potential to meet the needs and aspirations of future generations" (IUCN, 2013). Protected areas were historically placed under conservation status in order to preserve natural beauty (Wiens et al., 2009), which is apparent still in many land management groups' mission statements (Table 2.1). Currently there are not only many reasons why a place is determined to be in need of conservation, but land areas are also categorized by importance level (Chape, 2003; Myers et al., 2000).

Table 2.1 Mission statements of various land management groups

Department	Acronym	Mission Statement	Remote Sensing Applications	Est.
Bureau of Indian Affairs	BIA	"...to enhance the quality of life, to promote economic opportunity, and to carry out the responsibility to protect and improve the trust assets of American Indians, Indian tribes and Alaska Natives."	Land use planning, responding to non-point source pollution affecting subsistence hunting and fishing, and climate change impacts such as sea level rise for coastal tribes	1824
Bureau of Land Management	BLM	"...to sustain the health, diversity, and productivity of the public lands for the use and enjoyment of present and future generations."	Remote sensing data combined with field-based measurements to monitor habitat, disturbance and land treatment activities	1946
Bureau of Reclamation	BOR	"...to manage, develop, and protect water and related resources in an environmentally and economically sound manner in the interest of the American public."	Monitors water consumption in western US by mapping irrigated crops and monitoring interstate/inter-basin water compact compliance	1902
Bureau of Ocean Energy Management	BOEM	"...to manage the development of the Nation's offshore resources in an environmentally and economically responsible way."	Monitors energy extraction in Gulf of Mexico	1982
National Park Service	NPS	"...to conserve the scenery, the natural and historic objects, and the wildlife in United States' national parks, and to provide for the public's enjoyment of these features in a manner that will leave them unimpaired for the enjoyment of future generations."	Baseline inventories and monitoring of geology, soil, vegetation, infrastructure	1916
Office of Surface Mining Reclamation and Enforcement	OSM	"...to protect America's natural resources and heritage, honors our cultures and tribal communities, and supplies the energy to power our future."	Surface mine inspection, possible monitoring toxic seeps and drainage reconstruction	1977
US Fish and Wildlife Service	USFWS	"...working with others to conserve, protect, and enhance fish, wildlife, plants, and their habitats for the continuing benefit of the American people."	Map habitats and inventory fish and wildlife	1940
US Geological Survey	USGS	"... to conduct the systematic and scientific classification of the public lands, and examination of the geological structure, mineral resources, and products of the national domain."	Provides satellite data, monitors ecosystem health, emergency response and impact assessment of natural hazards and disturbance	1879

PAs are located in coupled human-natural systems where there are strong interactions between humans and ecology (Jones et al., 2009; Michener and Brunt, 2000). Humans have had such a large and widespread impact on the earth that PAs are essential in preserving nature (Nemani et al., 2008). It is estimated that approximately 133 000 worldwide PAs make up approximately 12.4% of the Earth's land surface today (Chape, 2003; Nagendra et al., 2013). However, the distribution of these zones is not often enough to keep up with the negative impact of humans on biodiversity (Kerr and Ostrovsky, 2003; Rodrigues et al., 2004; Scott et al., 2001; Wiens et al., 2009). PA conservation is threatened by disturbance events, climate change, land use/land cover change, invasive species introductions, and deforestation (Chape et al., 2005; Gillespie et al., 2008; Pereira and Cooper, 2006; Rodrigues et al., 2004); all of which are discussed in this paper.

2.3.2 Why is ecological monitoring important?

Ecosystem monitoring refers to recurrent observed measurements collected and analyzed continuously for at least ten years, and is essential to determining the current health of an environment as well as the degree to and location in which this is changing (Kerr and Ostrovsky, 2003; Lindenmayer and Likens, 2010; Sergeant et al., 2012; Townsend et al., 2009). Data output and reports from monitoring studies may be focused on specific geographic areas and environmental problems in need of management. Several papers describing the applications of monitoring for conservation related goals (Lindenmayer and Likens, 2010) are focused on: Creating inventories of environmental status to compare future change and extreme event impacts (Keeling et al., 1995, 1996); assessing ecological response to disturbance (Schindler et al., 1985); change detection (Krebs et al., 2001); monitoring unusual events on a landscape (Zhan et al., 2006); providing evidence for environmental laws (Likens, 1992); creating hypotheses;

testing theory (Shrader-Frechette, 1993); developing computer simulation models; and data creation for environmental monitoring (Cole et al., 1994; Stelzer and Likens, 2006). Monitoring can be carried out by field-based ground measurements or via remote sensing technologies. Often these can be effectively used in combination.

Sustainable conservation land monitoring and management via *in situ* methods or remote sensing are applied optimally through a combination of natural resource knowledge, explicit policies concerning the resource, and the participation of stakeholders (Skidmore et al., 1998). Lindenmayer and Likens (2010) provide a review of the necessary components employed by effective ecological monitoring programs. Their review is focused on field-based measurements, but their assessment of effective monitoring components is also applicable to remote sensing-based monitoring. They conclude that effective programs contain specific characteristics such as: applicable questions, a conceptual model, collaboration between scientists, policy-makers, and managers, and consistent use of output data (Lindenmayer and Likens, 2010).

2.3.3 Why is remote sensing important to conservation monitoring?

Remote sensing is an efficient, unbiased, quantitative method useful for ecological monitoring at a wide variety of spatial and temporal scales (Cook and Hockings, 2011; Crabtree et al., 2009; Franklin et al., 2000; Kennedy et al., 2009; Miller and Rogan, 2007; Nemani et al., 2009; Rogan et al., 2002; Townsend et al., 2009; Wiens et al., 2009). Cost is often an issue because high resolution imagery tends to be the most expensive, making scale a key consideration in monitoring design (Gross et al., 2009; Wiens et al., 2009). There are tradeoffs between using the highest spatial resolution possible in order to correctly inventory ecological

indicators while balancing an appropriate continuous temporal resolution and minimizing cost (Nemani et al., 2009).

Monitoring at a landscape scale gives a broad perspective on the pattern of changes occurring throughout the entire conservation area and allows for a future downscaled focus on the cause of change (Kennedy et al., 2009). The drivers of change are often identified by choosing an ecosystem indicator, or an ecological mechanism that represents and quantifies the impacts on natural resources (Crabtree et al., 2009; Kurtz et al., 2001). Ecosystem indicators are defined as "a subset of monitoring attributes that are important because they are indicative of quality, health, or integrity of the larger ecological system to which they belong" (Jones et al., 2009). Standardized sets of these variables are available from: the National Land Cover Dataset, digital elevation models, digital maps, soil maps, climate data sets, or they can be generated through GIS (Crabtree et al., 2009). An example of these is the use of "vital sign" measures, which are used by the National Park Service (Table 2.2) and include indicators such as fire occurrence and intensity, land use pattern change, habitat type conversion, or detection of introduction and spread of non-native invasive species (Cameron et al., 2006). These applications are further discussed in section 2.4.2.

Table 2.2 Most common vital signs monitored by the National Park Service Inventory and Monitoring Program (modified from Fancy and Bennetts, 2012).

Indicator Category	Example Measures (varies by network)	Number of Parks
Weather and climate	Temperature, precipitation, wind speed, ice on/off dates	246
Water chemistry	pH, temperature, dissolved oxygen, conductivity	211
*Land cover and use	Area in each land cover and use type; patch size and pattern	203
Invasive/exotic plants	Early detection, presence/absence, area	200
Birds	Species composition, distribution, abundance	189
Surface water dynamics	Discharge/flow rates, gauge/stage height, lake elevation, spring/seep volume, sea level rise	158
Ozone	Ozone concentration, damage to sensitive vegetation	140
Wet and dry deposition	Wet deposition chemistry, sulfur dioxide concentrations	114
Visibility and particulate matter	IMPROVE network; visibility and fine particles	113
*Fire and fuel dynamics	Long-term trend of fire frequency, average fire size, average burn severity, total area affected by fire	105
*Vegetation complexes	Plant community diversity, relative species/guild abundance, structure/age class, incidence of disease	101
Mammals	Species composition, distribution, abundance	93
*Forest/woodland communities	Community diversity, coverage and abundance, condition and vigor classes, regeneration	93
Soil function and dynamics	Soil nutrients, cover and composition of biological soil crust communities, soil aggregate stability	91
*Stream/river channel characteristics	Channel width, depth, and gradient, sinuosity, channel cross-section, pool frequency and depth, particle size	89
Aquatic macroinvertebrates	Species composition and abundance	86
Threatened and endangered species and communities	Population estimates, distribution, sex and age ratios	85

Air contaminants	Concentrations of SOCs, PCBs, DDT, Hg	71
Groundwater dynamics	Flow rate, depth to ground water, withdrawal rates, recharge rates, volume in aquifer	69
Amphibians and reptiles	Species distribution and abundance, population age/size structure, species diversity, percent area occupied	54
*Grassland/herb communities	Composition, structure, abundance, changes in treeline	51
Fishes	Community composition, abundance, distribution, age classes, occupancy, invasive species	50
Insect pests	Extent of insect-related mortality, distribution and extent of standing dead/stressed/diseased trees, early detection	50
*Riparian communities	Species composition and percent cover, distribution and density of selected plants, canopy height	45
Nutrient dynamics	Nitrate, ammonia, DON, nitrite, orthophosphate, total K	45
*Primary production	Normalized differential vegetation index (NDVI), change in length of growing season, carbon fixation	41
*Wetland communities	Species composition and percent cover, distribution and density of selected plants, canopy height, aerial extent	40
Microorganisms	Fecal coliform, *E. coli*, cyanobacteria	30
Water toxics	Organic and inorganic toxics, heavy metals	30
*Invasive/exotic animals	Invasive species present, distribution, vegetation types invaded, early detection at invasion points	29
*Coastal/ oceanographic features and processes	Rate of shoreline change, sea surface elevations, area and degree of subsidence through relative elevation data	29

*indicates vital signs commonly detectable by remote sensing

Remote sensing methodologies are increasingly being created to address conservation monitoring needs (Franklin et al., 2000; Miller and Rogan, 2007; Pettorelli et al., 2014; Phinn et al., 2003; Rogan et al., 2002). However, there is often a gap between the rapidly evolving field of remote sensing science and the real world needs of conservation resource managers in decreed PAs. Managers and ground monitoring personnel do not always have remote sensing training or access to the imagery or analytic software necessary to develop and maintain a landscape monitoring database (Laurance et al., 2012). Thus there is a need to develop standard remote sensing methods that can be easily applied across a diversity of spatial scales and used efficiently by land managers.

2.3.4 Conservation-based land management groups

The United States contains over 6,770 terrestrial federally protected areas, totaling ~2,893,500 km^2 and representing more than 27% of the land area (Chape, 2003; Gergely and McKerrow, 2013). These protected areas lie under a variety of land management stakeholders, including private, public, and federally owned land. Many of the groups assessed in this paper exist for the purpose of protecting the land for both ecological and cultural purposes, such as the National Park Service (NPS), United States Fish and Wildlife Service (USFWS), National Forest Service (NFS), and the Bureau of Land Management (BLM). For example, a primary goal of the National Park Service is "to maintain native species and ecological processes," (Sellars, 1997) and is of importance to protect the natural beauty, 'geologic uniqueness', and history of the land being protected (Schullery, 2004). The National Forest Service's purpose is to "improve and protect land, securing favorable waterflows, and provide a continuous supply of timber." These are PAs managed for multiple conservation purposes, including outdoor recreation, and protection of rangelands, timber, watersheds, wildlife, and fish (Huang et al., 2009).

2.4 Methods and materials

A variety of remote sensing applications to conservation-based land management were assessed. The majority of literature reviewed included both peer-reviewed journal articles and ecological reports from conservation and land management groups in the United States. Searches for these studies and reports were conducted through online databases using search terms such as the keywords in this paper, "remote sensing; conservation; management; protected areas; ecological monitoring; change detection." The United States was selected as the region of focus since it is a country at the forefront of ecological management and monitoring as well as for ease of access of data and reports. The land management stakeholders of focus in this paper exclude those in the private sector, since results are often difficult to assess, are often unpublished, or are applied to regions outside of the US. Some of these groups, such as the Nature Conservancy (TNC), also base their management efforts on data collected from species inventories rather than remote sensing methods to determine threats such as development and disturbance (Wiens et al., 2009).

This review has three primary objectives: To provide an account of remote sensing ecological monitoring 1. change detection methods, and 2. applications for conservation in the United States using recent case studies; as well as 3. to provide recommendations for the most effective use of these current methodologies. First, common change detection methods encountered in the field of remote sensing are reviewed. Then recent advances in United States conservation-based land management groups are addressed relating to changes in land use land use and land cover, ecological disturbance, phenology. Finally, suggestions are provided for how to improve overlap between organizations and standardize methods available at present and into the future.

2.5 Results and discussion

2.5.1 Change detection methods

There is increasing interest in assessing the effectiveness of monitoring and management of natural areas, and remote sensing methods have vastly improved these conservation abilities (Cook and Hockings, 2011; Lindenmayer and Likens, 2010; Pettorelli et al., 2014; Sergeant et al., 2012). Common issues specific to remotely sensing methodologies are associated with: data availability and cost (Wang et al., 2009; Wiens et al., 2009), atmospheric contamination from sources such as haze, clouds, and shadows (Kerr and Ostrovsky, 2003; Nagendra et al., 2013), errors in the sensor (Wang et al., 2012), and differences in temporal/spatial scale in need of monitoring versus the scale of sensor data available (Spanhove et al., 2012). In order to effectively monitor and manage a region, an inventory of status and changes must be tracked.

Change detection is the procedure used to identify differences in the state of an object or phenomenon by observing it at different times (Singh, 1989). In monitoring PAs, this method is often used to monitor "landscape dynamics," or changes in area and distribution of ecological systems (Wang and Zhou, 2008). Change detection methods identify variations from the normal spectra of pixels from remotely sensed data to detect areas undergoing rapid changes such as from land use and land cover (Coppin et al., 2004; Defries et al., 2000; Friedl et al., 2002; Kennedy et al., 2009; Lu et al., 2004; Rogan et al., 2002; Singh, 1989) or disturbance (Cohen et al., 2010; Huang et al., 2009; Kennedy et al., 2009; Nagendra et al., 2013; Nemani et al., 2008).

The first step in change detection is the delineation of study area and choice of appropriate spatial and temporal resolution (Kennedy et al., 2009; Townsend et al., 2009). Delineation of study area should consider the inclusion of buffer zones either adjacent to or

within the borders of PA boundaries to account for outside ecological influences (Gross et al., 2009; Hansen and DeFries, 2007; Jones et al., 2009; Svancara et al., 2009). The Protected Area Centered Ecosystems (PACE) framework follows this model and is considered best practice for determining study area (Hansen and Davis, 2011).

Spatial and temporal scale must match up with the phenomenon studied to ensure that changes in the remotely sensed data are representing the correct ecological process (Table 2.3) (Jensen, 2007; Nagendra et al., 2013; Rogan and Chen, 2004; Sergeant et al., 2012; Wiens et al., 2009). In remote sensing, spatial scale is often referred to as coarse, medium, or fine resolution, referring to approximately 250-500 m, 30 m, and <1 m pixel size respectively. Pixel sizes for monitoring purposes usually range from ~0.5 m – 500 m. For example, a medium resolution (30 m pixel) sensor such as Landsat may be used to monitor vegetation community-type changes, yet is not appropriate to monitor species-type change. The next factor of scale which should be considered is temporal resolution; how long should the process be measured for and how often? Effective change detection should be carried out over a time period of at least ten years (Huang et al., 2009). The temporal sampling interval will depend on the ecological application and system being monitored, but typically ranges from 1 to 16 days.

Table 2.3 Example of a [2014] cost-benefit analysis for choosing appropriate satellite imagery.

Satellite	Background Information	Spatial Resolution	Nominal Revisit Time	2014 Base cost for archived images (per km^2)	2014 Base cost for custom images (per km^2)	Spectral Resolution	Applications
MODIS	NASA product on Terra and Aqua satellite, launched 1999	250m (bands 1-2), 500m (bands 3-7), 1000m (bands 8-36)	1-2 days	Free	n/a	36 bands available at different resolutions	Phenology
Landsat TM/ETM+/OLI	NASA product since 1972	30m	16 days	Free	n/a	7 bands on Landsat 5, 8 bands on Landsat 7	Land use/land cover change
IKONOS	First high resolution color imaging satellite since 1999, owned by DigitalGlobe	0.80m pan[a], 2.4m multi[b]	3-5 days	$10 (minimum order 25 km^2)	$20 (minimum order 100 km^2)	Pan[a], multi[b] (4-band), natural color (3-band), color IR[c] (4-band) pan-sharpened, or pan[a] + multi[b]	Data validation
GeoEye-1	Highest resolution commercial color imagery satellite since 2008, owned by DigitalGlobe	0.46m pan[a], 1.84m multi[b]	<3 days	$13-29 (minimum order 272 km^2)	$22-38 (minimum order 100 km^2)	Pan[a] or multi[b] (4-or 8-band)	Data validation
Quickbird	Owned by DigitalGlobe, launched 2001	0.61m pan[a], 2.4m multi[b]	1-3.5 days	$13-29 (minimum order 272 km^2)	$22-38 (minimum order 100 km^2)	Pan[a] or multi[b] (4-or 8-band)	Data validation
SPOT 1-7	Launched in 1986, owned by Spot Image, France	2014: 1.5m pan[a], 6m multi[b]; 2002-2014: 2.5-5m pan[a], 10m multi[b] 1986-2002: 10m pan[a], 20m multi[b]	1-3 days	$32 (minimum order 60 km^2)	$24-72 (minimum order $3600)	Pan[a] or multi[b] (4-band)	Data validation
ASTER	NASA product on Terra	15m visible near	16 days	$1.50/ imagery	n/a	15 bands	Supplementary data source,

satellite, launched 1999	IR[c], 30m shortwave IR[c], 90m thermal IR[c]	$0.75/ DEM[d]	DEM[d]

a pan – panchromatic includes one greyscale band of combined red, green, and blue of visible electromagnetic spectrum

b multi – multispectral covers multiple bands along the electromagnetic spectrum

c IR – Infrared

d DEM – Digital Elevation Model

Change detection commences with image classification analysis, or the process of associating observed or vector-based land cover classes with remote sensing spectral data. When choosing datasets it is necessary to account for future data continuity and systematic improvements in remote sensing technology (Gross et al., 2009). Many standard vector-based datasets are based on a large spatial scale, and can be scaled to a finer resolution by integrating satellite-based data with high resolution satellite, aerial-based, or *in situ* data (Kerr and Ostrovsky, 2003; Nagendra et al., 2013). The chosen classification system should be applicable to a variety of land cover types to allow for comparison of land cover data, satellite data, and output change results between PAs.

Change detection has historically been used to look at changes in land use/land cover and disturbance using binary comparisons contrasting conditions during two discrete time periods (Cohen et al., 2002; Collins and Woodcock, 1996; Coppin et al., 2004; Franklin et al., 2002; Goetz et al., 2011; Healey et al., 2005; Lu et al., 2004; Nelson, 1983; Reed et al., 2006; Townsend et al., 2006; Wiens et al., 2009), and have been reviewed in the past (Healey et al., 2005; Rogan et al., 2002; Woodcock and Ozdogan, 2004). Techniques are increasingly using automated approaches to detect multi-temporal changes over a large stack of imagery representing a number of discrete time periods (Antonova et al., 2010; García-Haro et al., 2001; Goetz et al., 2011; Goodwin et al., 2008; Hansen and Davis, 2011; Healey et al., 2006; Hostert et al., 2003; Huang et al., 2010; Kennedy et al., 2007; National Park Service, 2014; Nemani et al., 2008; Viedma et al., 1997; Vogelmann et al., 2009).

Automated algorithms such as the Landsat-based Detection of Trends in Disturbance and Recovery (LandTrendr) and Vegetation Change Tracker (VCT) have expedited the process for change detection by comparing deviations in multiple images and dates (Huang et al., 2009,

2010; Kennedy et al., 2010). Both programs can either track slow processes over time or abrupt events (Kennedy et al., 2010), and can also detect errors or background noise inherent in data, which are predicted to increase with climate change (Hicke et al., 2006; Logan et al., 2003).

In order for any method of change detection to be effective, the appropriate pre- and post-processing calibration and validation are needed, and must also improve to keep up with the refinement in temporal scale created by automated algorithms (Rogan and Chen, 2004). Cohen et al. (2010) have begun to address this by creating an automated validation tool, TimeSync, which also can be used to output spectral changes with their biological applications.

2.5.2 Ecological monitoring applications

The most common remote sensing-based applications used by conservation managers were found to be monitoring of changes within their protected zones. Change detection is used as an overarching method to analyze 1. uniform conversions between land use and land cover classes; 2. irregular variations such as disturbance; and 3. continuous fluctuations such as seasonal plant cycling. Each application is first defined here, followed by a discussion of methods, and finally techniques to standardize these methodologies are suggested.

2.5.2.1 Uniform change detection case studies: land use and land cover change

Land use and land cover change (LULCC) is a primary cause of significant recent alterations to the biosphere, and increased climate change is expected to amplify its effects in the future (Cohen et al., 2010; Lambin et al., 2001; Parmesan and Yohe, 2003). LULCC has increased globally, especially in areas surrounding protected lands (Hansen et al., 2004), which is likely to progressively impact landscapes within protected zones.

Land cover describes features covering the land such as natural vegetation, crops, buildings, and water. Land use is defined as human uses of the land such as for open space, agriculture, and residential areas. LULCC monitoring often aims to identify which areas of land are changing, the extent of change, and which class it is changing to/from (Wang et al., 2009). This information is fundamentally important to planners, researchers, and other groups interested in managing PA's. Remote sensing is specifically vital to monitoring LULCC in many PA's where direct access is not often available to easily monitor from the ground and identify where changes are occurring (Wiens et al., 2009).

Human-induced land cover change can occur in the forms of agricultural land-clearance, suburban sprawl, and timber harvests and influences processes, organisms, and natural resources within and surrounding protected areas (Hansen and Rotella, 2002; Lambin et al., 2001; Sala et al., 2000; Soulé, 1991; Wang et al., 2009; Wessels et al., 2012). This introduces higher levels of human disturbance, causing changes in air, water, and natural disturbance, generates natural habitat loss and fragmentation, and ultimately severely threatens biodiversity (Grumbine, 1994; Hansen and DeFries, 2007; Jones et al., 2009; Theberge, 1989).

2.5.2.1.1 LULCC monitoring methods

Well-designed management plans minimize negative impacts from LULCC on protected areas by maximizing connectivity and habitat size, minimizing fragmentation, targeting migration zones, and keeping a close eye on human impacts especially around edges of protected zones (Hansen and DeFries, 2007). For example, the Land Cover Trends Project of the USGS was created to map large-scale changes in major land cover types using Landsat imagery from 1973-2000 (Loveland et al., 2002). Projects such as these can help create an inventory of where

and how land cover classes are changing over the landscape. These inventories may then be utilized to change environmental policy and to focus management needs.

LULCC techniques are applicable to a variety of ecosystem types. Several current examples of these applications include monitoring changes between grasslands and mixed grass/sagebrush in rangelands (Huang et al., 2010); evaluating sensitive areas in the Florida Everglades for land use change and biogeochemistry based on vegetative health and condition (Hogan et al., 2012; Jones et al., 2011); and mapping vegetation across National Parks; and the Midwest USFWS lands (UMESC, 2014).

Landsat products, including the Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), and Operational Land Imager (OLI), have ideal sampling characteristics for monitoring diverse land cover types at a regional and historic scale due to their global coverage (Cohen and Goward, 2004; Kennedy et al., 2010; Miller and Rogan, 2007; Rogan and Chen, 2004). The 30 m spatial resolution of Landsat sensors allows for spatial detail to be captured at a scale appropriate for monitoring vegetation structure and composition. The Landsat Data Continuity Mission (LDCM), with OLI sensor may be used for current monitoring purposes since its launch in early 2013. Other freely available satellite data may be used as replacements in future analyses as well, such as from the European Space Agency's Sentinel-2.

However, managers of some protected areas find high spatial resolution data more optimal, such as the use of QuickBird in the USFWS Desert National Wildlife Refuge (USGS, 2012). Other space borne sensors used for LULCC by PAs in the USA include IKONOS/Geoeye, Advanced Land Observing Satellite (ALOS), Earth Observing Mission 1 (EO-1), Advanced Land Imager (ALI), and Advanced Spaceborne Thermal Emission and Reflection

Radiometer (ASTER) (Wiens et al., 2009). Many of these sensors do not offer freely available data, and a cost-benefit analysis must often be run before considering the utilization of these generally higher resolution satellites (i.e. Table 2.3).

LULCC is quantified using both binary and automated change detection methodologies. A supervised-type classification is the most intuitive method for land cover classification, which uses baseline data often collected in the field or from an existing land cover dataset to assign classes to certain pixels (Rogan and Chen, 2004). The spectral information within those pixels is then used to apply the assigned landscape classes to the remainder of an image, thereby creating a baseline land cover image. The accuracy of this image can then be tested for errors.

There is error inherent in the ability of remote sensing to describe on the ground LULCC, which is a trade off with its ability to assess an entire landscape. Accuracy is maximized by identifying error sources with multiple analysis runs, and then applying appropriate changes to the algorithm. Sources of error are identified via ground-based field validation and/or visual interpretation of high resolution images (Congalton, 1991; Huang et al., 2009; Stehman and Czaplewski, 1998). Validation points for land use classes can be chosen based on a randomized draw, such as the Geometric Stratified-Random Sampling Technique (Wiens et al., 2009).

Once classes are randomly tested, an accuracy assessment may be run, which validates a classification by comparing its output to input ground-truth data in a confusion matrix format. The overall accuracy is expressed as a percentage value, and for land management purposes is typically deemed acceptable if above 85% (Fitzpatrick-Lins, 1980). The percentage accuracy and numerical pixel value are reported for each land use class along with the number of misclassified pixels.

2.5.2.1.2 LULCC standardizing techniques

Either automated or binary change detection using Landsat imagery is common for monitoring LULCC. Associated methods are rapidly evolving due to free access to data, increased automated algorithms, and detailed information becoming available over large geographical swaths (Cohen et al., 2010). Different satellites ensure that varying scales of vegetation can be studied; Landsat is useful for vegetation communities, whereas SPOT or QuickBird may be used for species- or genera-specific vegetation change monitoring. For example, the BLM uses high-resolution aerial imagery along with QuickBird to monitor changes in sensitive ecosystems such as upland, riparian, and aquatic habitat in Oregon and Wyoming (USGS, 2012). General changes in land cover classes are detectable through Landsat, such as conversion between agricultural land and water resources in Nevada/Utah (USGS, 2012).

National standardized vector datasets have been developed for country-wide comparison of land cover, many of which were created with remotely sensed data, such as the National Land Cover Dataset by the USGS based on Landsat data (Homer et al., 2004). The USGS GAP Analysis Program is another example of a vector dataset, was created from Landsat imagery in 2001, and is deemed 85% accurate by field validation. GAP data are commonly used in LULCC studies or for habitat mapping (Davis et al., 1995; Lowry et al., 2005). The USGS is also working with the USFWS to standardize vegetation classification maps across several states, including Texas, Oklahoma, Louisiana, Mississippi, and Alabama (USGS, 2012). The National Vegetation Classification System is a program specifically developed by conservation organizations and used for wildlife habitat monitoring (Kerr and Ostrovsky, 2003). Site-specific land cover datasets such as that used by the Southern California Association of Governments

(SCAG) in some cases may be more accurate, but often do not contain standardized vegetation and land use types for multiple locations (SCAG, 2014).

2.5.2.2 Irregular change detection case studies: disturbance

Ecological disturbance to a protected area is defined as "a cause; a physical force, agent, or process, either abiotic or biotic, causing a perturbation (which includes stress) in an ecological component or system; relative to a specified reference state and system; defined by specific characteristics" (Rykiel, 1985). Disturbance types monitored in US protected areas occur across a variety of scales and rates of change, and include fire, invasive plant and animal species, disease, grazing, flooding, and deforestation (Dennison et al., 2009; Jones et al., 2013; USGS, 2012; Wiens et al., 2009). Satellite-based remote sensing is essential to the study of disturbed areas, since remote studies do not increase the amount of disturbance on the ground especially in sensitive ecological zones or areas cut off to public access (Dennison et al., 2009; Wiens et al., 2009).

2.5.2.2.1 Disturbance monitoring methods

Disturbances are classified based on differences in the behavior of the spectral changes. For example, disturbance by insect infestation is evident in remotely sensed data by looking at slow deterioration or spectral changes that occur over a longer period of time (Kennedy et al., 2012). In contrast, fire is a large scale, sporadic occurrence, which in turn limits *in situ* access due to the danger it introduces to humans (Kennedy et al., 2012). Remote sensing is used to monitor fire potential, severity, frequency, post-fire scarring, and recovery by looking at multiple years of spectral data in a series (Jones et al., 2013; Wiens et al., 2009). Results can be used to capture the location of the fire event, as well as the full multi-annual effects of fire on the

vegetation. Fire is monitored across a variety of ecosystem types, such as the Florida Everglades, Alaskan boreal forest, and grasslands in Buenos Aires National Wildlife Refuge in Arizona (Jones et al., 2009; USGS, 2012; Wiens et al., 2009).

The effects of disaster events such as flooding, tornadoes, earthquakes, and tsunamis are tracked at a consistent time interval in a particular region after the event. Immediately after Hurricane Katrina, the USGS used remote sensing for post-disaster relief monitoring in Louisiana and Mississippi (USGS, 2012). Multiple occurrence disaster and natural disturbance events can also be monitored to determine potentially affected adjacent zones, such as the identification of floodplain locations based on flood regimes in the Connecticut River Watershed (Wiens et al., 2009). Studies in high security zones require remotely sensed monitoring due to lack of land access such as in the Eglin Air Force Base of the Florida Everglades (Wiens et al., 2009). An area may also be sensitive to ground-based monitoring due to possible impacts on water quality, riparian habitats, and endangered species presence (Dennison et al., 2009). For example, remote sensing is used in the Colorado River Plateau to maximize bioremediation by monitoring biocontrol of invasive tamarisk species using salt cedar leaf beetles (Dennison et al., 2009; Dudley et al., 2001).

2.5.2.2.2 Disturbance standardizing techniques

Automated change detection programs are recommended for monitoring disturbance since continuous temporal measurements help identify disturbance type and severity. Disturbance type and severity are classified according to the amount of time it takes for pixels to change and the manner in which they change, so it is difficult to offer a blanket approach for methods for all disturbance types. For example, fire occurrence and insect infestation are

reflected differently in pixel changes, and thus may require use of different input data. MODIS data are recommended for disturbances occurring over larger (50-100 m^2) swaths of land such as fire, whereas ASTER is useful in spectrally complex cases such as insect infestation due to its high spatial resolution (15-90 m^2) at multiple bands (Dennison et al., 2009). Landsat products (30 m^2) may also be useful for specific events, such as to determine fire extent (Jones et al., 2013).

Management efforts in sensitive areas such as the Eglin Air Force Base are exemplary for their collaborative efforts between conservation groups and stakeholders, in this case including: The Nature Conservancy, Eglin Air Force Base, USFWS, Florida Natural Areas Inventory, and the Joseph W. Jones Ecological Research Center (Wiens et al., 2009). The USGS has also led collaborative efforts to create fire-based national data products for fire potential, presence, and burn severity, including the Fire Potential Index (FPI), Landscape Fire and Resource Management Planning Tools (LANDFIRE), and Monitoring Trends in Burn Severity (MTBS) (USGS, 2012). These data are used by the USGS/USFS Burn Area Emergency Response (BAER) Teams to protect property, natural resources, human lives, and land cover recovery (USGS, 2012). For example, wildfires from 1972 to 2010 were mapped and evaluated in the Mojave Bioregion in order to gain knowledge on fire dynamics, local effects, and to identify useful management strategies to implement in future practices (USGS, 2012).

2.5.2.3 Continuous change detection case studies: phenology

Climate change has a significant effect on natural landscapes, and can affect ecosystem dynamics even on relatively a short timescale (Nemani et al., 2009). As climate change continues, it may eventually decrease biodiversity within protected areas regardless of direct

human influence. One of the known effects of climate change is reflected in changes to the local phenology of plants (Parmesan and Yohe, 2003). Phenology is the variation in seasonal patterns of natural phenomena in land surfaces, and can be detected via remote sensing by changes in spectral index values (Pettorelli et al., 2005; Reed et al., 1994; Zhang et al., 2004). Plant phenology is often used as a proxy for climate change since it is a direct measure of the effects of climate change on plant vitality (Morisette et al., 2008; Nagendra et al., 2013; Schwartz, 2003). Changes in seasonal timing such as the start and end of season, duration of growing season, and maximum productivity can in turn have an impact on a large number of species that are dependent on natural cycles of vegetation.

2.5.2.3.1 Phenology monitoring methods

Changes in plant phenology are often measured through the use of the Normalized Difference Vegetation Index (NDVI) (Goetz and Fiske, 2009; Goetz et al., 2011; Justice et al., 1985; Melton et al., 2010; Nemani et al., 2008; Pettorelli et al., 2005; Piekielek et al., 2010; Zhang et al., 2003). NDVI is a useful indicator of photosynthetic capacity, measured as a band combination ratio from one of a number of satellites including NOAA AVHRR, MODIS, or Landsat, and is given by:

$$NDVI = (\rho NIR - \rho RED) / (\rho NIR + \rho RED),$$

where ρNIR is reflectance in the near infrared band and ρRED is reflectance in the red band (Dennison et al., 2005; Huete et al., 2002; Reed et al., 1994; Tucker, 1979; Zhang et al., 2003). Seasonality metrics may also be calculated from other spectral indices, such as the Enhanced Vegetation Index (EVI). EVI is used to calculate seasonality metrics in areas where NDVI is not

a valuable indicator of the change in seasons due to greenness saturation in areas of high biomass (Chéret and Denux, 2011).

The annual cycles of vegetation phenology that can be inferred by remote sensing are usually characterized by four key transition dates: 1) greenup, the date of onset of photosynthetic activity; 2) maturity, the date at which plant green leaf area is maximum; 3) senescence, the date at which photosynthetic activity and green leaf area begin to rapidly decrease; and 4) dormancy, the date at which physiological activity becomes near zero (Zhang et al., 2004). Analysis of the temporal variations in NDVI from MODIS datasets has become the most commonly used technique to measure these four transitions in phenological changes, and is used across the country in Shenandoah, Delaware, Rocky Mountains, Yellowstone, Yosemite, Santa Monica Mountains, Channel Islands, and Alaska National Parks (USGS, 2012). A decline in NDVI could be attributed to a number of climatic and environmental factors, including drought, temperature, precipitation, fire, insects, diseases, nutrient limitations (Goetz et al., 2005).

Changes in phenology are part of a complex system, and can be influenced by outside forces other than long-term climate change, such as precipitation or fire. These must be accounted for in monitoring methodologies, such as masking out fire areas to eliminate burn zone anomalies in NDVI values. Other anomalies in phenology indices may be explained by climate records such as soil moisture levels or precipitation events, which affect the short-term uptake of water by plants and may ultimately alter plan greenness (Bertrand et al., 2011; Zhang et al., 2013). These short-term influences may be eliminated by de-trending time series data, or they may be incorporated into the phenology cycles, depending on the monitoring intentions (Chéret and Denux, 2011).

2.5.2.3.2 Phenology standardizing techniques

Detecting changes in phenology requires the use of remotely sensed datasets with high temporal resolution. MODIS-derived indices are recommended for monitoring phenology in vegetation due to the variety of phenology-related data products (i.e. NDVI, EVI, Leaf Area Index (LAI), Albedo) and their high temporal resolution (8- and 16-day). MODIS has also recently created a data product (MCD12Q2) which produces direct estimates of phenological timing (*MODIS subsetted land products*, 2014).

A combination of satellite and ground-based data along with climate records or model simulations can be used to provide information about ecosystem phenology indicators (Nemani et al., 2003; Schwartz, 2003). Many climate modeling and forecasting systems are not utilized by managers of protected areas due to the lack of training or experience with modeling (Nemani et al., 2009). The automated program Terrestrial Observation and Prediction System (TOPS) is designed to facilitate in this process and to integrate remotely sensed, ground, and climate data along with climate models in order to predict ecological conditions such as phenology for protected areas (Ichii et al., 2008; Nemani et al., 2003, 2008: 200; White and Nemani, 2004).

Remote sensing-based phenological studies are most robust when performed in combination with *in situ* studies. The USGS is at the forefront of collaborative studies in phenology and in combining these datasets. One example is their extrapolation of ground-based data obtained by the US Phenology Network across the nation (USGS, 2012). The USGS is also in the process of developing a Land Surface Phenology Viewer using MODIS data in conjunction with the NPS and NASA (USGS, 2012). These initiatives often utilize citizen science by compiling data such as geo-located, time-stamped images of plants collected from

smart phones from the general public to increase sample size and accuracy (Brigham et al., 2009; Graham et al., 2011).

2.6 Conclusions

It is rare that scientists have extensive knowledge in ecology, management, and remote sensing, making collaboration between scientists and conservation groups crucial (Wiens et al., 2009). Effective remotely sensed monitoring programs contain elements of information, policy, and participation in order to improve communication between managers and scientists (Skidmore et al., 1998). Another effective way to ease this gap is through comprehensive written reviews. A review of remote sensing technologies available for land management application purposes was written over thirty years ago (Woodcock et al., 1983), but many reviews since with similar themes have not been written with conservation-based land managers as the primary audience (Gross et al., 2009; Pettorelli et al., 2014; *Remote sensing of protected lands*, 2012; Vacik et al., 2014). Many land management organizations integrate GIS programs to their conservation efforts, yet do not have access to remote sensing software (Woodcock et al., 1983). The fields of remote sensing and GIS are similar in scope and in scale, which makes communication between remote sensing scientists and land managers relatively simple. Not only increased collaboration, but improved interdisciplinary learning between ecologists, land management groups, and remote sensing experts will be essential to future effective monitoring of PAs (Nagendra et al., 2013).

Several working groups have formed in recent years in order to better communicate and combine efforts in remote sensing for conservation purposes. The USGS Land Remote Sensing Program contributes significantly to the remote sensing community by producing both data and

research. The USGS chairs the Department of the Interior Remote Sensing Working Group (DOIRSWG), which maintains a website with all current research project overviews (USGS, 2012). The DOIRSWG encompasses research from the following groups: Bureau of Indian Affairs (BIA), Bureau of Land Management (BLM), Bureau of Reclamation (BOR), Bureau of Ocean Management, Regulation, and Enforcement, National Park Service (NPS), Office of Surface Mining (OSM), US Fish and Wildlife Service (USFWS), and the US Geological Survey (USGS). This group produced a Land Imaging Report in 2012, and will likely continue to produce future reports. The North American Network for Remote Sensing Park Ecological Condition (NARSEC) is another working group, organized in 2005 by the National Park Service (*Remote sensing of protected lands*, 2012). However, a workshop in 2007 was the last reported NARSEC event, and these seem unlikely to continue. Collaborative working groups such as these are vital to the continuation and evolution of remote sensing standardization across PAs in the United States.

This review has provided a comprehensive assessment of remote sensing change detection methods currently employed for monitoring and management of protected lands in the United States. At present the United States is at the forefront of remotely sensed monitoring, contains a high concentration of successful conservation programs, and is a best practice model for land management applications worldwide. Change detection methods are useful for monitoring uniform, irregular, and continuous ecological dynamics for monitoring on-the-ground applications such as LULCC, disturbance, and phenology. Forming collaborations within and between working groups with improved communication between research scientists, field scientists, and land management groups, as well as elucidating current methods and highlighting

operative applications of remote sensing in land management are vital steps towards improving conservation in PAs.

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CHAPTER 3

3. Monitoring Landscape Dynamics in the Mediterranean Coast Inventory and Monitoring Network of Southern California: Land Cover Change

A version of: Willis, K. S., Gillespie, T. W., Ostermann-Kelm, S., Federico, F., Lee, L., and MacDonald, G. M.. (In Review). Baseline Report of Inventorying and Monitoring Land Cover Change in the Mediterranean Coast Network of Southern California. Baseline Report NPS MEDN NRR 2015. National Park Service, Fort Collins, Colorado.

3.1 Executive Summary

The mosaicked pattern of vegetation throughout southern California is due to a combination of external factors, including climate, topography, geology, fire, human land use, and the introduction of invasive plants and animals. The large number of human inhabitants and associated development has fragmented and changed the landscape, which has implications for biodiversity and ecosystem health in conserved areas. This is especially an issue in the Santa Monica Mountains National Recreation Area (SAMO) since preserved areas are discontinuous within the greater Park boundary. The Channel Islands National Park (CHIS) is minimally impacted by current land use change because of its remote location, yet is most in recovery from past historical grazing and current invasive plant species.

This report assesses landscape dynamics over two Parks in the National Park Service southern California Mediterranean Coast Network using Landsat imagery and identifies major areas of change using remote sensing by asking the following questions:

1. Can we create accurate maps of land cover/vegetation change?
2. Where should the National Park Service focus land management efforts?

Land cover and vegetation communities are compared for 1986, 2001, and 2011 to identify increases, decreases, or stability in land cover and vegetation extent at a 30 m pixel resolution.

Landsat imagery is calibrated and verified using vegetation type boundaries from the United States Geological Survey GAP Analysis Program and field data from National Park Service researchers. Validation points for land cover and vegetation classes are selected using a Generalized Random Tesselation Stratification method, and validated either in the field or using Google Earth to assess classification accuracy for 2011. Results had an overall accuracy of 61.6% for SAMO and 69.1% for CHIS in 2011. Highest land cover type accuracies were achieved in SAMO for agriculture (87.7%), sand (93.9%), and water (88.2%) and in CHIS for conifer/mixed woodland (94.4%) and strand (94.7%). Native vegetation types had moderate classification accuracies is SAMO (69.1%) and CHIS (65.1%) likely due to mixed land cover types within 30 m pixels.

SAMO was dominated in all years by developed land cover types, whereas CHIS was dominated by grassland vegetation type. Land cover change analyses in SAMO showed increasing developed land cover types and decreasing native vegetation. Major changes in CHIS included a decrease in nonnative grasses and a recent increase in native shrub and woodland cover due to eradication of grazers and invasive species. National Park Service land managers may utilize the georeferenced areas of change produced from this project to focus further conservation efforts and to report the success of enacted management efforts and policies.

3.2 Introduction

California's Mediterranean-type ecosystem has been identified as one of the earth's "biodiversity hotspots" (Myers et al., 2000). Though this ecosystem is home to a number of endemic flora and fauna species, it is also one of the most highly altered

ecosystems on the planet. The high degree of rapid urbanization along the southern California coastline has resulted in the loss of significant natural areas and increasing threats to the remaining natural systems. Land cover and vegetation changes are occurring due to this urbanization, as well as increased invasive species.

Humans substantially impact much of the terrestrial biosphere, currently at rates and spatial extents far greater than in any other period in human history (Grimm et al., 2008a; Kerr and Ostrovsky, 2003). Human activity in southern California has a significant influence on the landscape as this area is highly populated and these numbers continue to increase. Southern California contains 50% of California's population (20 million people), but only 10% of its land area (Barbour et al., 2007). The large number of human inhabitants and associated development and nonnative species introduction has decreased continuous natural areas, thus putting pressure on native flora and fauna (Fancy et al., 2009; Grimm et al., 2008a, b). Land cover change can be monitored and used by natural resource managers to assess priority areas of conservation and restoration.

The purpose of the National Park Service (NPS) Inventory & Monitoring (I&M) Program is to develop and provide scientifically credible information on the current status and long-term positive and negative trends of the composition, structure, and function of park ecosystems, and to determine how well current management practices are sustaining those ecosystems. As part of the NPS effort to improve Park management through greater reliance on scientific knowledge, the primary role of the I&M Program is to collect, organize, and make available natural resource data and to contribute to the NPS institutional knowledge by transforming data into information through analysis, synthesis, and modeling of specific key vital signs. The I&M Program defines "vital signs" as a subset of physical, chemical, and biological elements and processes of park

ecosystems that is selected to represent the overall health or condition of park resources, known or hypothesized effects of stressors, or elements that have important human values (National Park Service, 2011). Landscape dynamics, or changes in land use and land cover, have been identified as a high priority by many of the NPS 32 Inventory & Monitoring networks.

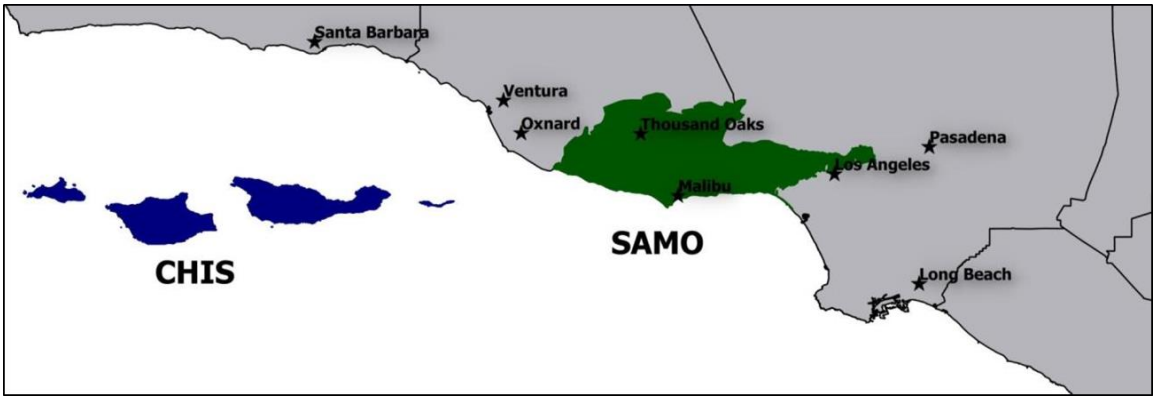


Figure 3.1 Mediterranean Coast Network Parks

The Santa Monica Mountains (SAMO) and Channel Islands National Park (CHIS) are part of the Mediterranean Coast Network (MEDN) I&M Program located in southern California (Figure 3.1). The MEDN contains high species richness, high endemism, and a high number of species on the International Union for Conservation of Nature (IUCN) Red List. Of the 1031 plant taxa identified, 25 are federally listed as threatened or endangered (Myers et al., 2000). SAMO contains 15 and CHIS hosts 75 endemic plant species. Much conservation planning is focused toward particular species threatened by the combined impacts of land use and climate change, which in turn are expected to cause some of the highest proportional biodiversity losses observed worldwide by 2100 (Sala et al., 2000; Underwood et al., 2009). The MEDN has a long history of inventorying and monitoring threatened species populations and threats *in situ*. However, natural resource

managers need baseline maps with critical geospatial data that quantify species habitats (often native vegetation zones) and land cover change at a broad scale.

In SAMO the greatest concerns of land cover changes are those from native vegetation (e.g. chaparral, coastal sage scrub, riparian) to developed land cover types (e.g. residential, commercial, or agricultural areas). Nonnative invasive plants cause particular issues for areas disturbed by development or fire, as well as environmentally sensitive areas along riparian corridors, highways, and trails. Many invasive plants in SAMO are introduced as decorative landscaping features and eventually become threats to the native vegetation (National Park Service, 2005). CHIS has a history of introduction (and more recently eradication) of nonnative plant and animal species. Several major eradications of nonnative species that have taken place on CHIS include: pigs and sheep from Santa Cruz Island, sheep from San Miguel Island, pigs from Santa Rosa Island, and rats and rabbits from Anacapa Island (see Table 3.1; National Park Service, 2005). Natural resource managers have expressed a need for landscape scale data on the extent and impacts of nonnative flora and fauna on land cover types and rates of ecosystem recovery after removing nonnative species.

Table 3.1 Historical presence (P=present in small quantities, E=eradicated) of nonnative mammals on northern Channel Islands, modified from (Knowlton et al., 2007).

Island	**Cats**	**Rats**	**Rabbits**	**Pigs**	**Horse**	**Sheep**	**Other**
San Miguel		P			E	E	E: (*Bos taurus*)
Santa Rosa				E	P		P: *Odocoileus*, *Cervus elaphus* E: (*Bos taurus*)
Santa Cruz				E	E	E	P: (*Bos taurus*)

Anacapa	E	E	E			E	

Remote sensing methods, especially in combination with Geographic Information Systems (GIS) and *in situ* field data, are cost-effective techniques for measuring landscape-level temporal changes over a continuous area (Franklin et al., 2000; Miller and Rogan, 2007; Rogan et al., 2003). Remote sensing is commonly used to map biodiversity, changes in land cover type, as well as landscape types and vegetation classes (Fraser et al., 2009; Nagendra et al., 2012; Nemani et al., 2009; Pereira et al., 2013). Remotely sensed monitoring is also extremely effective for evaluating the effectiveness of conservation management practices (Alcaraz-Segura et al., 2008; DeFries et al., 2010; Fancy et al., 2009; Jones et al., 2009; Kennedy et al., 2009; Willis, In Review).

The accuracy of space-borne vegetation classification is directly related to the satellite, sensor, and pixel size used and generally ranges from 1 cm to 1 km pixel resolution. Remotely sensed classification mapping can identify vegetation cover for macro-groups such as forests, shrublands, and grasslands using medium resolution imagery (~30 m). Certain land cover classes and individual vegetation types are often more accurately classified than others, such as forested types (Boyd et al., 2006; Hansen et al., 2013; Giri et al., 2011; Schmitt et al., 2009). The classification of shrublands and grasslands have been less successful, yet may be improved by combining multi-temporal imagery, optical, and radar data to estimate vegetation cover and extent (Huang et al., 2010; Lauver, 1997; Xian et al., 2012). Field- and high resolution imagery-based

validation can improve the accuracy of these vegetation classifications (Bayarsaikhan et al., 2009; Foody, 2002; Riemann et al., 2010; Zhang et al., 2009).

The Landsat series of satellites are medium resolution sensors appropriate for assessing vegetation classifications at the National Park spatial scale. There have been a number of studies that use Landsat to study vegetation types in protected areas (Fraser et al., 2009; Gillespie et al. 2008; Huang et al., 2009; Tang et al., 2010). Townsend et al. (2009) compared high-resolution imagery from Ikonos (4 m) and moderate resolution imagery from both SPOT (15 m) and Landsat (30 m) and found Landsat imagery to be adequate for characterizing landscape patterns. The freely available Landsat imagery may be the best data for mapping global vegetation macro-groups and has advantages over expensive or on-demand high spatial resolution sensors, which in turn may be better suited for validation (Gairola et al., 2013). However, there is a need for public field validated land cover data using standardized classification definitions over a global spatial scale to improve the accuracy of vegetation maps and allow for comparison between countries and world protected areas (Fancy et al., 2009; Foody, 2002).

This chapter presents results of monitoring land use and land cover change detection in the MEDN and seeks to answer:

1. Can we create accurate maps of land cover/vegetation change using Landsat imagery?
2. Where should the National Park Service focus land management efforts in SAMO and CHIS?

To answer the first question we create current (as of 2011) land cover and vegetation maps for SAMO and CHIS based on Landsat products and USGS GAP vegetation data. The aim for accuracy levels are 85% and above for each land cover type. To answer the second question we

determine the long term trends and areas of land cover/vegetation change over SAMO and CHIS from 1986-2011. It is expected that in SAMO native vegetation types are decreasing and being converted to developed land, and that native vegetation types are replacing nonnative grasslands on CHIS due to past conservation land management efforts.

3.3 Data and Methods

3.3.1 Land cover data

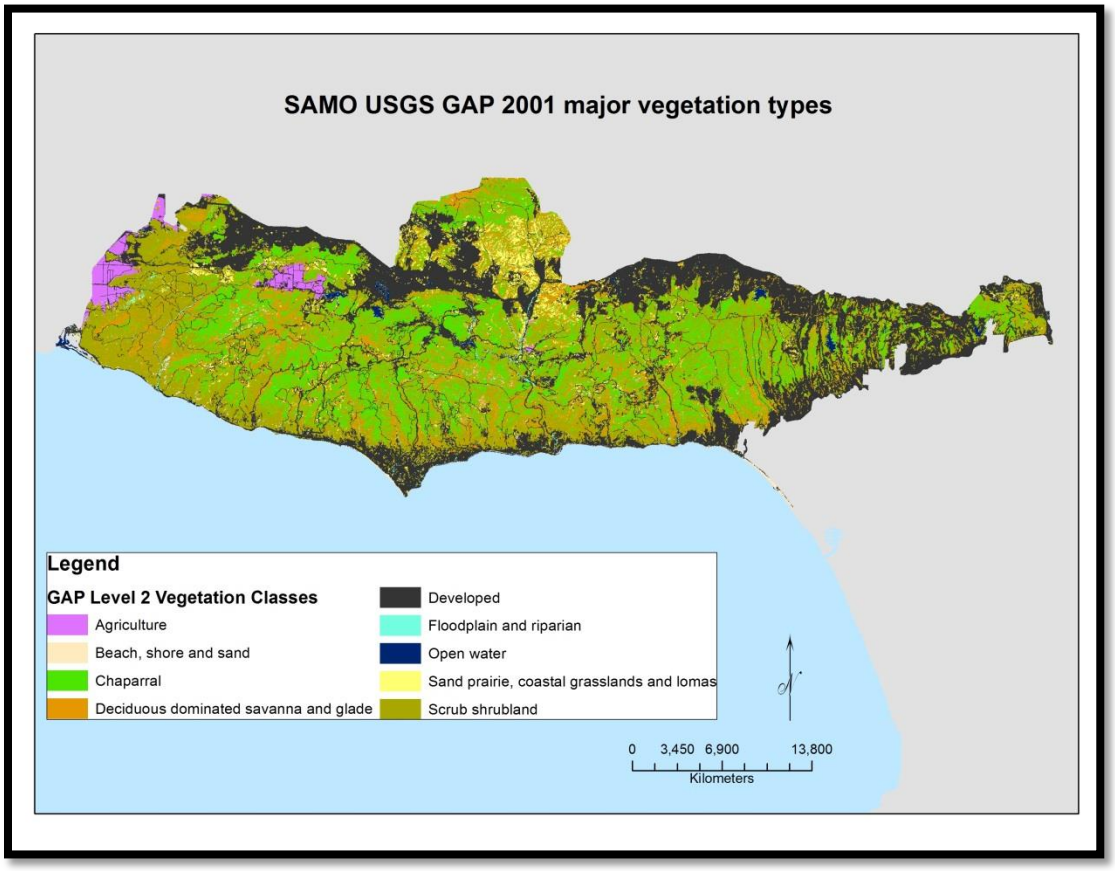


Figure 3.2 Gap Analysis map level 1 from Landsat imagery collected in 2001.

Appropriate data and methods were established in the MEDN Landscape Dynamics Protocol (Willis et al., In Review). The land cover and land use classes used

to create the baseline map were based on the USGS GAP Land Cover dataset (Figure 3.2). The GAP Analysis dataset provides land cover classes at a 30 m pixel resolution using the sensors on the Landsat series of satellites, which have been crosswalked to the five highest levels of the National Vegetation Classification System (http://gapanalysis.usgs.gov/gaplandcover/data/download/).

Table 3.2 Summary of GAP categories used in MEDN Objective 1: land cover land use change, and Objective 2: vegetation change analyses.

GAP Land Use / Land Cover Classification Level	Total number of GAP categories	Total number of categories applicable to CHIS	Number of categories used for CHIS analysis	Total number of categories applicable to SAMO	Number of categories used for SAMO analysis
Level 2	43	16	9	18	12
Level 3	590	25	0	37	4

The 590 land use classes in the GAP data set created in 2001 can be displayed at three levels of detail: Level 1 contains 8 land use classes and generalizes to the level of vegetative physiognomy (i.e. grassland, shrubland, forest); Level 2 contains 43 classes and incorporates information on elevation and climate; Level 3 contains 590 species-based classes for the entire United States. For this report, Levels 2 and 3 were chosen that were applicable to and appropriate for the MEDN (Table 3.2). Classes used for analysis were chosen if they had a more than 30 polygons per land cover type within each Park boundary (Table 3.3). The classes used are generalized land cover/vegetation types that encompass various species within each category (Table 3.4).

Table 3.3 GAP Land Cover Classification for land use, land cover, and vegetation types in MEDN. Types with an asterisk (*) were collapsed into a single type (woodland) for analysis.

GAP Land Cover Types

Level 2	**Level 3**
Agriculture	Developed – High Intensity
Beach, Shore, Sand	Developed – Medium Intensity
Chaparral	Developed – Low Intensity
Cliff, Canyon, and Talus	Developed – Open Space
Coastal Grassland	
Conifer Dominated Forest Woodland (Mesic-Wet)*	
Conifer Dominated Forest Woodland (Xeric-Mesic)*	
Deciduous Dominated Savanna Glade	
Floodplain Riparian	
Freshwater Herbaceous Marsh, Swamp, or Baygall	
Mixed Deciduous/Coniferous Forest and Woodland (Mesic-Wet)*	
Scrub Shrubland (Coastal Sage Scrub)	
Open Water	

Training data or Regions of Interest (ROIs) for SAMO and CHIS were created using the GAP data. In SAMO ROIs were created by selecting the 30 largest polygons for each land cover class from the GAP dataset and digitizing new ROIs around them in ENVI. For CHIS, preliminary field analysis found little overlap in the generalized GAP vegetation types and field observations. Thus training polygons were created using vegetation surveys previously collected in the field by the National Park Service using a basic Relevé method and crosswalked to general vegetation categories (Nueller-Dombois and Ellenberg, 1974; National Park Service, 2011). (Note: coastal sage scrub and scrub shrubland were separated into two classes for CHIS)

Table 3.4 GAP classes used and dominant vegetation types within each category. Types with an asterisk (*) were terms applicable to CHIS and were categorized by the National Park Service.

Land Cover/Vegetation Class	Description
SAMO	
Agriculture	Cultivated cropland, pasture, and hay
Barren*	Bare landscape
Beach, shore, sand	Mediterranean California southern coastal dune
Chaparral	California maritime chaparral, California mesic chaparral, and southern California dry-mesic chaparral
(CHIS) Chaparral*	Arctostaphylos, Chamise, oak
Cliff, Canyon, and Talus	Sparse and barren systems. Includes southern California Coast Ranges cliff and canyon
Coastal Grassland*	California central valley and southern coastal grassland
Coastal Sage Scrub*	Artemesia, Eriophyllum, Isocoma, lupine, Lycium, Rhin, Rhus, Salvia
Conifer Dominated Forest Woodland (Mesic-Wet)/ Conifer Dominated Forest Woodland (Xeric-Mesic)/ Mixed Deciduous/Coniferous Forest and Woodland (Mesic-Wet)	Great pinyon-juniper woodland, Mediterranean California dry-mesic mixed conifer forest and woodland, Mediterranean California mesic serpentine woodland and chaparral, and California coastal closed-cone conifer forest and woodland
Deciduous Dominated Savanna Glade	California central valley mixed oak savanna, California coastal live oak woodland and savanna, California lower montane blue oak-foothill pine woodland and savanna, and southern California oak woodland and savanna
Floodplain Riparian	California central valley riparian woodland and shrubland, North American warm desert riparian woodland and shrubland, and Mediterranean California foothill and lower montane riparian woodland.
Freshwater Herbaceous Marsh, Swamp, or Baygall	Temperate Pacific Freshwater Emergent Marsh.
Scrub Shrubland	Inter-mountain basins mixed salt desert scrub, Mojave mid-elevation mixed desert scrub, Sonora-Mojave creosotebush-white bursage desert scrub, and southern California coastal scrub
(CHIS) Scrub*	Acmispon, Baccharis, Coreopsisi, herbaceous
Strand*	Coastal strand
Open Water	Open water (fresh) and open water (brackish/salt)

Woodland*	Broad-leaved, ironwood, narrow-leaf, evergreen

3.3.2 Remotely Sensed Data

Landsat TM data (from Landsat 5) were downloaded for SAMO and CHIS for 1986, 2001, and 2011. These years were chosen in order to maximize the time range, minimize cloud cover, and utilize Landsat 5 satellite data consistently in order to reduce classification error. Landsat TM data were downloaded using GloVis online database (http://glovis.usgs.gov/). Images were chosen from the summer months (July through September) in order to: preclude the effects of winter rain which rapidly changes the spectral properties of the landscape, avoid cloud cover present along the coast in spring, and to maintain phenological consistency over time (Garcia et al., 2010).

An elevation dataset was also used in order to improve accuracy of classifications. A Digital Elevation Model (DEM) for this region was downloaded from the Shuttle Radar Topography Mission (SRTM) database and used in supervised classifications (http://www2.jpl.nasa.gov/srtm/). SRTM provides elevation, slope, and aspect data at 30 m pixel resolution which allowed for consistency in spatial scale with our land cover datasets.

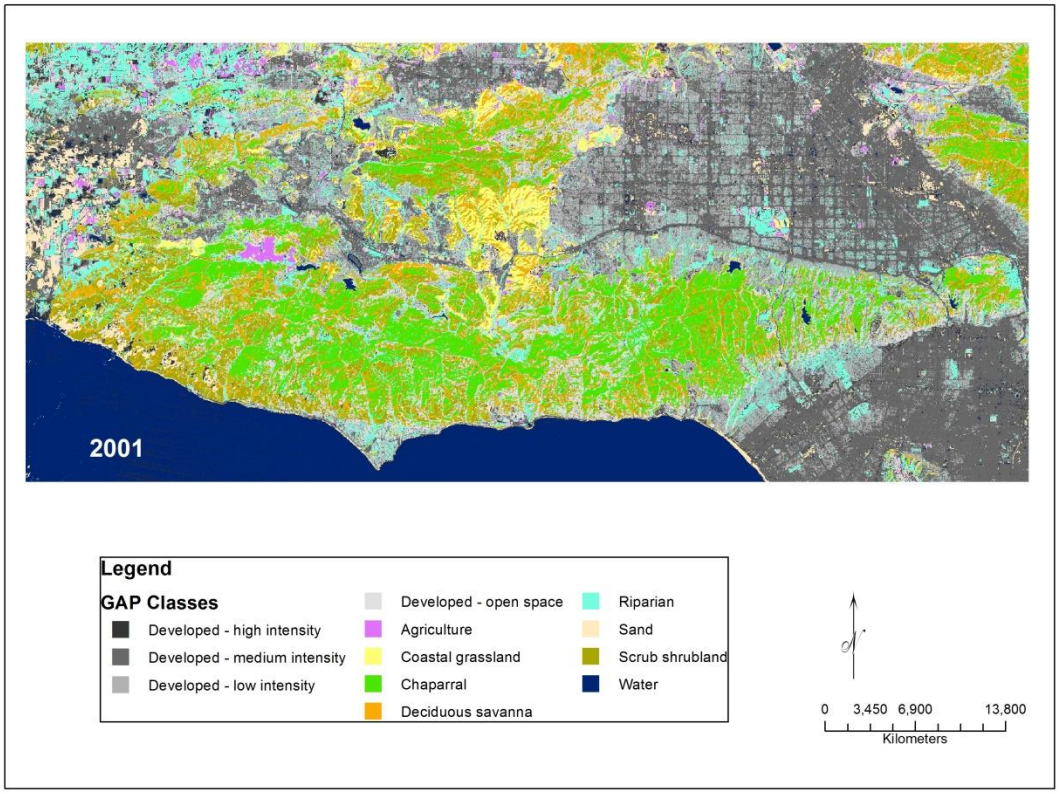
Each Landsat image was calibrated in ENVI using "Landsat calibration" and slope and aspect data were extracted from SRTM images using the "topological modeling" tool according to band metadata (Table 3.5). All Landsat and DEM data were then subset by the Park region.

Table 3.5 Landsat 5 image metadata used for calibration

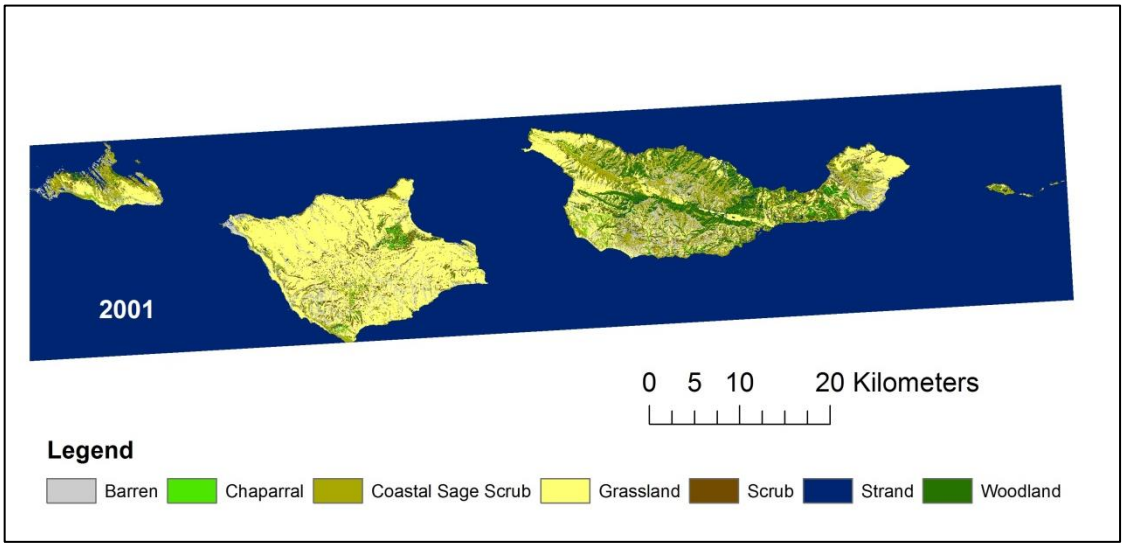
Park	Year	Landsat TM date collected	Landsat TM time collected	Sun Elevation
CHIS	1986	9/15	17:55:02	47.82
CHIS	2001	8/23	18:14:45	56.16
CHIS	2011	7/18	18:23:37	63.74
SAMO	1986	8/23	17:49:39	53.03
SAMO	2001	9/17	18:08:23	50.01
SAMO	2011	8/28	18:17:03	56.52

3.3.3 Image Classification

The training ROIs were overlaid on the 2001 stacked image with Landsat bands 1, 2, 3, 4, 5, 7, slope and aspect to create a maximum likelihood type supervised classification of the 2001 baseline image for SAMO and CHIS. Maximum likelihood was determined to be the most appropriate classification method for these maps based on highest overall accuracy of results and consistency within Parks (Willis et al., In Review). The baseline image was then used to apply a maximum likelihood classification to 1986 and 2011 images using the "endmember collection" function by "import from another ROI" (2001 baseline image) file.



(a)



(b)

Figure 3.3 Baseline images. (a) Baseline image of SAMO created from maximum likelihood classification using GAP 2001 dataset. (b) Baseline image of northern four CHIS created from maximum likelihood classification using field data and 2001 Landsat image.

The types of changes considered in this chapter were categorical changes, or changes occurring between different land cover classification types. Thresholds were set

for each landscape category according to their spectral properties, and a basic change detection analysis was applied to the data for interannual comparison. Percent of total land cover change was calculated for variation from each land use type to another. Finally, certain land cover classes were combined to display changes between native (chaparral, woodland, coastal sage scrub, riparian, strand, scrub shrubland), nonnative (deciduous savanna, coastal grassland), and developed landscape (developed, agricultural).

3.3.4 Accuracy assessment

There is error inherent in any remote sensing study, which is an effect of the ability of remote sensing to assess an entire landscape. The amount of error present in this analysis has been minimized by multiple runs of the analysis and applying the appropriate changes to the methodology after identifying the sources of error. After analyses were carried out, field and satellite validation were used to further improve accuracy.

Validation points for land use classes were chosen based on a randomized draw; specifically, a Generalized Random Tesselation Stratification (GRTS) approach was used. GRTS is a method used to draw spatially-balanced samples weighted by probability. It uses a combination of true probability with systematic sampling drawn using R-Statistical Software. The exact process of GRTS is described in detail in Stevens and Olsen (2003; 2004).

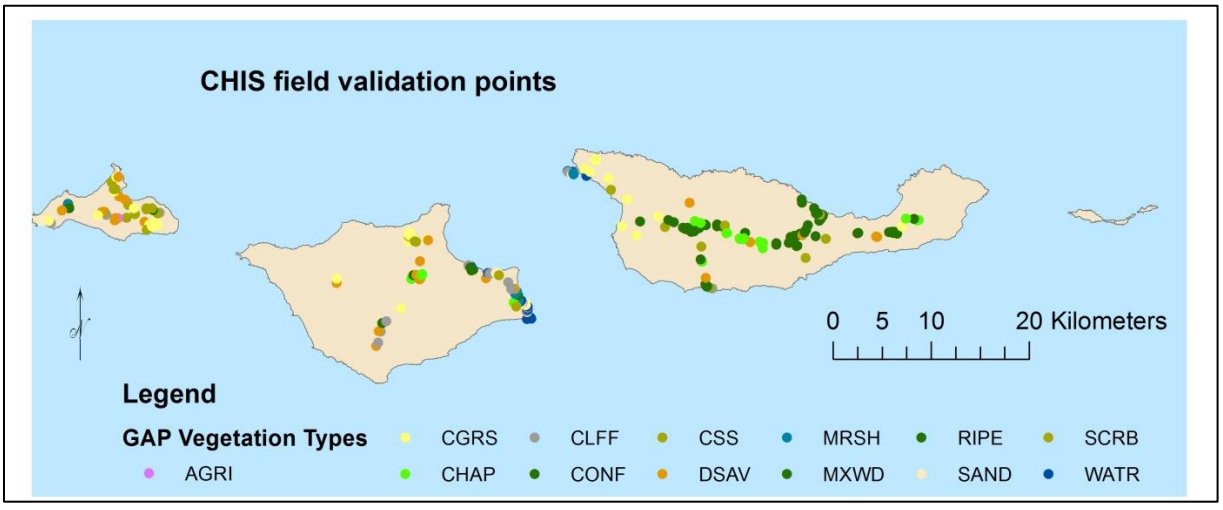


Figure 3.4 All field validated points visited over CHIS.

A total of 100 validation points per land cover class were chosen for each SAMO and CHIS. Field validation was completed on CHIS from 2012-2013 by importing GRTS points to a Garmin Oregon 650 GPS unit (Appendix 3B) and accessing the maximum amount of points possible given time and funding constraints (Figure 3.4). Accuracy assessments were conducted *in situ* on CHIS using the Relevé method in order to determine the dominant land cover type similar to GAP. The CHIS vegetation classes provided by CHIS for training data were translated to fit into the GAP categories accordingly (Table 3.4). Google Earth imagery from 2010-2012 was used for accuracy assessment in SAMO (Figure 3.5). Validation points were compared to the maximum likelihood 2011 classifications to calculate an error matrix and accuracy percentages. It was assumed that the land cover classes present in 2011 were similar or the same as those assessed *in situ* from 2011-2013.

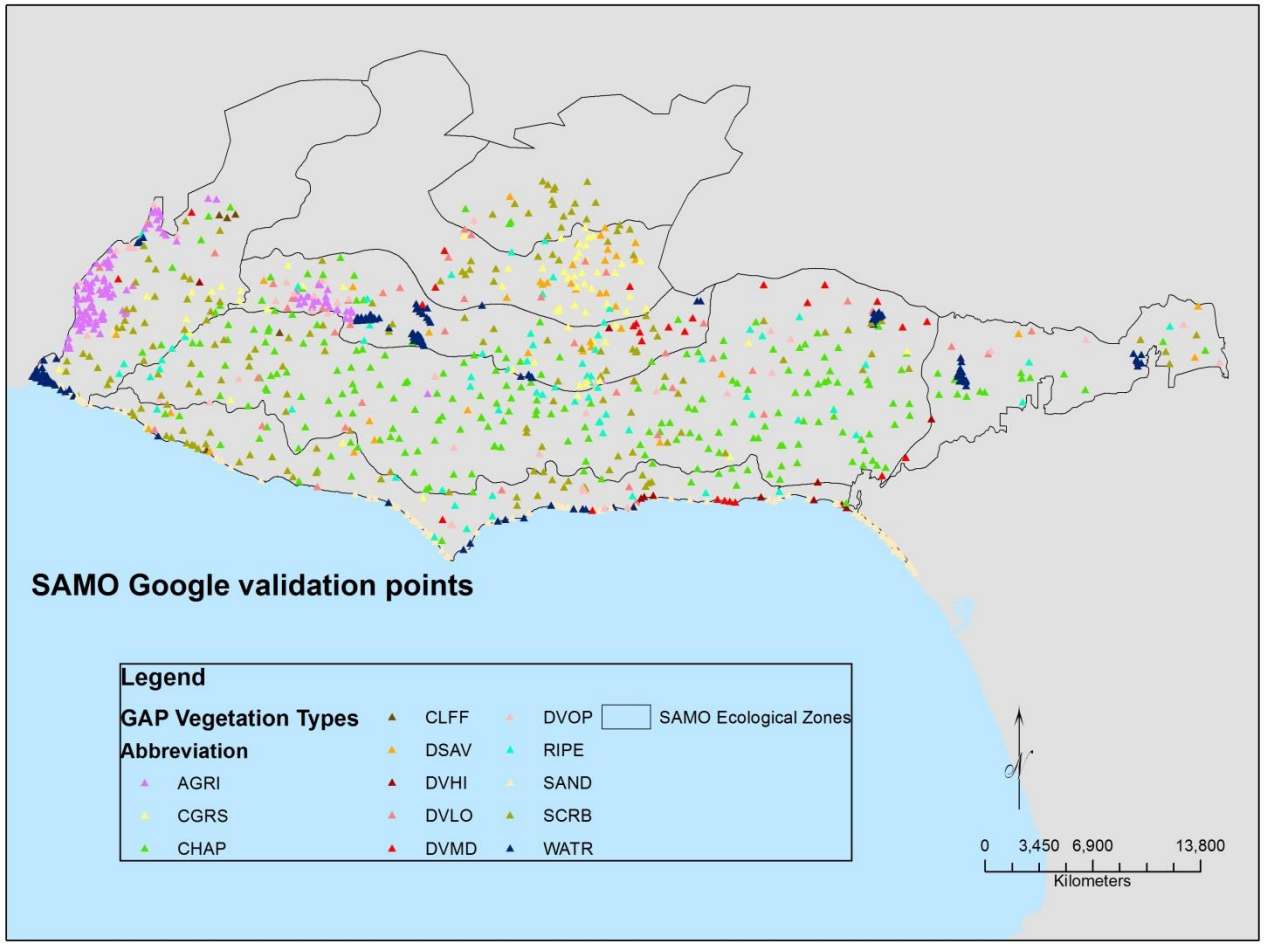


Figure 3.5 Google Earth validation of GRTS and Google Earth validated points in SAMO.

3.4 Results

3.4.1 Classification maps

There were 371 points validated *in situ* for CHIS and 1737 validated by Google Earth for SAMO (Table 3.6). The land cover classes that achieve this level on SAMO include sand (93.9%), water (88.2%), agriculture (87.7%), and sand prairie, coastal grasslands, lomas (87.7%). Further grouping these categories into native and nonnative vegetation and developed land returned medium accuracy results in SAMO: 69.1% for native vegetation, 71.0% for nonnative vegetation, and 60.8% for developed landscapes. On CHIS only two land cover classes achieved high accuracy levels: conifer/mixed woodland (94.4%) and sand (94.7%). Native vegetation was classified as 65.3% accurate and nonnative vegetation was 60.4% accurate on CHIS.

Table 3.6 Validation points and percent accuracy in SAMO and CHIS 2011. *Google Earth number of points may be greater than GRTS number of points since additional points were added from other vegetation categories

Land Cover Class	GRTS points (n)	Field Validated	Google Earth Validated*	Percent Accuracy
SAMO	1736		1582	61.6
Agriculture	69		114	87.7
Chaparral	149		235	48.5
Scrub shrubland	135		174	41.4
Floodplain/riparian	175		69	84.1
Deciduous dominated savanna/glade	110		42	45.2
Sand prairie, coastal grasslands, lomas	73		65	87.7
Sand	101		99	93.9

Water	87		136	88.2
Developed	837		648	0.56
Developed – High Intensity*	123		164	68.9
Developed – Medium Intensity*	260		138	58.0
Developed – Low Intensity*	205		215	52.1
Developed – Open Space*	249		131	44.3
Native vegetation	459		552	69.1
Non-native vegetation	183		76	71.0
Developed	906		463	60.8
CHIS	770	341		69.1
Barren	70	24		75.0
Chaparral	70	33		69.7
Coastal sage scrub	70	25		30.4
Grassland	70	62		71.0
Scrub	70	34		41.1
Strand	70	19		94.7
Conifer woodland (woodland)	70	18		94.4
Mixed woodland (woodland)	70	34		
Native vegetation	140	126		65.2
Non-native vegetation	420	58		73.0

3.4.2 Landscape change

Mapped results from the analysis show the qualitative differences between 1986 and 2011 land cover and land use (Figure 3.6). Categories in SAMO that appear to be increasing in cover include deciduous savanna, coastal grassland, as well as increasing

levels of developed intensity. Many chaparral and scrub shrubland areas appear relatively stable between the 1986 and 2011 image. CHIS (northern four islands displayed) show overall increases in native vegetation cover. This includes increases in woodland types, chaparral, and scrub shrubland (Figure 3.7). Coastal grassland dominates most islands, especially Santa Rosa Island. Woodland and chaparral areas are increasing especially on Santa Cruz Island in 2011.

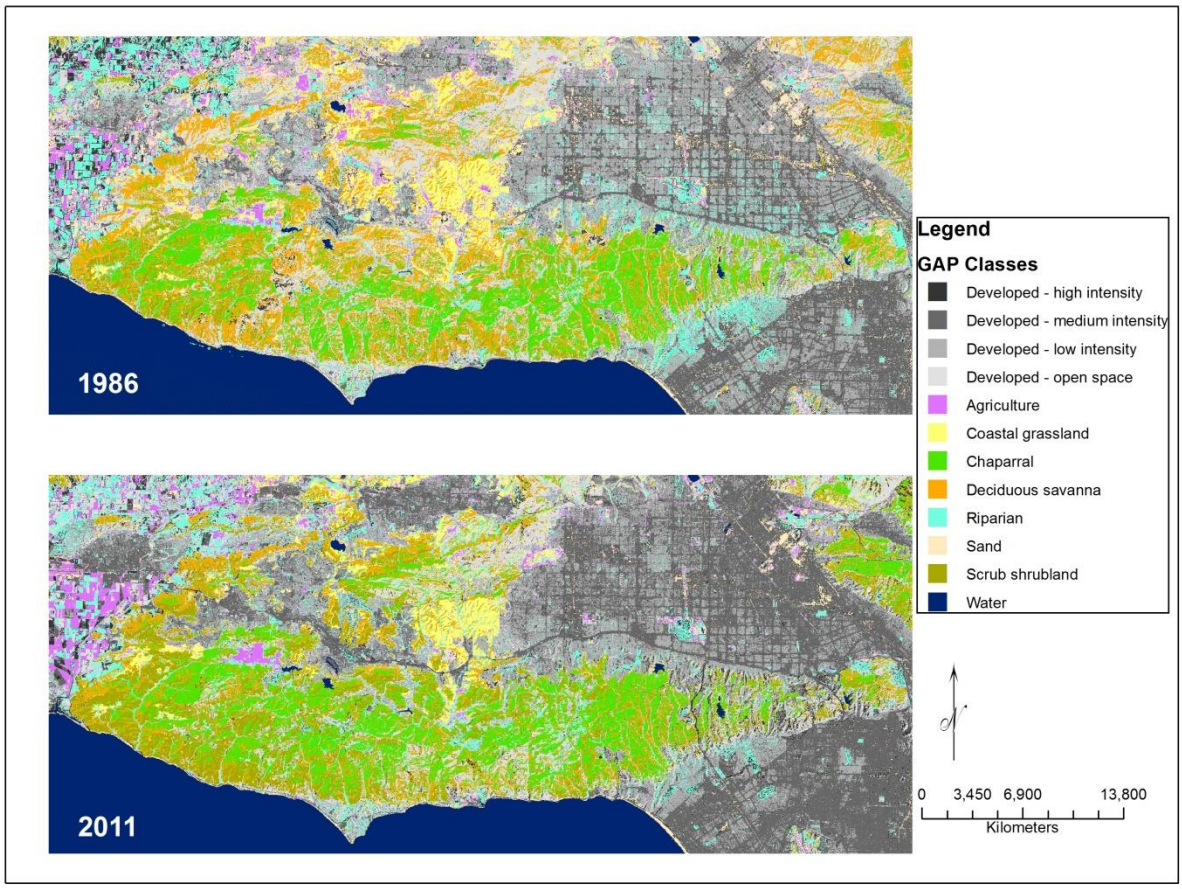


Figure 3.6 Initial (1986) and final (2011) images of SAMO created from maximum likelihood classification.

Change statistics are provided in detail in Appendix 3C. In SAMO the water, scrub shrubland, sand, and developed medium intensity land cover types are stable. Developed landscapes are increasing, especially levels of low and medium intensity. Native chaparral is experiencing conversion to deciduous savanna, which is interpreted as a mixed pixel-based landscape (see Appendix 3A). In turn, deciduous savanna is mostly converting to native vegetation types. CHIS results indicate a different story. Many nonnative grassland, scrub shrubland, and woodland areas are converting to chaparral. Chaparral in turn is stable, with some areas converting to woodland. Barren landscapes are decreasing and in many areas are being replaced by grasslands.

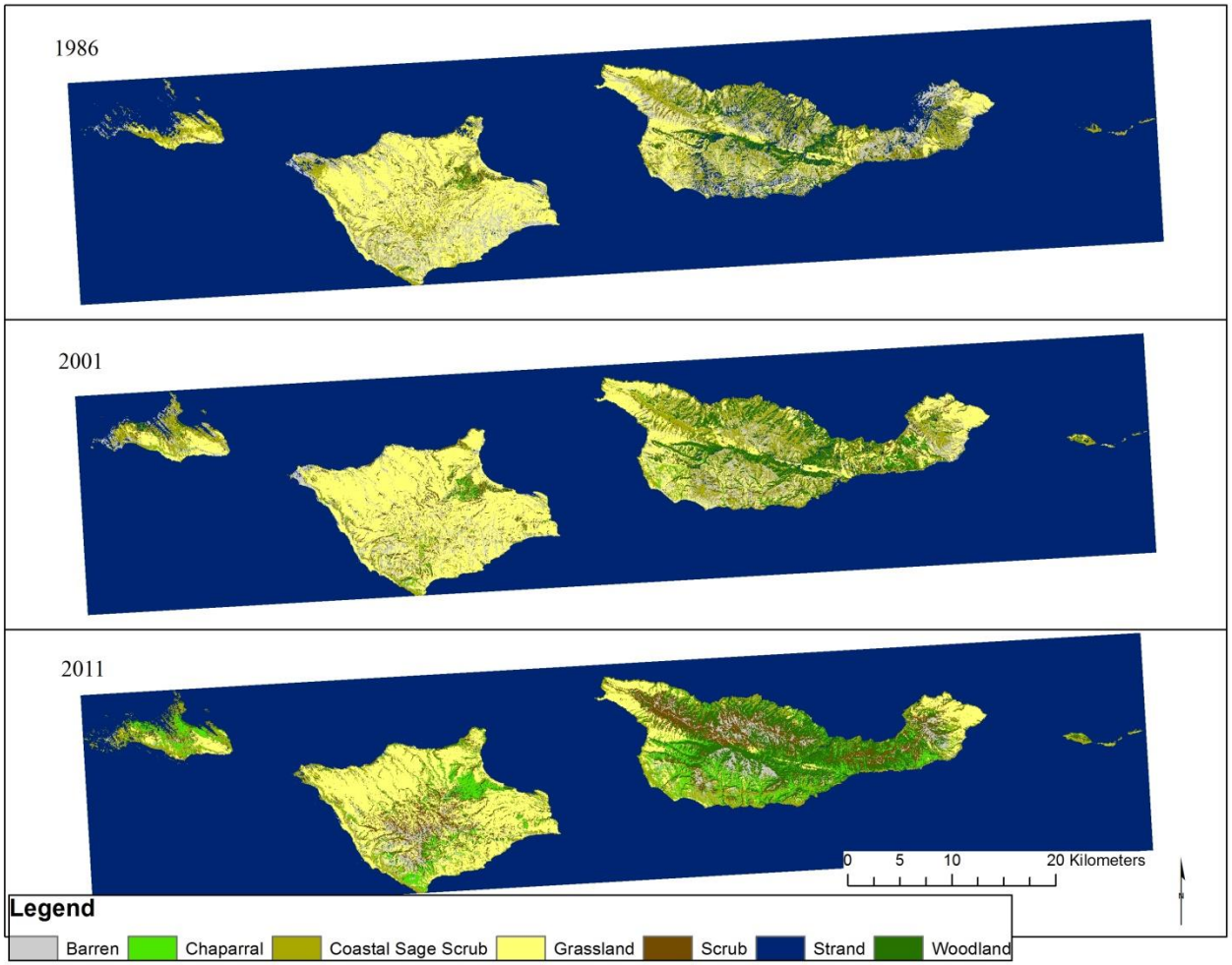


Figure 3.7 Initial (1986), intermediate (2001), and final (2011) images of northern four CHIS created from maximum likelihood classification. Several categories have been re-named (i.e. barren as cliff/canyon/talus, coastal sage scrub as deciduous savanna, strand as sand) based on field assessments to more accurately describe these vegetation classes.

3.5 Discussion of results

3.5.1 Classification maps

The overall map accuracy is 61.6% for 2011 for SAMO and 69.1% for CHIS. Low accuracy of land cover mapping is common in Mediterranean environments, especially at 30 m resolution due to the mixed pixel nature of the environment and similar spectral signatures of many vegetation types (Appendix 3A) (Rogan et al., 2002; Rocchini et al., 2015). However, a number of individual land cover classes achieve high accuracy levels (conifer/mixed woodland, sand, water, coastal grassland), which can be used to interpret long-term trends.

3.5.1.1 Key high accuracy (> 85%) land cover types

Some of the highest accuracy levels were achieved for forested vegetation types, which are vital for ecological monitoring. Riparian forests are one of the most threatened vegetation types in California, due to factors such as insect damage and drought (Barbour et al., 2007). These woodlands include several native species such as the Engelmann Oak (*Quercus engelmannii*), California sycamore (*Platanus racemosa*) and the California Walnut (*Juglans californica*) (Riordan et al., 2014). The woodland classification type on CHIS notably contains several endemic species such as Catalina Ironwood (*Lyonothamnus floribundus*), federally Endangered species such as Torrey Pine (*Pinus torreyana*), and Bishop Pine (*Pinus muricata*), the rarest pine species in the United States. Riparian ecosystems are also vital for animal habitats, including federally-listed endangered species such as the California red-legged frog (*Rana aurora*). Both riparian and woodland-type forests benefit the environmental health of

SAMO by reducing local temperatures and urban runoff, and by increasing air quality, aesthetics and economic value (Pincetl et al., 2013).

Nonnative grasslands are also classified under high accuracy in SAMO (CGRS). This group of species pose a significant threat to native species if they continue to expand, and thus are key to monitor. For example, Fountain grass (*Pennisetum setaceum*) is an invasive species monitored by the National Park Service for its rapid colonization of south facing slopes in SAMO.

3.5.1.2 Key medium (60-85%) and low accuracy (30-60%) land cover types

Medium accuracy (60-70%) was achieved for barren, chaparral, and grassland land cover type in CHIS. Notably, the barren classification type likely indicates locations of eroded landscape caused by past ranching and grazing activity over the islands. Change results indicate a decrease in barren between 1986 and 2011, with changes to grassland and other shrub types. This suggests landscape recovery, via reduction in eroded land and increased plant cover since 1986.

Developed classification accuracies for SAMO ranged from 44% for Developed Open Space, to 69% for Developed High Intensity. The Developed Open Space class contains a spectral signature similar to nonnative and native grasslands, making it difficult to classify accurately (see Appendix 3A). Developed High Intensity is important to accurately map, since it includes land cover such as freeways, shopping malls, and other barriers for terrestrial biodiversity.

It is surprising that the classification accuracy was not higher in CHIS given the extensive number of high quality of the field points (latitude, longitude, floristic data)

used. Most studies report an overall accuracy of 57% to 69% when examining multiple vegetation types (Rogan et al., 2002). The low classification accuracy of chaparral, coastal sage scrub, and deciduous savanna may be due to similarity in spectral signatures or due to the mixing of vegetation types within pixels (Appendix 3A).

3.5.2 Landscape change

Trends of land cover change and vegetation shifts are apparent in the data despite the accuracy limitations of the classification maps (Table 3.7). There is an overall shift in SAMO to land cover types associated with mixed pixels, such as deciduous savanna and developed – medium intensity (see Appendix 3A). This indicates increasing fragmentation and discontinuous stands of native vegetation. On the other hand, CHIS displays patterns associated with natural succession; native vegetation types such as woodland and chaparral are replacing nonnative grasslands and barren land cover over much of the island landscape.

Table 3.7 Description of changes occurring in each land cover/vegetation class from 2001-2011. Several categories have been re-named (i.e. barren as cliff/canyon/talus, coastal sage scrub as deciduous savanna, strand as sand) based on field assessments to more accurately describe these vegetation classes.

Land cover class	**Summary of main changes occurring**
SAMO	
WATR	Stable
SCRB	Stable; mainly converted to developed – open space
SAND	Stable; becoming more developed
RIPE	Becoming more developed
DVOP	changing to developed – low
DVMD	Stable
DVLO	Changing to developed – medium
DVHI	Changing to developed – open/medium
DSAV	Changing to chaparral and coastal sage scrub
CHAP	Changing to deciduous savanna
CGRS	Changing to developed – open/low
AGRI	Changing to developed – open/medium/low
CHIS	
BARREN	Changing to a variety of classes, mostly grassland
CHAP	Stable; mainly converted to woodland
CSS	Changing to a variety of classes, mostly scrub
CGRS	Stable; changing to scrub and chaparral
SCRB	Changing to woodland and chaparral
STRAND	Stable
WOODLAND	Stable; changing to chaparral

3.5.2.1 SAMO: vegetation mixing and fragmented landscapes

Native vegetation types are relatively stable in SAMO from 1986-2011; chaparral is 68% stable and scrub shrublands are 77% stable (Figure 3.9; Appendix 3C). However, scrub shrublands are converting to developed lands (16% to Developed Open) in many areas of SAMO, indicating a direct impact of human development on the natural ecosystem. Chaparral has mostly converted to deciduous savanna (15%) since 1986 (Figure 3.10) and coastal sage scrub has turned to developed- open space (16%), which could indicate more vegetation type mixing and less continuous stands of vegetation on the ground. Sand areas have also been developed since 1986, which could be due to beach erosion or increased coastal housing developments. Riparian forests and woodland have decreased in SAMO from 1986 to 2011.

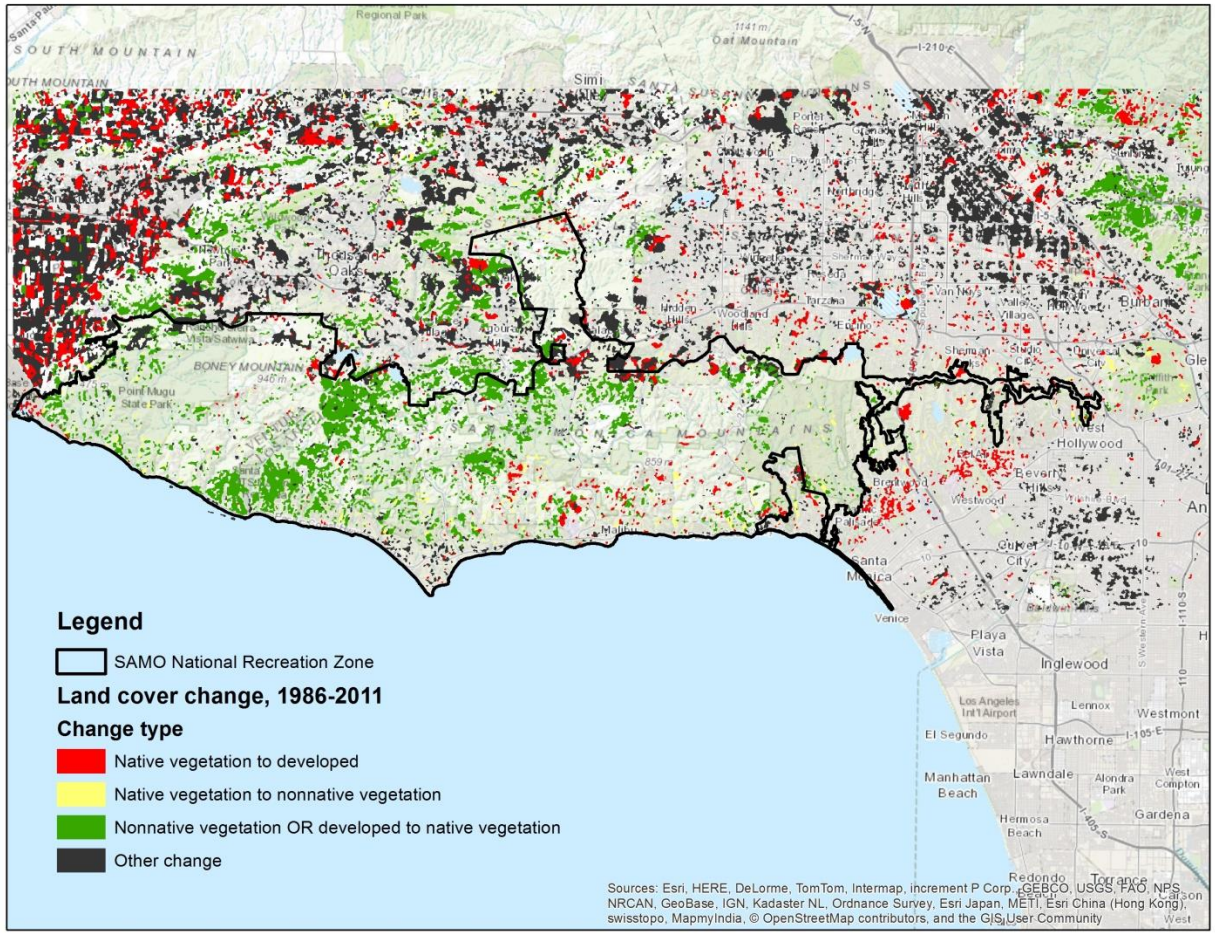


Figure 3.9 Change map of SAMO from 1986 to 2011 based on Maximum Likelihood spectral classification of Landsat imagery. Areas of red indicate regions changed from all vegetation types to developed land cover types, areas of yellow indicate regions changed from native vegetation types (riparian, chaparral, scrub shrubland) to nonnative vegetation types (coastal grassland, deciduous savanna), areas of green indicate regions changed from nonnative or developed to native vegetation types.

Regionally, there has been significant fragmentation of native vegetation types particularly in the Eastern section of SAMO with very little continuous native vegetation corridors. Developed areas appear to have increased around SAMO especially in the North and East. A number of developed-open space and -low areas have been converted to developed-medium since 1986, which indicate a trend of increasing intensity of development. However, many areas in the central portion of SAMO have converted to native vegetation cover (Figure 3.9). These areas can be used by Park managers as exemplar zones of ecological management or land protection.

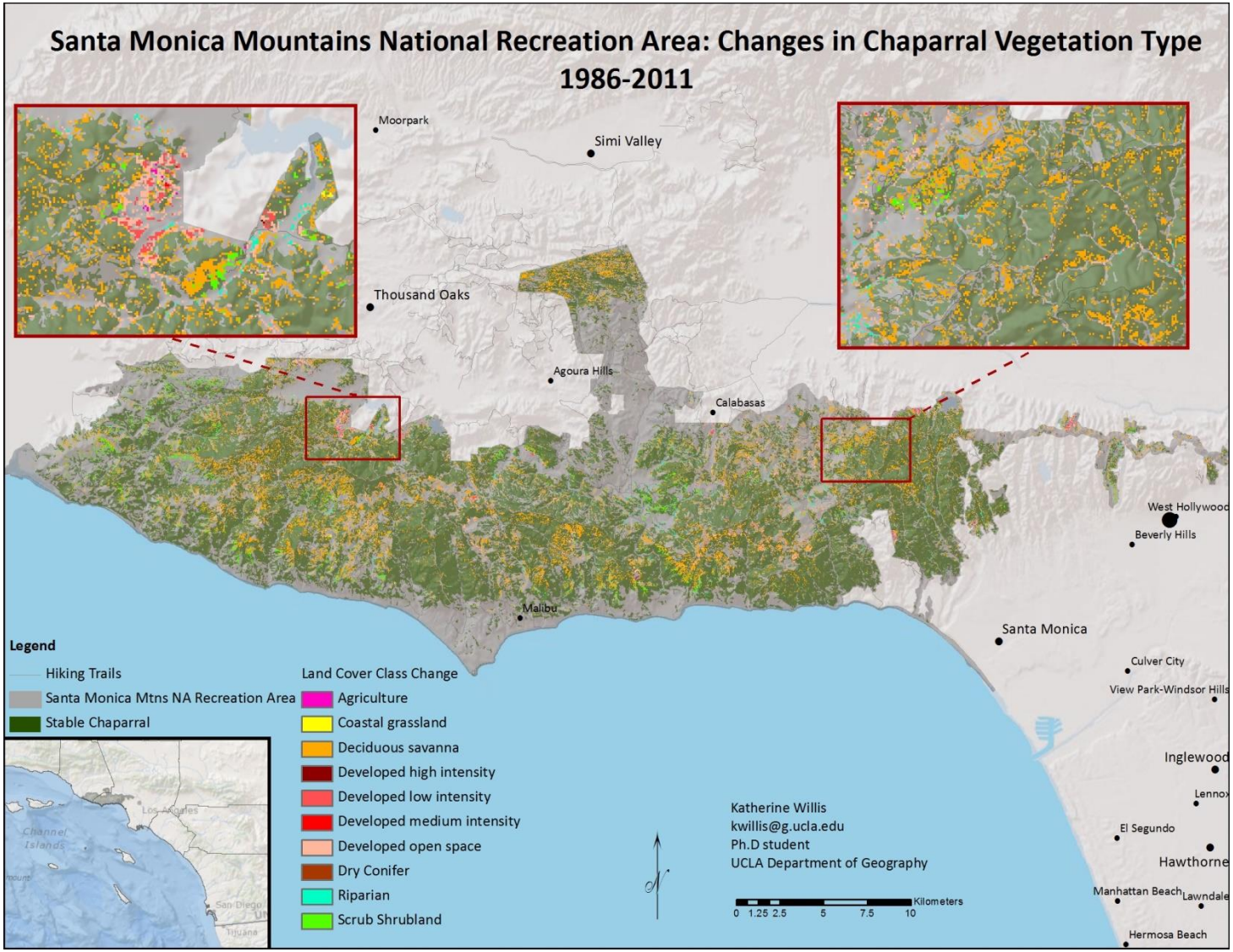


Figure 3.10 Detailed map of changes from chaparral to various land cover types from 1986-2011 in SAMO.

3.5.2.2 CHIS: a landscape management success story

The most stable types of vegetation in CHIS are strand (95%), woodland (94%), barren (75%), and grassland (71%). Strands are ideal habitat for pinnipeds and other species that breed along the coast. Notably, this study found significant long term changes in vegetation on the Channel Islands (Figure 3.11). There has been an overall shift in barren and nonnative grasslands to shrublands and grasslands, while many grasslands are shifting to scrublands and chaparral cover types. These trends are positive for ecological vitality, and are most likely due to the previous removal of nonnative plant and grazing animal species by the National Park Service. However, monitoring and ecological remediation efforts should continue on CHIS to protect the sensitive species present. For example, there are a number of ecologically vital scrubland species on CHIS that Park managers consider in need of monitoring, including dune scrub, coastal bluff scrub, *Coreopsis* scrub, seablite scrub, caliche scrub, *Baccharis* scrub, maritime cactus scrub.

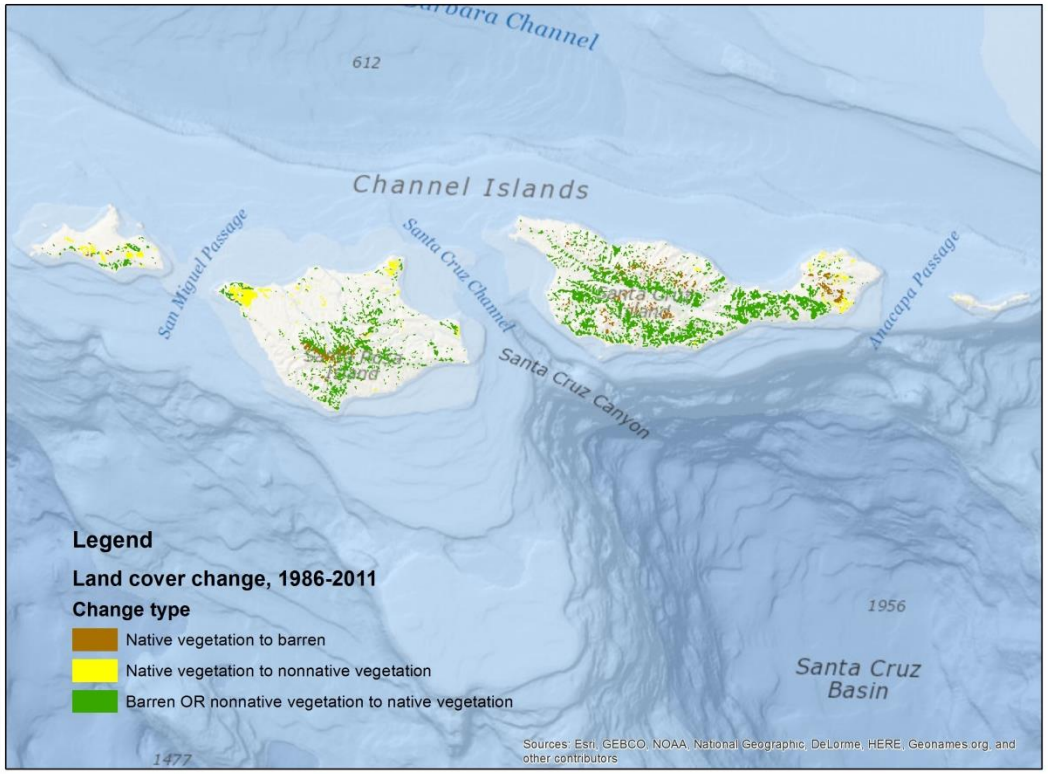


Figure 3.11 Change map of northern four CHIS from 1986 to 2011 based on Maximum Likelihood spectral classification of Landsat imagery. Areas of yellow indicate regions changed from native vegetation types (chaparral, strand, conifer/woodland, marsh, mixed woodland, riparian, scrub) to nonnative vegetation types (coastal grassland, deciduous savanna), areas of green indicate regions changed from nonnative to native vegetation types.

3.5.3 Management applications

These land cover and land use change maps have been created for the National Park Service to address the sources of change and to enact conservation policies accordingly. Quantifying the variability and long-term trends in land cover communities will help managers understand how vegetation is responding to human impact, and will inform management actions such as land preservation and invasive species eradication efforts. This project provides 371 field validated points on CHIS and 1737 Google imagery validated points in SAMO from 2011-2013. There are a number of statistical and spatial assessments that can be undertaken by local land use managers using products from this chapter. SAMO comprises a seamless network of local, state, and federal parks interwoven with private lands and communities (e.g. private ownership (48%), National Park Service (15%), California State Parks (23%), SMM Conservancy/MRCA (10%), other (4%) who may find these data of use.

3.5.4 Future research

Future analyses may be conducted to enhance the results of this report. If improved accuracy is needed, classifications of individual vegetation types such as chaparral or coastal sage scrub could be conducted (Boyd et al., 2011). The methods in this report may be applied to other ecologically protected areas in order to determine national/global trends of change, or to compare changes among Parks nationwide. The new Landsat Data Continuity Mission (LDCM) launched in 2013 with Operational Land Imager (OLI) sensor is recommended for future monitoring purposes due to its improved performance and monitoring longevity.

These results may also be utilized for additional analytical methods such as assessment of habitat fragmentation. The increase in native vegetation cover in certain areas may have

provided more habitat for urban carnivores such as mountain lion (*Puma concolor*) and bobcat (*Lynx rufus*) in SAMO, yet other increased high and medium intensity development may have reduced landscape connectivity. On CHIS, habitat of local fauna has also likely changed due to changes in land use and land cover. The change from grasslands to shrublands may have increased the habitat of the island fox (*Urocyon littoralis*), thus creating cover and protection from predation by golden eagles (*Aquila chrysaetos*). These native vegetation types are also habitat for island scrub-jay (*Aphelocoma insularis*) and logger head shrike (*Lanius ludovicianus*).

Further habitat analyses may be carried out by use of connectivity analysis to identify trends, barriers, and corridors. Connectivity analyses are complex and depend heavily on the species or taxa in question and the impacts of barriers, dispersal, and establishment of populations. However, standard connectivity indices for vegetation types such as FRAGSTATS, and those based on line graph theory such as LQGraph or ArcRstats can be calculated for all native vegetation types and surrounding regions to provide time series data on area, isolation, and connectivity of vegetation types (Goetz et al., 2009; Kupfer, 2012).

3.6 Conclusions

The objectives of this baseline report were to answer: 1. Can we create accurate maps of land cover/vegetation change using Landsat imagery?; and 2. Where should the National Park Service focus land management efforts in SAMO and CHIS? The 61.6% classification accuracy for SAMO and 69.1% for CHIS achieved suggests that higher-resolution imagery is needed to assess fine-scale landscape changes. However, general

trends are still possible to identify using Landsat. In SAMO these trends include a shift to mixed vegetation types such as deciduous savanna and medium-intensity developed land. These results reflect the changes of increased fragmentation over SAMO likely due to human development and provide spatial information as to where land managers should focus their efforts. CHIS change maps tell a different story of ecological recovery displayed by recent increases in native vegetation types over areas that were nonnative grasslands. These results indicate that remote sensing can be used to direct land management needs as well as quantify effective ecological restoration efforts.

3.7 Acknowledgments

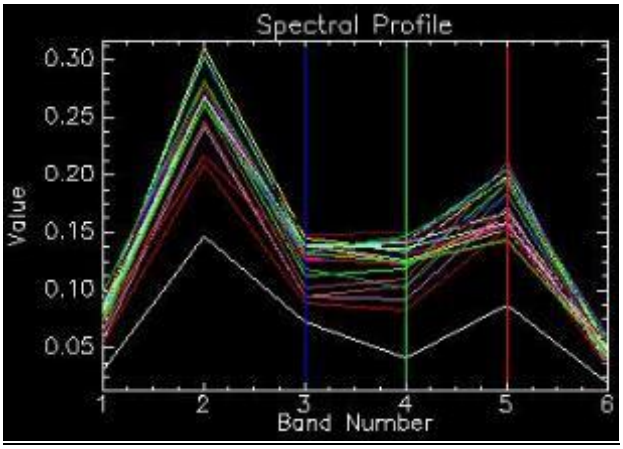
We would like to acknowledge the help of John Tiszler, Kate Faulkner, Denise Kamradt, Rocky Rudolph, Christy Brigham, Ken Neissen, Ian Williams, Dirk Rodriguez, Lyndal Laughrin, Kathryn Mceachern, and Keith Lombardo from the National Park Service as well as Travis Longcore, Kai Fung Chum, Katherine Glover, Lauren Brown, Dylan Connor, Tyler Harlan, David Gao, and Olivia Jenkins from UCLA for research, GIS, and field assistance. We would also like to thank the peer editors Gregory S. Okin and Yongwei Sheng from UCLA, and Tom Phillipi and Bill Monahan from the National Park Service. The protocol was improved through comments from P. Latham, J. Bakker and an anonymous reviewer.

3.8 Appendix A: Land Cover Classification

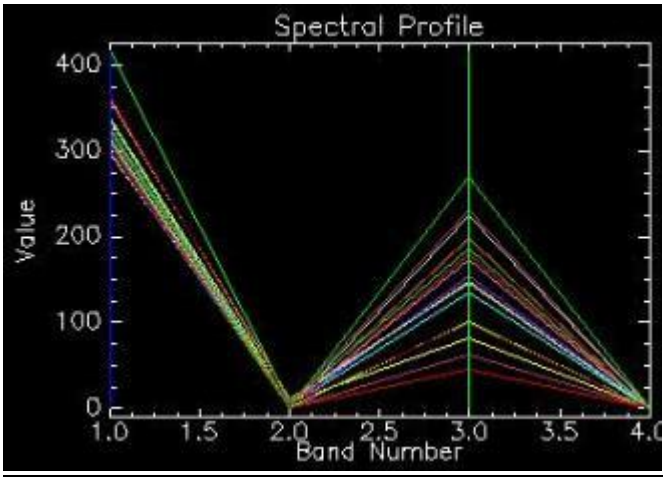
Class	Abbreviation
Agriculture	AGRI
Beach, Shore, Sand	SAND
Chaparral	CHAP
Cliff, Canyon, and Talus	CLFF
Conifer Dominated Forest Woodland (Mesic-Wet)	CONF
Conifer Dominated Forest Woodland (Xeric-Mesic)	CONF
Deciduous Dominated Savanna Glade	DSAV
Developed – High Intensity	DVHI
Developed – Medium Intensity	DVMD
Developed – Low Intensity	DVLO
Developed – Open Space	DVOP
Floodplain Riparian	RIPE
Freshwater Herbaceous Marsh, Swamp, or Baygall	MRSH
Mixed Deciduous/Coniferous Forest and Woodland (Mesic-Wet)	CONF
Open Water	WATR
Sand Prairie, Coastal Grassland, and Lomas	CGRS
Scrub Shrubland (Coastal Sage Scrub)	SCRB

Note: Each color curve in the graphs below represents the spectral signature of one particular pixel of the given land cover class.

Agriculture
Classified under Level 1 – Human Land Use. Includes cultivated cropland, pasture, and hay.



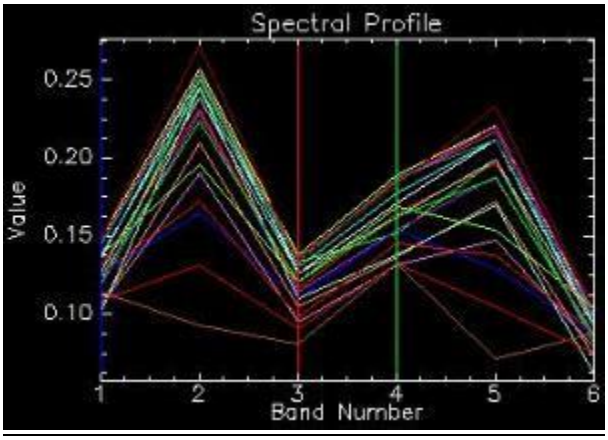
Landsat spectral information for Agriculture (Landsat bands order 1,2,3,4,5,7)



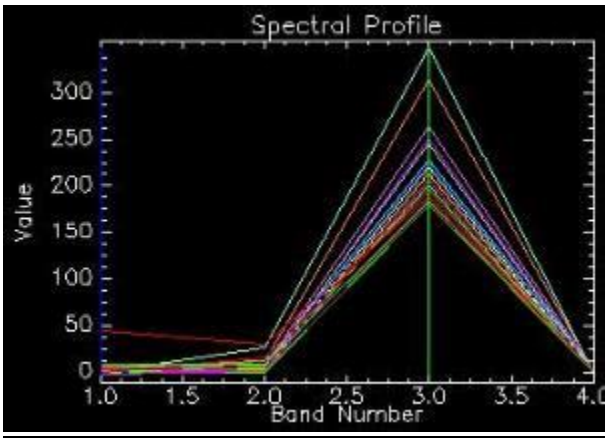
SRTM elevation data for Agriculture (elevation, slope, aspect, relief)

Aerial image of Agriculture (from GoogleEarth)

Beach, shore, sand
Classified under Level 1 - sparse and barren systems. Defined as including Mediterranean California southern coastal dune.



Landsat spectral information for beach, shore, sand (Landsat bands order 1,2,3,4,5,7)

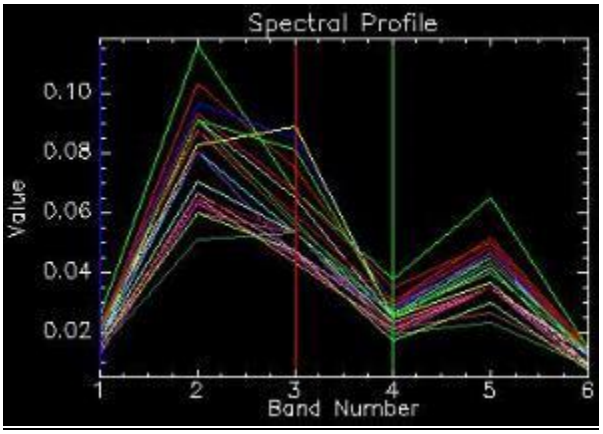


SRTM elevation data for beach, shore, sand (elevation, slope, aspect, relief)

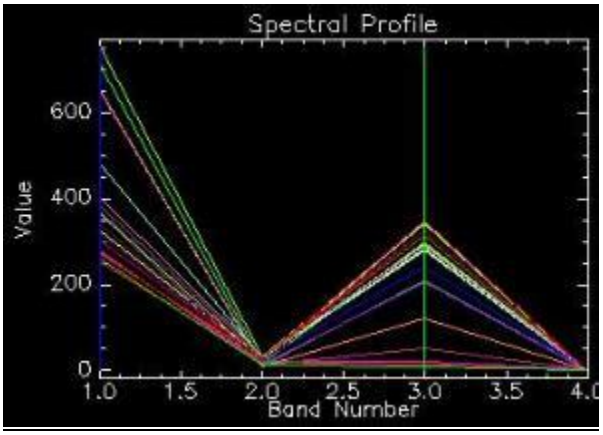
Aerial image of beach, shore, sand (from GoogleEarth)

Chaparral

Classified under Level 1 – Shrubland, steppe and savanna systems. Includes California maritime chaparral, California mesic chaparral, and southern California dry-mesic chaparral.



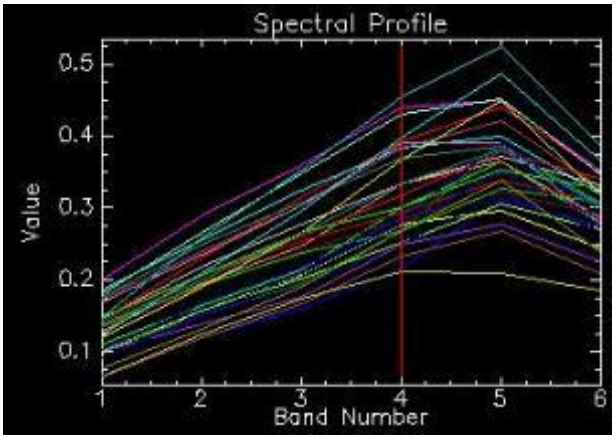
Landsat spectral information for chaparral (Landsat bands order 1,2,3,4,5,7)



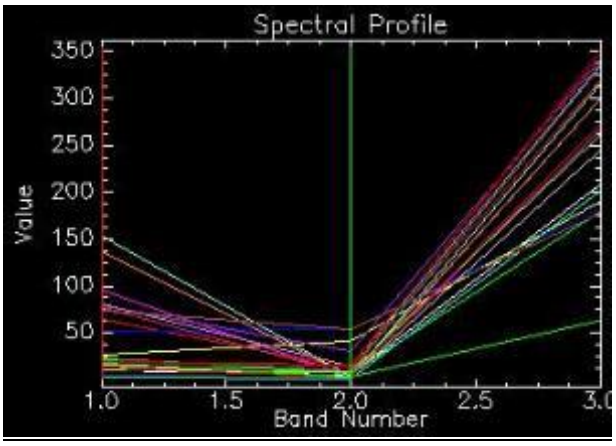
SRTM elevation data for chaparral (elevation, slope, aspect, relief)

Aerial image of chaparral (from GoogleEarth)

Cliff, Canyon, and Talus
Classified under Level 1 – sparse and barren systems. Includes southern California Coast Ranges cliff and canyon.



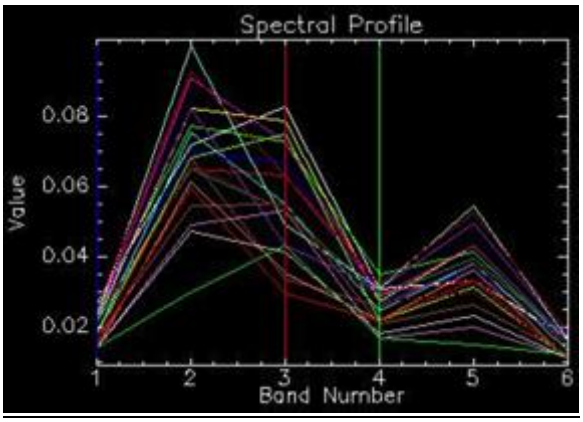
Landsat spectral information for Cliff, Canyon, and Talus (Landsat bands order 1,2,3,4,5,7)



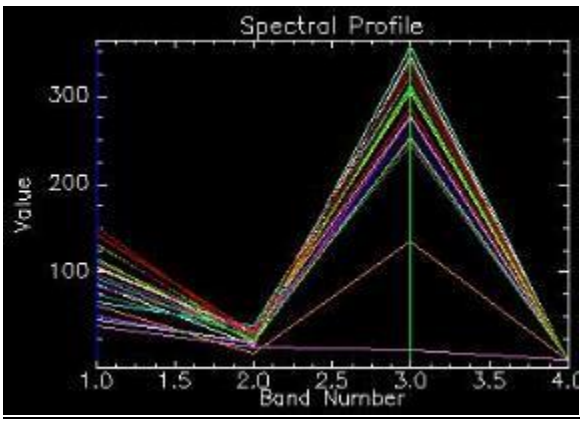
SRTM elevation data for Cliff, Canyon, and Talus (elevation, slope, aspect)

Aerial image of Cliff, Canyon, and Talus (from GoogleEarth)

Conifer: Conifer-dominated woodland (xeric-mesic)/ Conifer-dominated woodland (mesic-wet) / Mixed Deciduous/Coniferous Forest and Woodland (mesic-wet)
Classified under Level 1 – forest and woodland systems. Includes great pinyon-juniper woodland, Mediterranean California dry-mesic mixed conifer forest and woodland, Mediterranean California mesic serpentine woodland and chaparral, and California coastal closed-cone conifer forest and woodland.



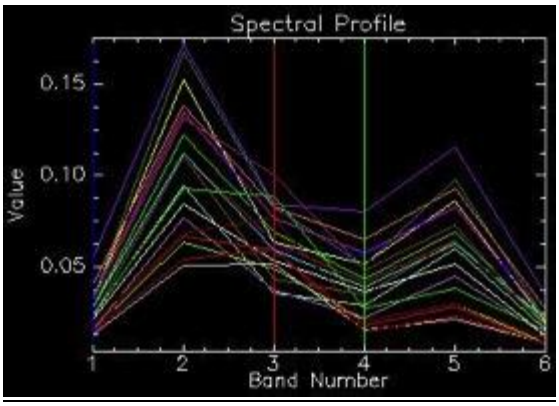
Landsat spectral information for Conifer (Landsat bands order 1,2,3,4,5,7)



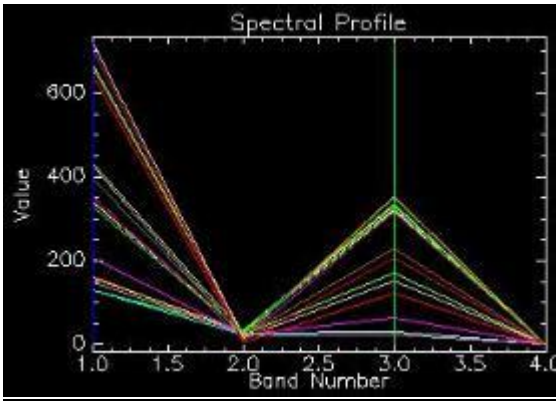
SRTM elevation data for Conifer (elevation, slope, aspect, relief)

Aerial image of Conifer (xeric-mesic) (from GoogleEarth)

Deciduous dominated savanna and glade
Classified under Level 1 – shrubland, steppe and savanna systems. Includes California central valley mixed oak savanna, California coastal live oak woodland and savanna, California lower montane blue oak-foothill pine woodland and savanna, and southern California oak woodland and savanna.



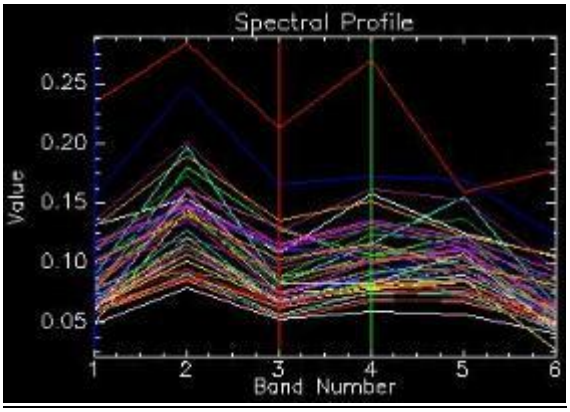
Landsat spectral information for Deciduous dominated savanna and glade (Landsat bands order 1,2,3,4,5,7)



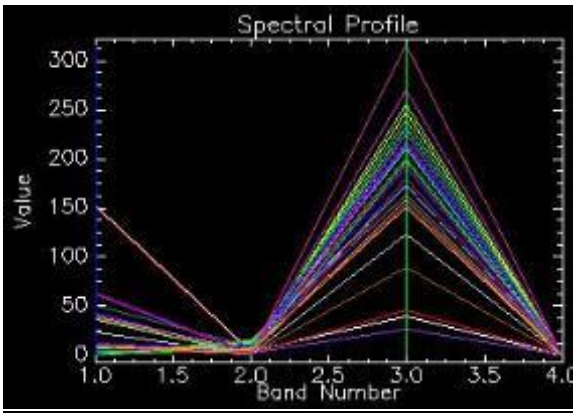
SRTM elevation data for Deciduous dominated savanna and glade (elevation, slope, aspect, relief)

Aerial image of Deciduous dominated savanna and glade (from GoogleEarth)

Developed – High Intensity
Classified under Level 1 – human land use.



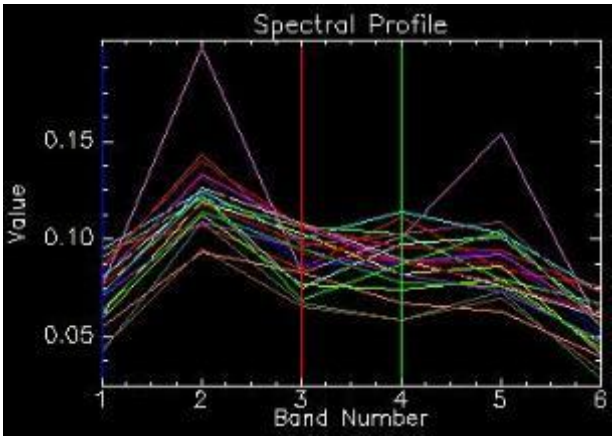
Landsat spectral information for Developed – High Intensity (Landsat bands order 1,2,3,4,5,7)



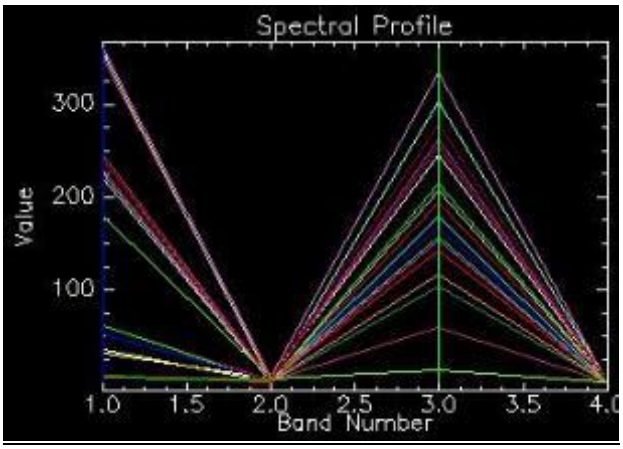
SRTM elevation data for Developed – High Intensity (elevation, slope, aspect, relief)

Aerial image of Developed – High Intensity (from GoogleEarth)

Developed – Medium Intensity
Classified under Level 1 – human land use.



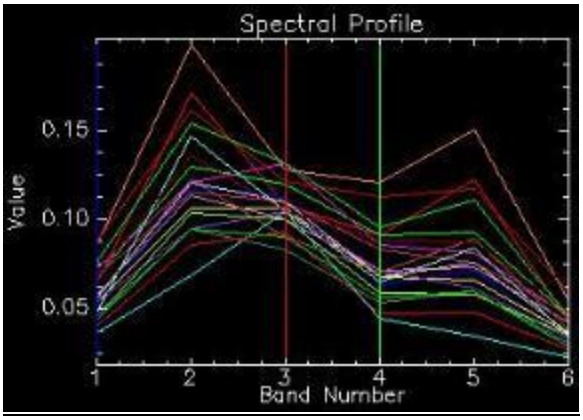
Landsat spectral information for Developed – Medium Intensity (Landsat bands order 1,2,3,4,5,7)



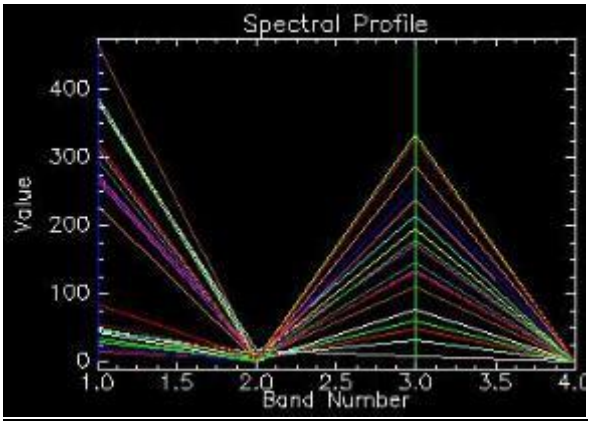
SRTM elevation data for Developed – Medium Intensity (elevation, slope, aspect, relief)

Aerial image of Developed – Medium Intensity (from GoogleEarth)

Developed – Low Intensity
Classified under Level 1 – human land use.



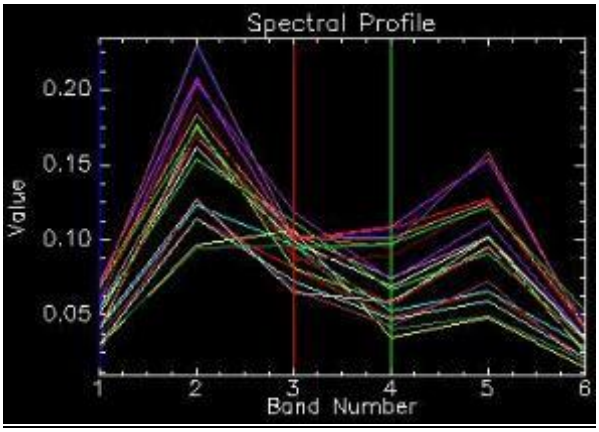
Landsat spectral information for Developed – Low Intensity (Landsat bands order 1,2,3,4,5,7)



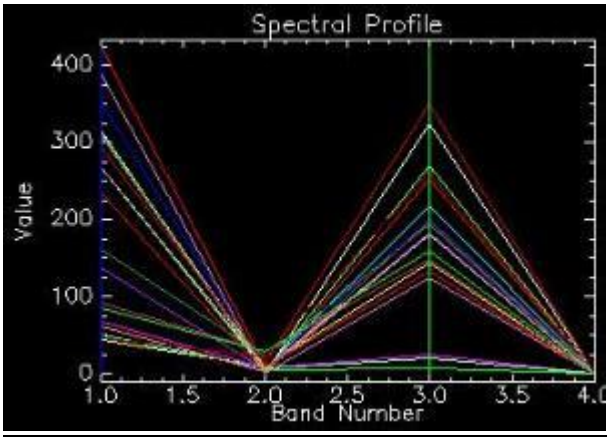
SRTM elevation data for Developed – Low Intensity (elevation, slope, aspect, relief)

Aerial image of Developed – Low Intensity (from GoogleEarth)

Developed – Open Space
Classified under Level 1 – human land use.



Landsat spectral information for Developed – Open Space (Landsat bands order 1,2,3,4,5,7)

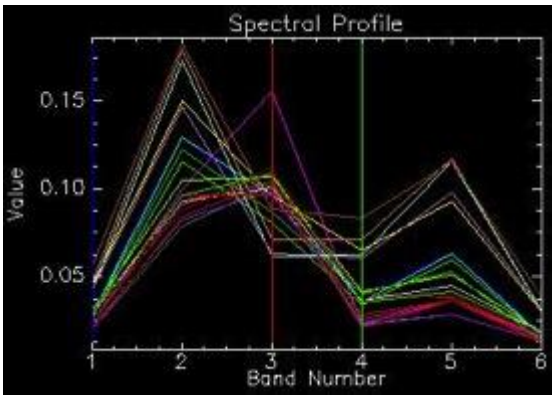


SRTM elevation data for Developed – Open Space (elevation, slope, aspect, relief)

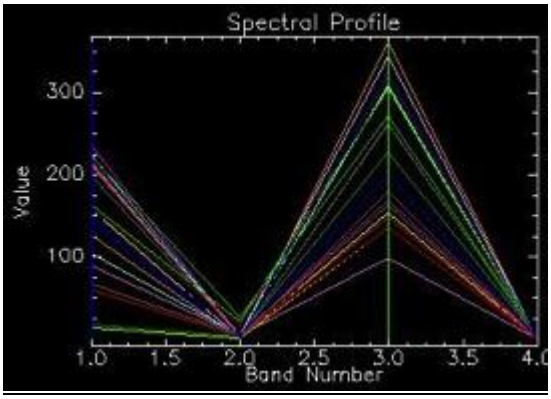
Aerial image of Developed – Open Space (from GoogleEarth)

Floodplain/riparian

Classified under Level 1 – riparian and wetland systems. Includes California central valley riparian woodland and shrubland, North American warm desert riparian woodland and shrubland, and Mediterranean California foothill and lower montane riparian woodland.



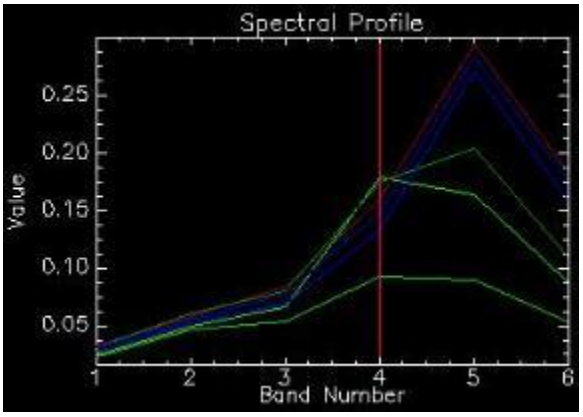
Landsat spectral information for floodplain/riparian (Landsat bands order 1,2,3,4,5,7)



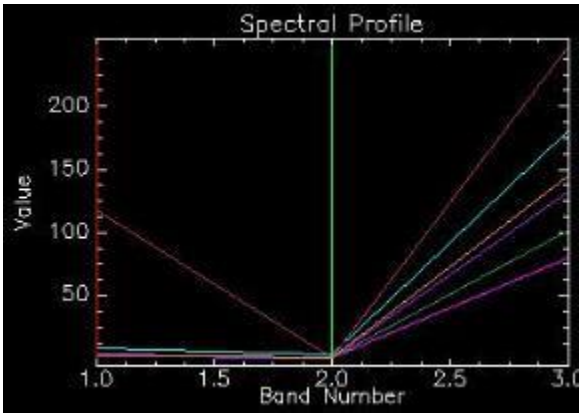
SRTM elevation data for floodplain/riparian (elevation, slope, aspect, relief)

Aerial image of floodplain/riparian (from GoogleEarth)

Freshwater Herbaceous Marsh, Swamp, or Baygall
Classified under Level 1 – Riparian and Wetland Systems. Includes Temperate Pacific Freshwater Emergent Marsh.



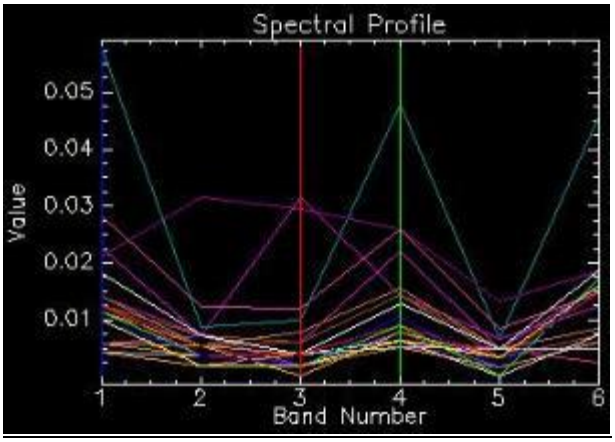
Landsat spectral information for freshwater herbaceous marsh, swamp, or baygall (Landsat bands order 1,2,3,4,5,7)



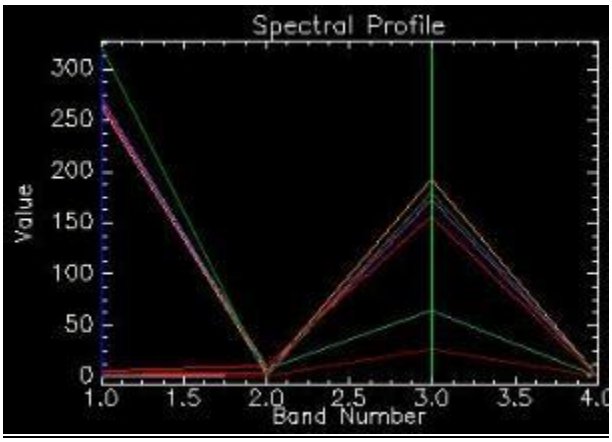
SRTM elevation data for herbaceous marsh, swamp, or baygall (elevation, slope, aspect)

Aerial image of herbaceous marsh, swamp, or baygall (from GoogleEarth)

Open Water
Classified under Level 1 – aquatic. Includes open water (fresh) and open water (brackish/salt).



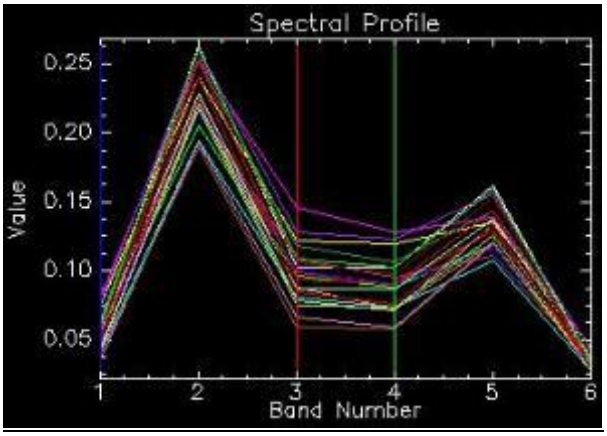
Landsat spectral information for open water (Landsat bands order 1,2,3,4,5,7)



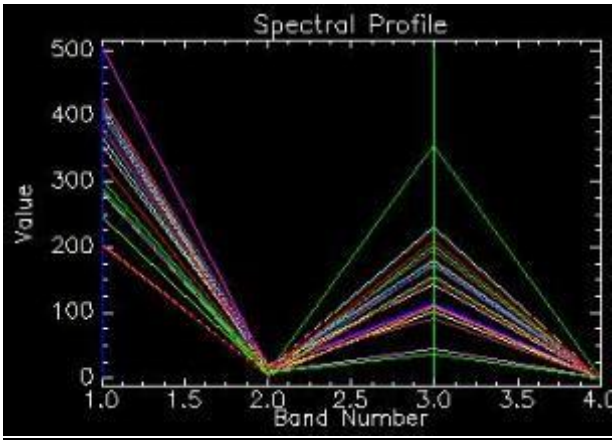
SRTM elevation data for open water (elevation, slope, aspect, relief)

Aerial image of open water (from GoogleEarth)

Sand prairie, coastal grasslands and lomas
Classified in Level 1 – grassland systems. Includes California central valley and southern coastal grassland.



Landsat spectral information for Sand prairie, coastal grasslands and lomas (Landsat bands order 1,2,3,4,5,7)

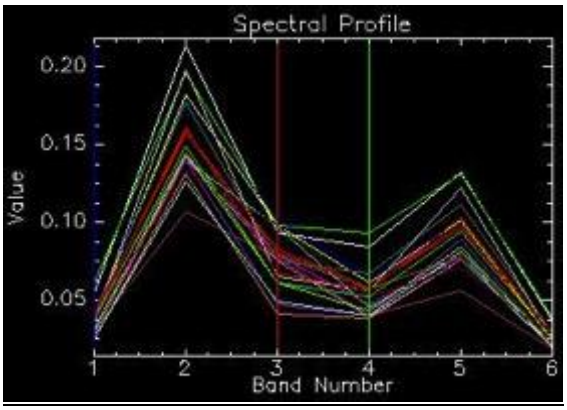


SRTM elevation data for Sand prairie, coastal grasslands and lomas (elevation, slope, aspect, relief)

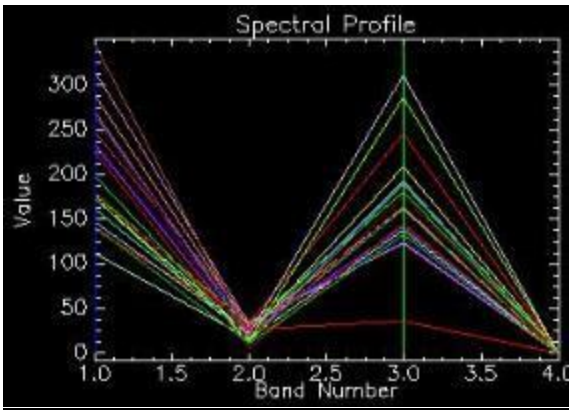
Aerial image of Sand prairie, coastal grasslands and lomas (from GoogleEarth)

Scrub Shrubland

Classified under Level 1 – shrubland, steppe and savanna systems. Includes inter-mountain basins mixed salt desert scrub, Mojave mid-elevation mixed desert scrub, Sonora-Mojave creosotebush-white bursage desert scrub, and southern California coastal scrub.



Landsat spectral information for scrub shrubland (Landsat bands order 1,2,3,4,5,7)



SRTM elevation data for scrub shrubland (elevation, slope, aspect, relief)

Aerial image of scrub shrubland (from GoogleEarth)

3.9 Appendix B: Field Validated Points, CHIS

Island name	Code
Santa Rosa Island	SRI
San Miguel Island	SMI
Santa Cruz Island	SCI
Anacapa Island	ACI

FID	Lat	Long	Class
SRI1	33.97928	120.1547	cgrs
SRI2	33.97555	120.1548	dsav
SRI3	33.92531	120.1196	x
SRI4	33.92417	120.1181	dsav
SRI5	33.92483	120.1162	dvlo
SRI6	33.92828	120.1151	dvlo
SRI7	33.92844	120.1153	dvlo
SRI8	33.93064	120.1154	dvlo
SRI9	33.93542	120.1135	clff
SRI10	33.93625	120.1154	dvlo
SRI11	33.93578	120.1152	dsav
SRI12	33.94089	120.1137	dvlo
SRI13	33.94228	120.1118	ripe
SRI14	33.92667	120.1162	clff
SRI15	33.94378	120.1078	clff
SRI16	33.95372	120.0934	cgrs
SRI17	33.94586	119.9716	sand
SRI18	33.94428	119.9706	watr
SRI19	33.94389	119.9706	cgrs

SRI20	33.94386	119.9707	cgrs
SRI21	33.94344	119.9696	sand
SRI22	33.94319	119.968	watr
SRI23	33.94261	119.9679	watr
SRI24	33.94244	119.9675	watr
SRI25	33.94206	119.9715	watr
SRI26	33.94733	119.971	watr
SRI27	33.94789	119.9716	cgrs
SRI28	33.94811	119.9716	cgrs
SRI29	33.94842	119.9717	clff
SRI30	33.94953	119.9708	watr
SRI31	33.95022	119.971	watr
SRI32	33.95044	119.9705	watr
SRI33	33.95128	119.971	clff
SRI34	33.95225	119.9707	watr
SRI35	33.95331	119.9722	sand
SRI36	33.95475	119.974	cgrs
SRI37	33.95483	119.974	dsav
SRI38	33.95497	119.9742	cgrs
SRI39	33.95489	119.9745	mrsh
SRI40	33.955	119.9748	cgrs
SRI41	33.95508	119.9727	cgrs
SRI42	33.95514	119.9745	sand
SRI43	33.95528	119.9745	sand
SRI44	33.95531	119.9746	clff
SRI45	33.95528	119.9745	sand
SRI46	33.95564	119.9753	clff
SRI47	33.95531	119.9761	mrsh

SRI48	33.95564	119.9763	sand
SRI49	33.95547	119.9765	cgrs
SRI50	33.95542	119.9767	cgrs
SRI51	33.95567	119.9768	cgrs
SRI52	33.95717	119.9764	watr
SRI53	33.95614	119.9773	sand
SRI54	33.97767	120.0731	chap
SRI55	33.97792	120.0764	chap
SRI56	33.97792	120.0764	dsav
SRI57	33.9785	120.0803	dsav
SRI58	33.97736	120.0823	chap
SRI59	33.97736	120.0823	chap
SRI60	33.97733	120.0824	chap
SRI61	33.97717	120.0824	chap
SRI62	33.97714	120.0824	chap
SRI63	33.97714	120.0824	chap
SRI64	33.97847	120.0804	chap
SRI65	33.98017	120.0803	mxwd
SRI66	33.98017	120.0787	mxwd
SRI67	33.98017	120.0782	ripe
SRI68	33.98042	120.0774	dsav
SRI69	33.97653	120.0743	dsav
SRI70	33.98006	120.0723	chap
SRI71	33.98086	120.0716	chap
SRI72	33.98592	120.0738	dvop
SRI73	33.98858	120.0741	dvop
SRI74	33.98975	120.0746	dvop
SRI75	33.99108	120.0734	dsav

SRI76	33.95558	119.9799	mrsh
SRI77	33.95558	119.98	mrsh
SRI78	33.95575	119.9801	mrsh
SRI79	33.95592	119.9788	cgrs
SRI80	33.95586	119.9785	cgrs
SRI81	33.95611	119.9786	cgrs
SRI82	33.95589	119.9781	dsav
SRI83	33.95572	119.9779	dsav
SRI84	33.95611	119.9779	sand
SRI85	33.95614	119.9777	sand
SRI86	33.95614	119.9773	sand
SRI87	33.95642	119.9772	watr
SRI88	33.95628	119.9781	watr
SRI89	33.95622	119.9782	clff
SRI90	33.95633	119.9783	watr
SRI91	33.95667	119.9792	mrsh
SRI92	33.95692	119.9793	mrsh
SRI93	33.95719	119.9794	mrsh
SRI94	33.95761	119.9791	mrsh
SRI95	33.9575	119.9798	mrsh
SRI96	33.95578	119.9839	chap
SRI97	33.95256	119.9817	scrb
SRI98	33.96169	119.9794	ripe
SRI99	33.96444	119.9804	mrsh
SRI100	33.96258	119.9823	mrsh
SRI101	33.96683	119.9823	dsav
SRI102	33.97608	120.0099	dsav
SRI103	33.97997	120.0081	watr

SRI104	33.97939	120.0067	clff
SRI105	33.97972	120.0056	clff
SRI106	33.9825	120.0239	conf
SRI107	33.98314	120.0221	conf
SRI108	33.98575	120.0241	watr
SRI109	33.98589	120.0246	watr
SRI110	33.98633	120.0265	clff
SRI111	33.98692	120.0266	clff
SRI112	33.98494	120.025	conf
SRI113	33.97994	120.0005	sand
SRI114	33.98028	120	sand
SRI115	33.97981	119.9995	sand
SRI116	33.98	119.9995	sand
SRI117	33.97967	119.9989	sand
SRI118	33.979	119.9975	sand
SRI119	33.97806	119.9976	scrb
SRI120	33.97217	119.9888	clff
SRI121	33.96697	119.9862	clff
SRI122	34.00711	120.0843	cgrs
SRI123	34.0095	120.0813	cgrs
SRI124	34.00978	120.0806	cgrs
SRI125	34.01067	120.0827	cgrs
SRI126	34.01053	120.0833	cgrs
SRI127	34.01069	120.0839	cgrs
SRI128	34.01078	120.0839	cgrs
SRI129	34.01106	120.0834	cgrs
SRI130	34.01125	120.0831	dsav
SRI131	34.01128	120.0829	dsav

SRI132	34.01158	120.0839	dsav
SRI133	34.01175	120.0835	dsav
SRI134	34.01128	120.0829	dsav
SRI135	34.01172	120.0828	clff
SRI136	34.01225	120.0829	cgrs
SRI137	34.01269	120.0833	clff
SRI138	34.01294	120.0836	cgrs
SRI139	34.01311	120.0837	cgrs
SRI140	34.01297	120.0832	cgrs
SRI141	34.01342	120.0827	cgrs
SRI142	34.01356	120.0823	cgrs
SRI143	34.01364	120.0825	cgrs
SRI144	34.01375	120.0829	cgrs
SRI145	34.01386	120.0836	cgrs
SRI146	34.01386	120.0836	cgrs
SRI147	34.01425	120.0831	cgrs
SRI148	34.01414	120.0823	cgrs
SRI149	34.00736	120.0779	scrb
SRI150	34.00708	120.077	scrb
SRI151	34.00847	120.0656	cgrs
SRI152	34.00803	120.0652	dsav
SRI153	34.00806	120.0586	dvop
SRI154	34.00719	120.0511	dvlo
SRI155	34.00675	120.051	dvlo
SRI156	34.00656	120.0507	dvlo
SRI157	34.00622	120.0506	dvlo
SRI158	34.00058	120.0508	dvlo
SRI159	34.00567	120.0508	dvlo

SRI160	34.00342	120.0514	dvmd
SMI1	34.04278	120.3546	scrb
SMI2	34.04725	120.3572	dsav
SMI3	34.04997	120.3632	dsav
SMI4	34.05375	120.368	cgrs
SMI5	34.05606	120.3665	scrb
SMI6	34.05597	120.3684	scrb
SMI7	34.06156	120.3705	scrb
SMI8	34.06566	120.3657	cgrs
SMI9	34.06556	120.3634	dsav
SMI10	34.03246	120.3565	scrb
SMI11	34.03252	120.3648	agri
SMI12	34.03249	120.3678	dsav
SMI13	34.03073	120.3681	dsav
SMI14	34.03531	120.3761	clff
SMI15	34.03767	120.378	scrb
SMI16	34.0378	120.3805	dsav
SMI17	34.03534	120.3844	cgrs
SMI18	34.04343	120.4124	mrsh
SMI19	34.04414	120.4127	cgrs
SMI20	34.0447	120.4126	dsav
SMI21	34.04505	120.4133	ripe
SMI22	34.04468	120.4133	mrsh
SMI23	34.04455	120.4131	mrsh
SMI24	34.0415	120.4121	ripe
SMI25	34.03997	120.4191	dsav
SMI26	34.02979	120.4301	clff
SMI27	34.03185	120.4321	cgrs

SMI28			scrb
SMI29	34.03195	120.4382	cgrs
SMI30	34.03173	120.4393	sand
SMI31	34.03548	120.3485	scrb
SMI32	34.02907	120.3392	dsav
SMI33	34.02688	120.3347	cgrs
SMI34	34.02241	120.3373	scrb
SMI35	34.02526	120.3324	cgrs
SMI36	34.02509	120.3316	cgrs
SMI37	34.02778	120.3309	cgrs
SMI38	34.02636	120.3263	cgrs
SMI39	34.03616	120.3244	clff
SMI40	34.03553	120.3261	scrb
SMI41	34.03833	120.3307	ripe
SMI42	34.03991	120.3319	scrb
SMI43	34.03979	120.3373	scrb
SMI44	34.03892	120.3374	scrb
SMI45	34.04003	120.3493	cgrs
SCI1	34.00133	119.7415	dvlo
SCI2	34.0056	119.7543	dvlo
SCI3	34.01337	119.7956	conf
SCI4	34.01402	119.7965	conf
SCI5	34.01228	119.7849	conf
SCI6	34.01144	119.8021	conf
SCI7	34.01117	119.8023	conf
SCI8	34.01061	119.8048	conf
SCI9	34.0105	119.8055	mxwd
SCI10	34.01042	119.8056	mxwd

SCI11	34.00983	119.8064	conf
SCI12	34.00869	119.8072	mxwd
SCI13	34.00833	119.8096	conf
SCI14	34.00844	119.8101	mxwd
SCI15	34.01089	119.8043	conf
SCI16	34.01128	119.8036	conf
SCI17	34.0155	119.7977	dvlo
SCI18	34.01367	119.7845	ripe
SCI19	34.01183	119.7793	mxwd
SCI20	34.0125	119.7774	scrb
SCI21	34.00603	119.7579	mxwd
SCI22	34.03192	119.8108	dsav
SCI23	34.01508	119.8007	chap
SCI24	34.01508	119.8007	chap
SCI25	34.01689	119.8062	chap
SCI26	34.02156	119.8416	cgrs
SCI27	34.01939	119.8439	dvlo
SCI28	34.01994	119.8466	dvlo
SCI29	34.01994	119.8526	dvlo
SCI30	34.021	119.8625	dvlo
SCI31	34.01444	119.8768	cgrs
SCI32	34.00706	119.8628	cgrs
SCI33	34.01778	119.8591	ripe
SCI34	34.01286	119.8352	scrb
SCI35	34.01842	119.8318	conf
SCI36	34.01636	119.8266	conf
SCI37	34.01194	119.8179	conf
SCI38	34.01047	119.8152	conf

SCI39	34.01172	119.8134	conf
SCI40	33.99714	119.7279	ripe
SCI41	33.99839	119.7153	dvlo
SCI42	33.99736	119.7148	ripe
SCI43	33.99689	119.7158	ripe
SCI44	34.00167	119.7139	ripe
SCI45	34.00247	119.7105	ripe
SCI46	34.00203	119.7087	mxwd
SCI47	34.00278	119.7074	mxwd
SCI48	34.00397	119.7047	mxwd
SCI49	34.00269	119.7026	dsav
SCI50	34.00481	119.7003	mxwd
SCI51	34.00683	119.6987	mxwd
SCI52	34.00725	119.6986	mxwd
SCI53	34.01075	119.697	ripe
SCI54	34.01889	119.6835	mrsh
SCI55	34.01878	119.6828	mrsh
SCI56	34.01825	119.6832	clff
SCI57	34.01825	119.6826	mrsh
SCI58	34.01806	119.6821	mrsh
SCI59	34.01842	119.6819	ripe
SCI60	34.01842	119.6821	ripe
SCI61	34.01739	119.6824	ripe
SCI62	34.01719	119.6834	ripe
SCI63	34.01647	119.6833	ripe
SCI64	34.01611	119.6839	ripe
SCI65	34.01533	119.6842	ripe
SCI66	34.01431	119.6845	dvop

SCI67	34.01347	119.6856	dvop
SCI68	34.01392	119.6858	ripe
SCI69	34.01889	119.6849	css
SCI70	34.02025	119.687	mxwd
SCI71	34.02	119.6886	mxwd
SCI72	34.02428	119.6902	ripe
SCI73	34.02561	119.6977	
SCI74	34.02883	119.7019	mxwd
SCI75	34.03164	119.7019	ripe
SCI76	33.99569	119.7281	ripe
SCI77	33.9845	119.6999	scrb
SCI78	33.99953	119.6301	dsav
SCI79	33.99961	119.6311	dsav
SCI80	34.00303	119.6185	mxwd
SCI81	34.00231	119.6145	mxwd
SCI82	34.00311	119.6134	mxwd
SCI83	34.00286	119.6125	mxwd
SCI84	34.00306	119.6153	mxwd
SCI85	34.00306	119.6153	mxwd
SCI86	34.00306	119.6153	mxwd
SCI87	34.00306	119.6153	mxwd
SCI88	34.00144	119.6106	mxwd
SCI89	34.00694	119.6059	cgrs
SCI90	34.01156	119.5914	chap
SCI91	34.01178	119.5892	chap
SCI92	34.01281	119.5938	mxwd
SCI93	34.01342	119.6018	chap
SCI94	34.00281	119.6491	mxwd

SCI95	34.00286	119.6491	mxwd
SCI96	34.00306	119.6484	mxwd
SCI97	34.00303	119.6483	mxwd
SCI98	34.00303	119.6483	mxwd
SCI99	34.00303	119.6483	mxwd
SCI100	33.99314	119.7413	chap
SCI101	33.99778	119.7409	chap
SCI102	33.99861	119.744	chap
SCI103	33.99858	119.7533	dsav
SCI104	34.00103	119.7594	chap
SCI105	34.00103	119.7594	chap
SCI106	34.00103	119.7594	chap
SCI107	34.00167	119.7592	chap
SCI108	34.00111	119.7631	chap
SCI109	34.00186	119.7634	chap
SCI110	34.0065	119.7753	chap
SCI111	34.0065	119.7753	chap
SCI112	34.0065	119.7753	chap
SCI113	34.00628	119.7759	chap
SCI114	33.96219	119.7913	clff
SCI115	33.96292	119.7936	scrb
SCI116	33.96372	119.7964	mrsh
SCI117	33.96367	119.7961	mrsh
SCI118	33.96397	119.7961	mrsh
SCI119	33.96422	119.7968	ripe
SCI120	33.96519	119.7972	ripe
SCI121	33.96528	119.7976	ripe
SCI122	33.96564	119.7979	ripe

SCI123	33.96975	119.7992	x
SCI124	33.97106	119.7975	dsav
SCI125	33.98419	119.8005	chap
SCI126	33.98414	119.8007	ripe
SCI127	33.98411	119.8004	chap
SCI128	33.98583	119.8016	ripe
SCI129	33.99628	119.8007	scrb
SCI130	34.03594	119.871	cgrs
SCI131	34.04353	119.861	x
SCI132	34.04408	119.8866	scrb
SCI133	34.05336	119.8888	cgrs
SCI134	34.05606	119.9098	watr
SCI135	34.05922	119.9061	cgrs
SCI136	34.05986	119.9212	clff
SCI137	34.05942	119.9226	clff
SCI138	34.05961	119.9231	watr
SCI139	34.06017	119.9279	watr
SCI140	34.05958	119.9276	clff
SCI141	34.05736	119.9241	sand
SCI142	34.05822	119.9227	mrsh
SCI143	34.0575	119.9222	mrsh
SCI144	34.05922	119.9061	cgrs
SCI145	34.06161	119.9112	cgrs
SCI146	34.06839	119.9014	cgrs
SCI147	34.06933	119.9005	cgrs
SCI148	34.06853	119.8996	cgrs
SCI149	33.99839	119.7153	dvlo
SCI150	33.99736	119.7148	dvlo

SCI151	33.99417	119.7084	ripe
SCI152	33.99428	119.7079	ripe
SCI153	33.99428	119.7079	ripe
SCI154	33.99428	119.7079	ripe
SCI155	33.99439	119.7078	ripe
SCI156	33.99447	119.7078	ripe
SCI157	34.00172	119.6898	mxwd
SCI158	33.99914	119.68	scrb
SCI159	33.99706	119.7256	dvlo
SCI160	33.99706	119.7256	dvlo
SCI161	33.99714	119.7279	dvlo
ACI1	33.97928	120.1547	cgrs
ACI2	34.01481	119.3648	dvmd
ACI3	34.01411	119.3657	dvhi
ACI4	34.01428	119.3678	dvlo

3.10 Appendix C: Land Cover Change Statistics

SAMO												
	1986											
2011		WATR	SCRB	SAND	RIPE	DVOP	DVMD	DVLO	DVHI	DSAV	CHAP	CGRS	AGRI
	WATR	99.51	0.00	0.45	0.17	0.02	0.01	0.02	6.25	0.00	0.00	0.01	0.05
	SCRB	0.00	77.18	0.76	0.61	11.84	0.00	0.01	1.79	21.92	4.15	7.71	0.17
	SAND	0.07	0.55	19.29	0.43	0.65	2.01	0.75	3.15	0.07	0.01	0.73	2.29
	RIPE	0.00	0.08	3.52	37.39	9.27	0.50	2.09	10.80	5.05	3.54	7.21	8.36
	DVOP	0.01	16.13	9.39	14.38	38.42	0.45	3.07	17.77	8.62	5.15	18.15	18.18
	DVMD	0.15	0.01	41.22	6.24	4.75	87.86	41.76	16.80	0.07	0.07	3.59	18.33
	DVLO	0.01	0.21	10.15	20.40	15.20	7.25	48.56	11.38	0.89	0.71	10.67	17.64
	DVHI	0.26	0.43	7.02	7.15	3.30	1.71	2.87	15.63	3.45	1.77	2.03	4.15
	DSAV	0.00	3.91	0.19	1.83	6.08	0.01	0.09	2.13	37.29	15.71	5.30	0.05
	CHAP	0.00	0.72	0.06	4.42	2.88	0.02	0.01	3.48	20.79	68.80	0.11	0.01
	CGRS	0.00	0.73	0.59	0.22	3.96	0.01	0.04	0.48	1.76	0.06	40.20	6.42
	AGRI	0.00	0.05	7.37	6.77	3.63	0.17	0.74	10.33	0.08	0.05	4.29	24.37
	Class Changes	0.49	22.82	80.71	62.61	61.58	12.15	51.44	84.37	62.71	31.20	59.80	75.63

		CHIS						
		1986						
		BARREN	CHAP	CSS	GRASS	SCRUB	STRAND	WOODLAND
2011	BARREN	17.58	4.32	9.09	3.02	7.29	0.36	0.94
	CHAP	12.52	57.37	11.15	10.83	24.03	0.43	12.48
	CSS	12.04	4.44	19.91	2.57	5.08	0.78	1.95
	GRASS	23.52	2.30	11.80	68.59	8.47	0.24	0.32
	SCRUB	19.14	6.30	21.12	11.49	28.34	0.45	9.89
	STRAND	1.34	1.55	1.31	0.13	0.74	96.81	0.49
	WOODLAND	13.86	23.72	25.62	3.37	26.05	0.93	73.93
	Class Changes	82.42	42.63	80.09	31.41	71.66	3.19	26.07

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CHAPTER 4

4. The impact of drought on native southern California vegetation health: a remote sensing analysis using MODIS-derived time series

A version of: Willis, K. S., Gillespie, T. W., Okin, G. S., MacDonald, G. M. (in prep) Response of native southern California vegetation to drought using MODIS-derived time series. Global Change Biology.

4.1 Abstract

Remote sensing of vegetation can be an important tool for detecting the impacts of climate change on whole-ecosystem functioning. This study elucidates climate-ecosystem relations and the response of chaparral and coastal sage scrub-dominated ecosystems to recent drought. Whole ecosystem health for USGS GAP vegetation polygons was monitored for the period 2000-2014 using the Normalized Difference Vegetation Index (NDVI) derived from MODIS MOD13Q1. Time series regressions of Palmer Drought Severity Index (PDSI) anomalies and vegetation NDVI anomalies were used to assess the response of vegetation to drought. There was no increasing or decreasing trend in vegetation greenness over the given time period. However, vegetation greenness was influenced by anomalous PDSI on an intra-annual basis, signifying that unusual drought may have an impact on native vegetation health. Regressions indicated that drought had a higher impact on chaparral-dominated ecosystems (R^2=0.658) than coastal sage (R^2=0.481) over the entire region. The highest regional regression outputs were in Santa Barbara County chaparral (R^2=0.498). These results indicate that chaparral was likely driven by drought and soil water deficit at the multi-monthly timescale. Coastal sage scrub communities displayed higher intra-annual variability, and had a lower correlation with monthly PDSI. This suggests that shallow-rooted coastal sage types may

experience quick greening after discrete precipitation events, yet are less responsive to drought on a multi-monthly scale. Future predicted climate change and increased frequency, duration, and magnitude of drought in southern California may cause decreased vitality in native southern California ecosystems, especially in chaparral-dominated areas.

4.2 Introduction

Since 2001, large portions of the arid Southwest, including portions of southern California, have experienced prolonged drought (MacDonald, 2010). The current drought in California has lasted from 2012-2015, resulting in a discussion of its effects on water policy to agriculture to ecological disturbance (Diffenbaugh et al., 2015; Moore and Heath, 2015; Worland, 2015; Zilberman et al., 2015). Annual to multi-year dry spells such as this are expected to be exacerbated by warming in the future and may already be impacting native ecosystem health (Cook et al., 2015; Diffenbaugh et al., 2015). Global and regional climate models suggest that coastal southern California is a potential "hotspot" for climate change (Cayan et al., 2006).

California temperatures are expected to continue their warming trend, which increase potential evapotranspiration and intensify the effects of drying in vegetation. Although coastal warming is attenuated by the thermal inertia of the Pacific Ocean, southern California surface temperatures are expected to increase 2-4 °C by 2100 (State of the Climate Global Analysis Annual, 2011). Modest warming scenarios suggest an increase of 2.6 °C average over the Los Angeles Basin by 2050, and downscaled models built specifically for the Los Angeles Basin predict that mountainous zones will warm about 2.75 °C on average from 2041-2060 (Hall et al.,

2012). In particular, summer warming will manifest as two to three times increase in the number of extremely hot days along the coast (Hall et al., 2012; Hayhoe et al., 2004; Loarie et al., 2008).

Precipitation is more difficult to predict in relation to future drought (Williams et al., 2015). Predictions of precipitation changes vary, but even slight changes have an effect on local vegetation. For example, a slight decrease in California winter precipitation along would affect the normal winter growing seasons of native plants that rely on the minimal water supply (Hayhoe et al., 2004).

4.2.1 Study area and vegetation types

Chaparral and coastal sage scrub ecosystems contain some of the highest species diversity and endemism in the state, and are therefore vital to preserve (Fairbanks & McGwire, 2004; Rundel, 2007). The coastal southern California region has a Mediterranean climate with mild winters and seasonal summer drought. A marine layer can provide moisture via fog in the early summer, but many plants have their growing season in the moist winter months (Minnich, 2007). Mean precipitation ranges from 24-33 cm/year, and temperature from 10-13ºC in winter, and 17-21ºC in summer (Western Regional Climate Center, 2013). Interannual climate variability is high in southern California due to coupled ocean-atmosphere interactions such as the El Niño-Southern Oscillation and the Pacific Decadal Oscillation (Mantua & Hare, 2002; Minnich, 2007; Ropelewski & Halpert, 1986; Trenberth, 1997).

Native chaparral is the largest plant community in California, covering approximately 2.83 million hectares across the state (Quinn & Keeley, 2006). This vegetation group contains semi-arid shrubs averaging 1.5-3 m high that possess sclerophyllous, generally evergreen leaves and are both drought and fire adapted (Harrison et al., 1971; Rundel, 2007). Several of the most

common chaparral species include: *Ceanothus megacarpus* (big pod ceanothus), *Adenostoma fasciculatum* (chamise), *Arctostaphylos spp.* (Mixed chaparral), and sometimes *Quercus agrifolia* (coast live oak – also considered a woodland land cover species type) (Dennison & Roberts, 2003; Franklin, 2002). Summer drought patterns have been shown to limit chaparral seedling establishment, which ultimately limits its distribution in California (Keeley & Davis, 2007). Though evergreen, chaparral does see slight changes in its spectral properties depending on moisture availability and development of new leaves. Typically, chaparral experiences a slight yellowing and leaf loss during the summer from June until November (Rundel, 2007). The increased moisture from November until June leads to new growth in chaparral, which produces green leaves as seen at the plant scale (Halsey, 2005).

Coastal sage scrub is distributed along the coast and semiarid inland regions of southern California (Riordan & Rundel, 2009; Rundel, 2007). Dominant species include: *Artemisia californica* (California sage), *Eriogonum fasciculatum* (buckwheat), *Salvia mellifera* (California sage), and *Salvia apiana* (white sage) (Franklin, 2002). These shrubs tend to occur at lower elevations than chaparral in areas of shallow, coarse, granite- and sandstone-derived soils with less precipitation and a shorter winter growing season (Gray, 1982; Harrison et al., 1971; Kirkpatrick & Hutchinson, 1980). The coastal sage scrub community is dominated by drought-deciduous short shrubs averaging 1-2 m high that drop leaves during dry summer months as soil water availability decreases, and produce new leaves at the beginning of the winter wet season. Coastal sage contains a higher specific leaf weight, yet approximately the same relative allocation of tissue to leaves and stems as chaparral (Rundel, 2007). Stems may completely lose their leaves during times of extreme drought (Harrison et al., 1971), which is visible through remotely sensed data (e.g., Fairbanks & McGwire, 2004; Riaño et al., 2002; Serrano et al., 2000)

Mediterranean-type environments contain many drought tolerant vegetation species. However, an increase in water deficit might result in intra- and inter-annual changes in native vegetation health (Gordo & Sanz, 2010). In order to assess the future of these native ecosystems, we need to gain a better understanding of the relationship between vegetation and water deficit due to anomalous drought (Zhang et al., 2004). Remotely sensed data can be used to quantify ecosystem response to climatic change over a broad spatial scale; changes in vegetation density, composition, and condition can be estimated to represent the relative health of an ecosystem (Stow, 1995). The Normalized Difference Vegetation Index (NDVI) is the most commonly used vegetation index, and is a relative measure of ecosystem greenness (Kerr & Ostrovsky, 2003). NDVI is known as a proxy for ecosystem function, health, and productivity. It is strongly correlated with vegetation biomass, aboveground Net Primary Productivity and Absorbed Photosynthetic Active Radiation, thus holding major implications for terrestrial carbon flux (Cao et al., 2004; Kerr & Ostrovsky, 2003; Pettorelli et al., 2005; Turner et al., 2003).

Here the impacts and implications of climate variability on vegetation indices in southern California are studied using remote sensing to answer three research questions. 1. How does drought affect native vegetation health? It is expected that recent extreme drought has caused a decline in native vegetation health during the 21st Century. 2. How do chaparral- and coastal sage scrub-dominated ecosystems differ in response to unusual periods of drought? A higher correlation is predicted between coastal sage scrub-dominated ecosystems and anomalous drought months due to their drought-deciduous nature and shallow root systems. 3. What are the geographical variations of ecosystem greenness response to drought in southern California counties? It is hypothesized that southern regions experience greater decline in greenness during increased drought, given the intensified drought along a southern gradient.

4.3 Data and Methods

4.3.1 Remotely sensed data

The spectral data used for this study include NASA's Terra MODIS MOD13Q1 derived NDVI for MODIS 250m tile H08 V05 (*MODIS subsetted land products, Collection 5*, 2013). We downloaded 250-m data for February 1, 2000 until December 31, 2014. MOD13 NDVI data are 16-day composites inherently corrected for BRDF angle, cloud cover, and general image quality (Huete et al., 2002; Schaaf et al., 2002).

Normalized Difference Vegetation Index (NDVI) is useful in Mediterranean-type ecosystems since low greenness provides little chance of saturation, and is based on the red and near infrared bands to determine the greenness in remotely sensed vegetation, and is given by:

$$NDVI = (\rho_{NIR} - \rho_{RED}) / (\rho_{NIR} + \rho_{RED}),$$

where ρ_{NIR} is reflectance in the near infrared band and ρ_{RED} is reflectance in the red band (Dennison et al., 2005; Huete et al., 2002; Reed et al., 1994; Tucker, 1979; Zhang et al., 2004). MOD13 data are derived from the normalized BRDF-adjusted reflectance MODIS products (MCD43; Schaaf et al., 2002).

Vegetation polygons were identified as chaparral and coastal sage scrub-dominated areas by the USGS California Gap Analysis (GAP) program (Davis et al., 1995; Lowry et al., 2005). The GAP program provides high spatial resolution data (30-m resolution) with 40 land use/land cover types which can be used to assess native land cover (Davis et al., 1995). Polygons were chosen from GAP Level 2 data from San Luis Obispo County to the Mexican border (Lowry et al., 2005). Only chaparral and coastal sage scrub polygons that were more than 9000 square meters in size and less than 20 km from the coast were used in order to represent these southern

California coastal vegetation types in a Mediterranean climate zone (Figure 4.1). The region of interest was determined to be the combination of all polygons for each vegetation type. All chaparral or coastal sage scrub areas that had burned between 2001 and 2014 were removed from the study by omitting areas shown to have burned by one or more fires per 1 km pixel by the MODIS MOD14/MYD14 Fire and Thermal Anomalies product ("Active Fire Data," 2013).

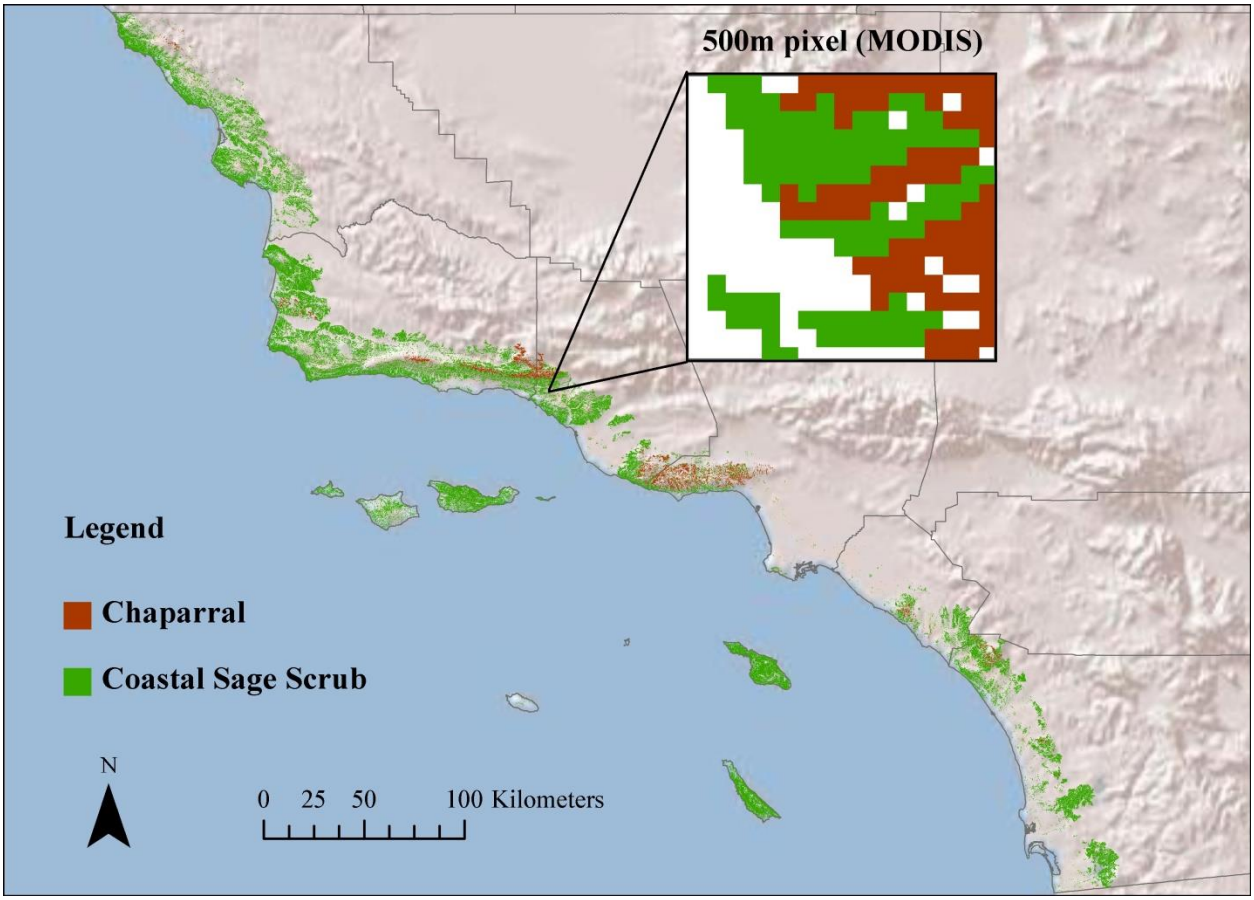


Figure 4.1 Study area of coastal southern California chaparral and coastal sage scrub shapefiles (USGS GAP, 2011).

Each MOD13 tile in the time series was subset by the region of interest created from the fire-removed vegetation polygons, and the mean NDVI value for the region of interest was calculated per 16-day time step. The 16-day time series was resampled to a monthly time series in order to match the monthly climate data in regression analysis. The average NDVI values of

the polygons were finally output as a time series of average chaparral or coastal sage scrub NDVI per time step for the 12-year period. Spatial averaging was used in order to remove strictly local variations and to obtain a picture of the overall vegetative response to climate across the entire area of the two vegetation types.

4.3.2 Climate data

Aggregated climate division data were downloaded for California Climate Division 6 and for each county within this climate division from the National Oceanic and Atmospheric Administration's National Climatic Data Center (*Daily GHCN-D Climate Data*, 2013). California's Climate Division 6 is one of 7 standard large geographic climate boundaries delineated by the US National Climatic Data Center, and encompasses all remotely sensed polygons used in this study (Guttman & Quayle, 1996). Data used are calculated from station data, and include monthly average Palmer Drought Severity Index (PDSI) from February 2000 – December 2014. PDSI represents drought severity based on moisture supply and demand, and ranges from -6 to 6, with negative values indicating dry periods and positive values indicating wet periods (Alley, 1984; Palmer, 1965). After climate data were downloaded, their values were converted to Z-scores based on the entire 15-year time period. Anomalous seasons were determined by re-calculating the climate and vegetation Z-scores with respect to the monthly average of the observation period. Focus drought years (2007-08, 2013-14) were chosen based on the lowest periods of PDSI in California Climate Zone 6, where PDSI remained at "extreme drought" levels (PDSI < -4) for more than one month (Heim Jr., 2002).

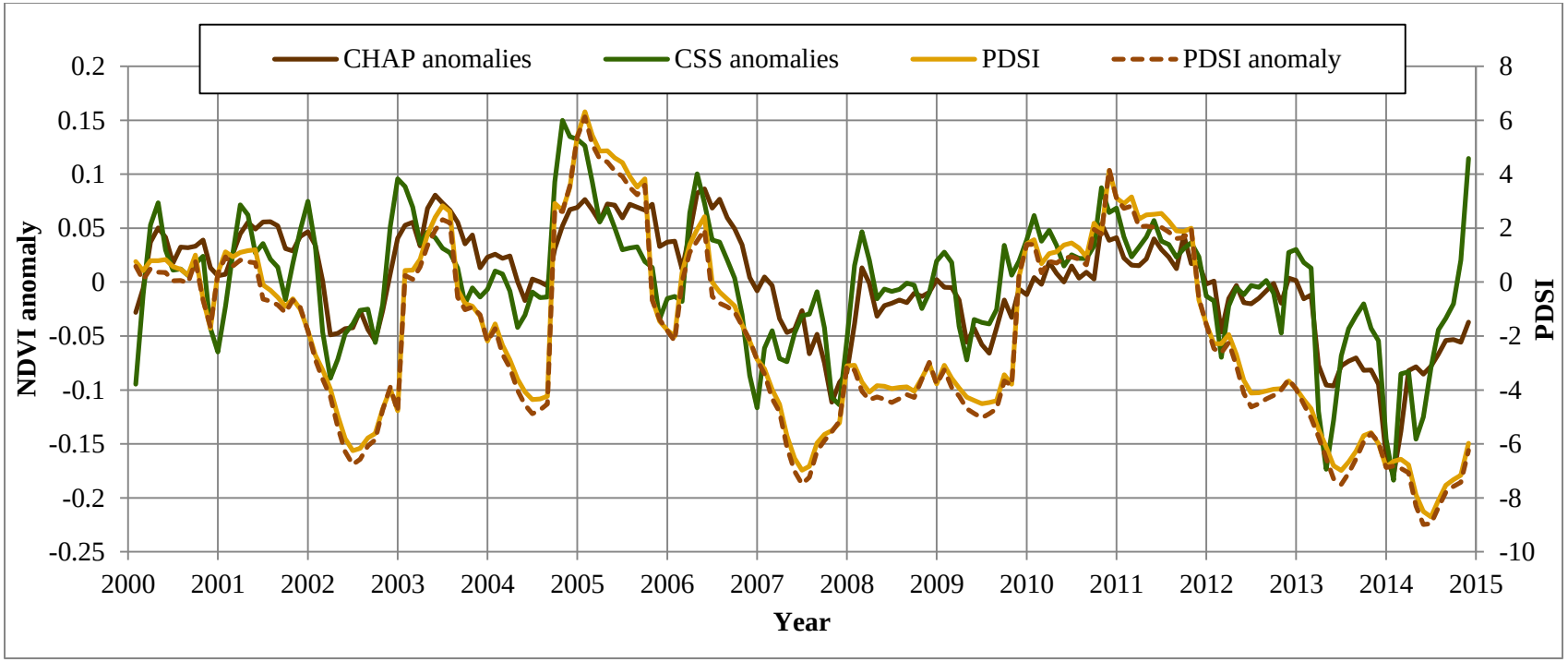


Figure 4.2 Time series of chaparral and coastal sage scrub monthly anomaly NDVI (MODIS) and Palmer Drought Severity Index (PDSI) with PDSI monthly anomalies.

4.3.3 Data analysis

Z-score PDSI and NDVI were used for regression analysis to determine simple coefficients of determination (Herrmann et al., 2005). The final regressions were run with climate (raw data and anomalies) as independent variables and NDVI (raw data and anomalies) as dependent variables. The resulting R^2 values represent the strength of the effect of each climate variable on vegetation. NDVI change maps were created based on pixel-by-pixel changes in season NDVI for each drought year (2007, 2008, 2013, 2014) minus the baseline of the entire time series (2000-2014). The average highest and lowest NDVI season was calculated over the entire time series and defined the dry season as June, July, August and wet season as January, February, March. These change maps are discussed qualitatively.

4.4 Results

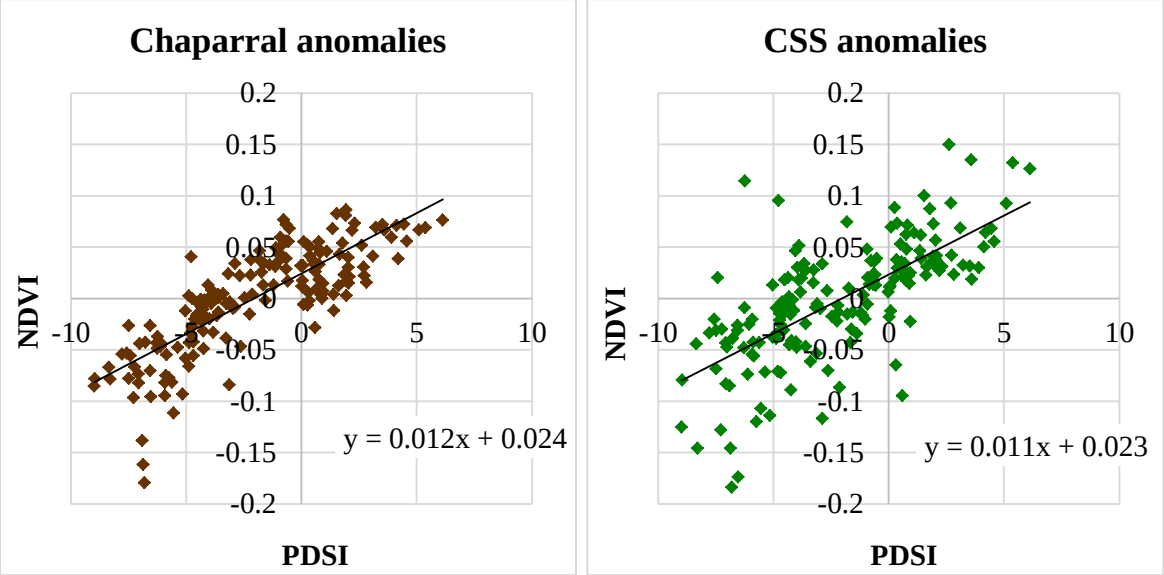
4.4.1 Climate and vegetation index regressions

Table 4.1 Basic statistics of raw NDVI values for vegetation types and regression results of monthly anomalies NDVI and PDSI time series.

Basic Statistics		
	Mean	**Standard Deviation**
Chaparral NDVI	0.599	0.063
Coastal Sage Scrub NDVI	0.496	0.101
PDSI	-1.81	3.459
PDSI anomaly	-2.074	3.465
NDVI and PDSI Anomaly Regressions		
	R^2	**P-value**
Chaparral anomaly	0.658	$p << 0.001$
Coastal Sage Scrub anomaly	0.481	$p << 0.001$

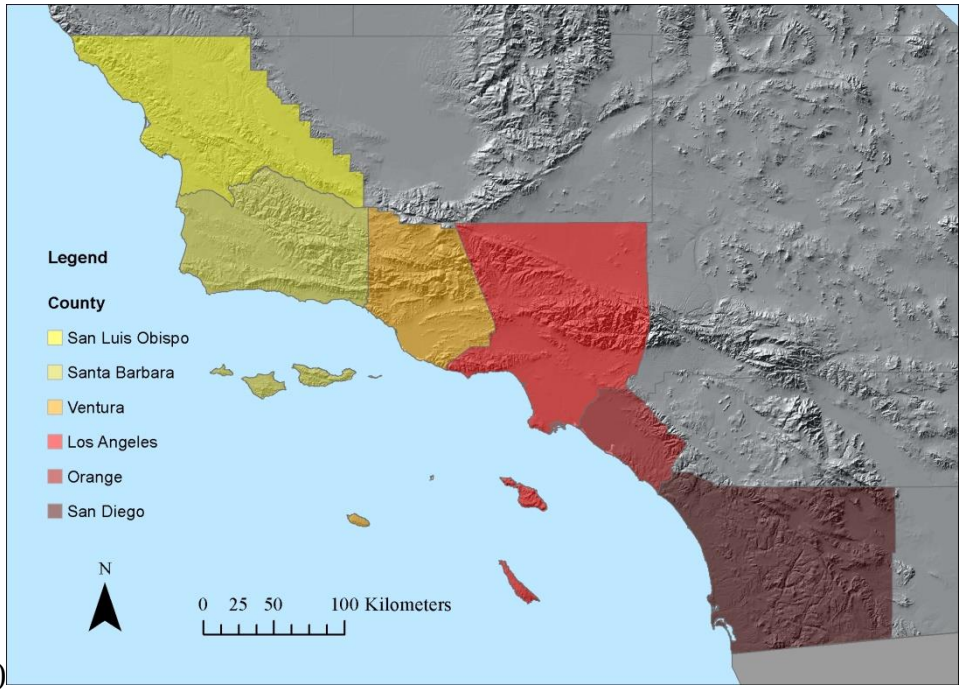
Vegetation greenness does not appear to be increasing or decreasing greatly over time, as displayed by the linear slope coefficients ($\beta_{chaparral} = 0.012$, $\beta_{coastal\ sage\ scrub} = 0.011$; Figure 4.3). Chaparral-dominated areas have higher greenness values throughout the time series than coastal sage scrub dominated areas (Table 4.1). There was similar timing of peaks and significant similarity ($p < 0.01$) between the NDVI time series of chaparral and that of coastal sage. However, coastal sage scrub shows much higher variability than chaparral, apparent in its higher standard deviation value (Table 4.1).

Figure 4.3 Scatterplots of chaparral and coastal sage scrub NDVI and PDSI anomalies with linear model equations

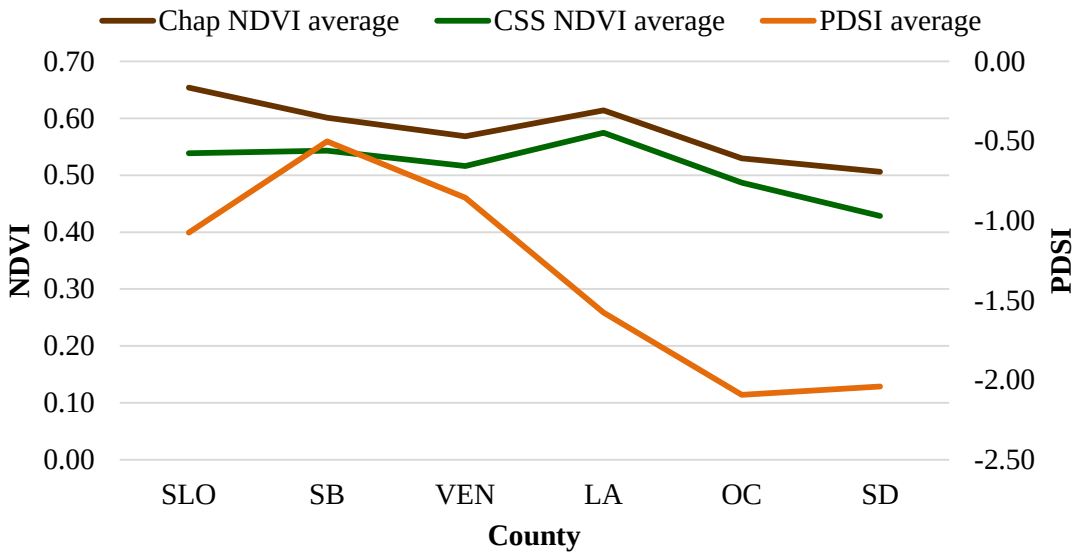


Deviations from the monthly climate normal (anomalies) are highly correlated with vegetation greenness patterns for the 15-year time series (Table 4.1). PDSI anomalies likely explain the majority of changes in southern California chaparral NDVI ($R^2 = 0.658$, $p << 0.001$). Coastal sage scrub regions yielded lower, yet still significant correlation values with anomalous drought months ($R^2 = 0.481$, $p << 0.001$).

4.4.2 Geographical differences in NDVI change



(a)



(b)

Figure 4.4 (a) Reference map of County regions in southern California. (b) NDVI and PDSI values by county/latitude (left to right represents north to south).

Raw NDVI values and PDSI values display a generally positive trend with latitude, with generally lower greenness and PDSI values further south (Figure 4.4), and PDSI highest in Santa Barbara County, and lowest in Orange County. Regression results are higher further south

(Table 4.2), with chaparral-PDSI regression results peaking in Santa Barbara County (R^2 = 0.498), and coastal sage-PDSI regression results peaking in Los Angeles County (R^2 = 0.361). The greatest difference between regressions of the two vegetation types is in Santa Barbara County (R^2 value difference = 0.309). Correlations run between the vegetation NDVI times series reveal chaparral and coastal sage to be most similar in Los Angeles County (R^2 difference = 0.983) and most dissimilar in Santa Barbara County (R^2 difference= 0.556).

Table 4.2 Regression results of monthly anomalies NDVI and PDSI time series by county.

PDSI vs. NDVI regressions per county		
	County PDSI	
	R^2	**p-value**
SLO Chaparral	0.163	$p < 0.001$
SLO CSS	0.102	$p < 0.001$
SB Chaparral	0.498	$p < 0.001$
SB CSS	0.189	$p < 0.001$
VEN Chaparral	0.356	$p < 0.001$
VEN CSS	0.234	$p < 0.001$
LA Chaparral	0.383	$p < 0.001$
LA CSS	0.361	$p < 0.001$
OC Chaparral	0.312	$p < 0.001$
OC CSS	0.240	$p < 0.001$
SD Chaparral	0.286	$p < 0.001$
SD CSS	0.234	$p < 0.001$

NDVI change from the current drought differs geographically, and some spatial patterning is clear throughout southern California (Figures 4.5, 4.6, 4.7). Areas at higher elevations, further inland, and on larger islands appear to retain their greenness more than other areas during both the dry and the wet seasons. Native vegetation types are more affected during the wet months than the dry months, with more areas displaying NDVI values decreasing more than 0.1. The decrease in NDVI is more extreme in the second year of drought during both 2-year drought periods chosen and for dry and wet seasons. This is displayed by greater decreases

in greenness in certain areas in 2008 and 2014 than in 2007 and 2013 (Figure 4.6, 4.7). The greatest decrease in NDVI over the entire map area is clearly seen in the wet season of 2014 (Figure 4.6).

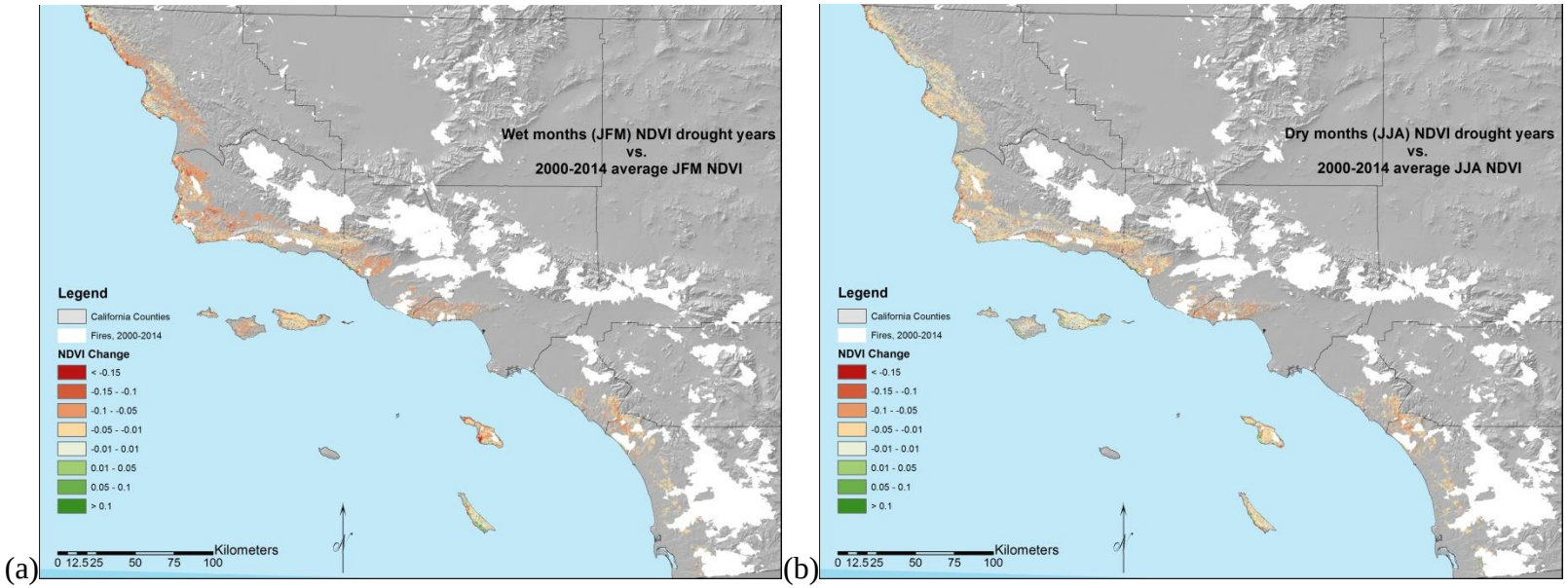


Figure 4.5 (a) Average NDVI during wet months (JFM) of drought years (2007, 2008, 2013, 2014) minus average during baseline years (2000-2014). (b) Average NDVI during dry months (JJA) of drought years (2007, 2008, 2013, 2014) minus average during baseline years (2000-2014).

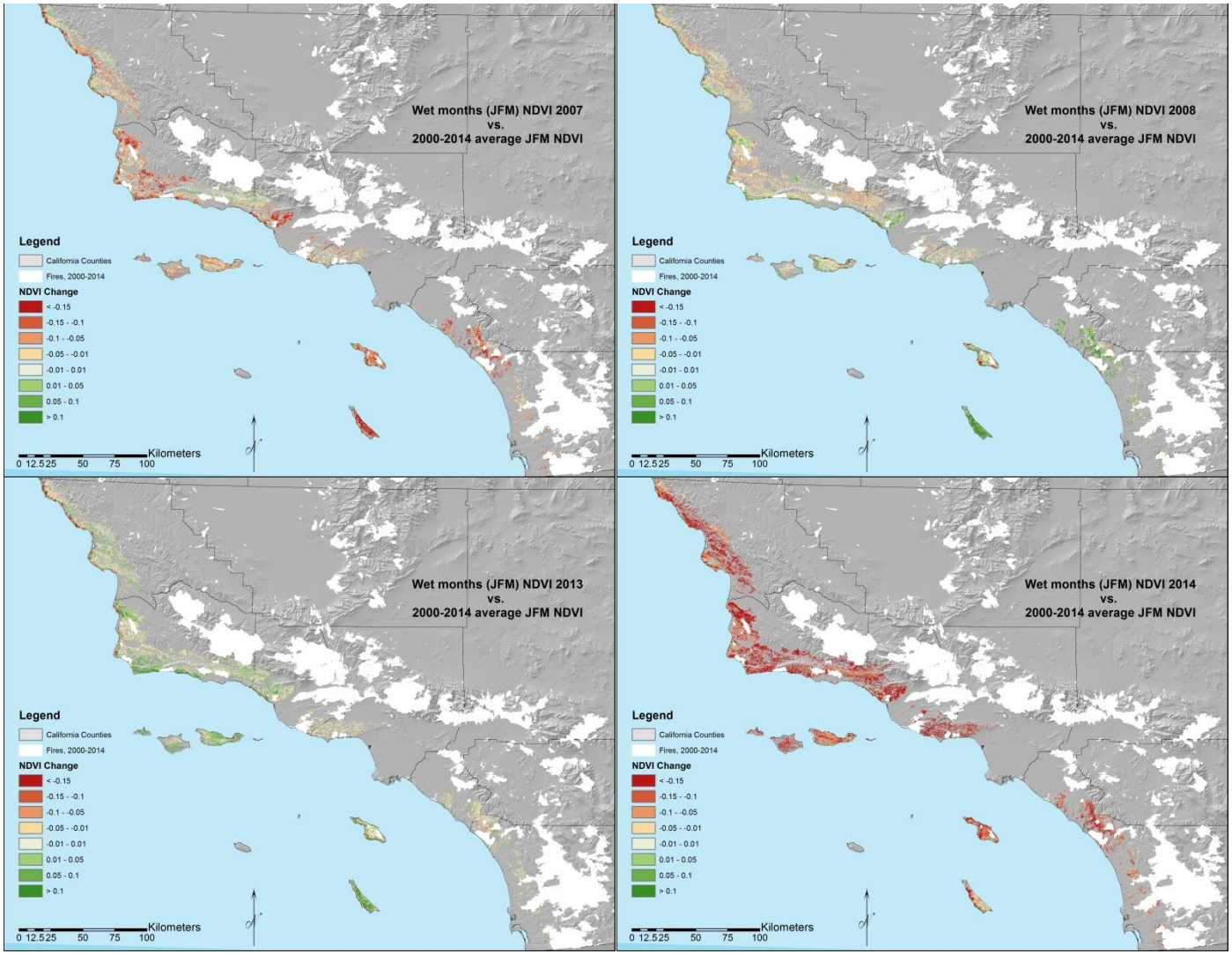


Figure 4.6 Average NDVI during wet months (JFM) of each individual drought year (2007, 2008, 2013, 2014) minus average during baseline years (2000-2014).

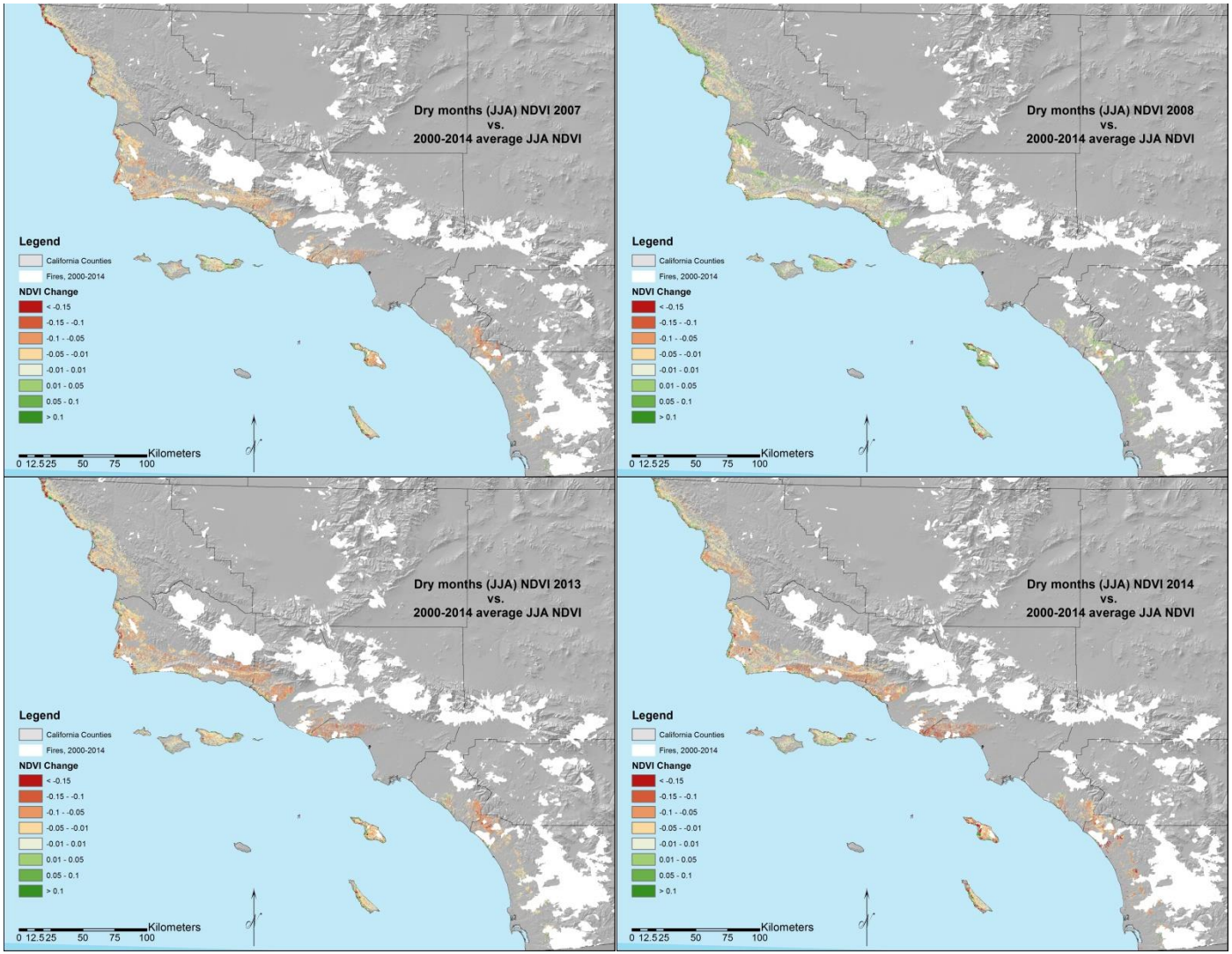


Figure 4.7 Average NDVI during dry months (JJA) of each individual drought year (2007, 2008, 2013, 2014) minus average during baseline years (2000-2014).

4.5 Discussion

4.5.1 How does drought affect native vegetation health?

The remotely sensed NDVI reflects the physiological ecology of the constituent plant species of the two vegetation types. The higher NDVI of chaparral speaks to its evergreen nature and deeper rooting, and the higher standard deviation of coastal sage areas represents the drought deciduous leaves and shallower rooting. Even though each vegetation type had interannual and annual fluctuations, neither displayed increased or decreased greenness over the entire time period. This may indicate that neither vegetation type is experiencing long-term health declines or decreasing aboveground net primary productivity (ANPP). However, individual drought periods appear to cause increased episodic ecosystem stress reflected in decreased NDVI.

4.5.2 How do chaparral- and coastal sage scrub-dominated ecosystems differ in response to unusual periods of drought?

The high correlation values among both vegetation types and PDSI indicate that anomalous drought seasons drive changes in native ecosystem health. The higher correlation with drought in chaparral ecosystems is surprising, and is likely due to ecological differences in climate response. There are many fine-scale ecological differences within individual chaparral and coastal sage scrub species that make it difficult to draw definitive conclusions from coarse-scale MODIS data, yet several possible contributing ecological factors are discussed here. For example, coastal sage scrub recovers quickly after discrete precipitation events, while chaparral takes longer to produce new, green leaves. Longer severe droughts also decrease deeper soil moisture reserves on which many chaparral species depend to a greater extent than coastal sage scrub.

The root systems of these plants may also play a role in the differing regression outputs. Along the coast, chaparral exists in deep aeolian sandy soils on marine terraces and contains fairly deep root systems (Harrison et al., 1971; Keeley & Davis, 2007; Kirkpatrick & Hutchinson, 1980). The root systems of coastal sage scrub are shallower than the evergreen chaparral roots. Thus, periods of water stress are likely to have a higher immediate impact on these communities, since the upper layers of soil tend to dry out more quickly than deeper soils where chaparral roots are present (Rundel, 2007). Coastal sage may therefore have a higher sensitivity to immediate climate shifts than deeply rooted chaparral responding to longer-term drought as indicated by PDSI. The high regression results indicate that increased unusual drought may lead to a decline in chaparral-dominated ecosystem health, especially if droughts become more extreme, prolonged and frequent.

4.5.3 What are the geographical variations of greenness in response to drought in southern California counties?

Both ecosystem types appear to be more affected by drought further south, and especially in high-density areas such as Los Angeles County. Drought values are more extreme further south, which may have an exponential negative effect on vegetation. It is likely that this relationship is complicated by factors such as topography. Further research would need to be conducted to understand these spatial relationships more clearly. For example, the southern coastal regions lack the elevation and precipitation patterns seen in the northern and south-facing slopes (Figure 4.8).

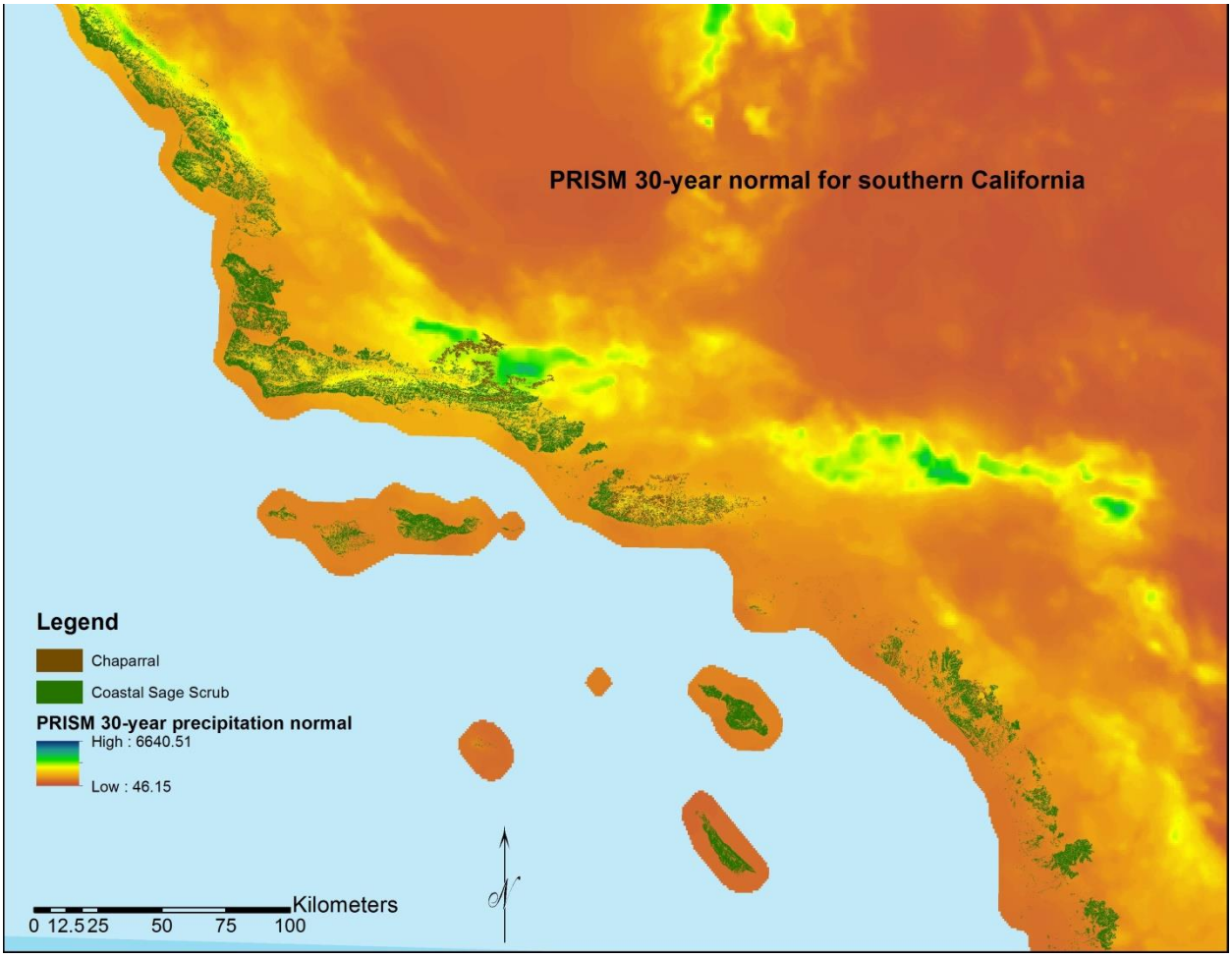


Figure 4.8 PRISM 30 year normal for southern California with vegetation polygons.

NDVI is most affected during the wet months than the dry months across southern California. Over the average of drought years, lower elevation areas appear to be most affected, whereas slightly higher elevation zones have higher NDVI including Santa Cruz Island and the transverse ranges in Santa Barbara. Dry months during both drought periods respond in a less clustered pattern, with browning and greening areas interspersed together. The extreme response seen in wet months of 2014 are indicative of the repeated stress put on local vegetation by continued lack of precipitation over the landscape. This season shows an intense contrast to the wet season of 2013, and displays the effect that multiyear drought can have on even drought adapted landscapes such as that in southern California.

4.5.4 What are the ecological implications for the response of chaparral- and coastal sage scrub-dominated ecosystems to drought?

According to this analysis, chaparral-dominated areas may experience more ecological stress than coastal sage scrub-dominated areas if the frequency and duration of long-term drought increases as predicted for the southwestern United States. Such droughts produce long-term depletion of deeper soil moisture, on which the chaparral depends. Southern California has experienced very minor fluctuations in temperature thus far, with most of the historical variability in precipitation due to the El Niño/Southern Oscillation (ENSO) cycle. Since these are the main drivers of coastal sage scrub, we are unlikely to see much change in future coastal sage scrub NDVI, at least insofar as the ENSO cycle does not change. Some studies do suggest that change is likely to occur in the ENSO cycle, in which case coastal sage scrub ecosystems may experience much higher greening cycle variability than at present (Timmermann et al., 1999; Walther et al., 2002).

Slower growth of chaparral and therefore longer recovery periods allow for short-lived species such as grasses to establish, especially after multiple disturbance events (Díaz-Delgado et al., 2002; Keeley et al., 2005; Syphard et al., 2006). The establishment of nonnative annual species, especially in chaparral-dominated areas, post-disturbance has been observed in southern California on similar scales (Keeley et al., 2005; Syphard et al., 2006). Nonnative grasses have historically been increasing in this landscape, and are known to persist once established (Eliason & Allen, 1997). This changes the natural progression of succession and disturbance regimes, and could eventually allow for other nonnative species to take over landscapes previously dominated by native species (Bond & van Wilgen, 1996; Mack & D'Antonio, 1998; Syphard et al., 2006). Ultimately, the distribution of chaparral-dominated ecosystems may change

significantly due to this feedback cycle, and ecosystem resilience may decrease (Díaz-Delgado et al., 2002).

4.6 Conclusions

Native plant vitality is likely driven by drought at the multi-monthly timescale. The response of chaparral and coastal sage scrub-dominated communities to drought differs by county, with southern regions most affected. However, correlations reflect a greater decline in anomalous chaparral greenness as a response to extreme drought. Coastal sage scrub ecosystems may recover more quickly from monthly extreme drought due to an immediate response of shallow root systems to discrete precipitation events. Chaparral-dominated ecosystems may experience more change than coastal sage scrub-dominated areas if the frequency, duration, and magnitude of drought increases as predicted for the southwestern United States.

4.7 Acknowledgments

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CHAPTER 5

5. Has California Browned? Geography of Vegetation Sensitivity to 21st Century Drought in California

A version of: MacDonald, G. M., Willis, K. S., Williams, A. P. (in prep) Has California Browned? Geography of Vegetation Sensitivity to 21st Century Drought in California. Environmental Research Letters.

5.1 Abstract

Analysis of MODIS-derived Normalized Difference Vegetation Index (NDVI) data and a newly constructed time series of the Palmer Drought Severity Index (PDSI) incorporating a more realistic estimate of potential evapotranspiration reveals a geographically differentiated and complex response by vegetation greenness to the impacts of the 2012-2014 California drought. The current drought has produced a greater degree of browning, particularly in the normally green winter (January, February, March), than earlier 21st century droughts, but this is focused on the southern portions of the state in the South Interior, South Coast, Central Coast and Southern Central Valley vegetation zones extending northward through the Northern Central Valley Zone. In addition to drought conditions being most severe in these regions, these areas are generally low-elevation and dominated by seasonally green annual grasslands, coastal sage, chaparral and oak woodlands which would be expected to display heightened seasonal responses in greenness to episodic drought. In the higher elevation and cooler/moister Sierra Nevada Mountains and northern coastal zones where vegetation is dominated by evergreen conifers the current drought is mainly manifest in great winter greenness due to decreased winter snow cover and warmer temperatures. A similar geography, but more attenuated degree of browning was observed during the drought of 2007. However, by 2008 the most appreciable browning of that drought was focused in the North Interior Vegetation Zone. Despite the general aridity of the 21st century

there is no trend towards greater brownness state-wide or in individual vegetation zones during 2000-2014. However, there has been a general decrease in the seasonal contrast in greenness between summer and winter.

5.2 Introduction

California is now in the fourth year of severe drought and it has been asserted that "As drought has taken hold, the Golden State is slowly becoming a more arid, brown state" (Mann and Gleick, 2015) as a result of vegetation response to the aridity. Not only might the current drought be having an impact on overall vegetation greenness, but it comes on the heels of a relatively hot and arid 21st century (MacDonald, 2010) that may presage the climate and changing condition of the vegetation over the 21st century (Diffenbaugh et al., 2015; Mann & Gleick, 2015). The State of California encompasses over four hundred thousand square kilometers of diverse topography and climate. Monitoring the vegetation impacts and possible land cover changes induced by factors such as drought over such a large and diverse area requires remote sensing approaches. Satellite-derived Normalized Difference Vegetation Index (NDVI) data have long been used to monitor the impacts of drought on vegetation greenness and show a high sensitivity to soil moisture conditions and vegetation responses with changing aridity (Gu et al., 2007; 2008; Karnieli et al., 2010; Kogan, 1995; Pettorelli et al., 2005; Reed et al., 1994; Williams et al., 2013). Large scale analysis of NDVI have for example shown that significant portions of the boreal zone in central Eurasia have indeed been browning over the past decade under the influence of increasing evapotranspiration rates and relative aridity (Buermann et al., 2014). However, global studies have also shown that despite increasing temperatures and evapotranspiration demands, many areas of the world, including arid and semi-arid regions have been experiencing increased greening rather than browning over the late 20th

and early 21st century. Furthermore, trends in NDVI are different in nature or sign depending upon vegetation type (e.g. Fensholt et al., 2012; Reed et al., 1994; Vicente-Serrano et al., 2013). For example, in shrubland and grassland regions changes in the amplitude of seasonal NDVI differences has been more important than changes in the mean state (Eastman et al., 2013). In that study, the amplitude of the annual seasonal signal in many grasslands and shrublands was accentuated as declines in NDVI in the green season were off-set by declines in the brown season. Similarly, typifying and comparing drought severity, particularly in the context of vegetation impacts, across such a large and climatically diverse region requires a relatively robust synthetic measure of drought that integrates precipitation and evapotranspiration to reflect soil moisture conditions. Although not without criticisms, the Palmer Drought Severity Index (PDSI) is widely used for such purposes (Dai, 2011; Vicente-Serrano et al., 2011). Recently, Williams et al. (2015) calculated records of PDSI for California with and without the observed century-long warming trend to show that warming has caused a steady decline in statewide mean soil moisture, amplifying the severity of an already severe drought during 2012-2014.

Here we use NDVI and PDSI for a comparative analysis of the impacts of the 2012-2014 drought on the major vegetation zones of California. We address the following questions regarding the potential browning of the State: 1. What is the sensitivity of greenness to drought on a statewide basis and in terms of individual vegetation zones for this and earlier droughts?; 2. What are the geographic patterns in changes in vegetation greenness in relation to the current drought and how do they compare to earlier 21st century droughts?; 3. Is there any evidence for a long-term secular trend towards decreasing greenness or changing amplitude of seasonal differences in greenness statewide or in individual vegetation zones over the 21st century?

5.3 Data and Methods

5.3.1 Remote sensing, vegetation and hydroclimatic data

The NASA MODIS 16-day composite (MOD13Q1 tiles h08v04, h08v05, h09v04) NDVI data product was downloaded from the NASA/USGS (https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mod13q1) for February 2000 through December 2014. NDVI is a widely used proxy for vegetation greenness calculated by a ratio including the measured albedo (α) of visible red and near infrared wavelength bands calculated in this general form from the MODIS spectral reflectance data

$$\text{NDVI} = \frac{\alpha_{0.86\mu m} - \alpha_{0.65\mu m}}{\alpha_{0.86\mu m} + \alpha_{0.65\mu m}}$$

and measured with a spatial resolution of 250-m. NDVI data have long been used monitoring the impacts of drought on vegetation and show a high sensitivity to soil moisture conditions and vegetation responses (Gu et al., 2007; 2008; Karnieli et al., 2010; Kogan, 1995). The nine major California vegetation zones (Figure 5.1) were downloaded as shapefiles from the United States Department of Agriculture CALVEG mapping zones (http://www.fs.usda.gov/detail/r5/landmanagement/resourcemanagement/?cid=stelprdb5347192). These upper-level vegetation zones are reflective of regional macroclimatic differences (Faber-Langendoen et al., 2014) and accordingly display some geographic correspondence to NOAA's seven California climate divisions (http://www.ncdc.noaa.gov/cag/). To further examine NDVI patterns within major vegetation zones we utilized overlays of the finer scale USGS National GAP Analysis derived vegetation types based upon vegetation structure and physiognomy. The National USGS GAP Land Cover Dataset Version 1 (http://gapanalysis.usgs.gov/gaplandcover/data/) was aggregated and smoothed in order to provide a background for qualitative visual analysis of NDVI change. The Level 1 vegetation

types used include: alpine sparse, desert barren, forest and woodland systems, grassland systems, human land use, riparian and wetland systems, and shrubland, steppe, and savanna systems (Figure 5.1). As NDVI estimates of vegetation response to climatic conditions such as drought can be confounded by the impacts of fires on groundcover and spectral reflectance (Verbyla, 2011), we have masked out large burned areas (Table 5.1). These recent (2000-2014) burn areas cover over 50,000 km^2.

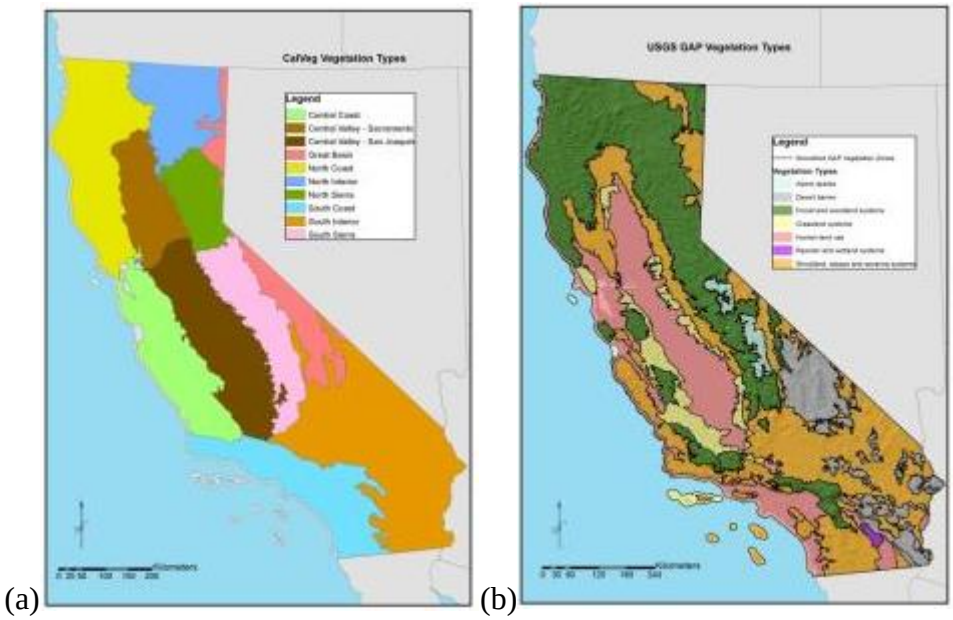


Figure 5.1 Maps displaying (a) CalVeg zones and (b) USGS GAP vegetation zones.

To represent variations in climatological drought severity we used the PDSI records generated for California by Williams et al. (2015). Within these PDSI calculations, potential evapotranspiration was calculated using the physically based Penman-Monteith equation, which accounts for effects of temperature, humidity, wind speed, and net radiation (Monteith, 1965). Williams et al. (2015) calculated PDSI from a wide range of climate products and we use the PDSI records derived from precipitation and temperature data from Vose et al. (2014) to be consistent NOAA climate division data, dew point data from PRISM (Daly et al., 2004), and

wind speed and insolation data from the second phase of the North American Land Data Assimilation System (Mitchell et al., 2004). The Williams et al. (2015) PDSI records have a geographic resolution of approximately 4 km. We spatially aggregated these monthly records for each of the nine major CALVEG mapping zones and California overall for the period 2000-2014. Time-series of monthly regional temperature and precipitation data for each CALVEG zone and the State overall were obtained for the appropriate climate divisions and State from NOAA (Vose et al., 2014) (http://www.ncdc.noaa.gov/cag/time-series/us).

Table 5.1 Total area burned in each vegetation zone.

GAP vegetation type	**Area burned 2000-2014 (approx. km^2)**
Alpine sparse	1,596.2
Desert barren	420.3
Forest and woodland systems	20,451.4
Grassland systems	1,599.7
Human land use	8,047.8
Riparian and wetland systems	0.0
Shrubland, steppe, and savanna systems	20,462.6

5.3.2 Analytic methods

Analysis and visualization of the remote sensing data was completed using Exelis ENVI/IDL and ESRI ArcMap software. The three relevant individual MODIS tiles overlying California were combined to provide coverage of the entire State. Individual vegetation zones were imported to ENVI as Regions of Interest (ROIs). The Central Valley zone was divided into two sections: the northern (Sacramento) and southern (San Joaquin) zone along the boundary of

California Climate Divisions 2 and 5 in order to compare NDVI to geographically associated climate zones. Vegetation zones include: Central Coast, Northern Central Valley/Sacramento, Southern Central Valley/San Joaquin, Great Basin, North Coast, North Interior, North Sierra, South Coast, South Interior, South Sierra. Median NDVI per vegetation ROI and per the entire State of California was calculated for each 16-day time step for the entire 2000-2014 time series.

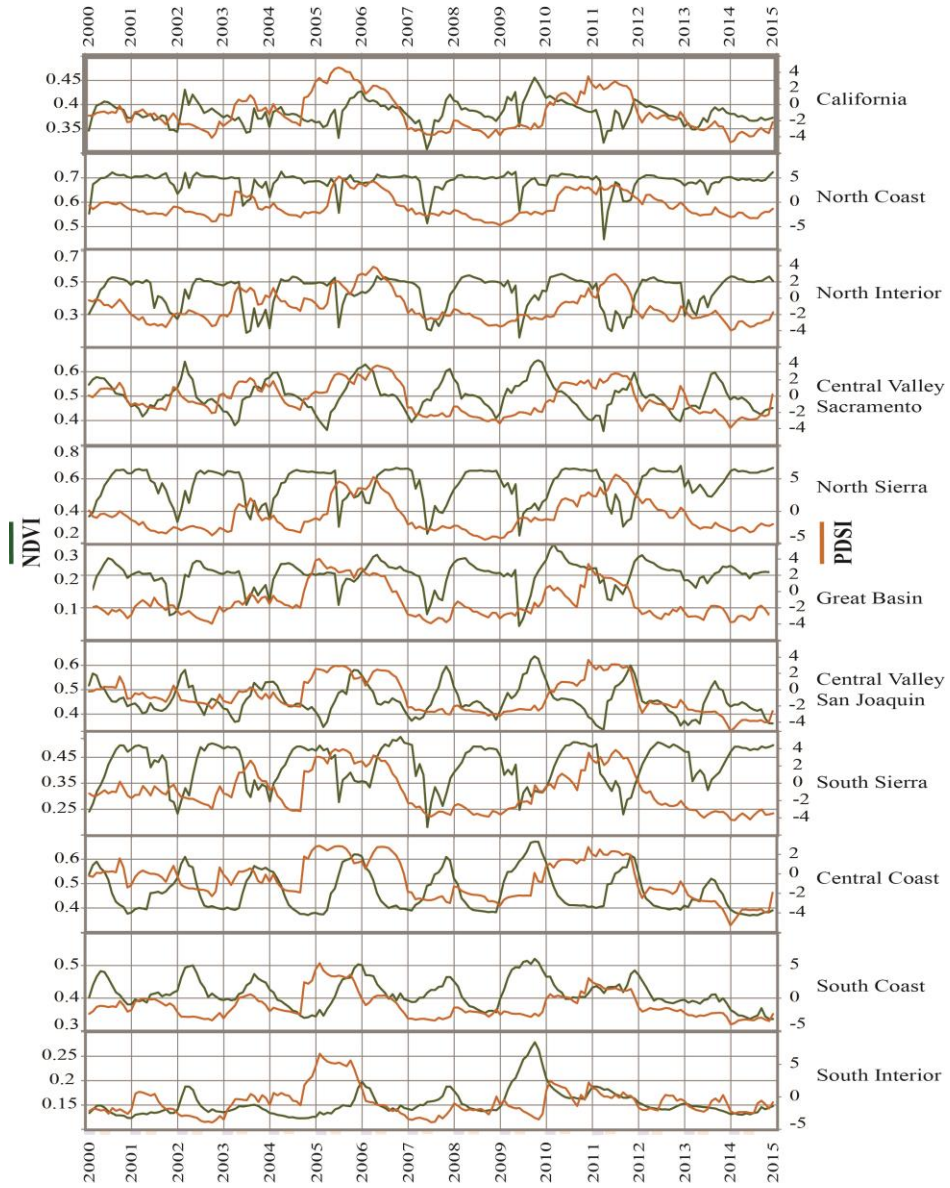


Figure 5.2 Time series of raw Palmer Drought Severity Index (PDSI) versus NDVI for each CalVeg zone.

Maps of average NDVI per pixel were created for each year. Average seasonal NDVI was calculated for a baseline of the time series (2000-2011). Seasons were defined as the maximum dry season (June July August) and maximum wet season (January February March). Drought years of 2007-2008 and 2013-2014 were chosen as years of "exceptional drought," or when California PDSI values were below -4 for multiple consecutive years (Heim Jr., 2002).

Change maps were created for each drought year by subtracting the time series seasonal average (2000-2011) from the drought year seasonal average. These were displayed by standard deviation of NDVI difference over the California average, and for the standard deviation per vegetation zone.

Time series data per vegetation zone were resampled to compute monthly average, and anomalies from the monthly average NDVI values to compare to anomalous monthly PDSI estimates for each vegetation zone and for the entire State. Statistical correlations and regressions were assessed for annual and wet (JFM) and dry season (JJA) PDSI and NDVI anomalies and the significance of resulting correlations was tested. Correlations between monthly and monthly lagged (6 and 12 month) NDVI and PDSI were also analyzed and it was found that monthly or lagged values offered no improvement in correlations.

5.4 Results

Table 5.2 Time series correlation and regression results of climate anomalies (independent variable) versus NDVI anomalies (dependent variable) for each CalVeg zone: Multiple R, R^2, p-value, slope coefficient (β).

PDSI anomaly vs. NDVI anomaly regressions per vegetation zone (seasonal)												
	PDSI anomaly (all months)				JFM PDSI anomaly				JJA PDSI anomaly			
	Multiple R	R^2	p-value	β	Multiple R	R^2	p-value	β	Multiple R	R^2	p-value	β
California	0.514	0.264	<0.001	0.004	0.289	0.083	0.057	0.003	0.918	0.843	<0.001	0.005
Central Coast Montane	0.694	0.482	<0.001	0.015	0.797	0.636	<0.001	0.026	0.925	0.855	<0.001	0.009
Great Basin	0.349	0.122	0.117	0.003	-0.283	0.080	0.063	-0.003	0.875	0.765	<0.001	0.008
Northern Coast	-0.088	0.008	0.002	-0.001	-0.399	0.160	0.007	-0.007	0.687	0.472	<0.001	0.003
Northern Interior	-0.170	0.029	0.023	-0.005	-0.463	0.215	0.002	-0.023	0.686	0.471	<0.001	0.006
Northern Sierra	-0.106	0.011	0.006	-0.003	-0.288	0.083	0.058	-0.015	0.461	0.213	0.001	0.002
Southern Coast	0.782	0.611	<0.001	0.012	0.678	0.460	<0.001	0.011	0.866	0.749	<0.001	0.012
Southern Interior	0.786	0.618	<0.001	0.007	0.839	0.703	<0.001	0.011	0.846	0.716	<0.001	0.005
Southern Sierra	-0.177	0.031	0.026	-0.002	-0.389	0.151	0.009	-0.008	0.403	0.163	0.006	0.002
Central Valley - Sacramento	0.358	0.128	<0.001	0.006	0.448	0.201	0.002	0.012	0.737	0.543	<0.001	0.005
Central Valley - San Joaquin	0.549	0.301	<0.001	0.009	0.673	0.467	<0.001	0.018	0.827	0.684	<0.001	0.006

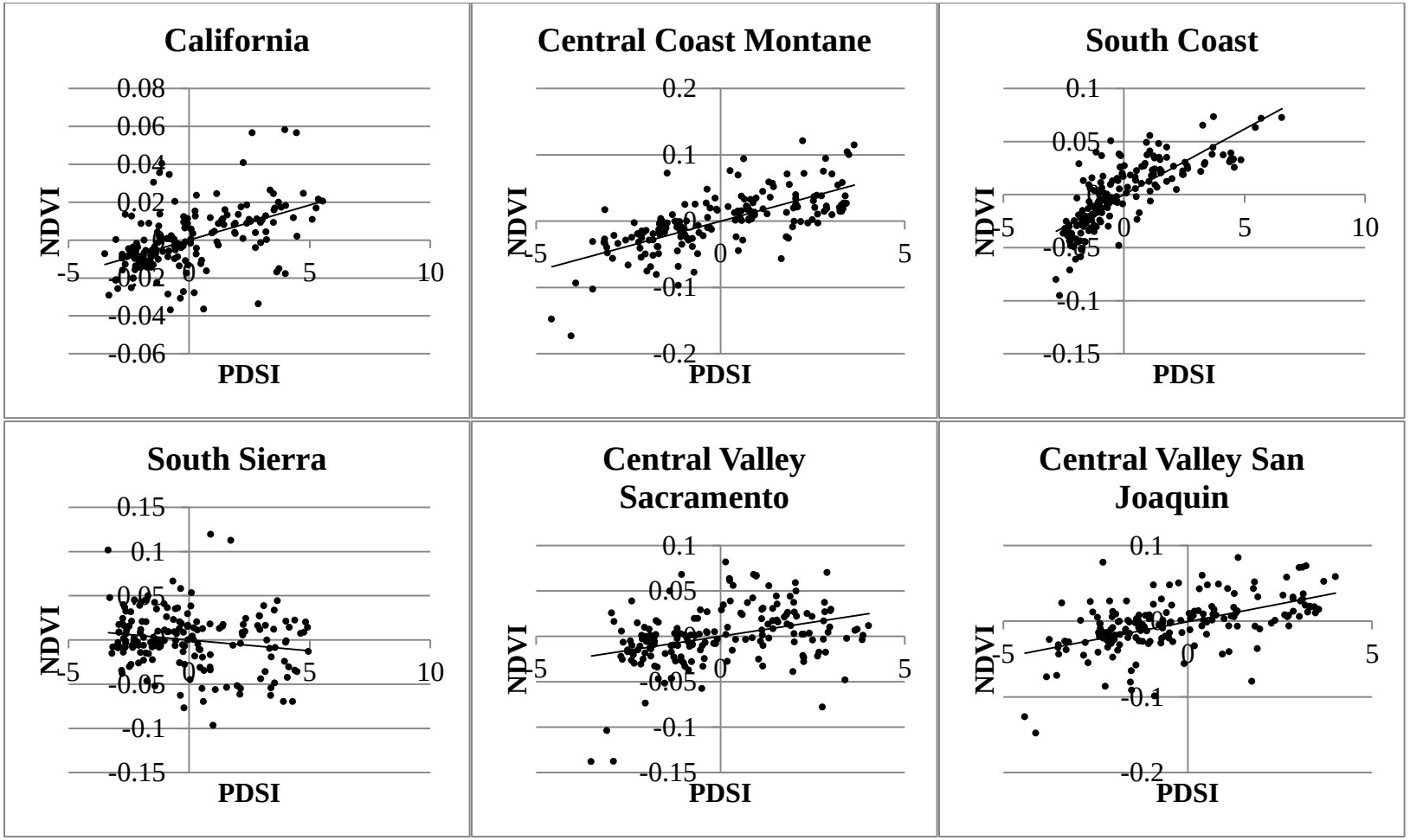
Overall California annual vegetation greenness anomalies as measured by NDVI anomalies shows a weak (R^2 = 0.264; R=0.514) but significant positive relationship with anomalous PDSI (Table 5.2; Figure 5.2). This annual overall positive relationship is driven by anomalous PDSI in three southern zones with highly significant ($p < 0.001$) annual correlations: the South Interior Zone (R^2 = 0.618; R = 0.786), South Coast Zone (R^2 = 0.611; R = 0.782) and the Central Coast Zone (R^2 = 0.482; R = 0.694). The South Central Valley also shows a highly significant ($p < 0.001$) but weaker correlation (R^2 = 0.301; R = 0.549). All linear slope coefficients return little strength of the correlation trends ($|\beta|_{all} \leq 0.015$; Figure 5.3).

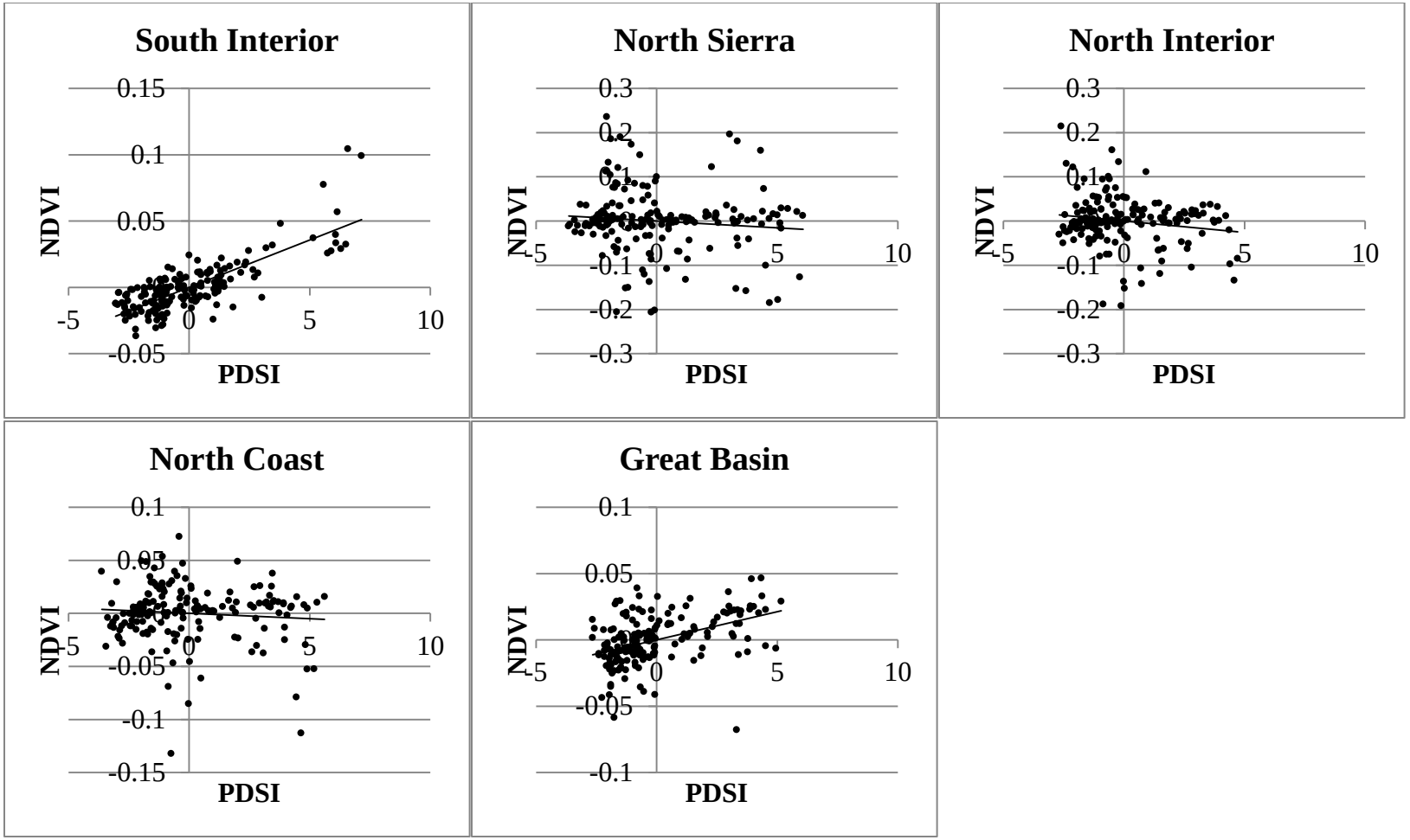
Wet season JFM does not display a state-wide significant correlation between anomalous NDVI and PDSI. In part this reflects a divergence in the response of winter vegetation greenness to drought conditions depending upon vegetation zone. The same four southern zones noted above (South Interior, South Coast, Central Coast and South Central Valley) display highly significant ($p < 0.001$) positive correlations for the JFM season but significant ($p < 0.002$ to $p < 0.009$) *negative* correlations are observed between anomalous JFM NDVI and PDSI in the cooler and/or higher elevation North Coast (R^2 = 0.160; R = -0.399), North Interior (R^2 = 0.215; R = -0.463) and South Sierra zones (R^2 = 0.151; R = -0.389). The apparent correlation between anomalous wet season greening and unusual drought is due to decreased snow cover and greater exposure of vegetation cover coupled with warmer temperatures and expanded growing season within these zones. All linear slope coefficients return low strength of the correlation trends ($|\beta|_{all} \leq 0.023$).

Dry season relationships between vegetation greenness and PDSI are all positive and highly significant ($p < 0.001$) to significant ($p < 0.006$) ranging from R^2 = 0.855 and R = 0.925

for the Central Coast Zone to $R^2 = 0.163$ and $R = 0.403$ for the South Sierra Zone. Most regions display correlations above 0.500, including (from highest to lowest in this range): California as a whole, Great Basin, South Coast, South Interior, Central Valley San Joaquin, and Central Valley Sacramento display particularly high correlations. South and North Sierra zone greenness anomalies are least explained by JJA anomalous drought. All linear slope coefficients return little strength of the correlation trends ($|\beta|_{all} \leq 0.012$).

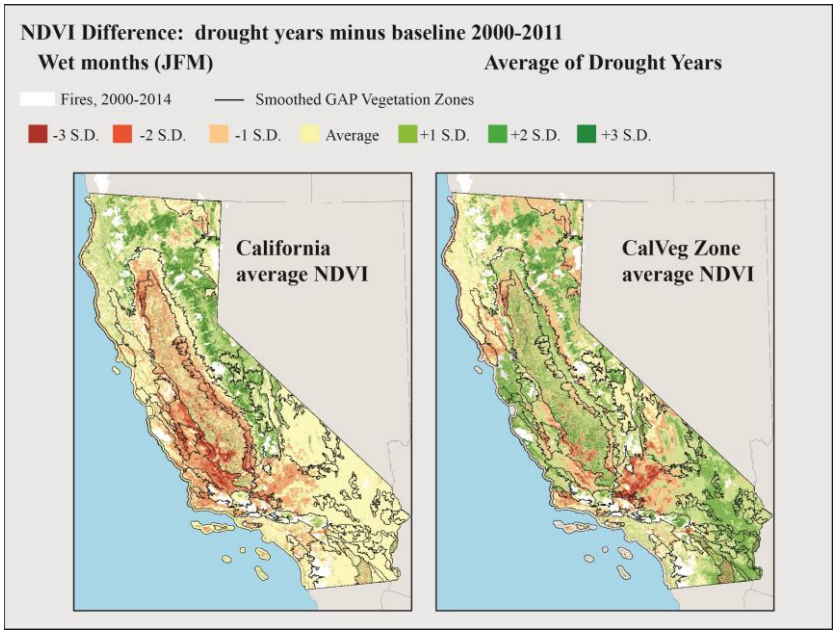
Figure 5.3 Scatterplots of PDSI and vegetation zone NDVI anomalies (California, Central Coast Montane, South Coast, South Sierra, Central Valley – Sacramento, Central Valley – San Joaquin, South Interior, North Sierra, North Interior, North Coast, Great Basin).




South Interior
NDVI
PDSI
0.15
0.1
0.05
-0.05
-5
0
5
10
North Sierra
NDVI
PDSI
0.3
0.2
0.1
-0.1
-0.2
-0.3
-5
0
5
10
North Interior
NDVI
PDSI
0.3
0.2
0.1
-0.1
-0.2
-0.3
-5
0
5
10
North Coast
NDVI
PDSI
0.1
0.05
-0.05
-0.1
-0.15
-5
0
5
10
Great Basin
NDVI
PDSI
0.1
0.05
-0.05
-0.1
-5
0
5
10

The geographic impact of the current drought (2013 and 2014) on vegetation greenness displays a high degree of spatial patterning in both seasons evaluated (Figure 5.4). In the context of the results presented above it is notable that although the correlations between unusual greenness and drought are the most consistent and strongest for JJA; the amplitude of difference between dry years and the average is higher for the wet season (Figure 5.4) and thus drought impacts and their geographical patterning are more striking on the JFM MODIS imagery (Figure 5.5). For the current drought, during 2014 this includes the browning of southern regions such as the South Interior, South Coast, Central Coast and South Central Valley zones. This magnified wet season response is particularly to be expected in lower elevation vegetation communities such as foothill and valley oak savanna formations, chaparral and sage shrublands and grasslands which exhibit greatest greenness in the mild and moist winter months and experience senescence, dormancy and leaf area reduction in the drier summer months. NDVI departures of ~-0.100 developed in the South Central Valley and adjacent South Coast and South Interior in JFM 2013 and browning intensified in magnitude and spatial extent in JFM of 2014 with NDVI anomaly values < -0.170 extending throughout much of the North and South Central Valley zones and the South Coast zone. Browning, represented by NDVI departures of -0.100 also extended further southward within the South Coast zone and westward into the southern edge of the North Coast zone.

(a)



(b)

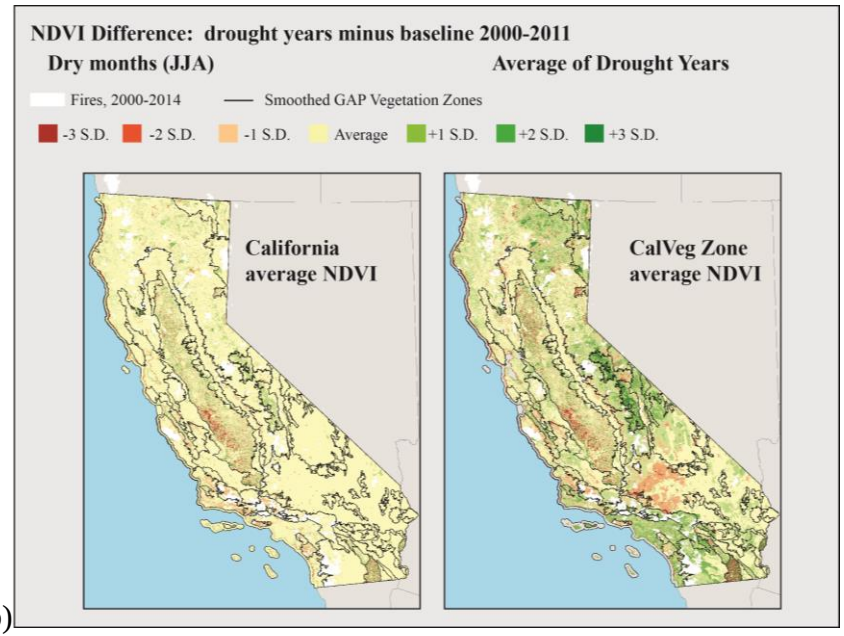


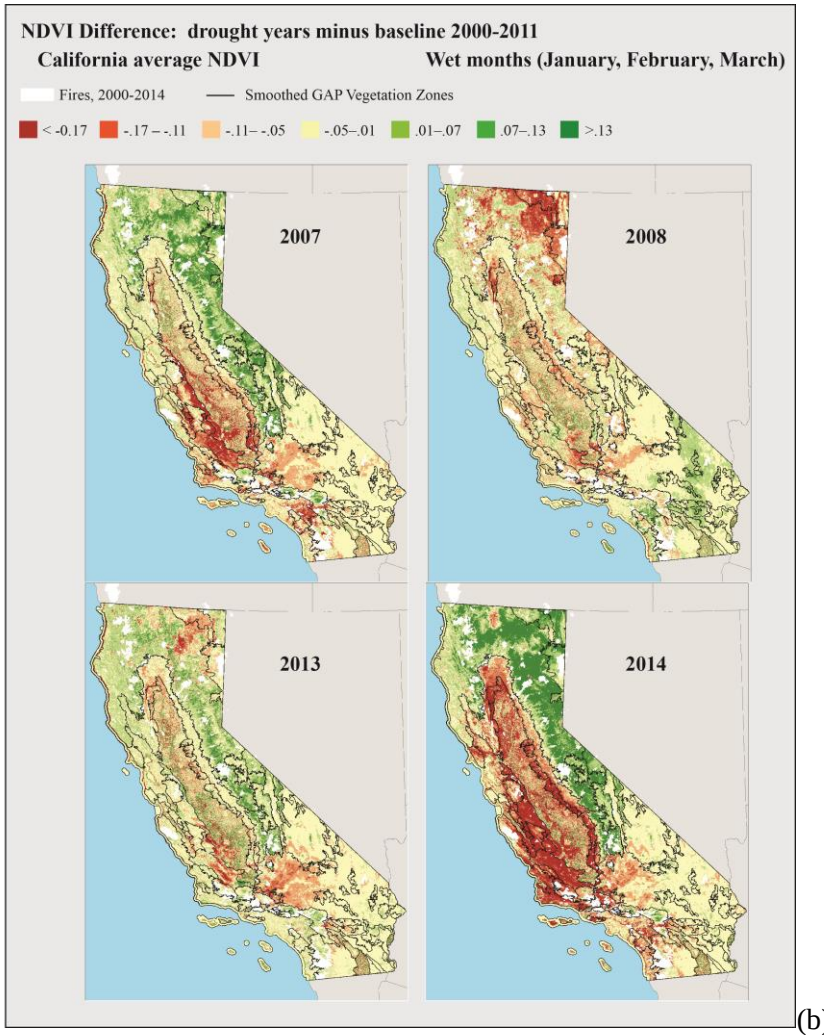
Figure 5.4 Difference of average NDVI during drought years minus the average NDVI during all years for the wet season (a) January February March; and the dry season (b) June July August, left – classified by NDVI average of all, right – classified by standard deviation of vegetation zones.

In the California standard deviation maps, a striking pattern of intense browning is observed in a narrow band along the periphery of the South Central Valley lower elevation Savanna Vegetation type that extends latitudinally on the western slope of the South Sierra zone.

As the North and South Central Valley zones are largely agricultural fields the browning there is influenced by reductions in the application of irrigation waters and fallowing. Despite increased groundwater withdrawals there was a net shortage in agricultural water of about 1.6 million acre feet in 2014 and the fallowing of 410,000 acres in the North and South Central Valley Zones (Howitt et al., 2014). Although not as striking, browning during 2014 is also apparent in the dry season for areas of the North and South Central Valley Zones, along the Savanna western periphery vegetation type and in the South Coast Zone based on the NDVI observations. Within the South Central Valley browning was most intense in the western San Joaquin River Basin. This area was strongly impacted by reduced transfers of water from the Sacramento-San Joaquin Delta and experienced the highest proportion of fallowing in the State during 2014 (Hewitt et al., 2014).

The maps of standard deviation per vegetation zone display the areas of most extreme change within each zone (Figure 5.4, Figure 5.6). In southern California the most browning is seen in the central portion of the South Interior Zone, as well as coastal areas including Santa Barbara and the northern Channel Islands. Most striking in the central California vegetation zones is decrease in greenness visible along the border of the Central Coast and South Central Valley zones during the wet months, likely due to the rain shadow effect. In northern California the lower elevations are most brown during wet months in drought years, such as the regions bordering Oregon. Standard deviations of individual vegetation zones reveal similar spatial patterning for individual years as for drought average years; most browning is consistently apparent in the central South Interior zone during wet months (Figure 5.6). The most browning appears during 2014 wet months, and spatial patterning within vegetation zones appears similar in 2014 as to in 2007.

(a)



(b)

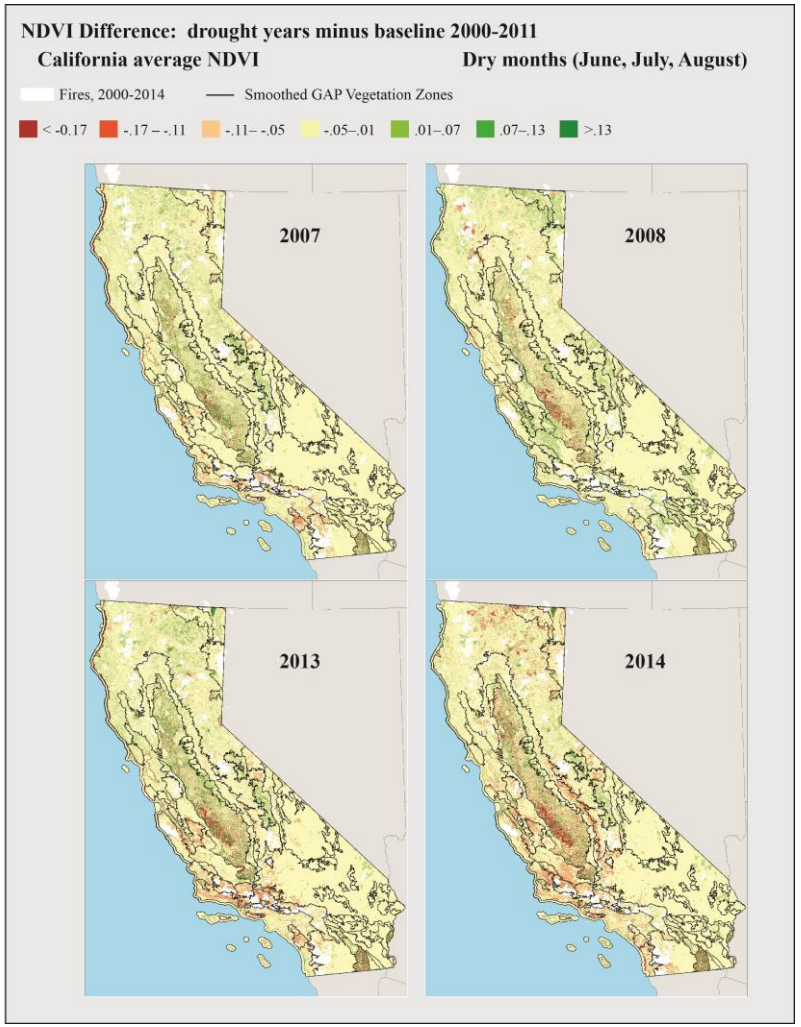
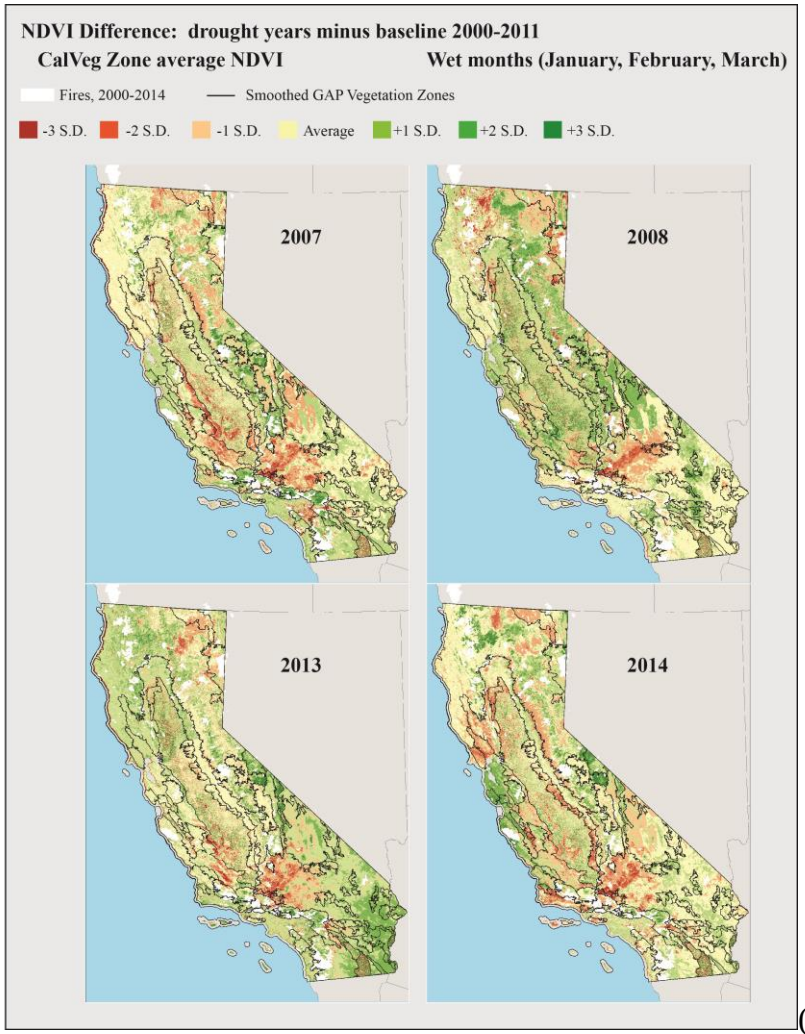


Figure 5.5 Difference of average NDVI during average of drought years and during each extreme drought year (2007, 2008, 2013, 2014) minus the average NDVI during baseline years (2000-2011) for the wet season (a) January February March; and the dry season (b) June July August, classified by California NDVI.

In contrast to the southern coastal regions and the Central Valley, the Sierra Nevada Mountains and southern Cascade and Klamath Mountains display increased winter greenness during 2014. This likely reflects the extremely warm winter temperatures of 2014 which broke records throughout the State (Figure 5.5) and the snow-free conditions of the mountains reflective of the extremely low snowpack. This phenomenon of winter greening is also observed in the San Gabriel and San Bernardino Mountains of southern California which lie on the boundary of the South Coast and South Interior vegetation zones.

The spatial patterning of browning during the 2013-2014 drought period displays similarities and differences with the patterning during the earlier 2007-2008 drought (Figure 5.5). 2014 and 2007 are somewhat similar in terms of a focus of browning during the winter period in the South Central Valley and adjacent South Coastal Zone and greening in the Sierra Nevada and northern mountains. However, the browning of the Central Valley is both more intense and extends more strongly northward into the Sacramento Valley during 2014 than is the case for 2007. In contrast, 2013 and 2008 display some intense winter browning in the far northeastern corner of the State in the North Interior Zone, less dramatic browning in the South Central Valley and South Coast and less intense greening of the Sierra Nevada and northern mountains. From 2008 on, the droughts all result in appreciable browning of agricultural lands in the western San Joaquin River region of the South Central Valley.

(a)



(b)

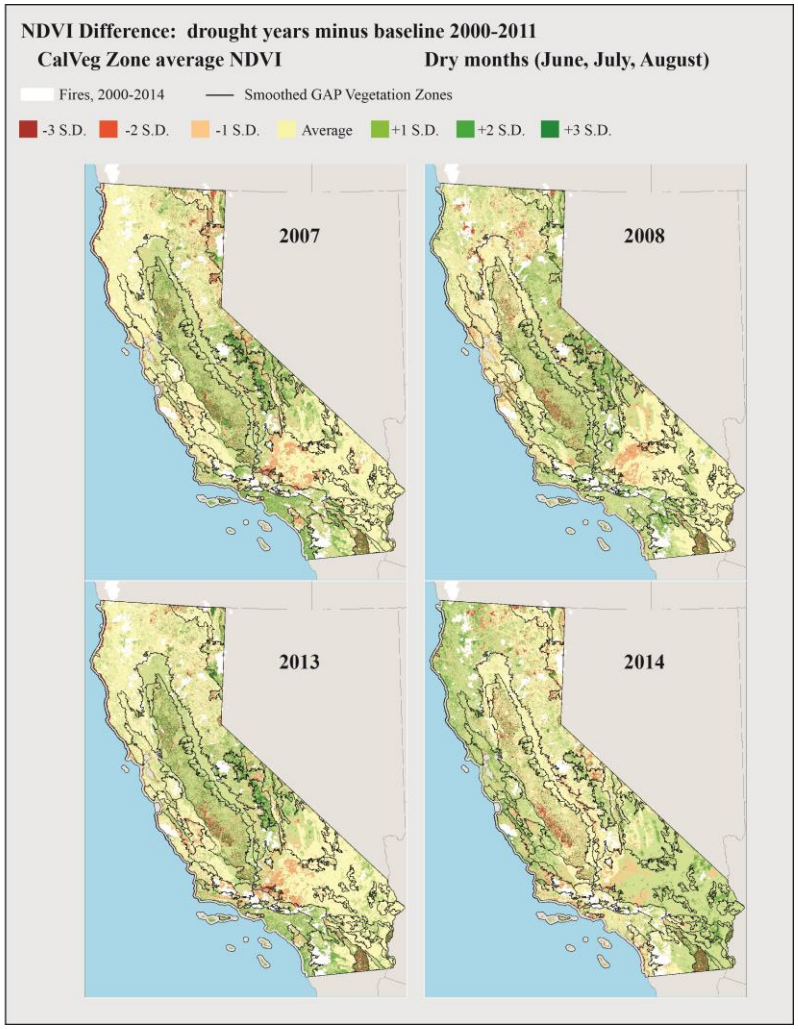


Figure 5.6 Difference of average NDVI during average of drought years and during each extreme drought year (2007, 2008, 2013, 2014) minus the average NDVI during baseline years (2000-2011) for the wet season (a) January February March; and the dry season (b) June July August, classified by vegetation zone NDVI standard deviations.

The exceptional winter browning of the Central Valley Zones and the adjacent South Coast areas (Figure 5.5) can be tied to exceptionally low PDSI values in these zones during 2014 compared to previous 21st century droughts (Williams et al., 2015). These values reflect a combination of both low precipitation and extremely high winter temperatures. This has resulted in prolonged depressions in both PDSI and NDVI commencing in 2012 and deepening through 2013 into 2014 for the Central Valley Zones and South Coast Zone and some southern portions of the South Interior Zone and North Coastal Zone (Figures 5.4, 5.5, 5.6). In contrast, based on PDSI and NDVI the drought of 2007-2009 had a similar depth and impact on the overall North Coast Zone and the North Interior Zone and greater impact on the North Sierra Zone (Figures 5.4, 5.5, 5.6). On a statewide basis the low southern region and Central Valley PDSI and NDVI values drive the winter browning to exceptional levels relative to earlier 21st century droughts.

Although the 21st century has experienced generally arid conditions relative to decadal averages in the preceding century (MacDonald, 2010) and the current drought manifests the deepest depressing in California PDSI values observed, there is no statistical evidence for a significant trend towards long-term browning over the 21st century. Linear regression analysis detects very low slopes in all of the time series. This is true both state-wide and for individual vegetation zones.

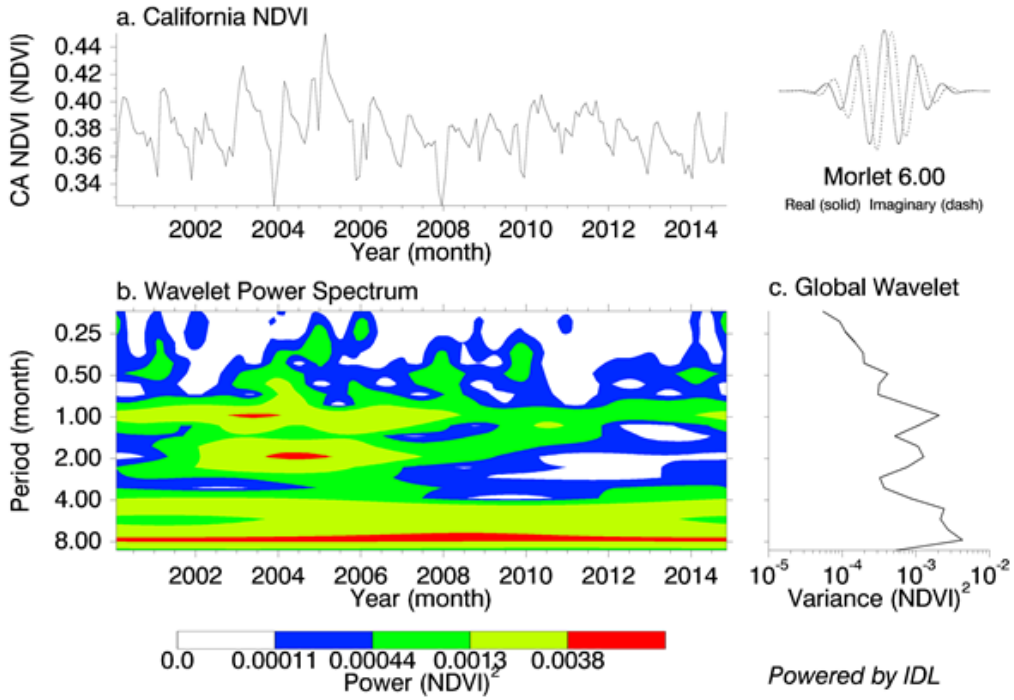


Figure 5.7 Wavelet analysis of monthly NDVI for California and major vegetation types. Areas bounded by lines are significant ($p < 0.05$) as tested against a white noise spectrum. Hashed area is cone of influence in which edge effects preclude reliable interpretation. (a) CA NDVI; (b) Wavelet Power Spectrum; (c) Global Wavelet.

On a state-wide basis wavelet analysis reveals a significant ($p < 0.05$) decrease in the annual seasonal variation in NDVI as tested against a white noise spectrum over the period 2000-2014 (Figure 5.7). Widespread decrease in the power of this signal is seen the various zones following 2012 with the exception of the irrigated Northern Central Valley. Significant declines occur in the Northern Coast Zone, Great Basin and South Interior. The decreases in seasonal contrasts following 2012 are apparent on the time-series of NDVI (Figure 5.2). The dampening of seasonal differences in NDVI during the current drought is a contrast to the situation during the 2007-2008 drought (Figures 5.5, 5.6). The current decreases in seasonal greenness contrast have two different dynamics. The higher elevation and cool winter areas of the Sierra Nevada, North Coastal, North Interior and Great Basin zones have experienced increased JFM greenness as a result of warmer temperatures and decreased snow cover. In contrast, the decreased

seasonal amplitude in the Central Coast, South Interior, South Coastal and South Central Valley zones have largely been a result of decreased peak wet season NDVI. The state-wide shift towards decreased season contrasts thus reflects two different causes specific to these different zones.

5.5 Discussion

5.5.1 What is the sensitivity of greenness to drought on a statewide basis and in terms of individual vegetation zones for this and earlier droughts?

Statistical analysis demonstrates significant state-wide and regional vegetation greenness sensitivity to drought in California. Although the highest correlations between greenness as measured by NDVI and drought as measured by PDSI are observed during the JJA dry period, the greatest deviations in greenness during drought years versus the long-term average occur in the relatively wet period of JFM. Decreases in greenness are observed most strongly in the south including the Southern Interior, South Coast, Central Coast and South Central Valley vegetation zones. A band of particularly notable depression in winter greenness is also observed in the oak woodland and grasslands of the lower mountain slopes flanking the Central Valley. The greater response of greenness in these southern zones and along the western flanks of the Sierra Nevada Mountains likely represents a combination of more severe drought conditions in the central and southern regions of the state as measured by PDSI and the phenological responsiveness of the seasonally green grasslands, shrublands of coastal sage and chaparral, and oak woodlands that predominate in these regions. Many of these species are drought tolerant, yet extreme drought does cause a change in phenological cycles, and may even lead to increased susceptibility to moisture loss, browning, and lower productivity (Gordo & Sanz, 2010; Harrison et al., 1971; Mission et al., 2011). A similar geographic pattern, but with less severe browning and lacking

the strong extension into the North Central Valley is apparent during the 2007 drought year. In both 2007 and 2013 however there was marked browning in the North Interior Zone. The marked decrease in greenness of the Central Valley is highly influenced by decreased applications of irrigation water to croplands. In cool northern and high elevation zones such as the North Coast, North Interior and South Sierra zones where evergreen conifers typically predominate there is a significant increase in JFM greenness likely due to decreased snow cover and warmer temperatures. This effect is observed in some other alpine areas such as the San Bernardino and San Gabriel Mountains of southern California.

5.5.2 What are the geographic patterns in changes in vegetation greenness in relation to the current drought and how do they compare to earlier 21st century droughts?

The current drought has produced a far greater degree of browning, focused on the southern portions of the state in the South Interior, South Coast, Central Coast and South Central Valley and extending northward through the North Central Valley. Although the geographic pattern is broadly similar to earlier 21st century droughts, the magnitude of drought in the areas most severely affected, as measured by PDSI, is greater than any earlier period in the 21st century (Williams et al., 2015) and this is reflected in the marked increase in the degree of browning during the current drought.

5.5.3 Is there any evidence for a long-term secular trend towards decreasing greenness or changing amplitude of seasonal differences in greenness statewide or in individual vegetation zones over the 21st century?

Although global analyses detect decadal or longer trends in vegetation greening or browning as measured by NDVI related to recent long-term changes in moisture from other regions (Barbosa et al., 2006; Fensholt et al., 2012; Vicente-Serrano et al., 2010), and despite the fact that current drought has produced historical depressions in PDSI and exceptional browning

in the southern portions of the State, California does not display any trend to greater browning during 2000-2014. Vegetation also browned over large areas during the 2007-2008 drought and subsequently recovered. The climate of California and the Southwest over the Holocene is typified by the occurrence of severe and prolonged droughts, some extending for decades (Cook et al., 2004; Griffin & Anchukaitis, 2014; MacDonald et al., 2008; Stine, 1994; Woodhouse et al., 2010) and vegetation is adapted to such disturbance. However, there has been a trend towards a decrease in the seasonal amplitude of NDVI differences. This reflects in the south the greater relative decrease in wet season greenness due to water stress relative to the decrease in the dry season in vegetation types that experience a regular pattern of summer senescence, dormancy and leaf area diminishment as part of the regular seasonal cycle in any case. If there is to be a long-term trend to a browner California we would expect this decrease in seasonal contrast to continue in these regions. Greater greenness in winter for high mountain regions and the far north may or may not continue based upon changes that might occur in vegetation types and density under prolonged drought.

The anomalous PDSI of the current drought is exceptional for southern regions (Griffin & Anchukaitis, 2014; Williams et al., 2015) and has produced a higher degree of browning as a state-wide average than earlier droughts, particularly in the southern zones. However, greenness recovery has been robust following earlier severe droughts. What occurs in the next few years climatically and in terms of vegetation will be critical in determining any long-term trajectory to a browner California.

5.6 Acknowledgments

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CHAPTER 6

6. Conclusion

6.1 Summary

This dissertation has provided a collection of studies centered on remote sensing-based monitoring of native California ecosystems. These chapters took the format of publications in both peer-reviewed academic journals as well as a government report, and were written in context of the questions laid out in Chapter 1:

1. *How do human-induced threats (climate change, land use change, and invasive species) affect southern California ecosystems?*
2. *How can we use remote sensing to better understand these threats?*

Monitoring landscape dynamics and quantifying these changes are crucial to identifying how human-induced threats affect the natural landscape. Each chapter utilized exemplar remote sensing data and methods clarified in Chapter 2 to evaluate aspects of change induced by these threats to California ecosystems. Chapters 3, 4 and 5 applied remote sensing to quantify on the ground processes and ecological phenomena. Although shrubland ecosystems are difficult to classify using medium-resolution imagery, the change maps created in Chapter 3 still reflected historical changes seen *in situ* such as increasing developed land in SAMO and ecological succession on CHIS. The significant and high R^2 values between changes in anomalous native vegetation greenness and monthly drought anomalies found in Chapter 4 clearly demonstrated the effects of ecological stress on these communities at the ground level. Finally, both time series regressions and greenness change maps in Chapter 5 clearly revealed the spatial patterns of browning across California, a phenomenon which has been publicized through state water

allocation policies and in the agricultural industry. The following paragraphs fully summarize the findings of each research chapter.

Chapter 2 reviewed remote sensing methods to formulate a best-practice model for monitoring landscape dynamics in protected areas. Certain commonalities were found between ecological conservation groups. Simple key methodological components before beginning any monitoring process were discussed, including the choice of appropriate study area, scale, data, and a key indicator or proxy to represent the ecological phenomenon at hand. Effective methods of change detection were discussed in relation to its ecological applications and how these methods have evolved. Monitoring land use/land cover, disturbance, and phenology were the most commonly significant ecological indicators identified by the majority of land management groups. Landsat products were the most common remote sensing data used for monitoring land use/land cover and disturbance, and data from the Moderate Resolution Imaging Spectrometer (MODIS) were recommended for monitoring changes in phenology. Careful validation of results was stressed, either by combination of remotely sensed datasets with high resolution imagery or *in situ* data, in order to increase accuracy and to better align the remotely sensed data to the scale of the on-the-ground processes. Above all, collaborations between ecologists, land managers, conservation groups, and scientists were emphasized as vital for successful integration of remote sensing-based monitoring of changes in protected areas.

Chapter 3 was an application of this best-practice model to the Santa Monica Mountains National Recreation Area and Channel Islands National Park in southern California. Land cover maps were created with medium accuracy for 1986, 2001, and 2011. Increased mixed and nonnative vegetation types along with medium-intensity developed land cover suggested that

human development has fragmented the landscape over SAMO. Native vegetation types in CHIS have increased since 1986, suggesting that nonnative plant and animal eradication efforts by Park managers have been successful. Reported results located and quantified both the areas in most need of future environmental management as well as areas where past efforts were successful.

Chapter 4 assessed the response of greenness in native southern California vegetation ecosystems to current drought at a monthly timescale. This was assessed using time seies regression analysis of anomalous monthly Palmer Drought Severity Index (PDSI) and monthly anomalous Normalized Difference Vegetation Index (NDVI) for chaparral and coastal sage scrub throughout southern coastal California as well as per county. Each vegetation type displayed a different response to anomalous drought months; chaparral-dominated ecosystems returned the highest correlations with drought indices, especially in Santa Barbara County. This suggested that chaparral-dominated ecosystems may experience more change than coastal sage scrub-dominated areas if extreme drought increases in frequency and duration as is forecast for southern California. Southern regions appeared to be more affected by drought, yet further studies are needed to assess the spatial differences in vegetation response.

Chapter 5 expanded this methodology using regression analysis of monthly anomalies to the entire California landscape, with both qualitative and quantitative analyses based around CalVeg vegetation zones during 21st century drought. Regression results revealed that Southern zones were more affected, according to higher regression outputs especially during summer anomalous drought months (June July August). However, many northern regions such as the Sierra Nevada experienced increased greening during winter months, indicating decreased

snowpack during extreme drought conditions. Vegetation was found to recover following the 2007-2008 drought, yet during 2014 experienced browning beyond past 21st Century drought conditions. Greenness during wet months (January February March) appeared to be more highly affected than during dry months (June July August). The most recent drought years also displayed a decrease in contrast of seasonal greenness. These changes imply a browner landscape over California into the future, with possibilities of dire human repercussions for water resources and in the US agricultural industry.

6.2 Research Contributions

This dissertation provides the following contributions to geographic research, natural resource managers, and to the scientific community at large:

1. A best practice model of methods to be used by natural resource land managers for remotely sensed change detection monitoring.
2. A comprehensive report on the status and changes of land cover and vegetation in the Santa Monica Mountains National Recreation Area and the Channel Islands National Park from 1986-2011, including shapefiles, maps, graphs, georeferenced land cover validation data, and recommendations for management efforts.
3. A study of landscape-scale elucidation of drought impact on native southern California vegetation.
4. A study evaluating the browning of California during 20th Century drought years.