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Publication Date
2020

Peer reviewed|Thesis/dissertation
Remote Sensing of Urban Vegetation during Drought in Southern California

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

by

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December 2020
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December 2020
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David Lauchlin Miller
ACKNOWLEDGEMENTS

Although this dissertation only has my name on it, no one should mistake this for being a solo effort. As many large projects are, this is the culmination of a broad swath of support from a wide array of people. I am extraordinarily thankful for all the help, thoughtfulness, and general TLC I have received over the years, as well as the always-important and well-placed constructive criticism that has gone into creating this document. Not only has this dissertation become far superior as a result, it has also had the fortuitous consequence of making me a better scholar and writer overall. And for that, I am grateful.

To begin I need to thank my advisor, Joe McFadden, and my committee members, Dar Roberts and Naomi Tague. I cannot thank you enough for the innumerable hours you have invested in me. Joe has been an invaluable source of support, always making sure that my research ideas are clear and will yield interesting results, as well as asking the hard questions before anyone else can (while providing plenty of assistance and encouragement). He is also the best editor I could ask for and knows how to make a scientific paper have a story arc like no one else. Dar has provided peerless remote sensing knowledge through many classes and NASA SARP, and he is the technical wizardry behind anything and everything spectral. He has always made me feel welcome as an honorary member of the Viper Lab, and in many ways has been a second advisor to me throughout graduate school. Naomi has been an excellent resource for plant-water interactions: to oversimplify things, she has made sure I know what drought is and how plants work with water, which turned out to be far deeper questions than I naively thought when I began this dissertation. Her lab group has also been an excellent resource and I feel fortunate to have been a part of many meetings over the past few years.

I am indebted to a few key former UCSB Geography grad students whose previous hard work has made this all possible. They have written the fundamental texts as far as this dissertation is concerned. Mike Alonzo produced an amazing tree species map in Santa Barbara that I used in my Chapter 1, and he’s also been a fantastic resource for urban forestry knowledge and scientific paper organization. Susan Meerdink organized a ridiculous (and I do mean ridiculous) amount AVIRIS imagery in the Santa Barbara region which I used in my Chapter 2, and I have relied on her well-written papers, IDL code, and overall input for many aspects of this research. Erin Wetherley showed how an urban fractional cover map could be done accurately and effectively, and inadvertently set the groundwork for my Chapter 3. She has been a great resource for an infinite number of things related to research and grad school (and always being a great friend and collaborator too). I also need to thank Sarah Shivers and Zach Tane for their influential AVIRIS research papers from their PhD dissertations, which I have relied on extensively and have hopefully cited sufficiently.

In my current lab group, a big thank you to Michael Allen for, among many things, always being able to answer my thermal remote sensing questions and acting as my personal clearinghouse for figures and tables. I will never look at contour plots the same again.
There are too many other people to thank within the geography department and elsewhere for helping with this dissertation and grad school in general, but I will try to make an incomplete list nonetheless: James Allen, Kelsey McBeain, S. Lucille Blakeley, Rafael Ramos, Ally Foot, Lauren Smyth, Fernanda Ribeiro, Gabriel Antunes Daldeğan, Alana Ayasse, Chris Kibler, Mingquan Chen, Rachel Green, Conor McMahon, Clare Saiki, Germán Silva, Seth Peterson, Olaf Menzer, Alex Feldwinn, Alycia Lewis, Zan Preston, Payam Rowghanian, Cascade Tuholske, Kate Voss, Corbin Hodges, Rachel Torres, Devyn Orr, Colin Jordan, Jon Wang, Kelly Whaling, Luna Whaling, Bryant Chow, Meagan Sobel, Ronald Hill, and many, many more. Thank you to everyone at the NASA Student Airborne Research Program as well.

I also absolutely need to thank my parents, brother, and larger extended family and friends for supporting this endeavor for the long haul. Thank you to the Oreglias for always welcoming me with a home away from home at many AGUs. And, of course, thank you Cat for being who you are.

This research was primarily supported by a NASA Earth and Space Science Fellowship (80NSSC18K1325). Additional funding for Chapter 1 was from the Belgian Science Policy Office in the framework of the STEREO III Program – Project UrbanEARS (SR/00/307). Thanks to the Jack and Laura Dangermond Geography Travel Scholarship for allowing me to present this work at many conferences, and thank you to the UCSB Department of Geography for the many years of TA funding. And special thanks to the NASA Jet Propulsion Laboratory for the AVIRIS and AVIRIS-NG imagery.

Dedicated to my grandmothers, for style and adventure
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ABSTRACT

Remote Sensing of Urban Vegetation during Drought in Southern California

by

David Lauchlin Miller

Plants can respond to drought events in a variety of ways, including adjustments in physiological processes and changes in canopy structure. Quantifying these changes over large spatial domains and through time can be challenging, especially with variable vegetation cover types. During 2012-2016, California experienced one of the most severe droughts in its modern history, with limited precipitation and exceptionally high temperatures over an extended time period. Urban vegetation, such as trees and turfgrass lawns, provides many ecosystem services for people living in cities, such as cooling through shading and evapotranspiration, but these benefits may be difficult to maintain through extreme drought, especially in water-limited cities. Therefore, it is critical to understand how drought response in vegetation may vary across urban landscapes.

In this dissertation, I used remote sensing time series to quantify how urban vegetation responded to drought in Santa Barbara and Los Angeles, California. In Chapter 1, I examined drought response in turfgrass and across nineteen urban tree species in the city of Santa Barbara using data from repeat flights of the Airborne Visible Infrared Imaging Spectrometer (AVIRIS) and AVIRIS-Next Generation (AVIRIS-NG). I compared many
spectral indicators that may be expected to change within plant canopies during drought. Compared with data from before the drought in 2011, all tree species and turfgrass had four or more spectral indicators with significantly lower mean values ($p < 0.05$) during the drought in 2014, and evidence of recovery was observed for some species in 2017, after the drought had ended. Based on the spectral indicators, turfgrass cover senesced in the middle of the drought but recovered soon after the drought ended. Nearly all tree species showed significant canopy changes in the middle of the drought, but in comparison to turfgrass, most tree species did not fully recover after the drought ended.

In Chapter 2, I evaluated how drought manifests seasonally and interannually during 2010-2019 across dominant types of trees and grass in the Santa Barbara area using Landsat and AVIRIS imagery. I compared the condition of dominant types of trees and grasses as they changed throughout the year using the Normalized Difference Vegetation Index (NDVI), difference in vegetation land surface temperature from impervious surfaces ($\Delta$LST), and equivalent water thickness (EWT). NDVI was lower and $\Delta$LST was closer to zero during drought years but they were seasonally correlated for only some vegetation types. Changes in EWT revealed seasonal adjustments by vegetation that were not readily apparent in the NDVI time series. I also assessed the correlations of NDVI and LST with the Standardized Precipitation Evapotranspiration Index (SPEI) to test the effects of drought length and severity on vegetation. NDVI and $\Delta$LST were most strongly correlated with SPEI during summer for most vegetation types, except for annual grass NDVI (winter). Annual grass was correlated with SPEI at spans $\leq 12$ months, whereas trees and turfgrass were correlated with SPEI at spans $> 12$ months in addition to seasonal time spans.
In Chapter 3, I assessed annual changes in fractional cover of trees, turfgrass, non-photosynthetic vegetation (NPV; e.g., senesced grass, plant litter), and non-vegetated urban surfaces across the Los Angeles metropolitan area during 2013-2018 using AVIRIS imagery. During the drought time series from 2013 to 2018, mean turfgrass cover decreased and NPV cover increased, but tree cover did not show a strong trend with drought until 2018. The interior valleys of the study area (San Gabriel and San Fernando) consistently lost more turfgrass than coastal areas, and the San Gabriel Valley had strong losses of total vegetation cover (tree + turfgrass + NPV) overall. I also used datasets of median household income from census tracts and of typical non-drought outdoor water use from postal carrier routes to compare the magnitude and timing of different vegetation cover type changes at different income and water use levels. There were larger absolute changes in vegetation cover in higher income and higher water use areas, likely due to the higher baseline of mean vegetation cover in these areas. Once normalized for their mean values, the magnitude of changes often became more similar across different income and water use levels, but not always, with lower income and water use areas showing greater relative changes for trees.

Overall, this dissertation quantifies drought responses across different urban vegetation types during a severe, long-term drought event at an array of spatial and temporal scales, providing implications for vegetation sustainability planning in cities with frequent droughts.
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Introduction

Plants are affected by droughts due to the creation of a water deficit that limits plant growth and transpiration (Bréda et al., 2006). Droughts can develop on a variety of time scales, from within days to across years and decades, and at a range of spatial extents (van der Molen et al., 2011; Otkin et al., 2018; Williams et al., 2020). Drought can affect vegetation in many ways, with several major effects including: reduced growth rates, changing carbon cycling, modified nutrient allocations, and structural damage or mortality, either directly through a carbon starvation and hydraulic disfunction or indirectly by reducing a plant’s resilience to pests, diseases, and fire (Bréda et al., 2006; McDowell et al., 2008; Van der Molen et al., 2011; Schlesinger et al., 2016; Stocker et al., 2019). Drought can also cause long-term shifts in vegetation cover, especially in areas where droughts are increasing in frequency, duration, and/or severity, leading plants to develop chronic water stress (Allen and Breshears, 1998; Mueller et al., 2005).

In 2012-2016, the state of California experienced one of the most severe droughts in its modern history (Lund et al., 2018), with estimates of a recurrence frequency of 1200 years (Griffin and Anchukaitis, 2014). Even in normal conditions, drought is a dominant feature of the state’s Mediterranean climate, with cooler, wet winters and hot, dry summers. However, the 2012-2016 drought was exceptional by many standards, with not only reduced precipitation but also high temperatures, which may have been responsible for up to 25% of cumulative moisture deficit (Lund et al., 2018). It is likely that the anthropogenic influence from climate change had influenced this drought’s likelihood and severity, and more intense droughts have the potential to become more frequent in the future (Diffenbaugh et al., 2015; Williams et al., 2015).
The 2012-2016 drought had severe impacts on many regions and ecosystems in California (Lund et al., 2018). There were large losses of canopy water content in forests throughout the state (Asner et al., 2016) and record tree mortality in the Sierra Nevada (Fettig et al., 2019). Because of the drought’s magnitude and extent, there were regional differences statewide in the effect of drought on natural vegetation, with areas in southern California generally more affected by the drought than areas in northern California, likely due to higher regional aridity (Dong et al., 2019). Within coastal southern California, chaparral-dominated ecosystems were more affected by the long-term drought than were coastal-sage scrub ecosystems, which may be related to differences in soil type and elevation (Okin et al., 2018). There were also shifts in agricultural production, and many agricultural regions had to draw more exclusively from groundwater to maintain existing orchards (Lund et al., 2018). However, there has been comparatively less research investigating the effects of the drought on vegetation in urban areas.

Cities were affected by the drought and many metropolitan areas throughout the state implemented water-use reductions to meet statewide reduction goals (Palazzo et al., 2017; Lund et al., 2018). A major consequence was the limitation of outdoor irrigation, with landscape watering increasingly curtailed as the drought progressed (Pincetl et al., 2019). California’s Mediterranean climate requires that urban landscaping be irrigated throughout the dry summers to maintain vegetation greenness, especially in the case of turfgrass lawns (Quesnel et al., 2019). This requires importation of water over large distances (Lund et al., 2018) and local irrigation can heavily modify local streamflow behavior, which might otherwise be dry during the summers (Manago and Hogue, 2017; Reyes et al., 2020). Because of extensive irrigation and the mild climate, vegetation in California’s cities is
diverse and often exotic (Clarke et al., 2013; Alonzo et al., 2014; Avolio et al., 2020), much more so than cities that are restricted by cold winter temperatures (Jenerette et al., 2016). Consequentially, different vegetation types and species may experience differential responses to drought. For example, where cities have developed in coastal southern California, native tree species are primarily from riparian zones (Pincetl et al., 2013), and they may not be particularly water efficient due to their normal access to groundwater at depth (e.g., California sycamore (*Platanus racemosa*), McCarthy and Pataki, 2010; Bijoor et al., 2012). Some native tree species, such as various species of California oaks (*Quercus spp.*), have various drought adaptions to tolerate and offset the timing of seasonal drought conditions (Knops and Koenig, 1994), but non-native species are not necessarily well-adapted to drought conditions, although many species planted in southern California cities are from dry climates (e.g., Canary Island pine (*Pinus canariensis*), McCarthy and Pataki, 2010). To reduce water use during droughts, cities like Los Angeles have sometimes incentivized residents to replace their turfgrass lawns with non-vegetated surfaces and/or xeriscaping to reduce outdoor water use (Pincetl et al., 2019).

Despite the need for irrigation in many California cities, there are major benefits in the form of ecosystem services from vegetation (Bolund and Hunhammar, 1999; McPherson et al., 2017; Monteiro, 2017). While there are many benefits that urban plants provide (e.g., stormwater infiltration, windbreaks, noise reduction; Bolund and Hunhammar, 1999), during hot and dry conditions, benefits related to cooling of the urban environment are of high importance (Shashua-Bar et al., 2009; Norton et al., 2015; Wheeler et al., 2019). These benefits are primarily provided through tree shading and latent heat loss through evapotranspiration in both trees and lower stature, herbaceous vegetation such as turfgrass
lawns. Stronger cooling rates can also be produced through combinations of trees and grass in the landscape (Shashua-Bar et al., 2009), and both can cool neighborhood areas around large vegetated patches, such as parks (Spronken-Smith et al., 1998) and forested stands (Ziter et al., 2019). Trees and grass can also produce disservices, for example related to allergies and harming infrastructure, and they must be placed with consideration to mitigate these potential negative effects (Lyytimäki et al., 2008; Roman et al., 2020). In general, the benefits from ecosystem services can become more difficult for urban vegetation to provide during drought conditions due to water limitations (Norton et al., 2015).

Urban trees and turfgrass can have a multitude of responses in relation to drought and can be affected by an array of different factors, including types of tree species and water availability. Drought responses can differ across tree species, and drought tolerance is often a necessary consideration for urban tree planting programs in cities with dry or seasonally dry climates, including when trying to inform irrigation scheduling (May et al., 2013; Gillner et al., 2014; Roman et al., 2015). Urban trees can also be affected by the surrounding environmental conditions during drought. For example, trees surrounded by pavement can have greater drought vulnerability and higher susceptibility to water stress due to greater heating from the surface as compared to trees over pervious soil or vegetated surfaces (Savi et al., 2015). Water availability can become limited for urban vegetation during drought and can modify evapotranspiration rates. Among many local factors, relationships between tree transpiration rates and vapor pressure deficit can vary by tree species (Litvak et al., 2017b). It can be challenging to both measure local water losses and city-scale variability through upscaling techniques, especially with differences between trees and lawns (Litvak et al.,...
2017a; Liang et al., 2017). Even if irrigation rates do not change during drought, turfgrass can still senesce due to high atmospheric demand for water (Quesnel et al., 2019).

Remote sensing has proven to be a valuable technique to investigate vegetation across a larger urban environment. Urban areas are often approached as a combination of surfaces, often reflecting Ridd’s (1995) definition of urban areas as a matrix of vegetation, impervious, and soil surfaces (i.e., the V-I-S model). Modern analyses often rely on high spatial and/or high spectral resolution imagery (van der Linden et al., 2018) due to the high spatial heterogeneity of urban areas (Cadenasso et al., 2007). Common applications include mapping urban tree and other cover types (e.g., Moskal et al., 2011; McPherson et al., 2011; Erker et al., 2019), with more detailed analyses using LiDAR (e.g., Alonzo et al., 2014) or thermal (e.g., Leuzinger et al., 2010) data as well. Other studies have investigated the variability of canopy condition across the urban environment (e.g., Degerickx et al., 2018). Unfortunately, high quality remote sensing data in urban environments is often acquired infrequently (Schwarz et al., 2015; van der Linden et al., 2018).

Addressing how vegetation canopies have changed due to a drought requires monitoring change over time. For example, Quesnel et al. (2019) used high spatial resolution aerial photography to compare lawn watering conditions in Redwood City, California during the recent drought. For studies at larger spatial extents, this is best accomplished through regular acquisitions from spaceborne monitoring platforms such as Landsat or MODIS, such as regional California comparisons (e.g., Okin et al., 2018; Dong et al., 2019). Broadband sensors can measure vegetation greenness and land surface temperature, and they are valuable to construct long time series (e.g., Imhoff et al., 2010; Melaas et al., 2016).
Compared with broadband sensors, imaging spectroscopy can provide much more information on subtle adjustments in vegetation status and cover type differences, measuring hundreds of narrow bands of spectral reflectance (Ustin et al., 2004). This includes changes in plant pigments (e.g., Ustin et al., 2009) and water content (e.g., Serrano et al., 2000), among many spectral features (Ustin et al., 2004) which can be related to plant canopy traits (Singh et al., 2015). For example, techniques such as Multiple Endmember Spectral Mixture Analysis (MESMA; Roberts et al., 1998) can take advantage of this spectral diversity to map cover types as subpixel fractions, among other related methods (e.g., Somers et al., 2011; Okujeni et al., 2013). Imaging spectroscopy has been applied in many urban vegetation studies, including those mapping urban tree species (e.g., Alonzo et al., 2014; Liu et al., 2017), forest composition (Gu et al., 2015), and cover types more generally (Franke et al., 2009). It has also been applied in several drought-related studies in California, including: forest canopy water content (Asner et al., 2016), vegetation productivity analyses (DuBois et al., 2018), forest mortality mapping (Brodrick and Asner, 2017; Tane et al., 2018), natural vegetation cover change (Coates et al., 2015; Meerdink et al., 2019a), and agricultural cover change (Shivers et al., 2018). Data from imaging spectrometers are currently restricted to airborne platforms, with few exceptions (e.g., EO-1 Hyperion). Future spaceborne systems, such as the Surface Biology and Geology (SBG) and Environmental Mapping and Analysis Program (ENMAP) missions, have been identified as a key data source for improving vegetation studies and understanding terrestrial ecosystem function (Schimel et al., 2015; Jetz et al., 2016). Prior to the studies presented in this dissertation, urban vegetation has very rarely been approached using imaging spectroscopy to study drought.
Despite imaging spectroscopy data often being limited in spatial extent and temporal frequency (e.g., van der Linden et al., 2018), during our study period there were many repeat acquisitions of airborne imaging spectroscopy at a range of spatial extents, allowing for comparison and mapping of vegetation through time during the drought. Specifically, during the 2012-2016 California drought, repeat flights of Santa Barbara and Los Angeles were acquired using Airborne Visible Infrared Imaging Spectrometer (AVIRIS; Green et al., 1998) and AVIRIS-Next Generation (AVIRIS-NG; Hamlin et al., 2011), with many additional flights of AVIRIS as part of the HyspIRI Preparatory Campaign (Lee et al., 2015). These data have been used in urban studies such as Wetherley et al. (2018), in which the authors used imaging spectroscopy from AVIRIS and thermal imagery from MASTER to quantify the effects of drought within and across trees and turfgrass in Los Angeles in August 2014.

In this dissertation, I quantified the effects of drought on urban vegetation in Santa Barbara and Los Angeles, California using multiple time series of remote sensing imagery. The following chapters addressed changes in vegetation related to drought at increasing scales in the urban environment, from canopy adjustments within small patches of individual trees to total cover change across a large metropolitan area. First, I compared within individual patches of trees and turfgrass lawns in order to attribute differences in drought response between different tree species and turfgrass. I tested a variety of remote sensing metrics that were measurable from imaging spectroscopy to be able to contextualize the variability in canopy changes due to drought. Second, I investigated the interactions between seasonal and interannual time scales of drought within common urban vegetation types. From this, I was able to determine the seasonal aspects of drought on urban vegetation that
are a regular feature of California’s Mediterranean climate, and compare these impacts to the severity of a multiyear drought event. Third, to be able to understand the potential magnitude of cover changes that occurred as a result of a long-term drought, I investigated metropolitan scale changes in cover among different urban vegetation types. Collectively, from these studies I was able to compare the differences in drought responses across tree species and vegetation types in terms of: the magnitude of effects within canopies; the layering of seasonal vs. interannual drought response timing; and spatial cover changes across large areas.

In Chapter 1, I quantified drought response in turfgrass and nineteen urban tree species in the city of Santa Barbara, using repeat flights of imagery from AVIRIS and AVIRIS-NG at 7.5 m spatial resolution (Miller et al., 2020). Turfgrass polygons were selected from open parks and recreational areas, and trees were monitored as patches (i.e., groups of adjacent trees) with tree crown polygons derived from airborne LiDAR produced by Alonzo et al. (2014). Drought-induced change and initial recovery were tracked using three dates of imagery: from before the drought in July 2011, during the peak of the drought in June 2014, and after the main part of the drought ended in June 2017. Changes in vegetation were quantified using a suite of spectral indicators related to canopy structure and greenness, plant pigments, and water content. The spectral indicators included fraction of green vegetation cover derived from MESMA, vegetation indices, and continuum-removed absorption features. I also evaluated canopy changes as they varied based on pre-drought estimates of leaf area index and aboveground carbon biomass from Alonzo et al. (2016).

In Chapter 2, I compared the effects of seasonal and interannual drought on dominant vegetation types in the Santa Barbara urbanized region, applying time series
imagery from both Landsat and AVIRIS. I mapped vegetation types using 4 m AVIRIS-NG imagery from June 2014 using a random forest classifier, specifically to track: broadleaf trees, needleleaf trees, Eucalyptus trees, coast live oak trees, annual grass, and green turfgrass. To track these cover types through time, I extracted Landsat (30 m) and AVIRIS (18 m) pixels that were dominated by specific vegetation types (>90% of pixel). Using Landsat from 2010 to 2019, I tracked monthly estimates of the Normalized Difference Vegetation Index (NDVI) and the difference in land surface temperature between vegetation and urban surfaces (ΔLST); using AVIRIS, I used nine dates from 2013 to 2015 to quantify changes in canopy water content, estimated via equivalent water thickness (EWT). To evaluate the seasonal vs. interannual effects of drought, I also correlated the Landsat data to a drought index, the Standardized Precipitation Evapotranspiration Index (SPEI), which can be calculated to estimate drought at a range of time scales.

In Chapter 3, I estimated the changes in land cover in the Los Angeles metropolitan area during drought using an annual time series of AVIRIS imagery. Cover estimates were quantified using MESMA to calculate subpixel fractional cover of trees, turfgrass, non-photosynthetic vegetation (NPV), and non-vegetated urban surfaces for May/June 2013-2018. I assessed mean changes in cover through time and investigated in fractional cover changes from 2013 to 2018 based on metropolitan-scale climatology and physiography. I also compared how vegetation cover type changes occurred based on median household income from 2018 for census tracts and estimates of outdoor water use from 2006 for postal carrier route polygons. This analysis compared both the total amount of year-to-year change for different categories of income and water use and the relative amount of change compared the mean of the time series.
This research allows for comparisons of drought responses in urban vegetation across a variety of spatial and temporal scales. It also builds on technical knowledge of how to approach using repeat hyperspectral imagery in time series, which are rarely available, especially in urban areas. Overall, this dissertation contributes to improve our collective understanding of the variety of responses in urban vegetation to drought and can inform future planning and analysis to account for droughts in urban regions.
Chapter 1: Drought response of urban trees and turfgrass using airborne imaging spectroscopy

with Michael Alonzo, Dar A. Roberts, Christina L. Tague, and Joseph P. McFadden

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Abstract

Vegetation growth and physiological functioning, including carbon uptake and transpiration, can be strongly affected by drought. During water-limited conditions, urban vegetation may be limited in its ability to provide ecosystem services, such as shading and evaporative cooling. While there has been extensive research on drought response in natural vegetation and agricultural systems using remote sensing, drought impacts on urban vegetation have remained understudied. With >50% of people worldwide living in cities and the increased potential for future droughts, it is important to understand how urban vegetation will respond and to evaluate potential impacts. Here, we used repeat flights of NASA airborne imaging spectroscopy (AVIRIS and AVIRIS-NG) to quantify the responses of common urban tree species and turfgrass in downtown Santa Barbara, California, USA to the 2012-2016 California drought. The effects of the drought on vegetation were quantified using several spectral indicators: fractional cover from multiple endmember spectral mixture analysis (MESMA), vegetation indices, and continuum removed absorption features. We used existing tree crown object polygons that were classified to species and had associated estimates of pre-drought leaf area index and biomass. We also included polygons of turfgrass parks and recreational fields. All tree species and turfgrass had four or more spectral indicators with significantly lower mean values (p < 0.05) during the drought in 2014, and evidence of recovery was observed for some species in 2017, which was after the drought had ended. In general, needleleaf and native trees were more affected than broadleaf and non-native trees, respectively, but with considerable interspecific variability. Based on the spectral indicators, turfgrass cover senesced in the middle of the drought but recovered soon after the drought ended, whereas the majority of tree species had not fully recovered.
Mean green vegetation cover declined in most tree canopies during the drought, primarily exposing paved surfaces and/or non-photosynthetic vegetation, depending on the site type and tree patch size. Drought impacts as expressed in spectral indicators were generally more severe in tree patches with high pre-drought leaf area index, suggesting that denser, leafier canopies were more difficult for trees to maintain during the drought. Most spectral indicators were correlated with one another (R > 0.4), suggesting co-occurring adjustments of greenness, water content, and plant pigments.
1. Introduction

Drought has many negative effects on vegetation growth and physiological functioning, including directly affecting terrestrial carbon cycling by limiting vegetation primary production (Van der Molen et al., 2011), modifying nutrient allocation (Schlesinger et al., 2016), and increasing tree mortality rates, even after drought has ended (Trugman et al., 2018). These effects can modify forest structure and regrowth patterns (Bréda et al., 2006), often leading to long-term changes in vegetation cover types, especially under changing climatic conditions (Allen and Breshears, 1998). The 2012-2016 drought in California was particularly severe, with prolonged periods of low precipitation and unusually high temperatures producing significant soil moisture and surface water deficits (Griffin and Anchukaitis, 2014; Robeson et al., 2015; Lund et al., 2018). With potential changes in climate, there is increased likelihood for similarly severe droughts to reoccur (Diffenbaugh et al., 2015). While there have been numerous studies on the impacts of the drought on vegetation in natural and agricultural areas (e.g., Asner et al., 2016; Dong et al., 2019; Shivers et al., 2019), there has been comparatively limited work to date investigating impacts on urban vegetation (e.g., Liang et al., 2017; Pincetl et al., 2019).

In cities, urban vegetation provides ecosystem services, including air and surface temperature reduction, recreational space, pollution mitigation, and hydrological buffering and filtering (Bolund and Hunhammar, 1999; Monteiro, 2017; Ziter et al., 2019). At the same time, it also produces some disservices, such as pollen production and pest refugia (Lyytimäki et al., 2008). Many ecosystem services are provided primarily as a function of leaf area (Nowak et al., 2008), which can be reduced during drought as turfgrass senesces (Monteiro, 2017; Quesnel et al., 2019) and urban trees adjust their biomass (Savi et al.,
Among trees, both ecosystem services and drought response can vary by species, many of which can be exotic in urban environments (Gillner et al., 2014; Jenerette et al., 2016). The diversity of urban tree species can be prescribed by local climate and aesthetic preferences (Jenerette et al., 2016; McPherson et al., 2018), but existing species may not be as viable under future climate conditions, potentially jeopardizing their long-term potential for providing consistent ecosystem services (McPherson et al., 2018). This is especially the case in semi-arid regions like California, where urban vegetation is largely reliant on irrigation in an increasingly drought-prone climate and normal applications of water may not be sufficient to maintain vegetation condition during hotter droughts (Diffenbaugh et al., 2015; McPherson et al., 2017; Quesnel et al., 2019).

While we expect an overall decline in vegetation function during drought, it remains unclear how drought response varies across an urban environment of turfgrass, different tree species, and trees of different sizes and leaf areas. In general, drought conditions lead to loss of evapotranspiration from urban vegetation, but the magnitudes may be highly location-dependent (Pataki et al., 2011; Liang et al., 2017). Deeply-rooted trees may experience drought on a lagged timescale as compared with shallow-rooted turfgrass, which can exhibit water stress in a few short weeks (Kaufmann, 1994; Bijoor et al., 2012), and different species of trees in an urban environment have differing transpiration behaviors and distinct responses to drought stress (McCarthy and Pataki, 2010; Litvak et al., 2012; Gillner et al., 2014). In addition, larger trees have been shown to be preferentially affected by drought in many natural areas globally (Bennett et al., 2015), but it is unclear if these patterns extend to urban forests, especially given the unique dynamics of urban tree growth and stress (Gillner et al., 2014; Smith et al., 2019). Quantifying drought impacts in situ across a range of urban
vegetation types would require repeated field surveys and continuous instrumentation, ideally before, during, and after the drought event (Bialecki et al., 2018; Liang et al., 2017). While many studies have instrumented urban trees and turfgrass to compare transpiration, carbon cycling, and canopy condition (McCarthy and Pataki, 2010; Peters et al., 2011; Bijoor et al., 2012; May et al., 2013), such direct sampling at a city-scale would likely be prohibitively expensive and time-consuming over a multi-year drought.

Remote sensing techniques are well-suited to characterize the differential effects of drought on urban vegetation across a city in a spatially explicit and timely manner. Since urban areas are spatially and spectrally heterogeneous, fine-scale imaging spectroscopy (i.e., hyperspectral imagery) has proven valuable for tree species classification and to quantify the condition of many urban surfaces and vegetation types, especially when combined with high-density lidar and/or thermal imagery (Roberts et al., 2012; Alonzo et al., 2014; van der Linden et al., 2018). However, until recently there have not been repeat imaging spectroscopy data available at appropriate spatial resolutions and timing to quantify urban vegetation’s response to drought. In natural areas, imaging spectroscopy has been used extensively to quantify drought response of vegetation, including changes in green fractional cover (Coates et al., 2015), vegetation type distributions (Meerdink et al., 2019a), photosynthesis and carbon uptake (Asner et al., 2004; DuBois et al., 2018), canopy water content (Asner et al., 2016), and mapping tree mortality (Tane et al., 2018). Previous remote sensing studies of drought impacts on urban vegetation are limited in number and primarily use multispectral and thermal imagery, evaluating evapotranspiration and irrigation water use as they relate to vegetation cover, greenness, and drought sensitivity (Kaplan et al., 2014; Quesnel et al., 2019), land-use development patterns related to drought (Gao et al.,
2011), and drought damage to park trees estimated via photointerpretation (Holopainen et al., 2006).

Here, we exploited repeat airborne imaging spectroscopy data to quantify the response of urban tree species and turfgrass to a multi-year drought. We used tree crown and turfgrass polygon spectral reflectance values to compare changes in condition across different key vegetation types within the urban area. While we did not have field data during the drought to compare with our remote sensing measurements, we used a set of spectral indicators that have been robustly tested against field data in many previously published studies (e.g., Pu et al., 2003; Degerickx et al., 2018; Roberts et al., 2019b). We evaluated changes in spectral indicators during the drought, as well as potential recovery based on a return to pre-drought values from 2011. In general, it is not known how urban trees and turfgrass may respond to drought and how those responses will be expressed across a range of spectral indicators retrieved from imaging spectroscopy. More specifically, we sought to answer four main questions:

1. How does green vegetation cover vary through time during a drought in an urban area?
2. How does drought response vary among urban tree species and turfgrass as indicated by spectral indicators?
3. How does drought response vary by pre-drought leaf area index and biomass in urban trees?
4. How consistently do different spectral indicators capture changes in canopy condition due to drought?
2. Methods

2.1. Study area and drought impacts

Our study area was downtown Santa Barbara, California, USA (Fig. 1.1; 22 km²; 34.42° N, 119.69° W). Santa Barbara is a city of ~90,000 (United States Census Bureau, 2019) located on a narrow coastal plain, with the Pacific Ocean to the south and the Santa Ynez Mountains to the north. The region has a Mediterranean climate (Köppen Csb) with warm, dry summers and cooler, wet winters, receiving nearly all of its precipitation between November and April (mean annual temperature = 15 °C, mean annual precipitation = 45 cm; National Centers for Environmental Information, 2019). The moderate climate allows for a highly diverse mix of urban vegetation given sufficient summertime irrigation, with some native and many introduced urban tree species (Alonzo et al., 2014). We limited our study extent to that of previous urban forestry studies by Alonzo et al. (2014, 2015, 2016) to leverage existing tree crown polygons previously classified to species. We excluded trees in the Montecito Club golf course on the eastern edge of the study area (bright green in Fig. 1.1A) due to its extensive redevelopment during the study period.

The urban area of Santa Barbara experienced drought conditions from early 2012 until the beginning of 2019, with the most severe conditions lasting from March 2014 to January 2017 (United States Drought Monitor, 2019). To contextualize the drought’s magnitude, a history (1895-2018) of drought severity in Santa Barbara using the Palmer Drought Severity Index (PDSI) is provided in the supplemental material (Fig. S1.1; Abatzoglou et al., 2017). The Santa Barbara City Council declared several stages of drought conditions, beginning in February 2014, with initial citywide water use reductions of 25% begun in May 2015 and subsequent updates to 35% in April 2016 and 40% in December.
2016, with this last update including a moratorium on lawn watering (Council of the City of Santa Barbara, 2017). In March 2017 the moratorium on lawn watering was eliminated due to winter rainfall, but 30% reductions of citywide water use persisted.

Fig. 1.1: (A) Santa Barbara study area shown in false color AVIRIS imagery (acquired July 19, 2011 at 7.5 m spatial resolution) over black and white NAIP orthophoto (acquired in 2014 at 1 m spatial resolution), with location indicated by yellow star in California outline. Gray box on (A) indicates extent of insets (B) and (C), showing examples of vegetation polygons over NAIP and false color AVIRIS, respectively. See Table 1.1 for vegetation type abbreviations. AVIRIS false color: R = 1652 nm, G = 821 nm, and B = 665 nm.
2.2. Imaging spectroscopy acquisition and processing

An overview workflow diagram is shown in Fig. 1.2. We used three sets of airborne imaging spectroscopy flightlines resampled to 7.5 m spatial resolution (specific flightline information and pre-preprocessing characteristics are in the supplemental material, Table S1.1). Dates were selected based on data availability to capture pre-drought conditions (2011) and subsequent stages of drought (2014) and initial recovery (2017). To mitigate effects from phenology, only June or July imagery were analyzed. We used image data from two sensors due to acquisition timing and the need for relatively high spatial resolution imagery. The 2011 and 2017 image data were collected from the Airborne Visible Infrared Imaging Spectrometer (AVIRIS) on an ER-2 aircraft at ~9 km altitude and gridded to native spatial resolutions of 7.0 - 7.7 m. The 2014 image data were collected from the Airborne Visible Infrared Imaging Spectrometer - Next Generation (AVIRIS-NG) on a Twin Otter aircraft at ~4 km altitude and gridded to native spatial resolutions of 3.9 - 4.2 m. Both sensors measure narrow bands of reflected radiance in the visible, near infrared, and...
shortwave infrared (360 - 2500 nm). AVIRIS measures 224 bands at 10 nm full-width half-maximum (Green et al. 1998), and AVIRIS-NG measures 432 bands at 5 nm full-width half-maximum (Hamlin et al. 2011).

The AVIRIS and AVIRIS-NG image data were initially radiometrically calibrated and orthorectified by the NASA Jet Propulsion Laboratory (JPL). The 2011 and 2017 AVIRIS imagery were converted to surface reflectance using ATCOR-4 (Richter and Schläpfer, 2002), similar to Roberts et al. (2015). The 2014 AVIRIS-NG imagery were converted to surface reflectance by JPL. To improve spectral consistency between surface reflectance retrievals, the imagery underwent further reflectance calibration to reduce spectral artifacts due to differences in atmospheric transmission estimation, as in Meerdink et al. (2019a). We ground-target calibrated the surface reflectance images against in situ ASD Field Spec 3 spectrometer measurements (Analytical Spectral Devices, Inc., Boulder, Colorado) of the United States Post Office roof in Goleta, California, which was within the extent of the original flightlines (Thompson et al., 2015). The 2014 AVIRIS-NG imagery was convolved to AVIRIS bands using a Gaussian model and full-width half-maximum values from AVIRIS. Bad bands affected by atmospheric water absorption and other features were removed from all images, leaving 178 AVIRIS bands in each image. We co-registered all images to National Agriculture Imagery Program (NAIP) orthophotos from 2014 using Delaunay triangulation and nearest neighbor resampling (NAD83, UTM Zone 11N), with initial pixel aggregation resampling to 7.5 m for the finer AVIRIS-NG imagery. The 1 m NAIP imagery was well-aligned to a reference 0.25 m lidar digital surface model basemap from which our tree polygons were based. Flightlines for each year were mosaicked, prioritizing the southern flightlines, and were subset to the common study area.
from Alonzo et al. (2016) (Fig. 1.1A). Based on visual inspection, there was at most a one pixel shift between the resulting mosaicked images and the NAIP basemap aggregated to 7.5 m pixels, with limited exceptions in more topographically complex areas. Example spectra from temporally invariant surfaces for each image are provided in the supplemental material (Fig. S1.2).

2.3. Tree species and turfgrass sampling

We used polygons from 19 of the mapped tree species from Alonzo et al. (2016) (Table 1.1). The tree crown polygons had been classified to 29 common tree species by fusing high pulse density airborne lidar (August 2010) and AVIRIS data (3.7 m; November 2010); specific details of acquisitions and processing are available in Alonzo et al. (2014). Due to the 7.5 m spatial resolution of the AVIRIS imagery used for this study, tree crown polygons of a given species class were aggregated into groups of polygons (i.e., tree patches) for crowns within 2 m of one another. Each tree patch retained for analysis had a minimum area of 225 m$^2$ (four 7.5 m pixels). The crown objects were further validated for tree species using Google Earth and Google Street View (Berland and Lange, 2017). For each species class, up to 50 of the largest groups of crown objects were selected, with the exception of the QUAG class, for which 100 of the largest groups of crown objects were selected due to their prevalence and large polygon areas. Ten of the 29 tree classes from Alonzo et al. (2014; 2016) were not retained due to small samples, mainly in small-crowned, sparsely-planted street tree species. This included all palms due to their small crown sizes.
**Table 1.1:** Selected tree species from Alonzo et al. (2014, 2016) used for analysis. EUGL includes other large eucalyptus species and PICA includes other large conifers not listed here. Tree leaf types are B = broadleaf and N = needleleaf. Common names and native areas are from the Urban Forest Ecosystems Institute (UFEI) SelecTree database (2019). Expected water needs for the South Coastal region are from Costello and Jones (2014) (L = Low, M = Medium). Mean tree patch area, LAI, and biomass C are derived from Alonzo et al. (2015, 2016) for our extracted sample polygons, weighted by tree polygon area.

<table>
<thead>
<tr>
<th>Species Code</th>
<th>Scientific Name</th>
<th>Common Name</th>
<th>Leaf Type</th>
<th>Native Region</th>
<th>Expected Water Needs</th>
<th>Mean Tree Patch Area (m²)</th>
<th>Mean LAI (m² m⁻²)</th>
<th>Mean Biomass C (kg m⁻²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CICA</td>
<td><em>Cinnamomum camphora</em></td>
<td>Camphor tree</td>
<td>B</td>
<td>China, Japan</td>
<td>M</td>
<td>365</td>
<td>4.23</td>
<td>8.72</td>
</tr>
<tr>
<td>CUMA</td>
<td><em>Cupressus macrocarpa</em></td>
<td>Monterey cypress</td>
<td>N</td>
<td>California</td>
<td>M</td>
<td>373</td>
<td>5.65</td>
<td>14.62</td>
</tr>
<tr>
<td>EUFI</td>
<td><em>Eucalyptus ficifolia</em></td>
<td>Red flowering gum</td>
<td>B</td>
<td>Australia</td>
<td>M</td>
<td>362</td>
<td>4.00</td>
<td>8.79</td>
</tr>
<tr>
<td>EUGL</td>
<td><em>Eucalyptus globulus</em></td>
<td>Blue gum eucalyptus</td>
<td>B</td>
<td>Australia</td>
<td>L</td>
<td>2047</td>
<td>5.30</td>
<td>17.98</td>
</tr>
<tr>
<td>FIMI</td>
<td><em>Ficus microcarpa</em></td>
<td>Indian laurel fig</td>
<td>B</td>
<td>Malaysia, Borneo</td>
<td>M</td>
<td>417</td>
<td>3.77</td>
<td>12.18</td>
</tr>
<tr>
<td>JAMI</td>
<td><em>Jacaranda mimosifolia</em></td>
<td>Jacaranda</td>
<td>B</td>
<td>Bolivia, Argentina</td>
<td>M</td>
<td>521</td>
<td>4.09</td>
<td>7.32</td>
</tr>
<tr>
<td>LIST</td>
<td><em>Liquidambar styraciflua</em></td>
<td>American sweetgum</td>
<td>B</td>
<td>Eastern US</td>
<td>M</td>
<td>357</td>
<td>4.41</td>
<td>9.55</td>
</tr>
<tr>
<td>MAGR</td>
<td><em>Magnolia grandiflora</em></td>
<td>Southern magnolia</td>
<td>B</td>
<td>South-eastern US</td>
<td>M</td>
<td>527</td>
<td>4.02</td>
<td>8.02</td>
</tr>
<tr>
<td>OLEU</td>
<td><em>Olea europaea</em></td>
<td>Olive tree</td>
<td>B</td>
<td>Mediterranean</td>
<td>L</td>
<td>396</td>
<td>4.21</td>
<td>6.72</td>
</tr>
<tr>
<td>PICA</td>
<td><em>Pinus canariensis</em></td>
<td>Canary Island pine</td>
<td>N</td>
<td>Canary Islands</td>
<td>L</td>
<td>490</td>
<td>6.57</td>
<td>20.90</td>
</tr>
<tr>
<td>PIPI2</td>
<td><em>Pinus pinea</em></td>
<td>Italian stone pine</td>
<td>N</td>
<td>Mediterranean</td>
<td>L</td>
<td>672</td>
<td>6.19</td>
<td>19.16</td>
</tr>
<tr>
<td>PIUN</td>
<td><em>Pittosporum undulatum</em></td>
<td>Victorian box</td>
<td>B</td>
<td>Australia</td>
<td>M</td>
<td>373</td>
<td>4.17</td>
<td>5.37</td>
</tr>
<tr>
<td>PLRA</td>
<td><em>Platanus racemosa</em></td>
<td>California sycamore</td>
<td>B</td>
<td>California (SB Native)</td>
<td>M</td>
<td>1368</td>
<td>4.87</td>
<td>11.22</td>
</tr>
<tr>
<td>POGR</td>
<td><em>Podocarpus gracilior</em></td>
<td>African fern pine</td>
<td>N</td>
<td>Eastern and southern Africa</td>
<td>M</td>
<td>411</td>
<td>4.20</td>
<td>9.38</td>
</tr>
<tr>
<td>QUAG</td>
<td><em>Quercus agrifolia</em></td>
<td>Coast live oak</td>
<td>B</td>
<td>California (SB Native)</td>
<td>L</td>
<td>6557</td>
<td>4.31</td>
<td>7.46</td>
</tr>
<tr>
<td>SCTE</td>
<td><em>Schinus terebinthifolius</em></td>
<td>Brazilian pepper</td>
<td>B</td>
<td>South America</td>
<td>M</td>
<td>332</td>
<td>4.03</td>
<td>5.92</td>
</tr>
<tr>
<td>SYAU</td>
<td><em>Syzygium australe</em></td>
<td>Brush cherry</td>
<td>B</td>
<td>Australia</td>
<td>M</td>
<td>510</td>
<td>4.02</td>
<td>9.62</td>
</tr>
</tbody>
</table>
We used pre-drought leaf area index (LAI; m² m⁻²) and aboveground dry-weight carbon biomass (kg) in a sensitivity analysis to examine whether trees with denser canopies or of larger sizes were more affected by drought, respectively. These parameters were calculated for each tree crown object from the airborne lidar and AVIRIS imagery used to create the tree crown object polygons and tree species classification; details are provided in Alonzo et al. (2015, 2016). We used one-sided leaf area, derived allometrically at the crown scale using separate equations for each leaf type. Tree crown objects did not overlap due to watershed segmentation, and leaf area was divided by crown area to estimate LAI. Aboveground dry-weight carbon biomass was estimated based on a scaling equation for each leaf type using lidar structural metrics. Biomass per tree crown area (kg m⁻²) was calculated by dividing aboveground dry-weight carbon per tree by tree crown area. We produced weighted mean estimates of LAI and biomass for each grouped tree patch, weighting by the area of the individual tree crowns within a patch.

Turfgrass polygons were delineated manually, mainly over recreational fields and parks. Due to the small sizes of housing lots in downtown Santa Barbara, residential lawns could not be reliably extracted with the imagery’s 7.5 m spatial resolution. We extracted 38 distinct turfgrass polygons and treated them similarly to the grouped polygons for the tree crown objects.
2.4. Spectral indicators of drought response

2.4.1. Spectral mixture analysis

We calculated endmember fraction images using Multiple Endmember Spectral Mixture Analysis (MESMA, Roberts et al., 1998) in Viper Tools 2 (Roberts et al., 2019a). We used a spectral library from Roberts et al. (2017) to estimate fractions of green vegetation (GV), non-photosynthetic vegetation (NPV; i.e., dead plant material, bark, litter), paved, roof, and soil endmembers. The spectral library was derived from AVIRIS image endmembers and reference endmembers of small surfaces, including sidewalks and composite shingle roofs, acquired with an ASD Field Spectrometer. The AVIRIS imagery was the same acquisition as our 2011 image in this study. Roberts et al. (2017) reduced the spectral library to 90 total endmembers with Iterative Endmember Selection (IES, Schaaf et al., 2011) and removal of degenerate spectra. For application in this study, we removed the three rock endmembers from the reduced library and spectrally corrected the library’s AVIRIS-derived endmembers, similar to our 2011 AVIRIS imagery. To find subpixel fractions, each of our images were unmixed with the resulting spectral library using a fusion of two-, three-, and four-endmember models (i.e., one-, two-, and three-endmember models plus shade). A more complex model was selected if it improved the RMSE by at least 0.7% (Roberts et al., 2012), and pixels that could not be modeled by the library with an RMSE \( \leq 2.5\% \) were left unmodeled. Endmember fractions were held to realistic limits of 0 to 100%, and photometric shade was limited from 0 to 80%. For a given pixel, only one endmember of a given class could be used for unmixing (e.g., only a single type of NPV endmember). The resulting fraction maps were shade normalized (Dennison and Roberts, 2003).
We extracted the resulting endmember fractions for each tree patch and turfgrass polygon, including all mixed pixels, and retained the pixels’ area contribution to each polygon. Area weights for each extracted pixel’s contribution to the overall polygon were kept due to the relatively large size of the 7.5 m pixels compared with the tree crown polygons. The weights were associated with the percent area of a given pixel that intersected with a polygon. For example, a pixel only half contained in the polygon would have 50% of the weight of a pixel that was fully contained in the polygon (‘extract’ function, R raster package). While the pixel weights did not correct for mixed pixels, they mitigated the influence of more mixed pixels on the periphery of canopies while retaining pixels where the pixel centroid was outside the polygon. Pixels that went unmodeled (complexity = 0) were removed, and we calculated weighted means for each endmember fraction for each polygon, weighting by pixel area contribution.

We assessed the accuracy of the MESMA fraction estimates produced by the spectral library by unmixing images of synthetic mixtures (Okujeni et al., 2013) for each image date. Synthetically mixed endmember fractions allow for estimating spectral library performance error at pixel scales by comparing controlled inputs of known endmember mixing fractions to spectral unmixing estimates of fractions (Wetherley et al., 2017, 2018). For the same locations in each image date, we selected three pure endmember pixels of each cover type (e.g., GV) and developed synthetic mixtures of all possible two-endmember combinations (e.g., GV vs. NPV) by mixing them linearly from 0 to 100% with 1% steps. For example, a synthetic mixture might use 75% GV and 25% NPV to produce a known mixed spectrum from pure GV and NPV endmembers (with no shade). This process produced 9090 synthetic mixing combinations for each image date. We unmixed the synthetic mixtures using
MESMA with the same spectral library, parameters, and steps as described above. The estimated MESMA fractions were compared to the known endmember fractions using linear regression, with 1:1 being a perfect match.

2.4.2. Vegetation indices

Reflectance values were extracted for each tree patch and turfgrass polygon with associated per-pixel fractional area weights, as in the MESMA fraction extraction. We calculated an area-weighted mean reflectance spectrum for each polygon using the reflectance values and the pixel weights. The resulting averaged spectra for each polygon were used as inputs for calculating vegetation indices (VIs). We chose VIs based on their relationships to vegetation structure and greenness, plant pigments, and water content (Table 1.2). To keep the direction of change consistent with other spectral indicators, MSI (Hunt and Rock, 1989) was multiplied by -1 (referred to as -MSI). Each grouped tree crown polygon and turfgrass polygon had a single value for each VI associated with it for each image date.
Table 1.2: Spectral vegetation indices tested in this study. \( \rho_{XXX} \) indicates the approximate AVIRIS band center wavelength (nm).

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Index Name</th>
<th>Equation in this study</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARI</td>
<td>Anthocyanin Reflectance Index</td>
<td>( \frac{1}{\rho_{550}} - \frac{1}{\rho_{704}} )</td>
<td>Gitelson et al. (2001)</td>
</tr>
<tr>
<td>CIrededge</td>
<td>Chlorophyll Index - Red edge</td>
<td>( \frac{\text{mean}(\rho_{753}, \rho_{763}, \rho_{772}, \rho_{782}, \rho_{792})}{\text{mean}(\rho_{694}, \rho_{704}, \rho_{714}, \rho_{724}, \rho_{733}, \rho_{743})} - 1 )</td>
<td>Gitelson et al. (2003)</td>
</tr>
<tr>
<td>MCARI</td>
<td>Modified Chlorophyll Absorption in Reflectance Index</td>
<td>( \frac{((\rho_{704} - \rho_{667}) - 0.2 \times (\rho_{704} - \rho_{550}))}{\rho_{704}} \times \frac{\rho_{667}}{\rho_{821}} )</td>
<td>Daughtry et al. (2000)</td>
</tr>
<tr>
<td>-MSI</td>
<td>Moisture Stress Index * - 1</td>
<td>( \frac{\rho_{1602}}{\rho_{821}} )</td>
<td>Hunt and Rock (1989)</td>
</tr>
<tr>
<td>NDVI</td>
<td>Normalized Difference Vegetation Index</td>
<td>( \frac{\rho_{802} - \rho_{667}}{\rho_{802} + \rho_{667}} )</td>
<td>Rouse et al. (1973)</td>
</tr>
<tr>
<td>NDWI</td>
<td>Normalized Difference Water Index</td>
<td>( \frac{\rho_{860} - \rho_{1244}}{\rho_{860} + \rho_{1244}} )</td>
<td>Gao (1996)</td>
</tr>
<tr>
<td>PRI512</td>
<td>Photochemical Reflectance Index 512 nm</td>
<td>( \frac{\rho_{530} - \rho_{511}}{\rho_{530} + \rho_{511}} )</td>
<td>Hernández-Clemente et al. (2011)</td>
</tr>
<tr>
<td>WBI</td>
<td>Water Band Index</td>
<td>( \frac{\rho_{899}}{\rho_{966}} )</td>
<td>Peñuelas et al. (1997)</td>
</tr>
</tbody>
</table>

2.4.3. Continuum removed absorption features

Continuum removal is a brightness normalization technique that fits a convex hull over the spectrum, with deviations that are related to absorption of the feature of interest (Clark and Roush, 1984). It is a band-depth measurement that can minimize brightness differences due to differing viewing and solar geometry and has been shown to be useful in mapping vegetation types and condition (Kokaly et al., 2003; Niemann et al., 2015; Tane et al., 2018). We used the average polygon reflectance values to calculate continuum removed absorption features for trees and turfgrass using ranges for features for forest cover types in Kokaly et al. (2003), namely a chlorophyll absorption feature centered at 680 nm and water
absorption features centered at 980 nm and 1200 nm (Table 1.3). The endpoints of each feature were averaged with the adjacent bands (three or four band average) to reduce the effects of sensor noise. For each continuum removed absorption feature, we extracted the maximum depth of the feature, the area of the feature below the continuum line, and the depth-normalized area of the feature, wherein all of the maximum depth values are scaled to zero and then the area is calculated.

Table 1.3: Continuum removed absorption features, modified from Kokaly et al. (2003), with AVIRIS band centers that were averaged at the endpoints of the continuum ranges.

<table>
<thead>
<tr>
<th>Absorption feature</th>
<th>Left continuum range band centers (nm)</th>
<th>Right continuum range band centers (nm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chlorophyll (680 nm)</td>
<td>521, 530, 540</td>
<td>743, 753, 763</td>
</tr>
<tr>
<td>Water (980 nm)</td>
<td>870, 879, 889, 899</td>
<td>1062, 1072, 1082</td>
</tr>
<tr>
<td>Water (1200 nm)</td>
<td>1091, 1101, 1110</td>
<td>1273, 1283, 1293</td>
</tr>
</tbody>
</table>

2.5. Statistical analyses

To evaluate year to year changes in fractional cover, we calculated mean endmember fraction values for the full study area for GV, NPV, paved, roof, and soil. We compared these values to fractions for all tree patches and turfgrass polygons.

We compared the drought response based on all spectral indicators across turfgrass and tree species, as well as grouped tree classes of broadleaf trees, needleleaf trees, trees native to Santa Barbara, and non-native trees (Table 1.1). Each grouped class used only extracted polygons for patches < 1000 m² for consistency in urban growing conditions, and QUAG was separated into groups greater and less than 1000 m² to test for differences in response. For each spectral indicator and vegetation class, we calculated the mean difference for 2014-2011 and 2017-2011 values across all extracted polygons of that class, weighting
the means by the areas of the polygons. Weightings were needed to characterize the effect of the drought of all canopy area rather than per individual tree: there was large variability in polygon areas, with different polygons contributing relatively different amounts to the overall change in a given class based on canopy area. We used one-tailed weighted t-tests to determine if there was a significant decrease in a spectral indicator from 2011 to 2014 and 2017. Sample sizes varied but were generally no more than 50 tree patches per class, except for a few of the grouped tree classes. For the grouped tree classes, a proportional sampling routine reduced the much larger sample sizes to approximately 50 patches, with tree species proportions determined by the number of patches of an individual tree species class out of the grouped class total. The sampling was without replacement and used a weighting to prioritize the larger patches. There were 50 iterations of sampling and one-tailed weighted t-tests, and the resulting p-values were averaged to mitigate outlier samples.

In addition, we compared the spectral indicator values of broadleaf vs. needleleaf trees and native vs. non-native trees directly within each year to determine if the drought response changed the hierarchy of reflectance characteristics between grouped tree classes. Retrieved spectral indicator values can be affected by many factors related to canopy architecture, leaf orientation, and visibility of surface background (Ollinger, 2011; Roberts et al., 2019b). For example, we might normally expect broadleaf trees to have greater near-infrared reflectance than needleleaf trees (Ollinger, 2011), but this could change with leaf-loss during drought. For this process we used two-tailed weighted t-tests with sampling and p-values calculated by the same routine as the one-tailed weighted t-tests.

We examined the sensitivity how the responses of spectral indicators differed depending upon the pre-drought LAI and biomass of urban trees. For each tree patch, we
linearly regressed the weighted average pre-drought LAI or biomass (independent variable) against the change in each spectral indicator from 2011 to 2014 and from 2011 to 2017 (dependent variable), and only a single indicator was used at a time for each regression equation (i.e., simple linear regression). For LAI, we used all tree patches, and for biomass, we used all tree patches with mean densities < 25 kg m\(^2\) to exclude a few large outliers. The relationships were evaluated within individual tree species as well.

Lastly, Pearson correlation was evaluated across all spectral indicators and years to assess similarity and consistency in response between the many indicators.

3. Results

3.1. Changes in fractional cover for full study area, turfgrass, and trees

The study area primarily lost GV and gained NPV cover during drought (Table 1.4). Mean GV percent cover declined from 45.0% in 2011 to 35.4% in 2014, and only partially recovered to 38.2% in 2017. While a small number of trees were removed during the drought (e.g., PIPI2 on Anapamu Street), the changes in GV were primarily due to canopy leaf loss and later regrowth. Mean NPV percent cover increased from 5.9% in 2011 to 8.4% in 2017, but the majority of the reductions in GV cover were replaced with increased non-vegetated surfaces. This was partly because street surfaces became more visible to the sensor with canopy leaf loss. However, estimated mean paved percent cover increased from 18.8% in 2011 to 31.8% in 2014, and decreased to 22.4% in 2017; roof and soil fractions were more stable but decreased in 2014, which is likely an erroneous change due to brightness substitution for an overestimate in paved fractions.
Within the extracted turfgrass polygons, mean GV percent cover declined from 79.3% in 2011 to 67.8% in 2014, and recovered to 77.2% in 2017. Unlike the fractions for the full study area, the majority of the GV cover lost in turfgrass was replaced by NPV and some soil cover during the drought. Mean NPV percent cover increased from 17.2% in 2011 to 25.9% in 2014, and decreased back to 15.6% in 2017. Mean soil percent cover increased from 1.7% in 2011 to 4.4% in 2014, and then further increased to 6.3% in 2017. Paved and roof fractions remained small throughout the drought.

Table 1.4: Percent green vegetation (GV), non-photosynthetic vegetation (NPV), paved, roof, and soil endmember fractions for each image date, stratified by: the full study area, turfgrass polygons only, all tree patches, all tree patches with area < 1000 m², and all tree patches with area < 500 m². For categories based on polygons or patches, percent is calculated as the mean weighted by area.

<table>
<thead>
<tr>
<th>Category</th>
<th>Year</th>
<th>GV</th>
<th>NPV</th>
<th>Paved</th>
<th>Roof</th>
<th>Soil</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full Study Area</td>
<td>2011</td>
<td>45.0%</td>
<td>5.9%</td>
<td>18.8%</td>
<td>16.5%</td>
<td>13.7%</td>
</tr>
<tr>
<td></td>
<td>2014</td>
<td>35.4%</td>
<td>7.1%</td>
<td>31.8%</td>
<td>14.2%</td>
<td>11.5%</td>
</tr>
<tr>
<td></td>
<td>2017</td>
<td>38.2%</td>
<td>8.4%</td>
<td>22.4%</td>
<td>17.0%</td>
<td>14.0%</td>
</tr>
<tr>
<td>Turfgrass Polygons</td>
<td>2011</td>
<td>79.3%</td>
<td>17.2%</td>
<td>0.6%</td>
<td>1.1%</td>
<td>1.7%</td>
</tr>
<tr>
<td></td>
<td>2014</td>
<td>67.8%</td>
<td>25.9%</td>
<td>0.3%</td>
<td>1.6%</td>
<td>4.4%</td>
</tr>
<tr>
<td></td>
<td>2017</td>
<td>77.2%</td>
<td>15.6%</td>
<td>0.2%</td>
<td>0.8%</td>
<td>6.3%</td>
</tr>
<tr>
<td>All Tree Polygons</td>
<td>2011</td>
<td>84.2%</td>
<td>5.1%</td>
<td>3.9%</td>
<td>3.8%</td>
<td>2.9%</td>
</tr>
<tr>
<td></td>
<td>2014</td>
<td>72.2%</td>
<td>12.0%</td>
<td>7.2%</td>
<td>5.6%</td>
<td>3.0%</td>
</tr>
<tr>
<td></td>
<td>2017</td>
<td>77.3%</td>
<td>9.2%</td>
<td>5.0%</td>
<td>4.6%</td>
<td>3.9%</td>
</tr>
<tr>
<td>Tree Polygons with Area &lt; 1000 m²</td>
<td>2011</td>
<td>72.7%</td>
<td>4.3%</td>
<td>10.0%</td>
<td>7.4%</td>
<td>5.6%</td>
</tr>
<tr>
<td></td>
<td>2014</td>
<td>63.4%</td>
<td>7.5%</td>
<td>16.1%</td>
<td>8.0%</td>
<td>5.0%</td>
</tr>
<tr>
<td></td>
<td>2017</td>
<td>67.9%</td>
<td>6.4%</td>
<td>11.0%</td>
<td>8.2%</td>
<td>6.5%</td>
</tr>
<tr>
<td>Tree Polygons with Area &lt; 500 m²</td>
<td>2011</td>
<td>69.5%</td>
<td>4.3%</td>
<td>11.5%</td>
<td>8.4%</td>
<td>6.3%</td>
</tr>
<tr>
<td></td>
<td>2014</td>
<td>60.4%</td>
<td>6.7%</td>
<td>18.3%</td>
<td>8.6%</td>
<td>6.0%</td>
</tr>
<tr>
<td></td>
<td>2017</td>
<td>65.4%</td>
<td>6.4%</td>
<td>12.1%</td>
<td>8.7%</td>
<td>7.5%</td>
</tr>
</tbody>
</table>

Changes in fractional cover varied by the size of the tree patches. For all areas of tree patches, GV was greatest in 2011, lowest in 2014, and partially recovered in 2017. Overall
GV percent cover was lower for smaller tree patches, likely due to greater influence of edge effects and greater mixing with other surfaces in the extracted pixels. NPV percent cover was lowest in 2011, greatest in 2014, and intermediate in 2017. NPV fraction was much greater for all tree patches rather than the smaller patches. Similarly, paved fraction was lowest in 2011, greatest in 2014, and then declined in 2017. In general, NPV fraction exceeded paved fraction only for the largest tree patches, and the proportion of GV fraction increased with the tree patch size (see supplemental material, Fig. S1.3). These patterns remained consistent through the drought, despite overall reductions in GV fraction and increases in NPV and paved fractions in 2014. Roof and soil fractions remained relatively small and constant during the drought across all tree patches, although roof fraction was greater for small patches than large patches.

Linear regressions between synthetic reference endmember fractions and MESMA estimated endmember fractions were best in GV and better in NPV than in paved, roof, or soil fraction estimates across image dates (Fig. 1.3). Slopes < 1 were expected based on past studies (Wetherley et al., 2017, 2018) and all regression p-values < 0.001. GV fraction estimates from MESMA were consistent with slopes close to 1 (0.97, 0.90, and 0.92) and high R² (0.92, 0.92, and 0.88) for all images (2011, 2014, and 2017, respectively); NPV fractions also had higher slopes (0.75, 0.65, and 0.96) and R² (0.73, 0.77, and 0.86). Non-vegetated endmembers were generally less accurate, potentially due to endmember substitution with variability in brightness, as has been shown in previous work (Roberts et al., 2012). For example, red tile roofs, which are common in Santa Barbara, are easily confused due to their spectral similarity to soil surfaces. Paved had slopes of ~0.4 and low R² (~0.2), as did Roof (slope = 0.3 - 0.4, and R² = 0.13 - 0.25) and Soil (slope = ~0.5, and R²
= 0.2 - 0.4). As a consequence, changes in fractions over time (Table 1.4) were most reliable for GV and, to a lesser degree, NPV, while non-vegetated endmember fraction estimates (Paved, Roof, and Soil) were less reliable overall.

3.2. Changes in distributions of green vegetation fraction by tree species and turfgrass

The distributions of GV fraction varied by tree species and turfgrass during the drought (Fig. 1.4). Many species had greatest values in 2011, smallest in 2014, and partly recovered in 2017. This temporal pattern included CICA, EUGL, OLEU, PLRA, PIPI2, and QUAG. Turfgrass also had this pattern, but with different year to year distributions, with a peak near 0.9 in 2011 that flattened in 2014 and shifted back to higher values in 2017. Some
tree species lost GV cover from 2011 to 2014 and nearly recovered in 2017, such as POGR, while others only minimally recovered in 2017, such as CUMA. A few species did not have any major year to year shifts in GV fraction and their distribution, including EUFI, FIMI, TISP, and ULPA.

Fig. 1.4: Area-weighted density plots of green vegetation (GV) fraction in 2011, 2014, and 2017 for each individual tree species class and turfgrass.

GV distributions shifted for groupings of broadleaf, needleleaf, native, and non-native trees: all had greatest values in 2011, smallest in 2014, and partly recovered in 2017 (Fig. 1.5). Broadleaf and non-native trees had more peaked distributions in 2014 than other years. Needleleaf and native trees had distributions in 2014 that were similarly peaked as in 2011, but with more symmetrical distributions in 2014 and left-skewed in 2011. This showed that in 2011, most of these trees had high GV fractions with a few lower GV fractions, but the majority of them had lower GV fractions in 2014. In general, the GV
distributions were more symmetrical in 2017 with values surrounded by 2011 and 2014, with the exception of needleleaf trees which had some progressively lower values as it did in 2011.

![Density plots of green vegetation (GV) fraction in 2011, 2014, and 2017 for broadleaf trees, needleleaf trees, native trees, and non-native trees.](image)

**Fig. 1.5**: Area-weighted density plots of green vegetation (GV) fraction in 2011, 2014, and 2017 for broadleaf trees, needleleaf trees, native trees, and non-native trees.

3.3. Changes in all spectral indicators by tree species and turfgrass

Turfgrass and nearly all tree species exhibited significant adjustments in spectral indicators at the height of the drought in 2014, but recovery in 2017 varied among species. **Fig. 1.6** shows p-values resulting from one-tailed weighted t-tests for differences between observed image dates, with mean values weighted by the areas of the polygons and differences between years calculated for each polygon. These tested if the mean difference between years (i.e., 2014 - 2011 and 2017 - 2011) was less than 0. Density plots for all spectral indicators, similar to **Figs. 1.4 and 1.5** for GV, are provided in the supplemental material, **Figs. S1.4-S1.37**.
In 2014, all tree species and turfgrass had at least 4 of 18 spectral indicators with significantly lower mean values (p < 0.05) than in 2011. Several vegetation types, including EUGL, PIP2, PLRA, QUAG > 1000 m², and SCTE, had significantly lower mean values in 2014 across all spectral indicators. Several other vegetation types had significantly lower mean values across all indicators except for the continuum removed 980 nm water feature’s maximum depth and/or the continuum removed 1200 nm water feature’s depth normalized area, including CICA, CUMA, MAGR, OLEU, PICA, and POGR. QUAG < 1000 m² was similar but had no significant difference in the continuum removed 680 nm feature’s depth.
normalized area as well. Turfgrass had significantly lower values in most spectral indicators, as did FIMI, JAMI, PIUN, and SYAU. ULPA had significantly lower values in 9 of the spectral indicators. EUFI, LIST, and TISP had the fewest spectral indicators (4 or 5) with significantly lower values. All the grouped tree classes had significantly lower mean values in 2014 than in 2011 for nearly all of the spectral indicators. Broadleaf trees and non-native trees had significantly lower values in GV, most of the VIs, and more than half of the continuum removed features’ measurements. Needleleaf trees had significantly lower mean values in all but one of the spectral indicators, except for the continuum removed 1200 nm water feature’s depth normalized area. Native trees were similar, except for the 980 nm water feature’s maximum depth.

In 2017, many, but not all, vegetation types had lower mean spectral indicator values than in 2011. In general, comparing to the response in 2014, fewer vegetation types had significantly lower mean spectral indicator values in 2017 than in 2011, and were less significant (often p < 0.05, whereas many were p < 0.01 for 2014). EUGL, PIPI2, QUAG > 1000 m², and SCTE still had significantly lower mean values across nearly all spectral indicators, as did CICA, CUMA, JAMI, OLEU, PICA, PIUN, and QUAG < 1000 m², but with a one or two more not significant spectral indicators. More than half of the spectral indicators for PLRA and POGR had mean values significantly less than in 2011, and LIST had 7 spectral indicators that were significantly less. The remaining vegetation types had very few (FIMI, MAGR, TISP, and Turfgrass) or no significant differences (EUFI, SYAU, and ULPA) across spectral indicators. Spectral indicators values in 2017 relative to 2011 varied by grouped tree class. Broadleaf trees and non-native trees had almost no spectral indicators with mean values in 2017 less than in 2011, except NDWI. Needleleaf trees still
had significantly lower mean values across the majority of the spectral indicators, with the largest exception in the 1200 nm water feature’s measurements. Native trees continued to have lower values across 8 of the spectral indicators.

When directly comparing spectral indicator values of broadleaf vs. needleleaf and native vs. non-native trees within image dates (2011, 2014, and 2017), broadleaf and needleleaf trees were not often significantly different, while native trees had significantly higher values than non-native trees for several spectral indicators. Fig. 1.7 shows significant p-values (p < 0.05) for two-tailed weighted t-tests comparing the means of spectral indicators for broadleaf and needleleaf trees and native and non-native trees on the left and right, respectively. Broadleaf trees never had significantly greater mean values than needleleaf trees across any of the spectral indicators for any date through the drought. In 2011, needleleaf trees had significantly greater mean values than broadleaf trees for nearly all measurements related to the 980 nm and 1200 nm water features, but not in any other spectral indicators. In 2014, needleleaf trees only had significantly greater values than broadleaf trees for the depth normalized areas of the 980 nm and 1200 nm water features, and in 2017, none of the mean spectral indicator values were significantly different. Native trees consistently had significantly greater mean values than non-native trees throughout the drought in GV, CIrededge, NDVI, and all the 680 nm chlorophyll feature’s measurements in 2011, 2014, and 2017. ARI and MCARI were greater in native trees than non-native trees in both 2011 and 2017, but were not significantly different in 2014. Native trees also had greater mean values than non-native trees in 2014 for the 1200 nm feature’s depth normalized area. Conversely, non-native trees had significantly greater mean values than native trees in 2014 for WBI and the 980 nm water feature’s maximum depth and area, and
in 2017 for the depth normalized areas of the 980 nm and 1200 nm water features. They did not have greater mean values than native trees for any spectral indicator in 2011. Several spectral indicators showed no significant difference at any point in time, namely -MSI, NDWI, PRI512, WBI, and the 1200 nm water feature’s maximum depth and area.

**Fig. 1.7:** P-values from two-tailed weighted t-tests for each image year (vertical axis) comparing: (left) broadleaf (sample n = 46) versus needleleaf (sample n = 51) trees; and (right) native (sample n = 50) versus non-native (sample n = 51) trees. Colored cells indicate significant differences in the weighted means (p < 0.05), with specific colors designating which grouped class had a greater value for a given spectral indicator (horizontal axis).

3.4. Sensitivity of drought response to tree LAI and biomass

Tree patches with greater pre-drought LAI showed greater response to the drought overall than tree patches with less pre-drought LAI. There were significant, negative linear relationships between the change in almost all spectral indicators during the drought and the amount of pre-drought LAI (*Table 1.5*). The slopes relative to 2011 were more negative in 2014 than in 2017, but for all regressions the $R^2$ was low ($< 0.1$), with lower values in 2017 than in 2014, implying that there was great variability in response between patches. When evaluating within individual species types, the linear trends were inconsistent, with some
positive, others negative, and others approximately zero depending on the tree species (data not shown).

Table 1.5: Slopes for simple linear regressions \((y = \text{slope} \times x + \text{intercept})\) with the pre-drought weighted mean LAI or pre-drought weighted mean biomass density \((x)\) and the weighted mean change in spectral indicator from 2011 to 2014 or 2017 \((y)\). LAI sample \(n = 810\), and biomass sample \(n = 789\). Slope significance levels: \(p < 0.05\) (*), \(p < 0.01\) (**), \(p < 0.001\) (***) and \(p > 0.05\) are considered not significantly different from zero slope and are left blank.

<table>
<thead>
<tr>
<th>Spectral Indicator</th>
<th>LAI (m² m⁻²)</th>
<th>Biomass (kg m⁻²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GV</td>
<td>-0.0283</td>
<td>***</td>
</tr>
<tr>
<td>ARI</td>
<td>-0.8323</td>
<td>***</td>
</tr>
<tr>
<td>CIrededge</td>
<td>-0.0192</td>
<td>***</td>
</tr>
<tr>
<td>MCARI</td>
<td>-0.0068</td>
<td>***</td>
</tr>
<tr>
<td>-MSI</td>
<td>-0.0274</td>
<td>***</td>
</tr>
<tr>
<td>NDVI</td>
<td>-0.0234</td>
<td>***</td>
</tr>
<tr>
<td>NDWI</td>
<td>-0.0092</td>
<td>***</td>
</tr>
<tr>
<td>PRI512</td>
<td>-0.0068</td>
<td>***</td>
</tr>
<tr>
<td>WBI</td>
<td>-0.0051</td>
<td>***</td>
</tr>
<tr>
<td>CR 680 nm max. depth</td>
<td>-0.0248</td>
<td>***</td>
</tr>
<tr>
<td>CR 680 nm area</td>
<td>-3.4746</td>
<td>***</td>
</tr>
<tr>
<td>CR 680 nm depth norm. area</td>
<td>-0.8782</td>
<td>**</td>
</tr>
<tr>
<td>CR 980 nm max. depth</td>
<td>-0.0037</td>
<td>***</td>
</tr>
<tr>
<td>CR 980 nm area</td>
<td>-0.3210</td>
<td>***</td>
</tr>
<tr>
<td>CR 980 nm depth norm. area</td>
<td>-0.0631</td>
<td>**</td>
</tr>
<tr>
<td>CR 1200 nm max. depth</td>
<td>-0.0058</td>
<td>***</td>
</tr>
<tr>
<td>CR 1200 nm area</td>
<td>-0.5665</td>
<td>***</td>
</tr>
<tr>
<td>CR 1200 nm depth norm. area</td>
<td>-0.2925</td>
<td>-1.0282</td>
</tr>
</tbody>
</table>

Pre-drought biomass often did not have significant relationships with the change in spectral indicators (Table 1.5). There were more spectral indicators with significant negative trends in 2014 (8) than in 2017 (6), and most of the spectral indicators with significant trends in 2014 and all in 2017 were associated with water: NDWI, WBI, CR 980 nm measurements, and CR 1200 nm measurements. Slopes for NDWI, WBI, and CR 980 nm area were negative and significant in both 2014 and 2017, and slopes were more negative in
2017 than in 2014. Similar to LAI, $R^2 < 0.05$ for all regressions with biomass, with much lower values in 2017 than in 2014. The linear trends with biomass within individual species were inconsistent, with variable slopes depending on the tree species (data not shown).

3.5. Comparison of spectral indicators

Many of the spectral indicators were related and shifted correspondingly in response to drought conditions (Fig. 1.8). Almost all spectral indicators were positively correlated as was intended for consistency in interpretation; the only exceptions were the CR 1200 nm depth normalized area’s correlations with MCARI and PRI512 ($R \approx -0.04$ in both cases). GV fraction had positive relationships with many spectral indicators, including expected near-linear trends with NDVI and the continuum removed 680 nm chlorophyll feature’s area. Its relationships with MCARI and PRI512 were more non-linear, especially in areas of healthy, less-mixed turfgrass. NDVI responded to changes in drought condition and the continuum removed 680 nm feature’s maximum depth and area had a strong linear relationship with NDVI. The 980 nm and 1200 nm continuum removed water features’ areas and maximum depths generally showed more similar shifts to other spectral indicators than did the depth normalized areas, which were relatively uncorrelated with the other spectral indicators. In general, the 980 nm water feature was more sensitive to changes between years than the 1200 nm water feature.
Fig. 1.8: (A) Scatter plot matrix for a selection of spectral indicators. Colors indicate years; shapes indicate vegetation type. Only Turfgrass and QUAG are included for clarity. (B) Pearson’s correlation coefficient (R value) matrix for spectral indicators from all sampled polygons for all dates. Orange cells are closer to 0, and purple cells are closer to 1. No spectral indicators were strongly negatively correlated.
4. Discussion

4.1. Utility of spectral indicators for measuring drought response

To characterize urban vegetation response to drought, we used spectral mixture analysis, broad and narrow-band vegetation indices, and continuum removed absorption features from imaging spectroscopy to track changes in plant pigments, canopy water, and vegetation structure. The spectral indicators were generally consistent in quantifying significant changes from 2011 to 2014 and from 2011 to 2017 (Fig. 1.6). Many spectral indicators were positively correlated (Fig. 1.8), indicating consistent spectral manifestation of plant response under drought conditions. For example, continued loss of canopy water content, shown in indicators related to water, will co-occur with reductions in leaf health and density, apparent in greenness and pigment indicators (Perry and Roberts, 2008). At the same time, vegetation can experience water stress without changes in greenness VIs (Asner et al., 2004); therefore, water indicators may be preferable in densely vegetated areas, but greenness indicators can be instructive where green canopy overall declines. The spectral indicators used here do not only respond to drought conditions, and there are potentially other factors, such as pests, diseases, pollution, and nutrient deficits, that may have caused changes during our study period (Roberts et al., 2019b). We do not anticipate these being large factors in our study region, although they may be in other urban areas nearby (e.g., shot-hole borer in the Los Angeles metropolitan area; McPherson et al., 2017).

Through spectral unmixing, we were able to monitor shifts from GV to NPV, paved, or soil fractions during the drought (Table 1.4). Spectral mixture analysis has been used to monitor vegetation drought response in California, including natural chaparral vegetation in the Santa Barbara region (Coates et al., 2015) and agriculture in the Central Valley (Shivers...
et al., 2019). Based on our assessment with synthetic mixtures, our observed trends in GV fractions were reliable across samples, as were trends in NPV, albeit less strongly, whereas paved, roof, and soil fraction trends were often confused (Fig. 1.3). In previous studies in our study area, bare soil and red tile roofs have been shown to be spectrally similar and difficult to distinguish, and soil surfaces have been overestimated relative to impervious surfaces (Roberts et al., 2012; Wetherley et al., 2017). We used the same spectral library in all images and did not restrict selected endmembers per pixel due to the subtle shifts in spatial registration between images. This potentially allows for endmember switching between dates, which may artificially change the derived fractions due to brightness differences between selected endmembers (Coates et al., 2015). We observed endmember switching between paved, roof, and soil fraction estimates between image dates, but this had minimal effect on our estimates of green vegetation fraction, which was the variable on which we based our drought response analysis. We also shade-normalized all image fractions, which partially mitigated brightness differences.

With our suite of VIs, we were able to quantify simultaneous adjustments of vegetation greenness (e.g., NDVI), water content (e.g., NDWI), and pigments (e.g., ARI) as vegetation canopy cover changed through the drought (Table 1.2; Fig. 1.6). The VIs we selected have been used previously to monitor drought sensitivity in natural vegetation in California, including NDVI (Dong et al., 2019), MSI (Hunt and Rock, 1989), and WBI (Claudio et al., 2006). VIs can have variable relationships with leaf chlorophyll content and LAI (Degerickx et al., 2018), and likely respond to other factors that may or may not be related to drought, such as nitrogen deficits (Perry and Roberts, 2008). While we observed decreases in all of our spectral indicators, some VIs related to pigments may in fact increase
in response to environmental stress, such as ARI, which would suggest an increase in pigment content (Gitelson et al., 2001; Roberts et al., 2019b). Narrow-band VIs can also be highly sensitive to precise band-wavelength selection (Hernández-Clemente et al., 2011), and the signal of interest can be confounded by surface mixing and lighting geometry (Roberts et al., 2019b). In general, compared with the mixed tree polygons, the turfgrass signal should be less variable and more directly reflecting vegetation condition.

The continuum removed absorption features were able to show trends in chlorophyll content and water status in addition to and in support of the VIs. While these indicators have not been previously used to directly quantify drought response in past studies, they have been shown to be reliable in tracking water status in California vegetation (Pu et al., 2003). Most of the continuum removed absorption features’ measurements had similar patterns to the VIs. In general, the 680 nm feature was well-correlated with NDVI (Fig. 1.8). This was expected since both are designed to track plant greenness based on a decrease in red reflectance relative to nearby wavelengths (Rouse et al. 1973; Kokaly et al., 2003). At the same time, the 980 nm and 1200 nm water features were able to highlight differences in needleleaf and broadleaf trees’ condition prior to the drought that did not persist after the drought, while water-related VIs were unable to find these differences (Fig. 1.7). In general, continuum removed absorption features may provide added value to accompany existing VIs, many of which rely on similar spectral features to quantify vegetation condition (Pu et al., 2003, Roberts et al., 2019b). There are many other measurements we could have drawn from the features, including slopes, widths at half depth, and areas in different parts of the absorption features (Niemann et al., 2015). The depth normalized measurements for the 980 nm and 1200 nm features did not correlate well with the other indicators, including each
other. These measurements may be overly sensitive to subtle changes in calibration between images and would require further testing, although some of them have been shown to be robust for monitoring canopy status in conifer forests (Niemann et al., 2015).

4.2. Drought response of turfgrass

Turfgrass areas were significantly affected in 2014, but after the drought abated in 2017, most recovered to near their pre-drought condition, although soil cover slightly increased (Table 1.4; Fig. 1.6). From 2011 to 2014, turfgrass showed significant changes in almost all spectral indicators, but only showed change in the depth normalized areas of the water features in 2017. Turfgrass in southern California is reliant on irrigation to maintain year-round greenness (Pincetl et al., 2019), and turfgrass will brown if irrigation is limited for as short as six weeks (Kaufmann, 1994). Under non-drought conditions, urban vegetation in nearby Los Angeles can have annual evapotranspiration rates comparable to dense meadows in Owens Valley, which has the highest evapotranspiration rate of any native ecosystem in California (Litvak et al., 2017a). In Los Angeles, turfgrass is responsible for 70% of all vegetation evapotranspiration (Litvak et al., 2017a), and 54% of single-family residential water is used to irrigate landscaping (Mini et al., 2014). In most regions of the US, outdoor water use is 50-75% of total residential water use, and increases in xeriscaping and wastewater recycling are likely needed to sustain water resources with urban expansion (Milesi et al., 2005).

Generally, the swift post-drought recovery suggests that, given sufficient future watering and maintenance, turfgrass areas will have limited memory of drought conditions, much more so than most tree species. Our sampled turfgrass areas were of parks and
recreational fields, which may be of high value in the community (Harris et al., 2018), leading us to anticipate recovery. For example, Quesnel et al. (2019) also found that non-residential turfgrass green cover recovered after the height of the 2012-2016 drought in Redwood City, California. In addition, turfgrass recreational areas often have higher evapotranspiration during the most productive times of the year compared with residential areas (Peters et al., 2011). We could not readily assess residential lawns due to our imagery’s spatial resolution, but we might expect the fate of residential turfgrass areas to be more variable than parks and recreational fields, based on owners’ personal potential for investment (Milesi et al., 2005; Harris et al., 2018). We did not include golf courses in our sample, which would have much more intensive management practices (Qian and Follett, 2002) and remained greener than other turfgrass areas throughout the drought. Turfgrass species may also vary by land use, leading to different drought responses (Ervin and Koski, 1998).

4.3. Drought response of trees

4.3.1. Summary of observed patterns across all trees

Several species we assessed here are among the most common in urban coastal California (e.g., CICA, EUGL, JAMI, LIST, MAGR, PICA, QUAG) and statewide (e.g., LIST, MAGR) (McPherson et al., 2016), and changes in their viability would have substantial effects on canopy cover in California cities (McPherson et al., 2018). Of these common species, EUGL was especially impacted in our results, suggesting it may not be robust in the face of future hot droughts in our study area. Many others of these species were
also strongly affected in our results (CICA, JAMI, QUAG, and PICA), but LIST fared well overall and MAGR recovered from being strongly impacted at the drought’s height in 2014.

Our results showed that during the drought, green tree canopy decreased and trees with greater LAI were more impacted overall, although there was wide variability in response between different tree patches and species. Since the fraction of paved surface cover visible from above increased as tree canopy GV fraction declined, tree shading was likely reduced, which would result in an overall increase in land surface temperature due to its negative relationship with percent vegetation cover (e.g., Weng et al., 2004; Roberts et al., 2015; Wetherley et al., 2018). Tree canopies with the greatest leaf area would normally provide the some of the greatest benefit in ecosystem services (Nowak et al., 2008), and at sufficient percent canopy cover, trees can reduce air temperatures tens of meters beyond the extent of their canopies (Ziter et al., 2019), with even more substantial reductions in local surface temperature (Gillner et al., 2015). Both of these benefits diminish during drought, but vary among tree patches based on our results. It is unsurprising that we observed high variability as drought’s impacts on tree growth in urban areas can be both species and site specific (McCarthy and Pataki, 2010; Gillner et al., 2014; Bialecki et al., 2018). Trees grown at more impervious sites have been shown to be more affected by drought than those at less impervious sites (Savi et al., 2015), and different tree species might be expected to have different responses due to variations in hydraulic anatomy and water use strategies (Carnicer et al., 2013). There is also likely considerable within-species variability in potential resilience to drought conditions (Bréda et al., 2006; McCarthy and Pataki, 2010), but this form of assessment was beyond the scope of this study. Overall, the drought’s effects on urban vegetation here were relatively small compared with the effect on natural vegetation.
in other parts of California, such as the catastrophic mortality observed in Sierra Nevada forests (Tane et al., 2018) and canopy water content, greenness, and productivity losses in forest canopies statewide (Asner et al., 2016; DuBois et al., 2018; Dong et al., 2019).

Although we found that tree patches with greater pre-drought LAI were generally more affected by the drought, tree patches with higher biomass were often not more affected than those with lower biomass (Table 1.5). All the regressions with changes in spectral indicators had very low $R^2$ values, implying large variability for individual tree patches. The regressions were not found to be consistent within species, likely due to small sample sizes in some species and inherent site-specific variability. The spectral indicators are designed to monitor canopy structure, leaf density, and condition, and so these trends with pre-drought LAI are expected (Ollinger, 2011; Roberts et al., 2019b). Although we approximated tree size with biomass, we were unable to assess the effect of individual tree size on drought response due to our imagery’s spatial resolution and the use of grouped tree patches rather than individual stems. Globally, larger trees can be more affected by drought due to their increased vulnerability to hydraulic stress as well greater radiation exposure and evaporative demand on their larger canopies (Bennett et al., 2015). To recover from drought, larger trees require greater investment of resources to replace a larger volume of cavitated xylem, which can lead to their increased mortality relative to smaller trees (Trugman et al., 2018).

However, some large trees have been shown to have quite low evapotranspiration in urban settings (Pataki et al., 2011). Our results show that while there are significant relationships between pre-drought LAI and spectral response, the high variability in responses (low $R^2$) suggests that LAI is not the dominant factor in urban trees’ fate during a drought.
Lastly, we used groups of crowns (i.e., tree patches) rather than standalone trees, and we found that, in general, smaller patches had lower GV fraction values, while larger patches had higher GV fractions (Table 1.4; Fig. S1.3). This is related to the size of the pixels (7.5 m) relative to the size of the tree patches (minimum 225 m²). All things being equal, larger patches will have higher values in the spectral indicators since the tree canopy will occupy more of a given pixel, reducing edge effects. This is mitigated by using differences between years, and direct comparisons within the same year may not be adequate to quantify differences in tree condition. It may also be that larger patches could have more modest change relative to individual street trees, partly because larger patches are more effective at moderating air temperatures (Ziter et al., 2019). Moreover, street trees experience greater stresses than trees in parks and natural areas, including soil compaction, root confinement, and increased heat and radiative flux from the asphalt surfaces (Gillner et al., 2014; Savi et al., 2015). Street trees can also have faster turnover than in forests (Smith et al., 2019).

4.3.2. Drought response by tree species

Of all tree species, EUFI and TISP were least affected by the drought overall according to the spectral indicators. Both are broadleaf species and had 4 spectral indicators change (p < 0.05) from 2011 to 2014, including ARI, MCARI, and 980 nm depth normalized area, but no spectral indicators change from 2011 to 2017. It is unlikely these trees were strongly affected since none of the other prominent greenness and water spectral indicators showed significant change. Unless otherwise noted below, descriptions of tree characteristics are from the Urban Forest Ecosystems Institute’s SelecTree database (2019).
EUFi is a small-statured tree native to Western Australia and is widely planted in California urban areas. It is considered to tolerate dryness and drought conditions and is evergreen with a relatively dense canopy, typically planted in Santa Barbara as an ornamental street tree. In contrast to our study, May et al. (2013) found that during a drought in Melbourne, Australia, EUFI did not stand out as exceptionally healthy among other tree species, although it was not in severe decline. TISP is also common in California cities, and is a medium-sized tree with compound leaves that is native to Bolivia and southern Brazil. It can tolerate a variety of soils and dryness conditions, and in Santa Barbara it is commonly planted as a shade tree over parking lots and along streets. Roman et al. (2015) found that TISP was part of a list of drought-tolerant species planted in East Palo Alto, California, but it was a very small percentage of planted trees and the list included species that performed well in their study but were strongly affected by drought in our study (e.g., OLEU, QUAG).

FIMI, LIST, MAGR, SYAU, and ULPA were moderately to strongly affected by the drought in 2014 but largely recovered in 2017 across spectral indicators. From 2011 to 2014, all showed significant change in NDWI, ARI, and 980 nm depth normalized area, and most showed change in CIrededge, MCARI, NDVI, and several other spectral indicators. From 2011 to 2017, only NDWI and WBI were consistent in showing significant differences across the three species (FIMI, LIST, and MAGR) that still showed changes. None of these species are native to California, and all but LIST generally require moist soil. FIMI and MAGR are both common California street trees that provide extensive shade with large, evergreen canopies. MAGR is notable in that it was very strongly impacted across almost all spectral indicators in 2014, but had nearly fully recovered in 2017. The others were not as comparatively affected in 2014. LIST is a large broadleaf tree that can tolerate a wide range
of soil types and conditions, and it had significant change in only a few of indicators in 2014 (5) and 2017 (7). SYAU is evergreen broadleaf and can be found in wide variety of shapes, and can be hedged, although this was not the case in our sample data. ULPA can produce moderate shade and is a medium-sized tree, and is the only one of these species listed as drought tolerant in the SelecTree database (2019).

The majority (12 of 19) of the tree species were strongly affected in 2014 and were still affected in 2017 across most spectral indicators to varying degrees, but needleleaf trees were universally affected (CUMA, PICA, PIPI2, and POGR) while broadleaf trees were not (Fig. 1.6). Needleleaf trees also had significantly greater mean values than broadleaf trees for the water related continuum removed absorption features’ measurements in 2011, but were not significantly different by 2017 (Fig. 1.7). Broadleaf trees had a greater number of species than needleleaf trees in our study, so it is perhaps unsurprising that they had a wider variety of responses, but several of the broadleaf species that are considered to be drought tolerant (e.g., EUGL, OLEU, PLRA, QUAG) were also strongly affected. At the same time, there are several reasons conifers may generally undergo more significant response than broadleaf trees during drought, including their earlier stomatal closure at high temperatures and greater difficulty repairing embolisms in xylem (Carnicer et al., 2013). However, our sampled needleleaf species are native to dry climates and might be expected to tolerate drought compared to most broadleaf trees. Also, since our PICA class was mixed with less drought-tolerant conifers, Pinus canariensis alone may have been less affected than our sampled polygons. Finally, it is important to note that declines in greenness (such as those observed here) are often indicators of biomass loss but not necessarily mortality. In some
cases, reductions in needles or LAI may in fact be adaptive responses to drought to reduce water loss and later mortality risk (Van der Molen et al., 2011).

Both of our native tree species (PLRA and QUAG) had overall strong responses to the drought across the majority of spectral indicators. QUAG was by far the dominant tree species in our study area and can normally withstand dry conditions. A study of nearby natural areas showed limited responses of *Quercus spp.* to the drought, especially compared to chaparral species, but showed increasing impacts of drought later in summer (Coates et al., 2015). Much of the native natural vegetation near the study area is dominated by chaparral shrublands rather than trees, and research has shown shifts in chaparral cover types and species during the drought (Meerdink et al., 2019a), which can significantly impact water and carbon cycling (Asner et al., 2016; DuBois et al., 2018). In contrast to QUAG, PLRA requires consistent groundwater access at depth and is relatively insensitive to depletion of shallow soil moisture (McCarthy and Pataki, 2010; Bijoor et al., 2012). McCarthy and Pataki (2010) found that PLRA as street trees had greater whole tree transpiration and sap flow than PLRA at natural and irrigated sites, but these street trees likely had access to subsurface water. PLRA has also been shown to use much more water than the non-native needleleaf PICA, which can withstand low shallow soil moisture conditions without access to water at depth (McCarthy and Pataki, 2010).

In comparison to native trees, non-native trees were more varied and were overall less responsive to drought (Fig. 1.6). Similar to other cities in California, the non-native trees in our study are from arid to mesic climates, leading to an array of responses (Pataki et al., 2011; McPherson et al., 2017). However, native trees often had greater spectral indicator values than non-natives (Fig. 1.7). This suggests that while the native trees may have
exhibited strong changes, they maintained greater green canopy than the non-natives overall. This was irrespective of tree patch size, which we initially tested by separating QUAG into two classes in Fig. 1.6 because smaller patches would generally have smaller proportions of the green tree canopy of interest in the extracted pixels. Since non-natives are primarily found near built surfaces, we might also expect non-natives to have more pavement background than natives and thus lower greenness values. However, QUAG in more natural settings in our study primarily had NPV in the background as opposed to green low vegetation due to summertime senescence of understory non-irrigated grasses. Changes in PLRA may be more connected to understory greenness since naturally-growing PLRA is primarily set in riparian areas with year-round green shrubs (McCarthy and Pataki, 2010), but changes in native trees overall were primarily due to tree canopy changes in QUAG due to its much larger area. Although non-native trees had lower spectral indicator values overall than native trees, many non-native trees were more likely to require irrigation than were native trees. Dry climates do not usually limit urban tree diversity (Jenerette et al., 2016) and in general, it is possible that non-native tree responses overall were tempered because they received more irrigation during the drought, while native trees did not under the assumption that were better adapted to dry conditions.

5. Conclusions

Our analyses of spectral indicators revealed a diversity of drought response in urban vegetation, and we considered several aspects of potential change. First, we examined how surface cover varied through time during the drought. The full study area’s GV cover declined from 45.0% in 2011 to 35.4% in 2014, and partially recovered to 38.2% in 2017. In
2014, pre-drought GV cover was primarily replaced by paved surfaces, largely due to leaf loss in street tree canopies, and NPV cover increased slightly as well. Second, we compared how drought response varied spectrally among urban tree species and between trees and turfgrass. All types of vegetation exhibited a negative shift in four or more spectral indicators (p < 0.05) in 2014, but the magnitude and type of change was variable among vegetation types. We observed the largest changes between 2011 to 2014, and partial recovery after the drought ended in 2017. Turfgrass declined strongly in 2014 but had recovered in 2017, whereas the majority of tree species did not fully recover by that time. Needleleaf trees continued to exhibit spectral changes resulting from drought in 2017, whereas broadleaf trees had mostly recovered. Similarly, native trees had greater continued response in 2017, while non-native trees had mostly recovered. Third, we explored how drought response varied by LAI and biomass in trees. Across all tree species, greater pre-drought LAI was correlated with larger decreases in spectral indicators during the drought, whereas greater pre-drought biomass was not correlated with larger decreases in most spectral indicators; however, both of these sets of relationships were highly variable, with \( R^2 < 0.1 \) for all relationships. Lastly, we examined how different spectral indicators captured the effects of the drought on vegetation. Most of the spectral indicators were correlated with one another (R > 0.4), with the most prominent exceptions being the depth normalized measurements of the 980 nm and 1200 nm absorption features. Many of the relationships between spectral indicators were linear, although some had nonlinear patterns (e.g., NDVI vs. PRI512).

This study illustrates the potential of repeat airborne imaging spectroscopy to track drought response of urban tree species and turfgrass, and it was only possible in its existing
form thanks to the availability of lidar-derived products from before the drought. We found simultaneous changes in spectral indicators associated with leaf pigments, canopy structure, and water content in urban trees and turfgrass during drought. However, the changes differed by tree species and vegetation type, indicating a variety of different adjustments and adaptive responses of urban plants. By evaluating how response varied by tree species during an unusually severe drought event, we also observed some drought responses and initial post-drought recovery that were not always consistent with our expectations based on published reports of species drought tolerances. For example, while we found needleleaf trees to have greater response than broadleaf trees, there were many broadleaf tree species that were also strongly impacted by the drought despite their purported drought tolerance (e.g., EUGL, OLEU). This suggests that remote sensing of spectral indicators over a range of species across a city, such as that reported here, could be of value to urban forest management, especially as cities experience increases in the severity and duration of hot and dry climate conditions.

**Acknowledgements**

This study was supported by a NASA Earth and Science Space Fellowship (80NSSC18K1325) and the Belgian Science Policy Office in the framework of the STEREO III Program – Project UrbanEARs (SR/00/307). Special thanks to JPL for providing the AVIRIS and AVIRIS-NG imagery; Daniel Schläpfer and Natalia García Villaseñor at ReSe Applications GmbH and Alex Feldwinn at UCSB Department of Geography for assistance with ATCOR-4; Susan Meerdink, Erin Wetherley, and Michael Allen for code, suggestions,
and feedback; and the two anonymous reviewers for constructive comments that greatly improved the manuscript.
Chapter 2: Seasonal and interannual dynamics of vegetation response to drought in a California urbanized area

with Michael Alonzo, Susan K. Meerdink, Michael Allen, Christina L. Tague, Dar A. Roberts, and Joseph P. McFadden
Abstract

The effects of drought can manifest in vegetation across an array of physiological responses and time scales. In metropolitan areas, vegetation provides shading and cooling during hot and dry conditions, but these benefits can be reduced with drought. While many studies have evaluated interannual vegetation drought responses, seasonal responses have rarely been studied at the same time, especially in cities that regularly experience seasonal drought (e.g., in Mediterranean climates). Here, we evaluated seasonal and interannual drought responses across the dominant types of urban trees and grasses in the Santa Barbara, California, USA metropolitan area, using Landsat imagery acquired 2010-2019 and repeat Airborne Visible Infrared Imaging Spectrometer (AVIRIS) imagery acquired 2013-2015. To track vegetation types, we produced a random forest classification from 4 m AVIRIS-Next Generation (AVIRIS-NG) imagery acquired in June 2014 (overall accuracy = 86%; kappa = 0.85), thresholding to >90% pure pixels for most vegetation types in the coarser time series imagery. We monitored drought from Landsat imagery using the Normalized Difference Vegetation Index (NDVI) and the difference in land surface temperature ($\Delta$LST) between vegetation and developed/impervious surfaces, as well as from AVIRIS using equivalent water thickness (EWT). NDVI was lower and $\Delta$LST was closer to zero during drought years but they were seasonally correlated for only some vegetation types. Changes in EWT revealed seasonal adjustments by vegetation that were not readily apparent in the NDVI time series. Overall, EWT varied nonlinearly with NDVI within a single image and varied linearly when comparing median EWT and NDVI values across dates. However, the slopes of these relationships were dependent on vegetation type, suggesting that EWT and NDVI are unlikely to be linearly correlated across vegetation types. To attribute vegetation
response to drought duration during different seasons, we examined the correlations of NDVI and ΔLST to the Standardized Precipitation Evapotranspiration Index (SPEI) calculated over a range of time spans. NDVI and ΔLST were most strongly correlated with SPEI during summer for most vegetation types, except for annual grass NDVI (winter). Annual grass was generally correlated with SPEI at spans ≤12 months, whereas trees and turfgrass were commonly correlated with SPEI at spans >12 months in addition to seasonal time spans. This study describes interactions between drought duration and response in different types of urban vegetation, and demonstrates the benefits of using multiple, functionally-distinct remote sensing variables (NDVI, ΔLST, and EWT) in tandem to quantify changes in vegetation canopy condition during drought.
1. Introduction

Drought is a phenomenon that unfolds over time, affecting vegetation on time scales from rapid-onset “flash drought” events (Otkin et al., 2018) to megadroughts spanning years to decades (Williams et al., 2020). Vegetation has a variety of responses to drought, such as reductions in growth and primary production, adjustments in phenology, modifications in nutrient cycling, and increased mortality (Bréda et al., 2006; Van der Molen et al., 2011; Schlesinger et al., 2016; Trugman et al., 2018), but these effects do not necessarily take place at the same time scales across all types of vegetation, even within a single drought-affected region (e.g., Paz-Kagan and Asner, 2017; Rita et al., 2020). With anthropogenic influence increasing the intensity and likelihood of recent and future drought events (Diffenbaugh et al., 2015; Williams et al., 2015), it has become increasingly important to evaluate the impacts of drought at a range of temporal scales (Vicente-Serrano et al., 2010; 2013). This is especially needed in climatic regions that experience interannual droughts while regularly undergoing seasonal water limitations.

In Mediterranean climates, where the majority of precipitation falls during the winter and summers have little or no rainfall, vegetation regularly experiences both seasonal and interannual droughts, which are expected to intensify with climate change (Hanson and Weltzin, 2000). In California, a Mediterranean climate covers much of the coastal zone of the state, which coincides with areas where most of the human population resides. Overlaid on this seasonally dry climate, during 2012-2016 California experienced one of the most severe droughts in its modern history (Lund et al., 2018). Given the increasing potential for future severe droughts in the state and Mediterranean regions in general (Diffenbaugh et al., 2015; Williams et al., 2015), there has been extensive research regarding how the 2012-2016...
drought affected vegetation in natural and agricultural areas (e.g., Asner et al., 2016; Shivers et al., 2018; Okin et al., 2018; Dong et al., 2019), but the timing of the effects on vegetation in urban areas remains relatively understudied (e.g., Pincetl et al., 2019; Quesnel et al., 2019).

During the 2012-2016 drought, many cities in California reduced water use (Palazzo et al., 2017), with noticeable impacts on urban trees and turfgrass (Quesnel et al., 2019; Miller et al., 2020). During hot and dry conditions such as drought events, air and surface temperature cooling through shading and evapotranspiration represent important ecosystem services of urban vegetation (Shashua-Bar et al., 2009; Manickathan et al., 2018; Ziter et al., 2019). Concerns about maintaining these benefits as part of urban heat-reduction strategies (Norton et al., 2015) has led to increasing research into ‘climate ready trees’ (McPherson et al., 2018) and lawn-replacement programs (Pincetl et al., 2019). Despite this, the timing, magnitude, and persistence of drought effects on existing types of urban vegetation remain unclear. In natural areas adjacent to urbanized regions in California, trees and grasses in oak-savannas have differing responses to annual patterns of water availability, with grasses senescing during the summer and evergreen oak trees often maintaining green canopies through deeper water access (Gamon et al., 1995; Baldocchi et al., 2004). Additional differences in drought responses may occur in urbanized areas where much of the vegetation cover is irrigated over the summer (Litvak et al., 2017a; Quesnel et al., 2019), there are many types of exotic and non-native vegetation (Alonzo et al., 2014; Avolio et al., 2020), and there are potentially widely varying microclimatic effects, including those related to impervious surface cover (Leuzinger et al., 2010; Savi et al., 2015; Manickathan et al., 2018).
Accounting for the varying time scales of vegetation drought sensitivity in an urban area requires both a synoptic and a local view of changes, both of which can be characterized through remote sensing data. However, the inherent trade-offs in remote sensing data between spatial and temporal resolution make it challenging to both generate finely-resolved maps and track dense time series of urban vegetation with a single data source (van der Linden et al., 2018). Mapping in urban areas often requires high spatial resolution data to account for the fine-scale heterogeneity in urban materials (Cadenasso et al., 2007), and it benefits greatly from imaging spectroscopy (i.e., hyperspectral imagery) to effectively discriminate different types of vegetation and urban materials (Herold et al., 2004). The availability of these types of remote sensing data is primarily limited to airborne sensors with relatively few acquisitions, inhibiting the temporal resolution that is necessary to track drought effects (Ustin et al., 2004; van der Linden et al., 2018). Sufficiently dense temporal observations are more readily achieved with broadband spaceborne monitoring satellites such as Landsat or Sentinel-2 (van der Linden et al., 2018). The use of multiple forms of remote sensing data sources in tandem is therefore needed to investigate the temporal aspects of urban vegetation’s response to drought.

The biophysical responses of vegetation to drought can vary with time. An initial plant response may be stomatal closure, leading to changes in leaf temperature and loss of leaf water content, while seasonal responses may include leaf senescence and, ultimately, mortality if the drought is sufficiently long and severe (Kozlowski et al., 1991; Bréda et al., 2006; Trugman et al., 2018). Different remote sensing measures will have different sensitivities to these plant responses. While greenness indices such as the Normalized Difference Vegetation Index (NDVI; Rouse et al., 1973) are often used to track vegetation
condition during drought (e.g., Vicente-Serrano et al., 2013; Okin et al., 2018; Dong et al., 2019), plants may express changes in canopy water content before significant changes in greenness and structure can be detected (Asner et al., 2004; Zarco-Tejada et al., 2012; Sims et al., 2014). Further, canopy or land surface temperature (LST) can be used as a proxy measure of vegetation evapotranspiration (Soer et al., 1980; Fisher et al., 2020) and, in urban areas, as a measure of vegetation cooling relative to impervious surfaces (ΔLST). Although it is strongly related to plant functioning, vegetation LST can be highly influenced by surrounding conditions and does not provide a direct measurement of canopy structure (Leuzinger et al., 2010; Meerdink et al., 2019b). Imaging spectrometer measurements of canopy water content, such as through equivalent water thickness (EWT), can provide a measure of leaf area index in dense canopies in addition to monitoring water (Roberts et al., 2004). Canopy water content measurements have been shown to effective in monitoring drought-induced canopy changes in California forests (e.g., Asner et al., 2016; Paz-Kagan and Asner, 2017), but are only rarely available at the temporal resolutions needed for tracking seasonal drought (e.g., Roberts et al., 1997; Dennison et al., 2003). By using complementary remote sensing data sets, studies can potentially capture changes that may not be readily apparent in a single index or measurement, more effectively constraining the timing of drought-induced changes in plant canopies.

Here, we leveraged multiple sources of remote sensing data to estimate the timing and influence of drought impacts on dominant vegetation cover types in the Santa Barbara, California, USA urbanized area. Specifically, we evaluated changes in prevalent tree (broadleaf trees, needleleaf trees, Eucalyptus, and oaks) and grass cover (annual grasses and turfgrass lawns) classes that may be expected to have distinct drought responses due to
differing plant functional strategies and water access. These classes occurred in sufficiently large patches to be tracked with coarser time series imagery. We took advantage of airborne imaging spectroscopy acquired over multiple seasons and years (Lee et al., 2015) as well as spaceborne satellite remote sensing time series (Dwyer et al., 2018) to examine the variable temporal effects of seasonal and interannual drought at a fine spatial scale across the metropolitan region. We addressed the following primary research questions:

1. How did the magnitude and timing of drought response compare across different vegetation cover types based on canopy greenness (NDVI), relative surface temperature (ΔLST), and canopy water content and leaf area (EWT)?
2. At which time spans (e.g., seasonal, interannual) are vegetation NDVI and ΔLST most correlated to drought based on the Standardized Precipitation Evapotranspiration Index (SPEI), and how does this vary by cover type and season?
3. How did EWT adjust seasonally in comparison to NDVI during this drought time series, and were there consistent linear relationships between EWT and NDVI across different vegetation types?

2. Methods

2.1. Study area

Our study area was 113 km² of the region surrounding and including Santa Barbara, California, USA (Fig. 2.1; 34.43° N, 119.75° W). The Santa Barbara urbanized area has a population of 196,000 (United States Census, 2012), and we defined our study area boundaries based on the availability of high resolution imaging spectroscopy data and a modified version of the United States Census boundary of the urbanized area. The climate is
Mediterranean (Köppen Csb), with the majority of the precipitation falling as rain in the winter months between November and April (mean annual air temperature 15 °C, mean annual precipitation 45 cm; National Centers for Environmental Information, 2019). The study area had persistent long-term drought conditions from early 2012 to early 2019, with reduced rainfall and high temperatures; the most severe drought conditions were from March 2014 to January 2017 (United States Drought Monitor, 2020).

**Fig. 2.1:** Land cover classification map derived from 4 m AVIRIS-NG imagery acquired June 3, 2014, with a background of 1 m NAIP imagery from 2014. Top panel shows the full extent of the study area, with three example insets (white squares) ordered west to east, left to right: (Left) Open space with annual grasses, large remnant stand of Eucalyptus, and adjacent golf course and residential neighborhoods; (Middle) Riparian area with oaks and other broadleaf trees surrounded by residential neighborhoods; (Right) Urban parks, dense residential, and commercial areas.
2.2. Land cover classification

To enable monitoring of different vegetation types within the study area during the drought, we produced a land cover classification from four flightlines of 4 m Airborne Visible Infrared Imaging Spectrometer - Next Generation (AVIRIS-NG) imagery acquired from a Twin Otter aircraft at 4 km altitude on June 3, 2014. This imagery provided sufficient spatial and spectral resolution to classify multiple dominant vegetation classes within our urban study area. AVIRIS-NG samples at 432 bands of spectral radiance at 5 nm spacing at approximately 350-2500 nm (Hamlin et al., 2011). The flightlines were radiance-calibrated and atmospherically corrected to surface reflectance by the NASA Jet Propulsion Laboratory (JPL). To provide greater internal consistency, we calibrated the AVIRIS-NG surface reflectance retrievals to ASD Field Spectrometer (Analytical Spectral Devices, Inc., Boulder, Colorado) measurements of a homogeneous, 25% reflectance flat white roof in Goleta, California (Thompson et al., 2015; Meerdink et al., 2019a). Each flightline was co-registered to 1 m National Agricultural Inventory Program (NAIP) orthophotos from 2014 using manually selected ground control points and Delaunay triangulation with nearest-neighbor resampling (NAD83, UTM Zone 11 N). The flightlines were mosaicked, giving precedence to the southern flightlines to favor the backscattering view geometry in overlapping areas. Bands adversely impacted by water vapor absorption were removed, leaving 312 bands. We applied continuum removal (Clark and Roush, 1984) on the remaining bands to mitigate the impacts of cross-track brightness and bidirectional reflectance distribution function effects between the mosaicked flightlines, as in Tane et al. (2018).
Land cover classes were selected to prioritize large patches of dominant urban vegetation types that could be reliably tracked with coarser time series imagery (18 - 30 m spatial resolution) and had potentially differing phenology and drought-response behaviors (Table 2.1). We evaluated Eucalyptus and evergreen oak trees separately from the generic broadleaf tree class due to their prevalence throughout the study area. The developed/impervious class included constructed surfaces such as pavement and roofs, and we also mapped bare soil and inland open water bodies due to their distinct spectral features. We created a combined training and validation dataset that consisted of single cover type pixels using the AVIRIS-NG imagery, 1 m NAIP orthophotos from 2014, multiple dates of high resolution imagery in Google Earth, Google Street View, the City of Santa Barbara’s street tree database, and the tree species classification from Alonzo et al. (2016). Each class sample size was initially set to ~250 single-pixel points, except for the small area classes of soils and water. We randomly sampled this dataset (1850 pixel spectra total) without replacement to develop training (70%) and validation (30%) data for each class.
Table 2.1: Classes and area estimates for the land cover classification, with non-representative polygons removed. Area and percentage of broadleaf trees exclude oaks and Eucalyptus, and in this study, broadleaf trees do not include Eucalyptus or oaks, unless specified otherwise.

<table>
<thead>
<tr>
<th>Class Name</th>
<th>Description</th>
<th>Area (km²)</th>
<th>Area (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Broadleaf</td>
<td>Broadleaf trees and shrubs, including native and non-native deciduous and evergreen, but not including Eucalyptus and oak (separate classes, see below)</td>
<td>13.19</td>
<td>12%</td>
</tr>
<tr>
<td>Needleleaf</td>
<td>Needleleaf trees and shrubs, primarily evergreen non-native</td>
<td>3.30</td>
<td>3%</td>
</tr>
<tr>
<td>Eucalyptus</td>
<td>Eucalyptus trees such as <em>Eucalyptus globulus</em>, a prominent broadleaf evergreen non-native tree</td>
<td>5.82</td>
<td>5%</td>
</tr>
<tr>
<td>Oak</td>
<td>Oak trees, predominantly <em>Quercus agrifolia</em>, a prominent broadleaf evergreen native tree</td>
<td>11.84</td>
<td>10%</td>
</tr>
<tr>
<td>Annual Grass</td>
<td>Annual grass and other low, primarily herbaceous, senesced vegetation in June 2014, likely non-irrigated</td>
<td>22.25</td>
<td>20%</td>
</tr>
<tr>
<td>Turfgrass</td>
<td>Turfgrass and other low, primarily herbaceous, green vegetation in June 2014, likely irrigated</td>
<td>9.08</td>
<td>8%</td>
</tr>
<tr>
<td>Developed/Impervious</td>
<td>Constructed urban surfaces including roads, roofs, and other impervious surfaces</td>
<td>45.25</td>
<td>40%</td>
</tr>
<tr>
<td>Soils</td>
<td>Bare soil surfaces and beach sand</td>
<td>1.35</td>
<td>1%</td>
</tr>
<tr>
<td>Water</td>
<td>Open water surfaces, ocean is excluded from classification</td>
<td>0.99</td>
<td>1%</td>
</tr>
<tr>
<td>TOTAL</td>
<td>Sum of all classes</td>
<td>113.07</td>
<td>100%</td>
</tr>
</tbody>
</table>

To create the land cover classification we used random forests, a nonparametric classification technique that generates an ensemble of decision trees and estimates the importance the input features (Breiman, 2001; Belgiu and Drăguț, 2016). We used a feature reduction technique (‘varSelRF’ package in R) to reduce the number of input continuum removed AVIRIS-NG bands from 312 to 88, similar to Tane et al. (2018). The 88 selected bands were input into a random forest model implemented in the ‘ranger’ package in R (Wright and Zeigler, 2017). We applied ‘ranger’ with 1000 trees, impurity importance, and otherwise default settings to generate the map. As a default, the number of features tried splitting at each node (mtry) was the square root of the number of input features (9).
After applying the random forest classifier to the AVIRIS-NG mosaic, we applied a 3x3 majority filter to smooth stray, misclassified pixels. To remove non-representative areas, we masked agricultural fields, marshes, and areas of major construction or redevelopment during the study time period. We also masked areas affected by the 2018 Montecito mudslide using polygons from Kean et al. (2019). For additional validation, we compared a subset of our land cover classification to the tree cover estimates for downtown Santa Barbara from Alonzo et al. (2016).

2.3. Landsat NDVI and ΔLST time series

We used all available Landsat Analysis Ready Data (ARD; Dwyer et al., 2018) scenes that were >30% clear for our study area between January 1, 2010 and December 31, 2019 (273 total). This included atmospherically corrected surface reflectance and thermal imagery from Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper + (ETM+), and Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS). All Landsat imagery were reprojected to match the AVIRIS-NG classification’s datum and projection (NAD83, UTM Zone 11N) using nearest-neighbor resampling; visual inspection on a subset of the Landsat scenes confirmed good spatial alignment of the 30 m Landsat imagery and the 4 m AVIRIS-NG classification. We calculated the NDVI for each Landsat scene (Fig. 2.2A), and the Landsat 8 OLI NDVI was rescaled to approximate Landsat 7 ETM+ NDVI (equivalent to Landsat 5 TM NDVI) using Roy et al. (2016):

\[ NDVI_{ETM+} = 0.0029 + 0.9589 \, NDVI_{OLI} \]  \hspace{1cm} (1)
To investigate changes in land surface temperature (LST) due to its relationship with vegetation evapotranspiration and canopy shading, we used the USGS Landsat Provisional Surface Temperature Product (Cook et al., 2014) as a disaggregated 30 m estimation for LST (bias accuracy < 1 K, total uncertainty 2.5 K RMSE; Makalar et al., 2018) across all Landsat imagery (Fig. 2.2B). Since Landsat thermal bands have much coarser and variable pixel sizes (60-120 m, depending on the sensor) compared to the surface reflectance bands (30 m), there is likely a variable influence of surrounding cover types on the retrieved LST within a given 30 m pixel (Makalar et al., 2018). However, these data can provide an adequate approximation of LST for the duration of our study time period and have been
applied in other urban studies (e.g., Hoffman et al., 2020; Zhou et al., 2020). We restricted our analysis for both NDVI and LST to the same clear pixels based on the associated quality flags.

The 4 m AVIRIS-NG land cover classification was resampled to the 30 m Landsat grid by calculating the fraction within each 30 m Landsat pixel that was represented by each cover type. To characterize trends for different cover types, we extracted trends for all available pixels with >90% fractional cover for each cover type, except for needleleaf trees (>60%) because of their relatively small stand areas (supplemental material, Table S2.1 and Table S2.2).

Values of NDVI and LST were aggregated to monthly median estimates for each cover type. To track the magnitude of relative cooling effect by vegetation type, we tracked LST at each month by subtracting the median LST for developed/impervious for each image from the median LST for each vegetation type (ΔLST). We then averaged ΔLST for each month, similar to studies of surface urban heat islands (e.g., Haashemi et al., 2016).

Although we expected the magnitude of LST to change with impervious surface cover through an annual cycle (Yuan and Bauer, 2007), ΔLST provided a more broadly applicable metric for LST by accounting for weather-related, day-to-day variations in ambient temperatures. For example, we could more directly compare the relative cooling provided by vegetation in April 2015 vs. April 2016 using ΔLST than using absolute temperature.

2.4. Correlations of SPEI drought index and Landsat variables

To attribute the response of NDVI and ΔLST to seasonal and interannual drought, we examined their correlation with the Standardized Precipitation Evapotranspiration Index
The SPEI is a drought index that quantifies differences from average water balance conditions based on precipitation and potential evapotranspiration; it is standardized such that negative values are indicative of drier than average conditions while positive values are indicative of wetter than average conditions. Importantly for this study, SPEI can be calculated for a range of time scales, usually as an integrated span of months prior to the time point of interest, and so it can be representative of water balance conditions over shorter or longer time periods. For example, a SPEI span of 6 months quantifies relatively how much drier or wetter than normal conditions have been during the prior 6 months. The SPEI has been applied to Mediterranean ecosystems to evaluate the effects of drought on vegetation greenness, phenology, growth, and mortality (e.g., Barbeta et al., 2013; Ivits et al., 2014; Gouveia et al., 2017; Rita et al., 2020). As it included precipitation but not irrigation water use, which was not available across the study domain, SPEI provided a metric of relative meteorological drought to which distinct vegetation types may show differential response during our study time period.

We used all available SPEI spans (i.e., length of time included in the index for a given date) calculated for the US Historical Climatology Network station in Santa Barbara, California (34.4167° N, 119.6844° W) from the WestWideDroughtTracker (Abatzoglou et al., 2017). This included 1 to 12-month spans to represent the effects of seasonal-to-annual drought and time scales longer than 12 months, up to a maximum of 72 months, to represent interannual drought (examples of different spans are shown in supplemental material, Fig. S2.1). For each vegetation type, we calculated Pearson’s correlation coefficient (R) for SPEI vs. NDVI, and SPEI vs. ΔLST, during different seasons: winter (December, January, February = DJF), spring (March, April, May = MAM), summer (June, July, August = JJA),
and fall (September, October, November = SON). We estimated SPEI correlations for seasons, rather than individual months, to allow for 28-30 data points when computing correlations. For example, a 6-month SPEI span for winter would include the months of June to December, July to January, and August to February for December, January, and February, respectively.

2.5. EWT time series from AVIRIS

To investigate adjustments in plant water content based on equivalent water thickness (EWT), we used 18 m Airborne Visible Infrared Imaging Spectrometer (AVIRIS) flightlines that were acquired as part of the HyspIRI Preparatory Campaign during 2013-2015 (Lee et al., 2015). We used the 18 m AVIRIS imagery because it included repeat acquisitions over multiple seasons. AVIRIS measures spectral radiance at 10 nm spacing in the range of approximately 360-2500 nm (Green et al., 1998). We used a subset of the flightlines (31 total) that were processed to surface reflectance by JPL (Thompson et al., 2015) and Meerdink et al. (2019a) to capture spring, summer, and fall conditions for each year of acquisition, excluding lines with severe cloud contamination or technical issues in our study area (Table 2.2). In addition to the primary spatial coregistration from Meerdink et al. (2019a), the images were further co-registered to a 1 m NAIP mosaic from 2014 using Delaunay triangulation with nearest neighbor resampling (NAD83, UTM Zone 11 N) to constrain spatial alignment needed for the Santa Barbara urbanized area. Clouds were masked using manually drawn polygons. To exclude anomalous reflectance values due to low solar elevation angles, we masked the north-facing, shadowed slopes of the imagery acquired on November 25, 2013. To mitigate brightness discontinuities at higher off-nadir
view angles towards the edges of the lines, lines at each date were mosaicked by averaging co-located pixels in overlapping flightlines using the ‘mosaic’ function in the R ‘raster’ package.

**Table 2.2**: Dates (Year.Month.Day) of AVIRIS flightlines (FL##) from the HyspIRI Preparatory Campaign’s Santa Barbara Box used in this study, derived from Meerdink et al. (2019a). Flightlines included in this study are marked with ‘x’ and excluded or missing lines are marked with ‘NA.’

<table>
<thead>
<tr>
<th>Date</th>
<th>FL05</th>
<th>FL06</th>
<th>FL07</th>
<th>FL08</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013.04.11</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>2013.06.06</td>
<td>NA</td>
<td>x</td>
<td>NA</td>
<td>x</td>
</tr>
<tr>
<td>2013.11.25</td>
<td>NA</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>2014.04.16</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>2014.06.04</td>
<td>NA</td>
<td>NA</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>2014.08.29</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>2015.04.16</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>2015.06.02</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>2015.08.24</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
</tbody>
</table>

We evaluated changes in plant leaf water across all vegetation types during the drought by calculating EWT ([Fig. 2.2C](#fig2.2c), Green et al., 1993; Roberts et al. 1997). EWT estimates the depth of liquid water, as described by Beer-Lambert Law, needed to approximate the shape of a measured vegetation spectrum. We used EWT as opposed to water-related vegetation indices because of the insensitivity of EWT to the varying solar zenith angles in our AVIRIS time series (Dennison et al., 2003; Cheng et al., 2006), although other vegetation indices may have stronger relationships to canopy water content (e.g., Serrano et al., 2000). Canopy water content and live fuel moisture estimated by EWT has been used multiple studies investigating the effects of drought on vegetation (e.g.,
We calculated EWT by minimizing the sum of squared differences by wavelength between the measured surface reflectance and estimated liquid water absorption:

\[
\min_{\lambda=850 \text{ nm}} \sum_{\lambda=850 \text{ nm}}^{1100 \text{ nm}} (\rho_\lambda - be^{-t\alpha_\lambda})^2
\]

where \(\rho_\lambda\) is the measured atmospherically-corrected surface reflectance at each wavelength, \(\alpha_\lambda\) is liquid water absorption (cm\(^{-1}\)) at each wavelength, \(t\) is EWT (cm), and \(b\) is a scaling offset parameter. The variables \(t\) and \(b\) were adjusted with a nonlinear optimization routine (‘optim’ function in R, method = “L-BFGS-B”; Byrd et al., 1995) with the constraint that \(t \geq 0\).

We estimated EWT for each AVIRIS image mosaic, including all bands between 850 and 1100 nm except the water vapor band at 928 nm, and we validated our EWT estimates using field-collected leaf water, leaf area, and spectra from Meerdink et al. (2016). To compare response in EWT to response in Landsat NDVI through the drought with matching pixel sizes and acquisition dates, we produced simulated Landsat 5 TM NDVI from the AVIRIS image mosaics by convolving the AVIRIS bands to Landsat 5 TM bands with spectral response functions in ENVI 5.2 Classic (L3Harris Geospatial, Broomfield, Colorado). Similar to the Landsat time series data extraction, we aggregated the 4 m AVIRIS-NG land cover classification to fractional cover estimates within the 18 m AVIRIS time series grid and extracted available pixels with >90% cover of a given vegetation cover type from each date of the AVIRIS EWT and simulated Landsat NDVI time series (supplemental material, Table S2.3 and S2.4). We then compared changes in time of these two variables for available AVIRIS dates. Specifically, we plotted all available EWT and
NDVI values against each other to assess their overall relationship for different vegetation types, and we produced linear regressions across dates to evaluate the similarities or differences in response of EWT and NDVI for different vegetation types.

3. Results

3.1. Land cover classification

The land cover classification from the 4 m AVIRIS-NG imagery and the random forest classifier is shown in Fig. 2.1. The overall accuracy and kappa of the land cover classification were 86% and 0.85, respectively (Table 2.3). Using all validation sample points, the mean user’s accuracy (UA) was 88% and the mean producer’s accuracy (PA) was 86%; weighted by final land cover class areas, mean UA was 85% and mean PA was 91%. Most of the land cover classes had accuracies >80%, with the exception of the more diverse broadleaf tree (UA = 75%, PA = 69%) and needleleaf tree classes (UA = 84%; PA = 77%), which were misclassified as other vegetation types more often than other classes. Variable importance from the random forest model is shown in the supplemental material (Fig. S2.2).

The full 113 km² study extent had 30% tree cover, 40% developed or impervious surfaces, 20% annual grass, and 8% green turfgrass (Table 2.2). Of the total tree cover, 90% was all types of broadleaf trees including Eucalyptus (17%), oaks (~35%), and other broadleaf trees (~39%), whereas only 10% was needleleaf trees. Our classification’s cover estimates for oak, needleleaf, and broadleaf trees, with or without Eucalyptus and oak trees included, were all similar to estimates from Alonzo et al. (2016) in a subset of the study area in downtown Santa Barbara (22 km², supplemental material, Table S2.5).
Table 2.3: Error matrix for land cover classification. Overall accuracy = 86%, kappa = 0.85. Note that unequal class sizes were necessary to rebalance the relative influence of different classes within the random forest model.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Broadleaf</th>
<th>Needleleaf</th>
<th>Eucalyptus</th>
<th>Oak</th>
<th>Annual Grass</th>
<th>Turfgrass</th>
<th>Developed/Impervious</th>
<th>Soils</th>
<th>Water</th>
<th>TOTAL</th>
<th>User’s Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Broadleaf</td>
<td>62</td>
<td>11</td>
<td>2</td>
<td>5</td>
<td>0</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>83</td>
<td>75%</td>
</tr>
<tr>
<td>Needleleaf</td>
<td>6</td>
<td>46</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>55</td>
<td>84%</td>
</tr>
<tr>
<td>Eucalyptus</td>
<td>3</td>
<td>0</td>
<td>69</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>72</td>
<td>96%</td>
</tr>
<tr>
<td>Oak</td>
<td>6</td>
<td>0</td>
<td>1</td>
<td>51</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>58</td>
<td>88%</td>
</tr>
<tr>
<td>Annual Grass</td>
<td>4</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>74</td>
<td>4</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>86</td>
<td>86%</td>
</tr>
<tr>
<td>Turfgrass</td>
<td>3</td>
<td>0</td>
<td>2</td>
<td>1</td>
<td>68</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>74</td>
<td>92%</td>
</tr>
<tr>
<td>Developed/Impervious</td>
<td>6</td>
<td>2</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>73</td>
<td>4</td>
<td>2</td>
<td>0</td>
<td>88</td>
<td>83%</td>
</tr>
<tr>
<td>Soils</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>24</td>
<td>0</td>
<td>26</td>
<td>92%</td>
</tr>
<tr>
<td>Water</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>13</td>
<td>13</td>
<td>100%</td>
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<tr>
<td>TOTAL</td>
<td>90</td>
<td>60</td>
<td>75</td>
<td>60</td>
<td>75</td>
<td>75</td>
<td>75</td>
<td>30</td>
<td>15</td>
<td>555</td>
<td></td>
</tr>
<tr>
<td>Producer's Accuracy</td>
<td>69%</td>
<td>77%</td>
<td>92%</td>
<td>85%</td>
<td>99%</td>
<td>91%</td>
<td>97%</td>
<td>80%</td>
<td>87%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3.2. Landsat NDVI and ΔLST time series

We evaluated seasonal and interannual time series of vegetation condition based on Landsat NDVI and ΔLST during 2010-2019, comparing the changes within individual years as well as the conditions for the same months across different years (Fig. 2.3).
Fig. 2.3: Landsat NDVI and ΔLST observations. A) Median NDVI aggregated monthly (vertical axis) for each year (horizontal axis) for each vegetation cover class. B) Median ΔLST aggregated monthly (vertical axis) for each year (horizontal axis) for each vegetation cover class. On both A and B, gray cells indicate missing observations, and black vertical lines describe approximate boundaries of drought condition from United States Drought Monitor (2020) for the Santa Barbara, California urbanized area: between dashed lines (2012-2013, 2017-2018) is “Abnormally Dry” to “Extreme
Drought;” between solid lines (2014-2016) is “Exceptional Drought,” the most severe drought category.

The major urban vegetation types exhibited distinct temporal patterns in NDVI in response to drought. Broadleaf trees had signals typical of winter deciduous trees, with highest NDVI values in the spring and, in wetter years, early summer. However, broadleaf NDVI declined during August and September during 2015 and 2016, likely related to earlier senescence during peak drought years. Needleleaf trees showed moderate NDVI values throughout the year (min. = 0.41, max. = 0.65), with slightly higher values in the winter and declines during the summers of 2016-2019, a later response than the broadleaf trees. The lower overall values of NDVI for needleleaf trees were likely related to mixed image pixels containing developed/impervious surfaces because needleleaf trees were sampled in patches as low as 60% fractional cover due to the rarity of large patches. Eucalyptus had its highest NDVI values in winter, but also showed severe winter reductions in NDVI during drought years. In general, NDVI values for Eucalyptus from 2013 onward were likely influenced by understory annual grasses as the Eucalyptus tree canopy declined during the drought. By comparison, the evergreen oaks, which do not experience a reduction in canopy cover, had relatively constant NDVI, with only slight declines during summer in 2016-2018 and some year-to-year variation in winter NDVI, with particularly low values in winter 2014. Annual grass showed high seasonal variability, with relatively high NDVI (~0.6) in wetter winters and very low NDVI (~0.3) in summer, responding to seasonal shifts from winter precipitation to summer drought. However, annual grass NDVI remained very low during winter 2014 and, to a lesser degree, 2018, and the low summertime values extended later into the fall during drought years (2013-2017). Turfgrass, due to irrigation, overall had
relatively consistent NDVI throughout all years and had higher wintertime values, but also had relative declines during summer in peak drought years (2014-2016).

To account for differences in weather in each image acquisition, we tracked vegetation ΔLST as the difference between median vegetation LST and median developed/impervious LST within each image; more negative values of ΔLST indicate cooler vegetation relative to developed/impervious surfaces. In general, ΔLST was closest to zero during winter for all vegetation cover types likely due to low solar elevation angles and greater shadowing of urban paved surfaces. The most negative values of ΔLST were from April to September when paved surfaces had more direct insolation and were relatively less shaded. Broadleaf, Eucalyptus, and oak showed stronger relative cooling during summer for the pre-drought years 2010-2011 (mean = -9.4 K, -8.2 K, -9.7 K, respectively) that was reduced in magnitude during the drought in 2014-2016 (-7.8 K, -6.1 K, -8.7 K, respectively). In general, there was a weakening of ΔLST vegetation cooling during summer in 2014-2016 (all vegetation mean = -5.8 K) compared to 2010-2011 (-7.2 K). In particular, annual grass had ΔLST values close to 0 throughout 2014 (annual mean = -0.6 K) compared to 2010-2011 (-5.7 K), with only slight cooling in the spring 2014 (-2.7 K), which was more similar to spring 2010-2011 (-3.0 K). The ΔLST medians for nearly all vegetation types were always negative (i.e., cooler than paved surfaces) for all months and years, except for annual grass during the late fall and winter of several drought years.

While we anticipated more leaf cover (higher NDVI) would be correlated with cooler relative surface temperatures (lower ΔLST), this relationship was not universal across vegetation types (Fig. 2.4). Broadleaf trees and annual grass showed the strongest negative correlations (Pearson’s R = -0.76 and -0.51, respectively) between seasonal changes in
NDVI and ΔLST. Broadleaf trees had the most linear response likely because they are deciduous, whereas annual grass showed a distinct separation between winter and spring because of its wintertime greening, with relative cooling being delayed. Needleleaf trees had an unexpectedly positive correlation (R = 0.44) between seasonal changes in NDVI and ΔLST, perhaps due to the abundance of impervious surfaces being the primary influence upon changes in ΔLST in these more mixed pixel samples, or the greater presence of winter shadows increasing near-infrared reflectance relative to red. Eucalyptus, oaks, and turfgrass did not show great variability in seasonal NDVI as compared to the observed changes in ΔLST, although Eucalyptus had a weak positive correlation (R = 0.25), perhaps also due to wintertime shadowing. In general, due to seasonal drought and the presence of evergreen vegetation in this study area during this time period, vegetation greening did not necessarily imply more relative cooling through an annual cycle.
Fig. 2.4: Landsat median NDVI vs. median ΔLST for each vegetation cover type, plotted with different colors for each month for all years. Pearson’s correlation R values, 95% confidence intervals, and p-values are shown in lower left of each plot.

3.3. Landsat NDVI and ΔLST correlations with SPEI spans

We examined the correlations of SPEI at different time spans to NDVI and ΔLST, respectively, to assess the impact of drought duration on vegetation response. Because SPEI is negative during drier conditions and positive during wetter conditions, in general, NDVI was positively correlated with SPEI and ΔLST was negatively correlated with SPEI. We compared the strength of these correlations during different seasons. At the same time, because SPEI at different spans summarizes conditions integrated over a range of time, we examined seasonal droughts with SPEI spans ≤12 months and interannual droughts with SPEI spans >12 months. Both NDVI and ΔLST showed distinct correlations with SPEI at different spans (i.e., drought duration) for different seasons of the year, which often varied...
by vegetation cover type (Fig. 2.5). The highest correlations for each vegetation type are shown in Table 2.4.

Fig. 2.5: Pearson’s R correlations between SPEI span (x) and NDVI (left column) or ΔLST (right column) for each vegetation cover type (row blocks, with right side labels). Each cover type’s correlations are tracked by season (y): winter = DJF, spring = MAM, summer = JJA, and fall = SON. Cells with significant correlations (p < 0.01) are marked with *. Note that the x-axis is not years, as in Fig. 2.3.
Table 2.4: Highest magnitude Pearson’s R correlations between SPEI span and NDVI (left columns) or ΔLST (right columns) for each vegetation cover type for different seasons: winter = DJF, spring = MAM, summer = JJA, and fall = SON.

<table>
<thead>
<tr>
<th></th>
<th>NDVI</th>
<th></th>
<th>ALST</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R</td>
<td>Season</td>
<td>SPEI Span (months)</td>
<td>R</td>
</tr>
<tr>
<td>Broadleaf</td>
<td>0.69</td>
<td>JJA</td>
<td>18</td>
<td>-0.71</td>
</tr>
<tr>
<td></td>
<td>0.65</td>
<td>JJA</td>
<td>36</td>
<td>-0.69</td>
</tr>
<tr>
<td></td>
<td>0.64</td>
<td>JJA</td>
<td>12</td>
<td>-0.65</td>
</tr>
<tr>
<td>Needleleaf</td>
<td>0.60</td>
<td>JJA</td>
<td>60</td>
<td>-0.56</td>
</tr>
<tr>
<td></td>
<td>0.58</td>
<td>JJA</td>
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<td>JJA</td>
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<td>JJA</td>
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<td>-0.77</td>
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<td>0.69</td>
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<td>JJA, SON</td>
<td>48 (JJA), 18 (SON)</td>
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<tr>
<td>Annual Grass</td>
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<td>DJF</td>
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<td>SON</td>
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The highest correlations between SPEI and NDVI were during summer (JJA) for most vegetation types, including broadleaf trees, needleleaf trees, Eucalyptus, oaks, and turfgrass. Annual grass NDVI had its highest correlations with SPEI during winter (DJF), which is indicative of its wintertime greening. Annual grass NDVI had significant correlations with SPEI spans ≤12 months exclusively, but this was not the case for other vegetation types. Most trees had their highest NDVI correlations with SPEI at spans of >12 months, likely due to their ability to use soil moisture at greater rooting depths, access stored carbon reserves, and delay phenological expression in biomass (Kozlowski et al., 1991). The NDVI of evergreen oak trees was an exception since it was poorly correlated with SPEI span.
overall. Turfgrass NDVI was most strongly correlated with SPEI during fall (SON) and winter for SPEI spans <12 months, but had many correlations during summer as well for spans >12 months.

In general, vegetation ΔLST was also most strongly correlated with SPEI spans during summer as opposed to other seasons. Broadleaf, Eucalyptus, oaks, and turfgrass ΔLST only had significant correlations (p < 0.01) with SPEI during summer (JJA) and during no other season. Although it had many correlations during summer as well, needleleaf trees’ ΔLST also had significant correlations with SPEI during spring (MAM) at 48 and 60 month spans. In addition to having its strongest correlations during the summer, annual grass was notable in that it was the only vegetation type that had significant ΔLST correlations with SPEI during all four seasons. However, while annual grass had the majority of its highest magnitude ΔLST correlations with SPEI spans ≤12 months, all other vegetation types had their highest magnitude (i.e., most negative) ΔLST correlations with SPEI spans >12 months. This may be due to shallow rooting depths in annual grass as compared with trees, as well as the lack of irrigation in annual grass compared to turfgrass leading to drying in surface soil. With prolonged interannual drought, trees’ modifications in leaf area may also affect their summer water use, leading to correlations between SPEI and ΔLST at long time spans, in addition to any short term adjustments at a seasonal scale.

3.4. EWT time series and comparison with NDVI

We calculated EWT from repeat AVIRIS imagery acquired during 2013-2015 to estimate changes in canopy water content. For most vegetation types, EWT values decreased from spring to fall, responding to continued summertime drawdown of available soil water
Annual grass only showed positive EWT values during spring, but annual grass EWT during summer and fall images were always equal to zero since it was senesced during these seasons. Trees generally had similar EWT values for similar seasons across years (e.g., comparing spring 2013 to spring 2015), and there was an apparent seasonal drawdown of available water from spring to fall corresponding to normal summer drought. However, oaks had anomalously high EWT during spring 2014 compared to 2013 or 2015. Turfgrass showed the greatest year over year declines in EWT during fall, with spring and summer declining from 2013 to 2015 as well; this suggests a reduction in irrigation watering as the interannual drought progressed.

**Fig. 2.6**: Box plots of equivalent water thickness (EWT, cm) at AVIRIS image dates (2013-2015) for each vegetation cover type; x-axis is continuous to show the relative timing of image acquisitions (labels are Year.Month.Day) with acquisition seasons colored. Note broadleaf does not include Eucalyptus or oak. Boxplot hinges extend to the 25th and 75th percentiles, whiskers extend to the farthest values within 1.5*interquartile range from each hinge, and outliers are omitted for clarity.
We compared changes in EWT to changes in simulated Landsat 5 TM NDVI from the AVIRIS time series. Box plots of NDVI by AVIRIS date, similar to Fig. 2.6, are shown in the supplemental material (Fig. S2.3). The overall relationship between EWT and NDVI was often nonlinear due to EWT approaching zero at moderate NDVI values, and EWT expanding to much higher values when NDVI did not change or was saturated at higher values (Fig. 2.7). At the same time, the relationships between median values of EWT and NDVI at each date were often linear (Fig. 2.8). The image acquired on 2013.11.25 was excluded from all regressions due to anomalously high NDVI, perhaps due highly off-nadir sun-sensor viewing geometry; in the regression for oaks, 2014.04.16 was also excluded due to anomalously high values of EWT. We were not able to create a regression for annual grass since its median EWT values were zero for all dates. Broadleaf, Eucalyptus, oaks, and turfgrass had slopes in the range of 1.09-1.25, while the slope for needleleaf trees was lower at 0.68. This indicates that needleleaf trees showed relatively little adjustment in NDVI relative to EWT compared to other vegetation types, which showed greater changes in NDVI with changes in EWT. Our calculated EWT approached zero even at moderate to high NDVI values (0.6-0.8) for the fall imagery for many vegetation types, suggesting a difference between overall vegetation greenness and water content. Despite lower NDVI values in Eucalyptus and needleleaf trees, EWT values showed seasonal adjustments similar to broadleaf trees, oaks, and turfgrass. Turfgrass NDVI was in a narrow range (0.64 - 0.70) for many dates; however, EWT showed wide variation in this same range of dates (0.026 - 0.100 cm).
**Fig. 2.7:** Two-dimensional kernel density estimates of equivalent water thickness (EWT, x) vs. simulated Landsat 5 TM NDVI (y) for all AVIRIS flights for dominant vegetation cover types. Kernel density color bar has been log$_{10}$-scaled for clarity. The blue box shows the range of *Fig. 2.8*’s axes. Note values adjacent to the y-axis have EWT \(\geq 0\) cm since EWT cannot be negative, and few outliers EWT > 0.6 cm are not shown for clarity.
Fig. 2.8: Linear regressions of medians for equivalent water thickness (EWT, x) vs. simulated Landsat 5 TM NDVI (y) from all AVIRIS flights for all vegetation types. Colors and shapes indicate the date of AVIRIS flight (Year.Month.Day), and error bars are interquartile range. All linear regressions exclude 2013.11.25, and oak regression additionally excludes 2014.04.16.

We compared our estimates of EWT using broadleaf tree and shrub water mass data and spectra from Meerdink et al. (2016). We found that our estimates of leaf water mass, based on EWT, were overestimated and were not appropriate for individual leaves. However, the data did show a linear relationship ($R^2 = 0.57$; supplemental material, Fig. S2.4) and our mapped values from AVIRIS were within the ranges reported for other studies, albeit slightly low likely due to long-term drought (e.g., Roberts et al., 1997; Dennison et al., 2003; Sims and Gamon, 2003). EWT retrieved from spectra often overestimates leaf water estimates but underestimates total canopy water estimates due to multiple near-infrared scattering in canopies (Roberts et al., 1997), and can vary depending on the spectral range used (e.g., Mobasheri and Fatemi, 2013). Additionally, EWT is most
associated with the water content in all thin tissues rather than leaves or total canopy water content (Sims and Gamon, 2003).

4. Discussion

4.1. Overview

We evaluated the temporal effects of seasonal and interannual drought on urban trees and grasses, and compared vegetation response to drought based on three remote sensing variables related to different forms of plant function and characteristics (NDVI, ΔLST, and EWT). While most trees and turfgrass vegetation types in our Mediterranean-climate study area expressed drought response most prominently during seasonally-dry summer months, annual grass showed its greatest NDVI adjustments related to drought during winter, when precipitation would usually occur in non-drought years. Annual grass primarily showed its strongest correlations with adjustments in drought duration, using the SPEI (Vicente-Serrano et al., 2010; Abatzoglou et al., 2017), at time scales ≤12 months (i.e., seasonal droughts), while other vegetation types also showed strong correlations at time scales >12 months (i.e., interannual droughts). We compared the seasonal timing of changes in NDVI and ΔLST and found that these remote sensing variables were correlated for only some types of vegetation, often showing distinct changes in vegetation function separately related to greenness and evapotranspiration, respectively. We also demonstrated how, for vegetation types with higher leaf areas (i.e., trees and irrigated turfgrass), canopy water content from EWT showed a more pronounced response to seasonal drought than NDVI during the seasonal transition through spring, summer, and fall.
4.2. Vegetation cover of study area

We developed a land cover classification to be able to track different vegetation types through drought, using the larger Santa Barbara urbanized area to take advantage of greater vegetation area and larger tree stands that could be tracked with coarser spatial resolution Landsat and AVIRIS time series imagery. This expansion led to a greater proportion of vegetation and tree cover than might be expected in more densely populated cities nearby. Our study area (113 km$^2$) had 58% total vegetation cover (Table 2.1), which is higher than estimates for metropolitan Los Angeles, California (38.6% including senesced vegetation, McPherson et al., 2011; 31%, Wetherley et al., 2018), and our study area had 30% tree cover, which is also higher than Los Angeles (20.8%, McPherson et al., 2011; 20%; Wetherley et al., 2018). However, the vegetation (41%, this study) and tree cover (~24%; Alonzo et al., 2016) estimates for the denser Santa Barbara downtown area used by Alonzo et al. (2014; 2016) are lower and more similar to estimates for Los Angeles.

Although the coarser spatial resolutions for time series used here limited our ability to directly evaluate street trees and residential lawns, Miller et al. (2020) found that coast live oaks in smaller, more-urban patches and in larger, less-developed patches within the Santa Barbara downtown area both experienced severe response to the drought. While urban street tree drought response may differ from less densely developed areas due to potential irrigation inputs (Liang et al., 2017; Litvak et al., 2017a) and increased thermal fluxes from impervious surfaces (Savi et al., 2015) for urban trees, Bijoor et al. (2012) found that some urban trees in metropolitan Los Angeles did not solely rely on irrigation for water and had remarkably similar water sources to non-urban riparian trees, which may enhance urban trees’ ability to withstand drought by tapping deeper water sources.
4.3. Measured remote sensing variables and plant functional changes during drought

We assessed vegetation response to drought by using three different remote sensing variables in tandem: NDVI, ΔLST, and EWT. NDVI has formed the basis of many remote sensing studies vegetation response to drought (e.g., Sims et al., 2014), including those related to the SPEI (e.g., Vicente-Serrano et al., 2013; Rita et al., 2020). Similar to our results, other studies in similar California ecosystems have shown that evergreen trees and shrubs, such as oaks in this study (predominantly *Quercus agrifolia*), show relatively limited adjustments in NDVI throughout the year; in contrast, annual grasslands, like our annual grass class, show distinctly high NDVI values in the winter (Gamon et al., 1995). However, we found that large-canopied, evergreen Eucalyptus and needleleaf trees often showed increases in NDVI during winter ([Fig. 2.3](#)), which may be in part due to greening of the understory, but also due to the presence of cast shadows preferentially boosting near infrared reflectance relative to red at low solar elevation angles (Roberts et al., 1997). This effect was not as pronounced in smaller, dense-canopied oaks and broadleaf trees. Our results support the consensus that although many changes in vegetation canopies can be observed with greenness indices such as the NDVI, many adjustments related to plant function and structure, such as leaf surface temperature or water content, can occur without greenness changes (Asner et al., 2004; Zarco-Tejada et al., 2012; Sims et al., 2014).

In general, vegetation LST is reduced by evapotranspiration due to latent heat loss (Soer, 1980), which is tightly related to photosynthesis (Baldocchi et al., 2004), as well as canopy shadowing. We assessed vegetation LST as ΔLST, a differential from developed/impervious LST, to provide more stable estimates of the cooling potential of
vegetation through time, taking account of variations in weather across the image acquisition dates. Estimates of ΔLST are likely related to soil water status and evaporation in addition to limited preceding plant growth. For example, since annual grass was senesced during all summers and would provide negligible transpiration cooling in any summer, the reduced ΔLST during summer 2014 is likely related to limited soil water evaporation during an exceptional drought year. Overall, the ΔLST between vegetation and developed/impervious surfaces was minimized in winter but was larger and more variable in summer, similar to other studies (Liu and Weng, 2008; Haashemi et al., 2016; Meerdink et al., 2019b). While turfgrass and oaks in our study experienced changes in ΔLST, NDVI remained relatively stable. The other vegetation classes showed correlations between monthly values of ΔLST and NDVI, albeit weakly in the case of Eucalyptus (R = 0.25; Fig. 2.4). Although our ΔLST estimates likely may also be influenced by surface mixing due to resampling of the Landsat LST to 30 m (Malakar et al., 2018), we found that trees were often cooler than grass in spring and summer based on our mid-morning measurements from Landsat (e.g., for June 2013: broadleaf median ΔLST = -8.4 K, turfgrass median ΔLST = -7.0 K) which is consistent with other studies (Crum and Jenerette, 2017; Wetherley et al., 2018). However, Wetherley et al. (2018) also found that, across the Los Angeles basin, tree LST was consistently warmer than turfgrass LST when measured in the afternoon. Since LST varies diurnally, this variability can be better assessed with a sensor such as ECOSTRESS (Fisher et al., 2020) or with airborne acquisitions (e.g., Quattrochi and Ridd, 1998). We used LST measurements rather than air temperature, and air temperature can differ strongly from LST, especially beneath tree canopies (Shashua-Bar et al., 2009) and in areas near large tree stands (Ziter et al., 2019), although the magnitude of these effects can be highly variable
(Manickathan et al., 2018). In general, tree canopy LST can often be significantly different from air temperature in this climate; this effect is more pronounced in summer and can also be highly variable by tree species (Meerdink et al., 2019b).

We found that EWT showed a more distinct seasonal response to drought than did NDVI for most vegetation types, as EWT was sensitive to vegetation drought responses in water content and leaf area that were undetected by NDVI. This supports conclusions of previous studies investigating seasonal changes in EWT (Roberts et al., 1997; Dennison et al., 2003; Ustin et al., 2004) and comparing EWT to vegetation indices (e.g., Cheng et al., 2006). EWT showed a nonlinear relationship with NDVI when evaluated at the pixel scale across all vegetation types and dates, which is consistent with previous studies (e.g., Roberts et al., 2004). At the same time, we also found that, for median values across dates, EWT showed a linear relationship to NDVI, but the slopes of that relationship varied by vegetation type. Combined, these results suggest that the relationship between EWT and NDVI is dependent on the type of vegetation canopy, and the two variables are unlikely to be linearly related within the same acquisition or across many types of vegetation. In particular, needleleaf trees had a lower slope (0.68) than other vegetation types (1.01-1.14). Cheng et al. (2006) also found that EWT had a poorer linear relationship with NDVI at conifer sites where NDVI appeared to saturate, as compared to grassland sites. We found that median EWT was always zero for annual grass, which is likely due to our acquisitions having occurred during a severe drought with low soil water outside of winter. Ustin et al. (2004) also showed that annual grasses had EWT of zero for low soil water conditions. Our tree EWT estimates were lower than in other studies for similar study areas (e.g., Dennison et al., 2003; Ustin et al., 2004; Paz-Kagan and Asner, 2017). This may include error due to
relatively large pixels (18 m) covering mixed surfaces, understory vegetation senescence, and any potential spatial misalignment between dates. However, these changes are also affected by extreme drought conditions during the AVIRIS acquisitions (2013-2015). Overall, although EWT requires measurements from imaging spectroscopy, our results suggest that future remote sensing studies of vegetation drought response would likely benefit from the addition of EWT estimates through time to supplement variables such as NDVI and ΔLST.

4.4. Seasonal and interannual drought expression in vegetation

We used the SPEI calculated at seasonal and interannual spans (Vicente-Serrano et al., 2010; Abatzoglou et al., 2017) to examine the correlation of NDVI and ΔLST across different vegetation types, following Vicente-Serrano et al. (2013) and Rita et al. (2020). This allowed us to separate impacts of seasonal variability in drought (expressed strongly in our annual grass vegetation class) from interannual trends in drought (apparent in our tree and turfgrass classes). The ability of trees to survive seasonal variability in drought matches our expectations from previous work that trees in Mediterranean climates can access deeper water and therefore show less sensitivity than grasses to seasonal variations in surface soil moisture, both in terms of phenology and photosynthesis (e.g., Richardson et al., 2013; Sousa and Davis, 2020). For natural landscapes near our study area, Coates et al. (2015) showed that trees are also often less sensitive to drought than nearby chaparral vegetation.

By using both NDVI and ΔLST, we were able to show that these effects may not be expressed at the same time of year for all urban tree and grass vegetation types. While summertime reductions of soil-water during drought affected the ΔLST of all vegetation, it
had little effect on the NDVI of annual grasses due to their summertime senescence even in years of normal rainfall. This implies that for our study area’s climate, monitoring in winter is much more important for annual grasses if using NDVI as a proxy for drought. At the same time, for trees, summer is the most important time of year for to monitor drought based on NDVI, although many trees show additional correlations during other seasons. Most vegetation cover types also did not show correlations with SPEI at the 15 months span included in the calculations by Abatzoglou et al. (2017), suggesting this span may be poor at capturing water status in this climate, perhaps due to extreme interannual variability in rainfall during the drought time period. Although we were not able to evaluate EWT as part of a correlation comparison with SPEI since it had too few dates from AVIRIS as opposed to the NDVI and ΔLST collected from Landsat, we may have observed additional seasonal correlations with drought for otherwise evergreen vegetation (e.g., turfgrass, oaks).

Our study also showed different types of responses among tree vegetation types. We found that oaks and needleleaf trees had relatively few significant correlations with SPEI compared to other tree classes, suggesting different resource allocation strategies to weather drought (e.g., Dietze et al., 2014; Palacio al., 2018). Most of the oaks in our study region are primarily *Quercus agrifolia*, an evergreen species that avoids summer drought by shifting additional growth to the rainier winter months (Knops and Koenig, 1994). The needleleaf trees did not often occur in large stands and are likely more affected by mixing with impervious surfaces, which may have limited observable interannual variability at 30 m pixels. Common needleleaf species in our study area include *Pinus canariensis* and *Pinus pinea*, which are generally drought-tolerant species but were often affected during the 2012-2016 drought in this area (Miller et al., 2020).
The other trees classes in our study area included broadleaf trees and Eucalyptus, and these had more significant correlations with SPEI. Although there are wide varieties of both deciduous and evergreen broadleaf trees species in our study area (Alonzo et al., 2014; 2016), the thresholding for coarser Landsat time series often captured riparian areas, which often includes deciduous species such as *Platanus racemosa* and *Salix spp*. Other broadleaf species, including urban street trees, may behave differently (Bijoor et al., 2012), given that riparian areas experience drawdown of available water later in the year than in other locations (Sperry and Love, 2015). Our Eucalyptus class included many eucalypt species (e.g., *Eucalyptus sideroxylon, Corymbia citriodora*), but it consisted primarily of *Eucalyptus globulus*. This species is often considered to be drought-tolerant, but Mitchell et al. (2013) found that it has high water use associated with its rapid growth rates. Specifically, *Eucalyptus globulus* keeps stomata open to maintain lower turgor pressure, which is beneficial for continued growth during moderate droughts but can cause swift hydraulic failure during more extreme water limitations due to the tree’s inability to downregulate its water use.

We used SPEI from a single location in downtown Santa Barbara to represent our full study area because of its relatively small size (113 km²) and due to the lack of scaling parameters for local variability. We expect that with a much higher density of meteorological stations, our results would have reflected more site-specific variability in the magnitude of drought impacts and evapotranspiration (Savi et al., 2015; Crum and Jenerette, 2017; Litvak et al., 2017a) due to differences including soil type and topographic effects (e.g., Paz-Kagan and Asner, 2017), as well as human management such as irrigation (Liang et al., 2017).
At the outset of our study, we had anticipated a more general disconnect of urban vegetation from drought due to the availability of irrigation. For example, Buyantuyev and Wu (2012) found that urban and riparian vegetation phenology in Phoenix, Arizona, were decoupled from local climate variability, whereas natural desert vegetation was strongly regulated by the preceding 3-5 months of precipitation and was negatively correlated with temperature. Turfgrass in our study area can be assumed to be irrigated because it was green at the height of the long-term drought in June 2014. Although our turfgrass samples also contained golf courses and recreational areas due the restrictive nature of the coarse resolution imagery, in residential areas, individual homeowners may have reduced lawn watering later in the drought due to water conservation regulations (Council of the City of Santa Barbara, 2017) and public awareness campaigns (McCumber, 2017). Only in the spring did our results from turfgrass support the notion of climatological disconnect from drought. Turfgrass NDVI showed correlation with SPEI spans of <12 months during fall and winter, and with SPEI spans >12 months for winter, summer, and fall. This indicates that even typically irrigated urban vegetation is not fully insulated from seasonal drought at the city scale, and it is consistent with other studies showing the impacts of interannual drought on turfgrass in metropolitan California (Quesnel et al., 2019; Miller et al., 2020).

5. Conclusions

Different functional types of urban vegetation can show a diverse array of responses to drought related to different plant canopy characteristics and seasonal timing. In this study, we evaluated both the magnitude and seasonal timing of spectral responses among urban
trees (broadleaf, needleleaf, Eucalyptus, and oak) and grasses (annual grass, turfgrass) to seasonal and interannual drought duration via the SPEI, addressing three main goals. First, we compared adjustments in NDVI and ΔLST (from Landsat) and EWT (from AVIRIS) among different vegetation types during the study time period. Broadleaf trees, Eucalyptus trees, and annual grass had distinct seasonal patterns in NDVI, while needleleaf trees, evergreen oaks, and turfgrass showed comparatively less seasonal change in NDVI. Seasonal patterns in ΔLST were largely similar among all vegetation types, with the most substantial difference between vegetation and developed/impervious LST observed during the summer. EWT showed seasonal reductions of water content for all vegetation types except for annual grass, which was primarily senesced in nearly all the 2013-2015 AVIRIS acquisitions due to long-term drought.

Second, to evaluate the seasonal variation of plant response to drought duration across different vegetation types, we examined the correlation of changes in NDVI and ΔLST to changes in SPEI calculated at a range of time spans. This correlation allowed us to both assess the length of drought most associated with vegetation response and determine the season that this response was most apparent. Generally, NDVI was positively correlated with SPEI, and ΔLST was negatively correlated with SPEI. In most of the vegetation types we studied, NDVI had the strongest correlations (i.e., most positive) with SPEI during summer, except for annual grass, which had its strongest NDVI correlations with SPEI during winter. Similarly, ΔLST correlations with SPEI were strongest (i.e., most negative) for all vegetation types during summer. Annual grass had nearly all its greatest correlations at SPEI spans of ≤12 months for both NDVI and ΔLST, indicating its primary response to seasonal variation in water availability. In contrast, although they showed seasonal response
as well, trees and turfgrass had many correlations with SPEI spans >12 months for both NDVI and ΔLST, indicating a significant response to interannual drought and reflecting trees’ ability access deeper water and utilize stored resources that are unavailable to annual grasses.

Lastly, using repeat AVIRIS acquisitions, we compared seasonal and interannual changes in EWT to changes in simulated Landsat NDVI to investigate the complementary information provided by this imaging spectroscopy measurement for our study period. These results suggest that EWT and NDVI provide different information regarding canopy condition, and cannot be directly regressed across many types of vegetation. For trees and turfgrass, EWT showed seasonal changes from spring to fall that was not as readily apparent in NDVI. EWT overall had a nonlinear response to NDVI when combining all available pixels across all dates for each vegetation type; however, although EWT generally had linear relationships with NDVI when comparing median values across dates, the slopes and intercepts of these relationships varied between different vegetation types. These results support past research studies that suggest EWT can be a valuable addition to remote sensing studies of vegetation canopy condition and drought, namely by often showing further adjustments in canopy water content and leaf area in canopies where NDVI may be relatively invariant, and this is an example of an important use-case of a potential spaceborne imaging spectrometer such as the NASA Surface Biology and Geology (SBG) mission.

Our results provide insights into the sensitivity of different vegetation types to drought at a range of temporal scales, and demonstrate how jointly using complementary remote sensing variables (NDVI, ΔLST, EWT) can improve assessment of drought-induced
change in vegetation canopies. With many cities likely to undergo changing climate
conditions, annual maps at a single time of year are unlikely to be sufficient to evaluate the
breadth of potential impacts to ecosystem services in urban vegetation, and many natural
areas may experience similar effects in regards to drought and climate. As a consequence,
the techniques used in this study are by no means unique to urban areas and could be
broadly applied to natural ecosystems to investigate vegetation response to drought.

Acknowledgments

This study was supported by a NASA Earth and Space Science Fellowship
(80NSSC18K1325). Special thanks to Erin Wetherley, Christopher Heckman, S. Lucille
Blakeley, Lauren Smyth, and James Allen for data availability, methodological comments,
and/or editorial suggestions.
Chapter 3: Annual changes in urban tree and turfgrass fractional cover during drought in Los Angeles

with Erin B. Wetherley, Dar A. Roberts, Christina L. Tague, and Joseph P. McFadden
Abstract

For water-limited cities, trees and turfgrass lawns provide many ecosystem services such as reducing temperatures and providing recreational amenities. Maintaining green vegetation cover during extended droughts requires significant investment of limited water resources and is made more challenging by the uneven distribution of drought effects on vegetation across space and time. Here, we tracked changes in vegetation cover across the Los Angeles metropolitan area, using early summer airborne remote sensing imagery acquired annually as drought conditions progressed from 2013 to 2018 (and coinciding with the exceptional 2012-2016 California drought). Land cover fractions for trees, turfgrass, non-photosynthetic vegetation (NPV; e.g., senesced plant material), and non-vegetated surfaces (e.g., pavement, roofs, soil) were calculated at subpixel scales at 18 m spatial resolution using Multiple Endmember Spectral Mixture Analysis applied to hyperspectral imagery from the Airborne Visible Infrared Imaging Spectrometer (AVIRIS). We compared overall fractional cover changes between trees, turfgrass, and NPV through time and evaluated in which climatological and physiographic regions of city were vegetation changes most pronounced. During the drought time series from 2013 to 2018, mean turfgrass cover decreased and NPV cover increased. Tree cover was generally more stable but decreased in 2018 as well. The interior valleys of the study area (San Gabriel and San Fernando) consistently lost more turfgrass than coastal areas, and the San Gabriel Valley had strong losses of total vegetation cover (tree + turfgrass + NPV) overall. We also used datasets of median household income from census tracts and of typical non-drought outdoor water use from postal carrier routes to compare the magnitude and timing of different vegetation cover type changes at different income and water use levels. We observed larger absolute changes in vegetation cover in
higher income and higher water use areas, likely due to the higher baseline of mean vegetation cover in these areas. Once normalized for their mean values though, the magnitude of changes often became more similar across different income and water use levels, but not always, with lower income and water use areas showing greater relative changes for trees.
1. Introduction

Urban vegetation is an important consideration in city planning and design, and a powerful tool for ameliorating urban heat (Norton et al., 2015). In cities with Mediterranean and other seasonally dry climates, urban vegetation provides benefits related to shading and air temperature reductions, but often at the cost of significant inputs of irrigation water (McPherson et al., 2011; Wheeler et al., 2019). Drought conditions can make urban vegetation maintenance more challenging, with extended drought periods increasing the likelihood of vegetation cover loss (McPherson et al., 2018; Pincetl et al., 2019).

Drought response of urban vegetation can be affected by many factors and can be highly variable between different plant types. For example, the meteorological conditions during drought, including high temperatures and high atmospheric demand for water, can induce senescence in turfgrass lawns even at irrigation rates that are recommended to meet plant water demand (Chen et al., 2015; Quesnel et al., 2019). There are many physiological and environmental factors that can influence the response of urban trees to drought, such as tree species, leaf area, and the amount of surrounding impervious surface cover (May et al., 2013; Savi et al., 2015; Miller et al., 2020). During extended, multiple-year droughts, these impacts may become magnified, with potential for significant changes to the land cover and character of the local environment (May et al., 2013; Pincetl et al., 2019). During 2012-2016, California experienced one of the most severe droughts in the state’s modern history, and many cities implemented urban water use restrictions to meet statewide reduction targets (Lund et al., 2018). Because the focus of these restrictions areas was often related to irrigation and other outdoor water uses (Palazzo et al., 2017), urban vegetation likely experienced reductions in water availability during this time period (Pincetl et al., 2019).
Trees and turfgrass lawns are the two dominant forms of urban vegetation in US cities (Peters et al., 2011) and they likely respond differently to long-term drought (Bijoor et al., 2012; Litvak et al., 2017a; Quesnel et al., 2019), especially in semi-arid cities that require urban irrigation (Mini et al., 2014; Reyes et al., 2020). Trees can be deeply rooted and may be able to obtain water from groundwater sources during drought, although many irrigated urban trees may have shallower roots (Bijoor et al., 2012). Compared to turfgrass, trees are a longer-lived form of vegetation cover, requiring years of investment and maintenance, and are not as readily replaceable (Roman et al., 2018). Trees also provide cooling through shading in addition to evapotranspiration (Norton et al., 2015; Wheeler et al., 2019). In contrast to trees, turfgrass lawns are more shallowly rooted and are likely to senesce rapidly under water limitation, but they also can be more readily reinvigorated with subsequent irrigation and can be regrown more easily (Kaufmann, 1994).

In large cities with spatially extensive metropolitan areas, both trees and turfgrass lawns can be affected by variations in climatological and physiographic conditions across the urban region. For example, the city of Los Angeles, California, has a coastal to interior gradient in climate conditions (Tayyebi and Jenerette, 2016). Coastal areas have a more moderate climate, with cooler and wetter conditions, than areas in the interior valleys, which are much warmer and drier. There is also large topographic variability, and with mountainous regions having lower development density than the flat areas in the basin and valleys. This can also influence solar exposure and, depending on the aspect the slopes, the intensity of drought conditions, which can be comparatively much more (south-facing) or less (north facing) intense than other parts of the city with flatter topography.
In irrigation-dependent cities, overall vegetation abundance and tree cover are greater in areas having higher household income and higher irrigation water use (Schwartz et al., 2015; Palazzo et al., 2017). It remains unclear how an extensive drought may affect these areas differently. It is possible that higher income areas are more buffered from vegetation decline due to their residents’ ability to pay for irrigation water during extended drought conditions (Kaplan et al., 2014), and they are less likely to meet water conservation targets (Palazzo et al., 2017). Alternatively, higher income areas could experience greater absolute losses of vegetation because they generally have larger amounts of vegetated land that could be affected by drought (Schwartz et al., 2015). At the same time, lower income and lower water use areas may suffer smaller losses of vegetation cover during drought because they have comparatively little vegetation to lose (Wolch et al., 2014; Tayyebi and Jenerette, 2016). Because of the high costs of landscape irrigation, the existing vegetation in lower income areas may be better acclimated to dry conditions experienced each year during the Mediterranean climate summertime drought, although people living in lower income areas are not necessarily more likely to support more drought-tolerant tree species (Avolio et al., 2015). However, an extreme, long-term drought could push even nominally drought-tolerant vegetation beyond its normal limits (e.g., Miller et al., 2020), and more vegetation could be lost because people living in lower income areas would be more less able to pay for additional outdoor water use (Palazzo et al., 2017).

Given the heterogeneity in urban vegetation density and type (e.g., trees and turfgrass), management practices, and metropolitan-scale climatic variability, there may be substantial spatial variation in drought responses. Urban areas are spectrally and spatially heterogeneous and it can be challenging to distinguish many different cover types.
In recent years, there have been many remote sensing studies mapping tree cover or green vegetation cover in urban areas. For tree cover mapping, many of these studies rely on a combination of high spatial resolution imagery (e.g., Moskal et al., 2011; O’Neil-Dunne et al., 2014) and/or airborne LiDAR (e.g., Alonzo et al., 2014; Liu et al., 2017; Degerickx et al., 2020). Such studies tend to be limited to a single date or for a relatively small area due to the expense of image acquisition and processing, although there has been recent work utilizing high resolution airborne imagery that is acquired on a biannual basis (Erker et al., 2019). Total green vegetation cover studies across larger areas often rely on broadband satellite imagery at coarser resolutions (e.g., Richards et al., 2017; Czekajlo et al., 2020). Studies of green vegetation cover from spaceborne multispectral systems can provide total estimates for many more dates due to regular acquisitions, but they cannot often easily distinguish between different vegetation types unless other characteristics are included in the analysis (e.g., temporal patterns using phenology; Schug et al., 2020).

Relative to broadband imagery, urban surfaces and vegetation types have been shown to be more readily separable using hyperspectral sensors with hundreds of narrow spectral bands (i.e., imaging spectroscopy; Herold et al., 2004; van der Linden et al., 2018). Spectral unmixing techniques, such as Multiple Endmember Spectral Mixture Analysis (MESMA; Roberts et al., 1998), have been used to successfully distinguish urban surfaces within subpixel fractions (e.g., Herold et al., 2004; Franke et al., 2009; Wetherley et al., 2017). Trees and turfgrass cover have been reliably separated by applying MESMA to analyze hyperspectral imagery, with overall brightness being a primary distinguishing feature (Wetherley et al., 2018). In addition, and in contrast to broadband imagery,
Hyperspectral imagery can capture the spectral detail necessary to distinguish non-photosynthetic vegetation (NPV; e.g., senesced grass, plant litter) from soil and other non-vegetated surfaces (Wetherley et al., 2017). Hyperspectral imagery rarely has been available within urban areas over large extents and typically only for a single date. However, the NASA HyspIRI Preparatory Campaign (Lee et al., 2015) acquired repeat flights across many regions in California as a test-case for a spaceborne hyperspectral sensor, now named the Surface Biology and Geology (SBG) mission. In the Los Angeles region, the HyspIRI Preparatory Campaign imagery were acquired at several dates throughout the year for 2013-2015 and then at a single date annually for 2016-2018. This provides an unprecedented opportunity to track an annual drought time series in an urban area using hyperspectral imagery, which may be a more common task as future spaceborne hyperspectral monitoring instruments become available.

As the likelihood of extreme droughts are projected to increase due to anthropogenic climate change (Williams et al., 2015), quantifying the drought-induced changes in urban vegetation cover will be critical for urban planning and climatic modification. Separately tracking trees, turfgrass, and NPV is especially needed for monitoring vegetation response during drought, as vegetation dieback from green vegetation to NPV is indicative of drought effects (Dennison et al., 2019). Some areas may only experience temporary declines in green vegetation cover but are still vegetated and pervious, while other areas may experience replacement of green vegetation with impervious surfaces and/or xeriscaping (Pincetl et al., 2019). These differences can have profound effects on energy budgets (Liang et al., 2017) and modify neighborhood appearance post-drought (Pincetl et al., 2019).
Here, we track changes in vegetation cover across the Los Angeles metropolitan area, using remote sensing imagery acquired each May/June as drought conditions progressed from 2013 to 2018, a time period that encompassed the exceptional 2012-2016 California drought. Specifically, we calculated subpixel fractions of tree, turfgrass, NPV, and non-vegetated surfaces (e.g., pavement, roofs, soils) at 18 m spatial resolution using MESMA derived from airborne hyperspectral imagery. We focused our analysis on the following research questions:

1. How did urban tree, turfgrass, and NPV cover change year-to-year during 2013 to 2018, a time period which included a severe multi-year drought event?

2. In which climatological and physiographic regions of the city were vegetation changes most pronounced?

3. How did changes in the major urban vegetation cover types of trees and turfgrass lawns vary based on household income and outdoor water use?

2. Methods

2.1 Los Angeles study area

Our study area was the large Los Angeles urbanized region (2,490 km$^2$) in southern California, USA, including the city of Los Angeles and surrounding cities in Los Angeles County (34.05° N, 118.25° W; Fig. 3.1). The study area boundaries were based on urbanized area extent from the US Census Bureau (2010), manually edited to remove undeveloped regions along the margins (Wetherley et al., 2018), and then subset to the boundaries of Los Angeles County. Los Angeles County has a population of 10 million (US Census Bureau, 2020) and the Los Angeles metropolitan area is characterized by expansive low-rise
suburban development (Davis, 2006). It has a Mediterranean climate with wet winters and dry summers (Los Angeles downtown mean annual precipitation = 37.9 cm, mean annual air temperature = 18.6 °C; National Centers for Environmental Information, 2020). A strong coastal climate gradient spans the area, generating comparatively cooler and wetter conditions near the Pacific Ocean (Köppen Csb) and warmer and drier areas in the interior valleys (Köppen Csa).

**Fig. 3.1**: Map of MESMA fractions from May 22, 2013 within the Los Angeles urban study area (red = NPV + soil, green = tree + turfgrass, blue = paved + roof), with background of darkened grayscale National Agricultural Inventory Program (NAIP) airphoto mosaic. Example inset on lower left near Culver City shows detail of 18 m imagery. Missing areas are due to removed clouds, image artifacts (e.g., diagonal section in northern part of study area), and unmodeled MESMA fractions.
The Los Angeles metropolitan area experienced severe drought conditions from 2012 to 2019, with nearly the entire urbanized region in experiencing exceptional drought conditions from mid-2014 to the beginning of 2017 (Table 3.1, US Drought Monitor, 2020). The first year in our time series in which HyspIRI Preparatory Campaign flights were available (2013) was already during drought. The years of 2013-2016 were progressive years of continuous drought, with 2014 being the most severe single year of drought. 2017 had nearly average rainfall, and 2018 saw a return to moderate drought conditions (Table 3.1). The drought affected many cities in California, with many water restrictions implemented at both statewide and more local levels (Lund et al., 2018). Extensive irrigation is normally used to maintain urban vegetation during the dry summers, especially for turfgrass (Mini et al., 2014).

As opposed to cities in wetter climates, increases in urban tree cover in the Los Angeles region are a direct result of the city’s development. Because of its climate, the Los Angeles region did not have extensive tree cover prior to urbanization (except for agricultural orchards), instead being dominated by coastal sage scrub and chaparral with comparatively few trees along riparian corridors (Pincetl et al., 2013). In general, the city of Los Angeles has increased in tree canopy cover and stem density with urban development over the 20th century, although with wide variability in different parts of the city (Gillespie et al., 2012). The combination of a mild climate and extensive irrigation allow for a highly diverse number of tree species in the urban forest, with an estimated over 200 species in the city (Clarke et al., 2013). Different parts of the city often may have urban forest diversity defined by tree nursery availability at different time periods of development, with relatively
few native trees in the overall urban forest species palette (Pincetl et al., 2013; Avolio et al., 2020).

**Table 3.1:** AVIRIS image dates and related drought information. Drought Severity and Coverage Index (DSCI; no drought = 0, maximum drought = 500) values are from the US Drought Monitor (2020) for the Los Angeles-Long Beach-Anaheim, CA urban area from nearest available dates. The Palmer Drought Severity Index (PDSI) and 6-month estimates of the Standardized Precipitation Evapotranspiration Index (SPEI) and precipitation are from the US Historical Climate Network Station in Pasadena, California (Abatzoglou et al., 2017). Both PDSI and SPEI values are normalized such that more negative values are associated with drier conditions.

<table>
<thead>
<tr>
<th>AVIRIS Image Date</th>
<th>DSCI</th>
<th>PDSI</th>
<th>SPEI</th>
<th>Precip. (cm)</th>
<th>Precip. (% of average)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013.05.22</td>
<td>200</td>
<td>-4.68</td>
<td>-1.43</td>
<td>19.5</td>
<td>42.3</td>
</tr>
<tr>
<td>2014.06.13</td>
<td>400</td>
<td>-6.56</td>
<td>-1.49</td>
<td>15.3</td>
<td>38.6</td>
</tr>
<tr>
<td>2015.05.28</td>
<td>496</td>
<td>-3.95</td>
<td>-0.46</td>
<td>35.8</td>
<td>77.8</td>
</tr>
<tr>
<td>2016.06.16</td>
<td>496</td>
<td>-2.85</td>
<td>-0.73</td>
<td>26.1</td>
<td>65.6</td>
</tr>
<tr>
<td>2017.06.28</td>
<td>129</td>
<td>-2.18</td>
<td>0.19</td>
<td>40.0</td>
<td>100.6</td>
</tr>
<tr>
<td>2018.06.25</td>
<td>300</td>
<td>-4.87</td>
<td>-0.88</td>
<td>20.7</td>
<td>52.0</td>
</tr>
</tbody>
</table>

2.2 Hyperspectral remote sensing time series imagery

We used a repeat time series of hyperspectral imagery from the Airborne Visible Infrared Imaging Spectrometer (AVIRIS), which measures 224 narrow bands of spectral radiance from approximately 360 to 2500 nm at 10 nm full-width half-maximum (Green et al., 1998). We selected seven adjacent flightlines collected as part of the Southern California Box of the HyspIRI Preparatory Campaign (HPC, Lee et al., 2015) flown on an ER-2 aircraft at 20 km altitude in May/June of 2013-2018 (Table 3.1). The flightlines were atmospherically corrected Level 2 surface reflectance products produced by NASA Jet Propulsion Laboratory (JPL; Thompson et al., 2015). By applying nearest neighbor resampling with Delaunay triangulation based on up to 40 ground control points per line (supplemental material, Table S3.1), we spatially coregistered each flightline to an 18 m
grid of pixel-aggregated National Agricultural Inventory Program color-infrared orthophotos (NAD 83, UTM Zone 11N) to produce an AVIRIS surface reflectance product at 18 m spatial resolution.

Although all images were produced to satisfactory surface reflectance by JPL, images from different years were produced using slightly different atmospheric correction processes. To improve internal consistency in surface reflectance retrievals, we calibrated each set of atmospherically corrected imagery to AVIRIS imagery from August 28, 2014 used in Wetherley et al. (2018). Following Wetherley et al. (2018), we multiplied using in-scene temporally invariant targets (i.e., a large parking lot and a bare soil field) to develop band-by-band calibration coefficients (supplemental material, Figs. S3.1-S3.4). Clouds and cloud shadows were masked manually from all dates. While inspecting the data, the brightness of the northern edge of one flightline (FL06) was observed to be inconsistent with all other flightlines, so this was masked in order to remove it from analysis. Imagery within each date of acquisition was mosaicked. We removed all remaining bands that had remaining apparent atmospheric artifacts across all images, leaving 168 bands.

2.3 Multiple endmember spectral mixture analysis (MESMA)

We produced fraction maps following Wetherley et al. (2018), using MESMA (Roberts et al., 1998) in Viper Tools 2.1 (Roberts et al., 2019a). We produced fractional cover estimates from a spectral library developed by Wetherley et al. (2018) from AVIRIS imagery acquired in August 2014; image endmembers included: trees, turfgrass, NPV, soil, paved surfaces, and commercial roofs. We modeled non-vegetated surfaces separately (i.e., soil, paved surfaces, and commercial roofs) instead of as a single class because it increased
the number of modeled pixels in our results. We refer to Wetherley et al. (2018) for details regarding spectral library endmember selection and curation to a final set of 57 endmembers: 8 tree, 6 turfgrass, 9 pavements, 22 commercial roofs, 7 NPV, and 5 soils. Fractions derived from this spectral library were validated by Wetherley et al. (2018) for the August 2014 imagery, and linear regressions with reference estimates had slopes from 0.77 to 0.90, depending on the cover type. Fractions were estimated as 1, 2, or 3 endmember models plus shade using physically realistic fraction limits (0.00 to 1.00), a maximum shade endmember fraction of 0.20, and RMSE ≤ 2.5%, with a more complicated model only being selected if RMSE was improved by ≥0.7%. All fraction estimates were shade normalized (Dennison and Roberts, 2003). To retain the same sample of pixels through time, areas of cloud masking and unmodeled pixels (complexity = 0) were propagated across all image dates and were excluded from analysis.

2.4 Ancillary data and statistical assessment

We analyzed the change in vegetation cover through time, tracking changes in the fractional cover of trees, turfgrass, NPV, and non-vegetated surfaces (i.e., sum of pavement, roofs, and soil). We estimated mean fractional cover for the entire study area for each year. Since the distribution of individual pixel cover fractions was not normal (i.e., many values stacked at fractions of 0 and 1) and could not be tracked pair-wise through time, we used US census tracts as a unit of analysis to evaluate the dispersion in cover type distributions through time. Census tract boundaries were trimmed to the extent of our study area boundary in order to remove non-urban sections that could not be represented accurately with our vegetation cover classes (e.g., removing areas of chaparral shrubs). In order to
estimate error, we calculated the standard deviation of mean values across all census tracts, weighted by the number of pixels extracted within each census tract.

We also evaluated how the distribution of vegetation cover types changed as total overall vegetation cover increased within bins of census tracts. Specifically, we compared the distribution of trees, turfgrass, and NPV within census tracts as the overall sum of trees, turfgrass, and NPV increased.

To visualize and map the cumulative changes across the study area from the beginning (2013) to the end (2018) of the time series, we aggregated mean cover estimates by census tracts that contained at least 50 pixels (of any cover type, vegetated or non-vegetated), taking the difference from 2013 and 2018 vegetation cover estimates (i.e., trees, turfgrass, or NPV). Change in each census tract was displayed on a map of the study area.

We used US Census data and water use data from a recent severe drought to evaluate vegetation cover changes during the drought across areas of the city that differed in median household income and estimated outdoor water use. Median household incomes for 2018, aggregated for each 2010 census tract from the American Community Survey, were retrieved from Los Angeles County data portal (County of Los Angeles, 2020). We stratified the income levels based on $30,000 bins up to $120,000, with values >$120,000 in a single bin. Across these bins, we compared distributions in surface cover throughout the drought and changes in tree, turfgrass, and NPV cover types. Weighted mean values across census tracts were used to calculate standard deviations for cover type changes by income bins.

Finally, we examined vegetation change within areas of different irrigation regimes. For estimates of outdoor water use, we used single-family residential water use data aggregated to postal carrier route polygons within the City of Los Angeles (Chen et al.,
Data for the 2013-2018 study time period were not available. Instead, we used available water use data from 2006, an average rainfall year, to stratify outdoor water use. This allowed us to compare vegetation change based on different parts of the city that would normally have distinct levels of outdoor water use. Postal carrier route polygons with large golf courses were removed from analysis, and we included only polygons containing at least 50 image pixels.

For each postal carrier route, we estimated average single-family residential outdoor water use per household (i.e., m$^3$/ household). We estimated per household, rather than per area, because we were interested in totals areas of vegetation cover change rather than analyzing relationships between vegetation greenness and irrigation intensity. Total water use data were available as sums for each postal carrier route, and we divided the sums by the number of single-family households in each carrier route to estimate water use per household. Outdoor water use per household for each postal carrier route was estimated by calculating the difference of water use between February and June. This assumes that February, the wettest month of the year, is the least irrigated and is thus a proxy for calculating indoor water use. Subtracting this amount from water use in June, corresponding to the most frequent month used in this study, results in an estimate of outdoor water use. This is a likely minimum estimate for outdoor water use since outdoor water use also occurs in February in the study area, and true outdoor water use may in fact be higher (Chen et al., 2015). Postal carrier route polygons that violated this assumption (i.e., had lower water use in June compared to February) were removed from analysis (n = 8). Similar to the error estimation for income, weighted mean values across postal carrier routes were used to calculate standard deviations for cover type changes by water use bins.
Although outdoor water use can be affected by household income (Mini et al., 2014), we analyzed vegetation cover changes by water use separately from income due to scale differences in the data polygons. Polygons for median household income in 2018 were organized at the census tract scale across the entire study domain, while the outdoor water use data were estimated from postal carrier route polygons (mean size = 0.55 km²; Chen et al., 2015) within the City of Los Angeles, rather than Los Angeles County. This meant that the income census tract polygons were more appropriate for overall neighborhood-scale analysis across a broader domain of the Los Angeles County urban area, whereas the water use polygons were more sensitive to changes in single-family residential areas.

We used two main methods to compare the change through time of vegetation types based on both income and outdoor water use. In both cases, we compared changes for trees, turfgrass, and NPV relative to the mean value of the time series to assess year-to-year adjustments. First, we compared changes in terms of absolute fractional cover, meaning the raw fractional estimates retrieved for different binned categories. Second, we also compared percent changes relative to the mean of the time series, because of the expected differences in the baseline amounts of cover for the different income and outdoor water use bins. This normalized the cover changes so that we could assess how the cover changes might scale despite different baseline amounts of cover.

3. Results

3.1. Mean changes in vegetation cover across the study area

Overall land cover was assessed across the full study area. We report all mapped fractions and their absolute change estimates as a decimal value (i.e., 0 to 1), and all
estimates of relative percent change in fractions from the mean of the time series as a percentage (e.g., +10%). During the study period, non-vegetated surfaces were the dominant form of cover overall, composing a mean fractional cover of 0.709 of the area. Trees were the dominant form of vegetation cover (mean = 0.195), with turfgrass at a mean of 0.035 and NPV at a mean of 0.062 fractional cover (Table 3.2).

**Table 3.2:** Mean fractional cover (SD) across the entire study area of the major urban vegetation types for each year. NPV is non-photosynthetic vegetation (e.g., senesced grass, plant litter) and NON-VEG includes pavement, roofs, and bare soil. SD is calculated from the means of census tracts (n= 1935), weighted by number of available pixels within in census tract. All years had below average winter rainfall except for 2017, which had average rainfall for the study area.

<table>
<thead>
<tr>
<th>Year</th>
<th>TREE (SD)</th>
<th>TURF (SD)</th>
<th>TREE + TURF (SD)</th>
<th>NPV (SD)</th>
<th>TREE + TURF + NPV (SD)</th>
<th>NON-VEG (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013</td>
<td>0.194 (0.109)</td>
<td>0.036 (0.029)</td>
<td>0.231 (0.124)</td>
<td>0.058 (0.042)</td>
<td>0.289 (0.134)</td>
<td>0.711 (0.134)</td>
</tr>
<tr>
<td>2014</td>
<td>0.205 (0.103)</td>
<td>0.034 (0.033)</td>
<td>0.239 (0.119)</td>
<td>0.060 (0.044)</td>
<td>0.300 (0.133)</td>
<td>0.700 (0.133)</td>
</tr>
<tr>
<td>2015</td>
<td>0.196 (0.103)</td>
<td>0.033 (0.028)</td>
<td>0.229 (0.118)</td>
<td>0.057 (0.042)</td>
<td>0.285 (0.131)</td>
<td>0.715 (0.131)</td>
</tr>
<tr>
<td>2016</td>
<td>0.193 (0.097)</td>
<td>0.031 (0.029)</td>
<td>0.224 (0.111)</td>
<td>0.067 (0.046)</td>
<td>0.290 (0.127)</td>
<td>0.710 (0.127)</td>
</tr>
<tr>
<td>2017</td>
<td>0.198 (0.095)</td>
<td>0.039 (0.035)</td>
<td>0.237 (0.112)</td>
<td>0.062 (0.048)</td>
<td>0.299 (0.132)</td>
<td>0.701 (0.132)</td>
</tr>
<tr>
<td>2018</td>
<td>0.183 (0.095)</td>
<td>0.030 (0.028)</td>
<td>0.213 (0.110)</td>
<td>0.071 (0.047)</td>
<td>0.284 (0.126)</td>
<td>0.716 (0.126)</td>
</tr>
<tr>
<td>Mean</td>
<td>0.195 (0.101)</td>
<td>0.034 (0.030)</td>
<td>0.229 (0.116)</td>
<td>0.062 (0.045)</td>
<td>0.291 (0.131)</td>
<td>0.709 (0.131)</td>
</tr>
</tbody>
</table>

Annual changes in fractional cover for each cover type were assessed as percent change anomalies relative to the mean of the time series in order to gauge overall changes during the drought (Fig. 3.2). Cover fluctuated throughout the study period, with overall trends of reductions in turfgrass cover and increases in NPV, and less consistency in trees. Compared to its mean, tree fractions were higher in 2014 and lower in 2018, but otherwise oscillated around the mean for other years. Turfgrass had high fractions in 2013 and gradually lost cover as the drought progressed, apart from high fractions in 2017 after more average wintertime rainfall. NPV had low values in 2013, 2014, and 2015, but had higher
values in 2016 and 2018. At the end of the time series in 2018, trees and turfgrass had their lowest mean values and NPV had its highest mean values. There was considerable variability in the changes for individual census tracts, with one standard deviation from the mean change always overlapping the mean of the time series (i.e., zero change value).

**Fig. 3.2:** Annual mean percent change (2013-2018) anomalies of fractional cover from mean of the time series for the full study area for tree, turfgrass, and NPV. Error bars show ±1 SD based on weighted means of census tracts.

When aggregated to census tracts, the proportions of vegetation cover types were different based on the amount of total vegetation cover (i.e., tree + turfgrass + NPV), but these proportions were mostly stable during the drought time series (Fig. 3.3). In general, census tracts with low total vegetation cover (<0.25) had relatively fewer trees and more NPV in their vegetated areas than did census tracts with higher total vegetation cover.

Census tracts having >0.3 total vegetation cover had similar proportions of tree, turfgrass,
and NPV cover, although census tracts with very high overall vegetation cover (> 0.6) were more inconsistent year to year. Although these proportions did not undergo large changes through time, the proportion of tree cover decreased and NPV cover increased for census tracts having total vegetation fractional cover between 0.3 to 0.5.

**Fig. 3.3**: Annual distributions of vegetation cover types within bins of total vegetation cover (tree + turfgrass + NPV) as aggregated to mean fractional cover within census tracts.

Although mean tree and turfgrass cover decreased and NPV cover increased from 2013 to 2018 (**Table 3.2**), the nature of the change varied spatially across the study area. (Difference maps showing anomalies between mean of the time series and 2018 are provided in the supplemental material, **Figs. S3.5-S3.8**.) Turfgrass loss was more intense farther from the coast, with the greatest losses in turfgrass cover occurring north and east of the Los Angeles Basin in the San Fernando and San Gabriel Valleys (**Fig. 3.4**). Additional strong losses of turfgrass cover were present in the highly vegetated foothill areas at the
perimeter of the Los Angeles Basin near Beverly Hills and UCLA, Rancho Palos Verdes, and Whittier. By contrast, turfgrass cover increased south of downtown Los Angeles in residential areas and commercial districts near Vernon as well as closer the ocean in Santa Monica and Torrance.

**Fig. 3.4**: Mean cumulative changes in turfgrass fractions from 2013 to 2018 by census tracts. Note that bins in color scale are not of equal width. Census tract boundaries are trimmed to the extent of the overall study area, but not limited internally by clouds, unmodeled pixels, and excluded image artifacts, and so can still overlay the missing interior diagonal section of FL06 in the northern part of the study area, for example.
Overall tree cover changes were not as apparent as those in turfgrass, but from 2013 to 2018 more areas experienced tree cover losses than gains (Fig. 3.5). The tree cover losses were scattered throughout the Los Angeles Basin, as well as to the north and east in the San Fernando and San Gabriel Valleys. Tree cover fraction increased in the southwest of the San Fernando Valley near Woodland Hills, and as well as near UCLA and in Whittier.

Fig. 3.5: Mean cumulative changes in tree fractions from 2013 to 2018 by census tracts. Note that bins in color scale are not of equal width.

Increases in NPV cover fraction from 2013 to 2018 were common for most regions throughout the study area (Fig. 3.6). Increases in NPV were most apparent in areas that also lost turfgrass cover, such as in the San Fernando Valley and the hills to the south of the San Gabriel Valley. NPV cover also decreased in some areas where turfgrass increased, such as
in south of downtown Los Angeles. However, turfgrass losses in the San Gabriel Valley itself did not lead to as large increases in NPV proportionally as might have been expected. This suggests that this region may have experienced more conversion from turfgrass to non-vegetated surfaces than other areas. This is supported by Fig. 3.7, which shows changes in total vegetation cover (tree + turfgrass + NPV). Total vegetation cover was lost in the interior valleys, most strongly in the San Gabriel Valley, but increased in many parts of the Los Angeles Basin.

**Fig. 3.6**: Mean cumulative changes in NPV fractions from 2013 to 2018 by census tracts. Note that bins in color scale are not of equal width, and that color scale has been reversed compared to the other maps, such that brown colors represent areas with increases in senesced vegetation cover (i.e., NPV) and green colors represent areas with reductions in senesced vegetation.
Fig. 3.7: Mean cumulative changes in tree + turfgrass + NPV fractions from 2013 to 2018 by census tracts. Note that bins in color scale are not of equal width.
3.2. Vegetation change related to income and water use

3.2.1. Income

The proportions of vegetation cover types changed with median household income, and these proportions remained largely constant through all years of the time series (Fig. 3.8). The lowest income bin always had the least total vegetation cover (tree + turfgrass + NPV) and the most non-vegetated cover, while the highest income bin always had the most total vegetation cover and the least non-vegetated cover. Although the proportion of non-vegetated cover decreased as income level increased, the proportions of both tree and turfgrass cover increased as income level increased. The proportion of NPV cover was lowest in the middle income bins but was highest in both the lowest and highest income bins. This suggests that census tracts with very low or very high median household income have different vegetation cover distributions than most middle income areas, and likely have more unmaintained open space that would be NPV during the early summer. In general though, the relative proportions of cover did not change to a large degree through the drought. Although there were small year to year changes in vegetation cover estimates, these did not likely amount to dramatic changes in cover by median household income level in aggregate as the drought progressed.
We compared changes in vegetation cover based on absolute fractional cover for different levels of median household income (Fig. 3.9). For all except the lowest income bin, tree cover was lowest in 2018, but did not clearly decrease year to year as the drought progressed. The magnitude of year to year changes in trees often increased with income level, with the higher income levels having larger shifts in the yearly mean values, but individual bins had different relative high and low values. Turfgrass had a more consistent trend across income levels, with most income levels showing a general decrease in turfgrass cover over time, except for high values in 2017. The magnitude in year to year adjustments in turfgrass cover was also greater for higher income levels than for lower income levels. All income bins had relatively higher NPV cover in 2016 and 2018. Higher income bins only showed more consistent increases in NPV through time than the lower income bins. The highest income bin, $120k+, showed the most rapid increase from the beginning of the
drought, with far lower 2013 estimates in NPV relative to the mean than the other bins. However, higher income bins did not necessarily have greater increases in NPV than the other income bins, in contrast the greater shifts for higher income bins observed for trees and turfgrass.

**Fig. 3.9**: Mean change anomalies in absolute fractions from mean of time series of vegetation cover types by income bins. Error bars are ±1 SD from the census tracts, weighted by number of pixels per census tract.
When scaled relative the mean vegetation cover fraction for the entire time series, differences in cover change magnitudes between income bins were no longer as apparent for tree and turfgrass cover types (Fig. 3.10). For trees, the higher income bins did have relatively more change than the lower income bins when normalized by their mean fractional cover. In fact, many of the lower income bins had relatively similar changes through time (except for estimates in 2013), while the highest income bin, $120k+, had relatively smaller changes, likely due to its much higher baseline of tree cover. Once normalized to baseline mean fractions, changes in turfgrass were very similar throughout the time series and appeared to be largely independent of income level. However, the greatest losses in 2018 relative to the time series mean were more apparent in the low and middle income bins rather than the highest income bin. In contrast to trees and turfgrass though, NPV cover changes had very similar temporal patterns after normalizing for mean cover as they did for absolute fractional cover changes, and the greatest increases in NPV in 2018 relative to the mean were still in the middle income bins.
Fig. 3.10: Mean relative change (%) anomalies in fractions from mean of time series of vegetation cover types by income bins. Error bars are ±1 SD from the census tracts, weighted by number of pixels in each census tract.
3.2.2. Outdoor water use

After estimating typical single-family residential mean outdoor water use per household from an average rainfall year (2006), we considered outdoor water usage in the following quintile bins, in units of m³/household: very low (0 - 2.77), low (2.77 - 6.63), medium (6.63 - 15.71), high (15.71 - 24.54), and very high (24.54 - 588.99). This meant the highest water users applied an order of magnitude more outdoor irrigation water than any of the other water use bins.

In general, overall vegetation cover tended to increase as mean household outdoor water use increased, and these proportions were largely stable through time (Fig. 3.11). Mean fractions of tree and turfgrass cover increased as water use increased. The medium and high water use bins had very similar proportions of vegetated and non-vegetated cover, but the medium water use bin had greater NPV cover, having the greatest NPV cover of any water use bin.
Similar to the temporal comparisons for income, we compared the absolute fractional changes in vegetation cover types by bins of outdoor water use (Fig. 3.12). Tree cover changes in the high and very high water use bins showed more consistent year over year reductions through the time series than the very low, low, and medium water use bins. These lower water use bins generally showed much higher variability in the mean estimate of tree cover without an apparent trend between years, except for high values in 2017 and low values in 2018. Turfgrass fractions were higher in 2013 than the mean of the time series for all water use bins. In general, the higher bins showed greater variability in turfgrass than the lower water bins. The higher water use bins had increases in turfgrass cover in 2017 that were not as apparent as in the lower water use bins, and the lowest mean values in the highest water use bins were in 2015 rather than 2018. Year to year changes in NPV
generally showed increases through the time series, but this was more apparent in the higher water use bins than in the lower water use bins.

Fig. 3.12: Change anomalies in absolute fractions from mean of time series of vegetation cover types by water use bins. Error bars are ±1 SD from the postal carrier routes, weighted by number of pixels in each postal carrier route.
When scaled to relative change by the mean of the time series, the overall temporal patterns in water use bins were analogous to the observed shifts in absolute fraction totals (Fig. 3.13). However, for trees, the relative magnitude of changes was much greater for the lower water use bins than for the higher water use bins. By contrast, turfgrass changes were of a similar magnitude across all water use bins once scaled by the mean of the time series, although features of low values in 2015 and high values in 2017 were still apparent in the higher water use bins. In general, once scaled by the mean values, relative NPV changes were largely similar across all water use bins, although there was greater inconsistency between water use bins in 2013 and 2016. NPV values were greatest in 2018 for all water use bins. NPV values were lowest year in 2017 for the lower water use bins but were lowest in 2013 for the higher water use bins.
Fig. 3.13: Relative change (%) anomalies in fractions from mean of time series values of vegetation cover types by water use bins. Error bars are ±1 SD from the postal carrier routes, weighted by number of pixels in each postal carrier route.
4. Discussion

4.1. Importance of separating urban vegetation types through time with MESMA

We used MESMA to map fractional cover estimates from a multi-annual time series of airborne imaging spectroscopy data. Other remote sensing studies have tracked trees or turfgrass through time (e.g., Gillespie et al., 2012; Hedblom et al., 2017), but to our knowledge this is the first study to separately track trees and turfgrass while including NPV cover through time across a full urban landscape. Overall, our cover estimates (mean values: tree = 0.20, turfgrass = 0.03, NPV = 0.06; Table 3.2) were comparable to those measured for a single point in time in other recent studies in the Los Angeles area during summer, despite differences in year and month of acquisitions (Los Angeles city: tree/shrub = 0.21, irrigated grass = 0.12, dry grass/soil = 0.06, McPherson et al., 2011; Los Angeles metropolitan area: tree = 0.20, turfgrass = 0.04, NPV = 0.07, Wetherley et al., 2018).

Discriminating trees, turfgrass, and NPV separately was important to understand the dynamics of metropolitan-scale drought response in land cover, especially because we observed that they can have distinct temporal responses to drought and since they can affect the urban environment differently. Both trees and turfgrass can provide benefits related to cooling in urban environments, but they have different behaviors and characteristics (Norton et al., 2015). For example, turfgrass lawns have greater evapotranspiration rates than trees, but the rates can depend on whether the land use is residential or recreational (Peters et al., 2011). Although this implies that turfgrass can provide significant cooling through latent heat loss (Liang et al., 2017; Wheeler et al., 2019), tree evapotranspiration can also provide significant air temperature reductions for areas around sufficiently large stands (Ziter et al., 2019). Moreover, even if transpiration rates from urban trees can be highly variable by
species (Pataki et al., 2011), shading from tree cover is often a far more influential moderator of localized air and surface temperatures (Souch and Souch, 1993). NPV cover varies seasonally as grasses senesce during the summer-to-fall dry season in Mediterranean climate regions (Dennison et al., 2019), and it can be very sensitive to recent rainfall. Although these areas are not green and photosynthesizing, NPV-covered areas will be seasonally green and are likely to recover during the wetter winter months or in wetter years. This is very different from areas that are converted to non-vegetated surfaces such as artificial turf or woodchips during drought, as these are more permanent changes that are unlikely to return to vegetated cover after the drought ends (Pincetl et al., 2019).

We used hyperspectral imagery from AVIRIS to separate trees turfgrass, and NPV from non-vegetated and impervious surfaces in our study area. While green vegetation cover can often be reliably separated from non-vegetated urban surfaces, the greater spectral information enables classification of many different types of non-vegetated cover, which is critical for separating out landcover that was key to this study. In particular, NPV is often confused with soil and urban spectra at broadband spectral resolutions because the key discriminating wavelengths in the shortwave-infrared are not well-represented (Roberts et al., 1993). By being able to distinguish NPV from these other cover types, we could observe high increases in NPV in 2018 that were not vegetation losses (Fig. 3.2), and these areas will likely return to green vegetation during wet winters or with sufficient irrigation in non-drought years. At the same time, we could separate increases in NPV more generally from total vegetation cover losses, and increases in non-vegetated cover, that were apparent in the San Gabriel Valley (Fig. 3.7). Moreover, mapping cover at sub-pixel scales also allowed for detection and mapping of cover that occurs at scales below that of the full pixel, which can
be especially important for quantifying vegetation in highly impervious environments such as Los Angeles (Wetherley et al., 2018).

While we were able to separate trees from turfgrass cover based on spectral characteristics, determining consistent fractions of these distinct cover types through time required careful assessment of the image data. Turfgrass and trees were the least distinctive pair of spectral endmembers found by Wetherley et al. (2017). Here, as in Wetherley et al. (2018), the most important discriminating characteristic between turfgrass and trees was overall brightness across the spectrum, with turfgrass endmembers being brighter than tree endmembers, although there can be large variability in the spectral characteristics within tree canopies (Alonzo et al., 2014) and due to background materials (Franke et al., 2009). These methods required a more restrictive shade fraction maximum (20%) than in other MESMA studies (e.g., 80% in Shivers et al., 2019 and Miller et al., 2020) and careful image calibration and correction of brightness differences across many image acquisitions. This also required individual flightline assessment to limit the effects of varying solar geometries and view angles through many image acquisitions, which can manifest in bidirectional reflectance distribution function changes between flightlines. While cross-track correction methods have applied for vegetation mapping outside of urban environments (Jänicke et al., 2020; Cooper et al., 2020), these techniques are difficult to apply within urban environments due to spectral and spatial heterogeneity. For example, bright vegetation can dominate the spectral signal when mixed with otherwise dark impervious urban surfaces, creating the appearance of dark vegetation spectral signatures in neighboring pixels (Herold et al., 2004). Flightline-specific brightness artifacts will likely be less of an issue from spaceborne sensors, such as the proposed NASA SBG, with much smaller view angles of
acquisitions from much higher altitudes (~700 km) than the comparatively wide view angles and lower altitudes of airborne acquisitions used here (~20 km).

4.2. Impacts of drought on urban vegetation

The different drought responses observed between urban vegetation types were likely related to both physiological differences as well as the level of the amount of outdoor water use required over the duration of the event (Peters et al., 2011; McPherson et al., 2011; Wheeler et al., 2019). Overall, turfgrass cover declined and NPV cover increased between 2013 and 2018, while tree cover only declined in 2018 after varying year to year during the time series. Our results showed that turfgrass cover is was highly sensitive to winter rainfall and will recover during wetter years such as 2017, and that turfgrass covered areas were rapidly converted to NPV during dry conditions without irrigation (Quesnel et al., 2019). However, even after more average rainfall in 2017, there were large areas of NPV that returned in the drought year of 2018. Although there was likely more vegetation in general in 2018 that was primed for senescence after many successive years of drought, part of the reason for these high NPV values may be that lawn watering habits may have changed, despite the potential for reversion to past watering habits recorded in previous droughts (Pincetl et al., 2019). This is supported by water use reduction targets implemented throughout the city during the 2012-2016 drought (Palazzo et al., 2017).

While mean turfgrass cover consistently declined for the years of drought, we did not find mean tree cover to have a strong negative trend for most of the time series, with major reductions only occurring in 2018. Despite this, individual trees were almost certainly affected by the drought. For example, Miller et al. (2020) found that urban tree canopies in
Santa Barbara were in fact affected during the height of the drought in 2014, with some partial recovery in 2017. Scale differences between the small tree canopy patches studied in Miller et al. (2020) and the overall urban scale analysis in this study may be partly attributable to the differences in sensitivity. The reductions in tree cover in 2018, which was after the main drought had ended, are supported by other studies that have found larger declines in trees after drought in response to accumulated stress and weakened health affecting recovery (Trugman et al., 2018; Kannenberg et al., 2020). Overall, we did not find large changes in urban tree canopy cover in Los Angeles over the course of the time series. While large amounts of tree mortality have been observed in natural areas in other parts of California, such as in the Sierra Nevada (e.g., Fettig et al., 2019), the lack of significant and lasting reductions in tree cover fractions in our study implies that, compared to natural areas, mortality of urban trees was not widely spread during the drought, although urban tree death was reported in Los Angeles in some cases (e.g., Stevens et al., 2015). The spatial resolution of our imagery, at 18 m, also made it difficult to ascribe observed changes in tree cover to mortality specifically since we were working a pixel scale much greater than the crown of an individual tree. Mortality estimation would be more appropriate from imagery with higher spatial resolution in which individual trees could be uniquely tracked.

In addition, we found that proportions of vegetation cover can shift during a drought for certain cover thresholds, even as the proportions of total vegetation cover remains relatively consistent (Fig. 3.3). As a result, understanding of vegetation cover and its associated benefits cannot easily be addressed directly from green vegetation cover estimates without knowledge of spatial distributions of trees versus turfgrass (e.g., Franke et al., 2009; McPherson et al., 2011; Degerickx et al., 2020). Beyond this, there can be a wide
distribution of tree species in different parts of the study area (Alonzo et al., 2014; Avolio et al., 2015), which may provide different forms of ecosystem services. However, due to the high diversity of different trees in the Los Angeles region (Clarke et al., 2013) and the scale of our data, this form of investigation was beyond the scope of our analysis.

Due to the high spectral resolution of the AVIRIS imagery, we were able to separately estimate fractional cover changes in urban trees, turfgrass, and NPV, and therefore it was possible to quantify differences across geographic and socioeconomic units that are unlikely to be apparent in estimates of the total green cover. For example, Tayyebi and Jenerette (2016) found that, in the Los Angeles metropolitan area, the Normalized Difference Vegetation Index (NDVI) was lowest in coastal urban areas but greatest in inland areas, reaching a maximum at 40 km from the coast. Because our results were able to distinguish trees from turfgrass, we were able to attribute losses in green vegetation in the interior valleys of Los Angeles to losses of turfgrass cover, rather than tree cover (Fig. 3.4).

Cumulative turfgrass cover loss and NPV gains differed among large scale physiographic features and climatic regions across the Los Angeles metropolitan area. While areas of turfgrass loss from 2013 to 2018 occurred across the study area, they were more concentrated in the interior valleys to the north (San Fernando Valley) and east (San Gabriel Valley) of the Los Angeles Basin. These areas tend to be warmer and drier normally than the Los Angeles Basin (Tayyebi and Jenerette, 2016; Pincetl et al., 2019), and so preferential turfgrass loss might be expected. NPV cover gains were not as pronounced in these regions, suggesting greater conversion to non-vegetated urban surfaces. Instead, NPV cover gains were more prominent in the more topographically complex regions of the study area, where there may have been more limited urban development and lower population densities. This
suggests that these areas had more vegetated land area that could be converted to NPV during drought conditions. Tree cover changes were more inconsistent spatially, and there are likely more local scale factors that have biased tree cover distributions prior to the drought, limiting the overall impact of drought compared to turfgrass.

Our time series of showed that changes in vegetation cover types varied in areas of the city having different levels of median income. Many studies have shown that tree and overall green vegetation cover increase with income (Schwarz et al., 2015; Tayyebi and Jenerette, 2016). However, there has not been any research, to our knowledge, describing how vegetation cover may change differently during a long-term drought across areas having different levels of income. Higher income areas had greater absolute year to year changes in of tree and turfgrass cover and greater increases in NPV cover relative to 2013 than did lower income areas (Fig. 3.9). For example, higher income areas also had greater increases in turfgrass fractions average the wetter winter in 2017. This is largely because higher income areas had larger amounts of vegetation cover that could potentially be lost during drought. However, compared to their initial cover, middle-income areas often had similar or greater relative losses of turfgrass than did higher income classes (Fig. 3.10). Consequentially, although high income areas had greater absolute changes in fractional cover, they were able to continue to support a relatively greater proportion of their existing vegetation cover than lower income areas. This supports studies that have shown that relatively more of the higher income areas in Los Angeles were able to maintain their vegetation cover during the drought (Pincetl et al., 2019).

When organized into bins of typical outdoor water use from a non-drought year (2006), responsiveness in year to year cover changes varied based on vegetation type. Tree
cover changes in higher water use bins showed more consistent reductions from 2013 through to 2018 than did lower water use bins. Lower water bins showed greater relative variability in tree cover because of their lower baseline for existing tree cover relative to the observed change. These differences may be because trees in higher water use bins may be present in larger urban forest clusters and can be observed to shift consistently from the 18 m spatial resolution used here, whereas trees in lower water use bins may be more spatially dispersed and the signal is likely to be more affected by mixed pixels (e.g., Herold et al., 2004), making the estimated values of trees more uncertain.

However, although higher vs. lower water use bins showed differences in consistency of estimates for trees, we did not find this to be the case for turfgrass. In terms of absolute fractions, higher water use bins showed greater year to year changes in turfgrass that lower water use bins, and also had higher turfgrass recovery amounts in 2017. Once normalized to existing to the mean baseline, lower water use bins showed a greater drop off in turfgrass fractions to the remaining years of the drought. This suggests that the drought had a more immediate and lasting effect on the turfgrass cover of lower water use areas than on higher water use areas, meaning that typically lower water users may have consistently reduced their outdoor water use during the drought whereas the high water users did not. Since water use is often related to income, this is supported by Palazzo et al. (2017), in which the authors found that in Los Angeles water usage was reduced more in lower income neighborhoods than in higher income neighborhoods during the drought.

Year over year increases in NPV were more consistent during the drought time series for high water users than for low water users, and rescaling to the baseline mean amounts of NPV showed relatively similar overall magnitudes in the shifts of NPV across the different
water use bins. This indicates that all water use bins were affected by similar amount by the
drought, the timing of these effects depending on the amount of water use. The general
increases NPV fractions and losses of tree fractions in high water use areas suggests that
NPV was predominantly replacing trees in high water use areas. The greater temporal
inconsistency in NPV in low water use areas suggests it is likely replacing more of a mixture
of turfgrass and trees in the low water use areas. These differences are likely related to the
much higher relative availability of trees in higher water use areas to lower water use areas
(Fig. 3.11), especially since high water use is often needed for households with large
numbers of trees in Los Angeles (Schwarz et al., 2015).

4.3. Broader implications of droughts on urban areas and vegetation

Our results indicate that although turfgrass cover is rapidly affected by drought,
urban trees may take several years to exhibit long term effects. This implies that repeated
drought conditions are likely to affect urban forest cover over the long term, but these
impacts may not be easily perceptible from year-to-year during a drought and that long-term
analyses such as Gillespie et al. (2012) will also be important to complement future annual
analyses. Maintaining urban green vegetation cover for ecosystem services will likely be
increasingly challenging in cities in the future, especially in arid or semi-arid climates (e.g.,
McPherson et al., 2018). Although urban vegetation can produce disservices related to
allergies, nuisance litter, and harming infrastructure (Roman et al., 2020), it is often
critically important for shading and cooling (Norton et al., 2015; Wheeler et al., 2019). We
also observed consistent losses in turfgrass losses across our study area, both in terms of
temporary shifts to NPV and likely more permanent transitions to non-vegetated surfaces.
While replacing turfgrass areas with drought-tolerant, non-vegetated, and/or impervious surfaces will reduce water use, it will also likely affect energy budgets and increase local temperatures (Vahmani and Ban-Weiss, 2016; Pincetl et al., 2019). In combination with estimates of urban energy budgets (Norton et al., 2015), careful species planting considerations will also be needed, similar to efforts being made to reforest natural ecosystems that have been affected by recurring drought, fire, and insect attacks (North et al., 2018).

In general, vegetation cover loss or mortality is the most severe form of vegetation drought response, and the gradations of response in urban environments is likely to be variable with climate and biome. Drought can affect vegetation growth and structure in wetter climates as well (e.g., Chicago, Illinois; Bialecki et al., 2018) although with different time scales and dynamics than in Mediterranean climates (e.g., May et al., 2013). Tree species palettes within cities also vary based on prevailing climates, affecting local responses and likelihood of planting native species (Jenerette et al., 2016). Since the drought in California from 2012-2016 was so extreme by many standards (Lund et al., 2018), it could be indicative of potentially severe climate change-droughts that may be experienced in the future. Other cities will likely need to account for the effects of more extreme drought conditions when planting vegetation for the future (Norton et al., 2015), especially in seasonally dry regions like California (McPherson et al., 2018; Quesnel et al., 2019; Pincetl et al., 2019) due to potential anthropogenic influences on precipitation change and drought (Marvel et al., 2019; Williams et al., 2020).
5. Conclusions

We monitored annual vegetation cover changes in the Los Angeles metropolitan area from May/June 2013-2018, separately tracking fractional cover estimates of trees, turfgrass, NPV, and non-vegetated surfaces. First, we compared mean changes in cover through time across the entire study area. Mean turfgrass cover decreased and mean NPV cover increased during the drought time series, with 2018 having the greatest decreases in turfgrass and greatest increases in NPV relative to the mean of the time series. Mean tree cover showed variable changes over time, increasing in 2014 and 2017 but then decreasing in 2018 relative to the mean of time series. This suggests that over a large urban area, turfgrass is quickly responsive to drought through irrigation and precipitation reductions and greater temperatures, but trees are more buffered and tree cover changes take longer to develop.

Second, we evaluated the metropolitan-scale spatial patterns of cover changes between 2013 and 2018 as they varied by vegetation type, aggregating spatially by census tracts. We specifically focused on analyzing by macro-scale climatological and physiographic factors. Turfgrass cover losses were most apparent in the interior valleys to the north and east of the Los Angeles Basin, while several areas within the Los Angeles Basin experienced increases in turfgrass cover. Tree cover losses were less-readily apparent and more scattered throughout the Los Angeles Basin, with some additional losses to the north of the San Gabriel Valley. NPV cover increased for most of the study area, although increases were less severe in the San Gabriel Valley relative to the losses of turfgrass cover. There was greater loss in total vegetation cover (tree + turfgrass + NPV) in the interior valleys, and the San Gabriel Valley especially, than elsewhere in the study area. This indicates how climatological regions across the Los Angeles metropolitan area can have
differential responses to drought that can vary across different urban vegetation types. In addition, due to the difficulty in maintaining turfgrass cover in the interior areas during this drought, these results have implications for potential climate change responses to drought if cooler coastal areas might behave like hotter interior areas in the future.

Third, we investigated change in the fractional cover of the major urban vegetation types over the drought based on levels of median household income, binned by census tracts, and average outdoor water use per household measured during a non-drought year, binned by postal carrier route polygons. Throughout the drought time series, the proportion of total vegetation cover was greater for higher levels of income and water use than for lower levels. This was largely driven by greater amounts of trees and, to lesser extent, turfgrass, while NPV did not show as consistent increases across all bins. Overall, the highest income areas had the greatest absolute changes in tree and turfgrass cover. Once normalized to their means for the time series, the lower-income areas more often had the greatest cover changes trees, while turfgrass and NPV changes were more similar across all income levels. Based on levels of typical outdoor water use, trees showed more consistent reductions year over year at the higher water use levels than at the low water use levels. This was reversed in NPV, with higher water use levels showing more consistent increases year over year than low water use levels. Turfgrass had greater year to year variability in higher water use bins than in lower water use bins, but the magnitudes of changes overall were more similar across bins once changes were normalized based on mean turfgrass cover. Therefore, we might expect the largest absolute changes in urban vegetation cover in wealthier and more well-watered areas during future droughts. However, year to year changes may be more similar or even greater for lower income and water use areas once
normalized to mean baseline cover. Vegetation cover changes can be both spatially and temporally diverse, and monitoring changes at the neighborhood scale in addition to metropolitan-scale aggregate values are needed to more accurately describe changes in urban cover.

Year to year changes in urban vegetation cover can be highly variable across a large metropolitan area, even under the forcing of persistent drought. Our results indicate that trees and turfgrass cover changes respond at different time scales to drought and can show differing magnitudes of response based on broad scale patterns in urban climatology and physiography. They can also respond differently based on levels of income and outdoor water use, and so it is likely important to describe neighborhood characteristics when comparing changes within or across cities. Studies of urban vegetation cover changes likely need to consider relative changes of different vegetation types across neighborhoods in order to portray a more accurate picture of urban landscape heterogeneity, especially under potential future climatic factors such as drought.

Acknowledgements

This study was funded by a NASA Earth and Space Science Fellowship (80NSSC18K1325). Special thanks to Sarah Lundeen at JPL for help in obtaining AVIRIS image time series; Professor Susan Meerdink for spectral calibration code; and Michael Allen for helpful feedback on many figures.
Conclusions

Urban vegetation can exhibit a wide array of responses to drought, which can vary based on vegetation type, seasonal impacts, and drought duration. In this research, I have used remote sensing imagery from airborne imaging spectroscopy and broadband satellite data to investigate urban vegetation response to an extended, severe drought in California across a range of spatial and temporal scales.

In Chapter 1, I compared spectral responses to drought among urban tree species and turfgrass in Santa Barbara using airborne imaging spectroscopy imagery from 2011, 2014, and 2017. Of the three chapters in this dissertation, this had the finest spatial scale and the greatest diversity of spectral response variables, making it possible to quantify variations of drought response for individual tree patches and turfgrass lawns. In general, I observed large negative shifts in many spectral indicators related to canopy leaf density, water content, and pigments from 2011 to 2014, with partial recovery from 2014 to 2017. Turfgrass declined and then recovered when rainfall increased, while most tree species declined but had not fully recovered by 2017. Needleleaf trees were more affected by the drought than were broadleaf trees and, contrary to expectations, native trees were more affected than non-native trees. In addition, trees with higher leaf area experienced more negative responses during the drought than did trees with lower leaf area. This study demonstrated how repeat airborne imaging spectroscopy can track many aspects of drought response in urban vegetation that are expressed through spectral changes in the plant canopy, and it showed the diversity of responses in urban tree species and turfgrass lawns to drought and potential recovery.
In Chapter 2, I evaluated seasonal dynamics in drought response among the major urban vegetation types occurring in the Santa Barbara region by comparing responses in greenness (NDVI), surface temperature (ΔLST), and water content (EWT) using both Landsat and AVIRIS imagery. This study had the densest time series of the three chapters, allowing me to characterize the seasonal variability of drought responses in a Mediterranean climate overlaid on a severe, multiyear drought. Vegetation cover types were mapped at 4 m resolution using a random forest classification and AVIRIS-NG, and then larger Landsat and AVIRIS pixels were used to track areas dominated (>90%) by different vegetation types through time. For most vegetation types during drought years, NDVI was lower (i.e., less green) and ΔLST was closer to zero (i.e., vegetation temperatures were less differentiated from non-vegetated surface temperatures). However, the timing of these responses differed among vegetation types, with strong differences between those that are deciduous and senesce seasonally (annual grass, in summer; many broadleaf trees, in winter) versus those that are evergreen (needleleaf trees; some broadleaf trees; Eucalyptus trees; coast live oak trees; and turfgrass). Water content changes from EWT showed seasonal responses that were not as readily apparent in the NDVI, and they were important for comparing seasonal drought responses for evergreen trees that did not show prominent seasonal NDVI adjustments. The seasonal response of annual grass NDVI was correlated with a drought index (SPEI) at spans ≤12 months, while trees and turfgrass NDVI was typically correlated with SPEI at spans >12 months in addition to seasonal time spans. This study demonstrated how canopy response to drought development can be tracked more sensitively by using multiple remote sensing variables that each provide distinct information at a range of time
scales. It also showed how seasonal drought effects interact with long-term drought across different urban vegetation types in a Mediterranean-climate city.

In Chapter 3, I tracked changes in trees, turfgrass, NPV, and non-vegetated surface cover during drought in the Los Angeles metropolitan area (2,490 km²) using MESMA fractional cover estimates derived from an annual time series of AVIRIS imagery. This study had the largest spatial extent of the three chapters, making it possible to quantify metropolitan-scale shifts in vegetation cover. During the drought time series of May/June imagery from 2013 to 2018, turfgrass cover decreased and NPV cover increased overall. Tree cover was more stable during the drought, but it decreased in 2018. The hotter and drier interior valleys of the study area lost more turfgrass cover than did comparatively cooler and more coastal areas in the Los Angeles Basin. In the San Gabriel Valley, total vegetation cover (tree + turfgrass + NPV) was lost during the drought, rather than just a substitution of green vegetation (tree or turfgrass) for NPV, suggesting that some areas were converted from vegetation to non-vegetated urban land covers. In terms of absolute area, higher income areas of Los Angeles had greater losses in tree and turfgrass cover than did lower income areas. NPV changes were similar across income levels. When compared across areas of the city that varied in outdoor water use, based on absolute area trees showed more consistent reductions in areas of higher water use, but less year-to-year change in areas having lower water use. Turfgrass showed greater year-to-year variability in areas of higher water use than in areas of lower water use, but the magnitudes of changes overall were more similar across levels of water use once the changes were normalized by the mean turfgrass cover. This study demonstrated how imaging spectroscopy can be applied to separately track key vegetation types in a large urban area during a long-term drought, and it reveals the
variability in cover changes in different vegetation types and across levels of income and outdoor water use.

Many of techniques that I have applied here in southern California cities could be used elsewhere with available data in future studies, especially with the future NASA Surface Biology and Geology (SBG) mission. Given repeat data from a spaceborne imaging spectrometer having spatial (30 m) and temporal (16-day) resolution similar to Landsat and spectral resolution similar to AVIRIS (350-2500 nm, >200 bands), disparate components of this research could have been done all with a single sensor. SBG could track different spectral characteristics among different urban trees (in sufficiently large stands) as described in Chapter 1, evaluate the seasonal timing of these changes that required both Landsat and AVIRIS in Chapter 2, and also monitor large extents of fractional cover change as in Chapter 3. In the meantime, before SBG’s launch, existing broadband sensors such as Sentinel-2 may provide improvements to tackle these types of questions. Sentinel-2 has better spatial, temporal, and spectral resolution than Landsat, but it was not launched until the 2012-2016 California drought was nearly over (2015 and 2017 for Sentinel-2A and Sentinel-2B, respectively) and therefore it could not provide the time series needed for the studies in this dissertation.

In addition to spaceborne remote sensing sources, there are other sources of remote sensing imagery that have promise for analyzing drought response in urban vegetation, most notably repeat airborne LiDAR data. I relied on previously analyzed LiDAR data from Alonzo et al. (2014; 2015; 2016) in Chapter 1. I would have been unable to track patches of individual tree crowns if it were not a map of tree crown polygons derived from the processed LiDAR data. I was able to quantify differences in drought response based on leaf
area index (LAI) and aboveground biomass due to the inclusion of LiDAR from before the drought. Repeat high-density LiDAR data, while not commonly available, could offer extraordinary detail of urban tree crowns at extremely high precision, allowing for temporal comparisons within crowns and estimation of key canopy variables through time. Estimates of these variables through time, such as LAI, could offer precise estimates of ecosystem services provided from individual trees and the variations in their responses to drought when included in urban forestry ecosystem service models such as i-Tree (Nowak et al., 2008; Alonzo et al., 2016; Nowak, 2020).

More generally, there are still many opportunities for future investigations due to how urban vegetation responds to drought differently across scales of time and space. For example, in Chapter 1 I showed that individual trees species were affected by drought in 2014 and had not fully recovered in 2017. In contrast, results of Chapter 3 showed that overall tree cover was not strongly affected by drought until 2018, after the main part of the drought had ended. Due to the climatic and urban development similarities in the study areas (Santa Barbara and Los Angeles), I would have expected to see similar changes in the timing in the effect of trees between these two studies. However, when taken together these results suggest that in Chapter 1 we observed effects of drought on patches of individual crowns which did not result in the full removal or loss of the tree crown, whereas in Chapter 3 we observed losses in overall tree cover across a larger area. Because of the differences in spatial scale between these datasets used and the overarching goals of these particular studies, I was unable to test for timing of these effects and onset the tree removal after a necessary reduction in canopy density or condition (observed spectrally) during the drought. Future studies could address this type of questions by consistently using similar datasets to
both evaluate canopy condition and tree cover loss, and these types of results could also be applied to evaluate more detailed temporal changes across tree species. It is likely that some urban tree species experience a more rapid decline from observed drought stress to subsequent mortality (e.g., blue gum Eucalyptus (*Eucalyptus globulus*)) while others have longer, slower declines (e.g., coast live oak (*Quercus agrifolia*)), even if many are drought-tolerant species in Mediterranean-climate cities.

As shown in this dissertation, urban vegetation can be affected by long-term droughts, such as the 2012-2016 California drought, in ways that would not be readily apparent in measurements made over shorter drought events. This includes the seasonal droughts that occur each year in Mediterranean climate zones. Turfgrass quickly senesces during drought when not irrigated in semi-arid climates but it can be regrown or replaced more readily than urban trees. Turfgrass replacement strategies that are implemented to conserve water will also need to consider potential implications in the loss of cooling from evapotranspiration (Pincetl et al., 2019). Urban trees can show canopy-scale drought responses during the drought event itself, but overall tree cover losses may not occur until years later, perhaps after the main drought event has ended. Tree cover can be expensive to replace and it requires a long time to regrow, therefore special consideration may be needed when considering tree planting and water conservation policies (McPherson et al., 2018). With increasing global populations in cities and the potential for drying climates and more frequent droughts (Grimm et al., 2008; Diffenbaugh et al., 2015), investigations into urban vegetation changes with drought will be increasingly needed for long-term sustainability planning in relation to ecosystem services and urban forestry.
Appendix 1: Supplemental materials for Chapter 1

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Fig. S1.1: Palmer Drought Severity Index (PDSI) values for US Historical Climate Network station in downtown Santa Barbara, California (34.4167 N, -119.6844 E) from 1895 to 2018 (Abatzoglou et al., 2017; https://wrcc.dri.edu/wwdt/). Dots are monthly PDSI values, and solid black line is a smoothed 5-year moving average (± standard deviation in gray) calculated at monthly timesteps. Negative PDSI values are associated with enhanced drought conditions.
Table S1.1: Flightlines from 2011, 2014, and 2017 were used to develop a series of images through the drought. All imagery underwent further reflectance and co-registration calibration to improve consistency between images, similar to Meerdink et al. (2019a). Pixel resampling was through nearest neighbor (NN) (and in the case of AVIRIS-NG, pixel aggregation (PA) as well) to align images to the same 7.5 m grid.

<table>
<thead>
<tr>
<th>Date</th>
<th>Sensor</th>
<th>Flightline Position</th>
<th>Native spatial res. (m)</th>
<th>Solar Zenith</th>
<th>Solar Azimuth</th>
<th>Pixel Resampling</th>
<th>Atm. Cor.</th>
<th>Number of GCPs</th>
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Fig. S1.2: Reflectance spectra from temporally invariant surfaces for each image after pre-processing.
**Fig. S1.3:** Box plots showing green vegetation (GV), non-photosynthetic vegetation (NPV), and paved fractions for all tree patches, binned into quintiles (e.g., 0-20%) based on patch area for each image date. For each box plot, the middle line is the median, hinges are 25th and 75th percentiles, and whiskers extend to 1.5 * interquartile range (25th to 75th percentile) from the hinges, with outliers as dots.
Fig. S1.4: Area-weighted density plots of ARI in 2011, 2014, and 2017 for each individual tree species class and turfgrass.

Fig. S1.5: Area-weighted density plots of ARI in 2011, 2014, and 2017 for: broadleaf trees, needleleaf trees, native trees, and non-native trees with patch areas < 1000 m².
**Fig. S1.6:** Area-weighted density plots of CIrededge in 2011, 2014, and 2017 for each individual tree species class and turfgrass.

**Fig. S1.7:** Area-weighted density plots of CIrededge in 2011, 2014, and 2017 for: broadleaf trees, needleleaf trees, native trees, and non-native trees with patch areas < 1000 m².
Fig. S1.8: Area-weighted density plots of MCARI in 2011, 2014, and 2017 for each individual tree species class and turfgrass.

Fig. S1.9: Area-weighted density plots of MCARI in 2011, 2014, and 2017 for: broadleaf trees, needleleaf trees, native trees, and non-native trees with patch areas < 1000 m².
Fig. S1.10: Area-weighted density plots of -MSI in 2011, 2014, and 2017 for each individual tree species class and turfgrass.

Fig. S1.11: Area-weighted density plots of -MSI in 2011, 2014, and 2017 for: broadleaf trees, needleleaf trees, native trees, and non-native trees with patch areas < 1000 m$^2$. 
Fig. S1.12: Area-weighted density plots of NDVI in 2011, 2014, and 2017 for each individual tree species class and turfgrass.

Fig. S1.13: Area-weighted density plots of NDVI in 2011, 2014, and 2017 for: broadleaf trees, needleleaf trees, native trees, and non-native trees with patch areas < 1000 m².
Fig. S1.14: Area-weighted density plots of NDWI in 2011, 2014, and 2017 for each individual tree species class and turfgrass.

Fig. S1.15: Area-weighted density plots of NDWI in 2011, 2014, and 2017 for: broadleaf trees, needleleaf trees, native trees, and non-native trees with patch areas < 1000 m$^2$. 
Fig. S1.16: Area-weighted density plots of PRI512 in 2011, 2014, and 2017 for each individual tree species class and turfgrass.

Fig. S1.17: Area-weighted density plots of PRI512 in 2011, 2014, and 2017 for: broadleaf trees, needleleaf trees, native trees, and non-native trees with patch areas < 1000 m².
Fig. S1.18: Area-weighted density plots of WBI in 2011, 2014, and 2017 for each individual tree species class and turfgrass.

Fig. S1.19: Area-weighted density plots of WBI in 2011, 2014, and 2017 for: broadleaf trees, needleleaf trees, native trees, and non-native trees with patch areas < 1000 m².
Fig. S1.20: Area-weighted density plots of the continuum removed 680 nm absorption feature’s maximum depth (CR 680 nm max. depth) in 2011, 2014, and 2017 for each individual tree species class and turfgrass.

Fig. S1.21: Area-weighted density plots of the continuum removed 680 nm absorption feature’s maximum depth (CR 680 nm max. depth) in 2011, 2014, and 2017 for: broadleaf trees, needleleaf trees, native trees, and non-native trees with patch areas < 1000 m².
Fig. S1.22: Area-weighted density plots of the continuum removed 680 nm absorption feature’s area (CR 680 nm area) in 2011, 2014, and 2017 for each individual tree species class and turfgrass.

Fig. S1.23: Area-weighted density plots of the continuum removed 680 nm absorption feature’s area (CR 680 nm area) in 2011, 2014, and 2017 for: broadleaf trees, needleleaf trees, native trees, and non-native trees with patch areas < 1000 m².
Fig. S1.24: Area-weighted density plots of the continuum removed 680 nm absorption feature’s depth normalized area (CR 680 nm depth norm. area) in 2011, 2014, and 2017 for each individual tree species class and turfgrass.

Fig. S1.25: Area-weighted density plots of the continuum removed 680 nm absorption feature’s depth normalized area (CR 680 nm depth norm. area) in 2011, 2014, and 2017 for: broadleaf trees, needleleaf trees, native trees, and non-native trees with patch areas < 1000 m².
Fig. S1.26: Area-weighted density plots of the continuum removed 980 nm absorption feature’s maximum depth (CR 980 nm max. depth) in 2011, 2014, and 2017 for each individual tree species class and turfgrass.

Fig. S1.27: Area-weighted density plots of the continuum removed 980 nm absorption feature’s maximum depth (CR 980 nm max. depth) in 2011, 2014, and 2017 for: broadleaf trees, needleleaf trees, native trees, and non-native trees with patch areas < 1000 m².
Fig. S1.28: Area-weighted density plots of the continuum removed 980 nm absorption feature’s area (CR 980 nm area) in 2011, 2014, and 2017 for each individual tree species class and turfgrass.

Fig. S1.29: Area-weighted density plots of the continuum removed 980 nm absorption feature’s area (CR 980 nm area) in 2011, 2014, and 2017 for: broadleaf trees, needleleaf trees, native trees, and non-native trees with patch areas < 1000 m².
**Fig. S1.30:** Area-weighted density plots of the continuum removed 980 nm absorption feature’s depth normalized area (CR 980 nm depth norm. area) in 2011, 2014, and 2017 for each individual tree species class and turfgrass.

**Fig. S1.31:** Area-weighted density plots of the continuum removed 980 nm absorption feature’s depth normalized area (CR 980 nm depth norm. area) in 2011, 2014, and 2017 for: broadleaf trees, needleleaf trees, native trees, and non-native trees with patch areas < 1000 m².
Fig. S1.32: Area-weighted density plots of the continuum removed 1200 nm absorption feature’s maximum depth (CR 1200 nm max. depth) in 2011, 2014, and 2017 for each individual tree species class and turfgrass.

Fig. S1.33: Area-weighted density plots of the continuum removed 1200 nm absorption feature’s maximum depth (CR 1200 nm max. depth) in 2011, 2014, and 2017 for: broadleaf trees, needleleaf trees, native trees, and non-native trees with patch areas < 1000 m².
**Fig. S1.34**: Area-weighted density plots of the continuum removed 1200 nm absorption feature’s area (CR 1200 nm area) in 2011, 2014, and 2017 for each individual tree species class and turfgrass.

**Fig. S1.35**: Area-weighted density plots of the continuum removed 1200 nm absorption feature’s area (CR 1200 nm area) in 2011, 2014, and 2017 for: broadleaf trees, needleleaf trees, native trees, and non-native trees with patch areas < 1000 m².
Fig. S1.36: Area-weighted density plots of the continuum removed 1200 nm absorption feature’s depth normalized area (CR 1200 nm depth norm. area) in 2011, 2014, and 2017 for each individual tree species class and turfgrass.

Fig. S1.37: Area-weighted density plots of the continuum removed 1200 nm absorption feature’s depth normalized area (CR 1200 nm depth norm. area) in 2011, 2014, and 2017 for: broadleaf trees, needleleaf trees, native trees, and non-native trees with patch areas < 1000 m².
Appendix 2: Supplemental materials for Chapter 2

Table S2.1: Maximum number of sample Landsat-gridded classification pixels available for extraction for each land cover type at greater than set percentage thresholds (e.g., there are 188 pixels with >90% broadleaf tree cover). Note broadleaf tree class here excludes Eucalyptus and oaks, and we did not extract trends for water and soil. Bold cells were extracted for analysis, with developed/impervious cover pixels only retained for vegetation ΔLST calculation.

<table>
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<tr>
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<th>&gt;70%</th>
<th>&gt;80%</th>
<th>&gt;90%</th>
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Table S2.2: Mean pixel cover (%) within each sampled vegetation cover type at a Landsat pixel scale. All cover types are sampled at >90% threshold except for Needleleaf (>60%) due to a lack of available pixels. The number of sampled pixels is provided as n. Note that the number of sampled pixels at specific dates will vary due to cloud masking. Bold cells indicate target cover type (row) for a given thresholding column.

<table>
<thead>
<tr>
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<th>Broadleaf &gt; 90%</th>
<th>Needleleaf &gt; 60%</th>
<th>Eucalyptus &gt; 90%</th>
<th>Oak &gt; 90%</th>
<th>Annual Grass &gt; 90%</th>
<th>Turfgrass &gt; 90%</th>
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<td>n = 188</td>
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Fig. S2.1: Standardized Precipitation Evapotranspiration Index (SPEI, Vicente-Serrano et al., 2010) trends (2010-2019) calculated at three time spans from the US Historical Climate Network Station in Santa Barbara, California by Abatzoglou et al. (2017). SPEI values < 0 indicate time periods drier than average, and values > 0 are wetter for a given time range.
**Table S2.3:** Maximum number of sample 18 m AVIRIS-gridded classification pixels available for extraction for each land cover type at greater than set percentage thresholds (e.g., there are 2432 pixels with >90% broadleaf tree cover). Note broadleaf tree class here excludes Eucalyptus and oaks. Bold cells were extracted for analysis.

<table>
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<tr>
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<td>1807</td>
<td>1607</td>
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**Table S2.4:** Mean pixel cover (%) within each sampled vegetation cover type at AVIRIS pixel scale (18 m). All cover types are sampled at >90% threshold. The number of sampled pixels is provided as n. Note that the number of sampled pixels at specific dates will vary due to cloud masking.

<table>
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<tr>
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<th>Broadleaf &gt; 90%</th>
<th>Needleleaf &gt; 90%</th>
<th>Eucalyptus &gt; 90%</th>
<th>Oak &gt; 90% n = 7041</th>
<th>Annual Grass &gt; 90% n = 20905</th>
<th>Turfgrass &gt; 90% n = 4802</th>
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<td>Turfgrass</td>
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<td>0.98</td>
<td>0.09</td>
<td>0.45</td>
<td>0.44</td>
<td><strong>97.86</strong></td>
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<tr>
<td>Dev./Imp.</td>
<td>0.71</td>
<td>1.42</td>
<td>0.65</td>
<td>0.44</td>
<td>0.38</td>
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<tr>
<td>Soils</td>
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<td>0.00</td>
<td>0.01</td>
<td>0.00</td>
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<td>Water</td>
<td>0.02</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
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</tbody>
</table>
Fig. S2.2: Importance estimates for the 88 spectral bands input into ‘ranger’ (Wright and Zeigler, 2017) random forest model, with mean oak reflectance spectrum from training data, prior to continuum removal, overlaid for reference. (A) Mean decrease gini (MDG); (B) Mean decrease accuracy (MDA, %). Note that specific variable importance may change with similar random forest runs due to random input variable selection when building the model. In ‘ranger,’ MDG was estimated with impurity variable importance, and MDA was estimated with permutation importance scaled by the standard error (Breiman, 2001).
Table S2.5: Area estimates from Alonzo et al. (2016) Table 2 compared with this study’s classification in m². "RS" are the remote sensing estimates, and “ECO” are the iTree-ECO field-scaling estimates, both from Alonzo et al. (2016); "Majority smoothed" refers to 3x3 pixel majority smoothing (and the final classification), and “No smoothing” is without any filtering, both from this study. Note that for this comparison, we include *Podocarpus gracilior* (African fern pine) as needleleaf, while it is specified as a broadleaf in Alonzo et al. (2016) due to its relatively wide leaves/needles for a conifer for leaf area modeling.

<table>
<thead>
<tr>
<th></th>
<th>Alonzo et al. (2016)</th>
<th>This Study</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RS</td>
<td>ECO</td>
</tr>
<tr>
<td>Broadleaf (including Eucalyptus and Oak)</td>
<td>4,211,904</td>
<td>4,130,008</td>
</tr>
<tr>
<td>Broadleaf (no Eucalyptus or Oak)</td>
<td>2,634,146</td>
<td>2,228,389</td>
</tr>
<tr>
<td>Needleleaf</td>
<td>771,400</td>
<td>783,011</td>
</tr>
<tr>
<td>Eucalyptus</td>
<td>224,757</td>
<td>507,152</td>
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<tr>
<td>Oak</td>
<td>1,353,001</td>
<td>1,394,467</td>
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**Fig. S2.3:** Box plots of simulated Landsat 5 TM NDVI from AVIRIS acquired during 2013-2015 for each vegetation cover type; x-axis is continuous to show the relative timing of image acquisitions (labels are Year.Month.Day) with acquisition seasons colored. Boxplot hinges extend to the 25th and 75th percentiles, whiskers extend to the farthest values within 1.5*interquartile range from each hinge, and outliers are omitted for clarity.
Fig. S2.4: Linear regression for calculated equivalent water thickness (cm) versus measured leaf water thickness (derived from leaf water mass) across all available broadleaf genera from Meerink et al. (2016). Regression line: $y = 0.089x + 0.009$, $R^2 = 0.57$, $p < 0.001$. 
Appendix 3: Supplemental materials for Chapter 3

Table S3.1: Ground control point (GCP) information for each flightline (FLXX) collection date (fYRMDA). For context, place names are given for areas within each flightline.

<table>
<thead>
<tr>
<th>Flight Label</th>
<th>FL04</th>
<th>FL05</th>
<th>FL06</th>
<th>FL07 Beverly Hills</th>
<th>FL08</th>
<th>FL09 Manhattan Beach</th>
<th>FL10 Rancho Palos Verdes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Claremont</td>
<td>Pasadena</td>
<td>Glendale</td>
<td>Beverly Hills</td>
<td>Inglewood</td>
<td>Manhattan Beach</td>
<td>Rancho Palos Verdes</td>
</tr>
<tr>
<td>f13052</td>
<td>2</td>
<td>32</td>
<td>37</td>
<td>35</td>
<td>34</td>
<td>24</td>
<td>13</td>
</tr>
<tr>
<td>f14061</td>
<td>3</td>
<td>33</td>
<td>35</td>
<td>37</td>
<td>37</td>
<td>33</td>
<td>24</td>
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<tr>
<td>f15052</td>
<td>8</td>
<td>34</td>
<td>37</td>
<td>38</td>
<td>36</td>
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<td>24</td>
</tr>
<tr>
<td>f16061</td>
<td>6</td>
<td>34</td>
<td>37</td>
<td>38</td>
<td>40</td>
<td>34</td>
<td>24</td>
</tr>
<tr>
<td>f17062</td>
<td>8</td>
<td>19</td>
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<tr>
<td>f18062</td>
<td>5</td>
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<td>37</td>
<td>38</td>
<td>39</td>
<td>34</td>
<td>24</td>
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</table>

B. GCP error (deg. 1)

<table>
<thead>
<tr>
<th>Flight Label</th>
<th>FL04</th>
<th>FL05</th>
<th>FL06</th>
<th>FL07 Beverly Hills</th>
<th>FL08</th>
<th>FL09 Manhattan Beach</th>
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<tbody>
<tr>
<td></td>
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<td>Glendale</td>
<td>Beverly Hills</td>
<td>Inglewood</td>
<td>Manhattan Beach</td>
<td>Rancho Palos Verdes</td>
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<tr>
<td>f13052</td>
<td>2</td>
<td>0.9137</td>
<td>0.8680</td>
<td>0.7693</td>
<td>0.6219</td>
<td>0.9558</td>
<td>0.6857</td>
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<tr>
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<td>3</td>
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<td>0.8359</td>
<td>0.6858</td>
<td>0.6891</td>
<td>0.6999</td>
<td>0.5563</td>
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<tr>
<td>f15052</td>
<td>8</td>
<td>1.3521</td>
<td>0.7928</td>
<td>0.7612</td>
<td>0.7278</td>
<td>0.9111</td>
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<tr>
<td>f16061</td>
<td>6</td>
<td>0.7934</td>
<td>1.1284</td>
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<td>0.6971</td>
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<tr>
<td>f17062</td>
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<td>0.6603</td>
<td>0.7790</td>
<td>0.8856</td>
<td>0.8041</td>
<td>0.7623</td>
<td>0.5835</td>
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<tr>
<td>f18062</td>
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<td>0.8350</td>
<td>0.7271</td>
<td>0.9527</td>
<td>0.7800</td>
<td>0.6297</td>
<td>0.7785</td>
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Figs. S3.1-S3.4 refer to spectral calibration for AVIRIS flightlines for each set of dates.

**Fig. S3.1**: Original collected spectra for Santa Anita Park racetrack parking lot.
Fig. S3.2: Spectral coefficients for Santa Anita Park racetrack parking lot.
**Fig. S3.3:** Original collected spectra for CSU Dominguez Hills bare soil field.

**Fig. S3.4:** Spectral coefficients for CSU Dominguez Hills bare soil field.
**Fig. S3.5:** Mean anomalies in turfgrass fractions in 2018 from mean of the time series by census tracts. Note that bins in color scale are not of equal width.
**Fig. S3.6**: Mean anomalies in tree fractions in 2018 from mean of the time series by census tracts. Note that bins in color scale are not of equal width.
Fig. S3.7: Mean anomalies in NPV fractions in 2018 from mean of the time series by census tracts. Note that bins in color scale are not of equal width, and that color scale has been reversed compared to the other maps, such that brown colors represent areas with increases in senesced vegetation cover (i.e., NPV) and green colors represent areas with reductions in senesced vegetation cover.
Fig. S3.8: Mean anomalies in tree + turfgrass + NPV fractions in 2018 from mean of the time series to 2018 by census tracts. Note that bins in color scale are not of equal width.
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