WUI growth, fire activity, and vegetation types across Mediterranean-type landscapes

Kira A. Pfoch, PhD Program in Forestry

Committee: Volker Radeloff, Philip Townsend, Min Chen, Anthony Ives, Amy Trowbridge, and Patrick Hostert

Introduction

The Wildland-Urban Interface (WUI) defines areas where settlements intersect with high amounts of wildland vegetation cover which causes wildfire hazard (Radeloff et al. 2018). The WUI is expanding and causes many biotic and abiotic implications for the environment, including declining biodiversity, fragmentation of habitat, and changes in disturbance characteristics (Bar-Massada et al. 2014; Carlson et al. 2023; Syphard et al. 2009). Mapping and monitoring WUI expansion provide important information on where natural ecosystems are threaten (Lampin-Maillet et al. 2009; Radeloff et al. 2018; Stewart et al. 2009).

The Mediterranean-climate ecosystems are especially important as fire has an ecological role to preserve habitat for many endemic species (Keeley 2012; Keeley et al. 2011a), while also putting humans living within the WUI at high fire risk (Radeloff et al. 2018). Human activity is a major driver and stressor affecting environmental changes and disturbances in addition to climate variation (Balch et al. 2017; Bowman et al. 2020). This reduces ecosystem resilience, shifts the species composition, and may lead to persistent reorganization (Falk et al. 2022; Guiterman et al. 2022; Syphard et al. 2019).

WUI maps have been created based on information provided by national land cover maps and zonal or building-based housing density information (Bar-Massada 2021; Radeloff et al. 2018; Schug et al. in review). Datasets on housing density are not always though available (Bar-Massada 2021), limiting the mapping of WUI growth, its drivers, interaction with vegetation communities, and fire activity. Developing an approach that can assess the WUI growth on the basis of globally available and consistent data, such as Landsat and Sentinel-2, is therefore advantageous. The WUI is a widespread and growing land use that affects with wildland vegetation landscapes, creates expanding zones of conflict and threats to human safety and ecosystems (Bar-Massada et al. 2014; Radeloff et al. 2018). It is essential to quantify the rate of WUI growth across disturbance-prone Mediterranean-climate landscapes to manage fire risk effectively (Alexandre et al. 2015; Alexandre et al. 2016; Syphard et al. 2009) and develop conservation strategies (Bar-Massada et al. 2014; Carlson et al. 2022; Radeloff et al. 2010).

The drivers of WUI growth and losses depend on the settlement density and wildland vegetation cover. Expanding human activities often lead to more houses in natural landscapes (Buxton et al. 2011; Godoy et al. 2019; Radeloff et al. 2018), while changes in vegetation cover are typically a minor effect contributing to WUI growth (Kaim et al. 2018; Miranda et al. 2020; Pereira et al. 2018). Monitoring drivers of WUI changes across different regions provides insights and supports development strategies for addressing social, economic, and environmental challenges (Alexandre et al. 2016; Carlson et al. 2022; Hammer et al. 2009). Additionally, investigating the trend of vegetation and build-up structures within stable and new WUI areas supports land-use planning and policymakers to improve fire management, sustainable development, and nature protection (Carlson et al. 2022; Syphard et al. 2009).

The semi-arid biogeographic conditions of Mediterranean ecosystems promote predictable fire disturbances, and native vegetation has developed adaptive traits (Keeley 2012). Human activity is a major driver of environmental change, reshaping fuel settings and increasing fire ignition and fire frequency (Balch et al. 2017; Bowman et al. 2011; Bowman et al. 2020). WUI growth is therefore likely to contribute to an increase in fire frequency and possibly more burned areas adjacent to settlements, which poses a significant challenge for fire management (Buxton et al. 2011; Radeloff et al. 2018; Syphard et al. 2009).

Persistent or transitional vegetation type conversion occurs when changes in vegetation communities happen as a result of environmental stressors, human activity, and invasion (Guiterman et al. 2022; van Mantgem et al. 2020). The conversion of chaparral to invasive grass species is widespread in southern California and a result of increasing fire intensity and frequency (Keeley et al. 2022; Syphard et al. 2022). Many native woody species within the Mediterranean climate ecosystems are sensitive to shorter fire return intervals because this reduces regeneration and reproductive capacity (Bowman et al. 2020; Falk et al. 2022; Syphard et al. 2011). Thus, I will investigate how WUI growth and fire activity may contribute to vegetation type conversion (woody to non-woody) across different study regions.

In summary, the objective of my research is to develop a mapping approach to map and assess WUI expansion across different regions within the Mediterranean climate landscapes in Australia, California, Chile, Portugal, and South Africa. I aim to quantify WUI growth and losses between 1990-2022 with Landsat data and identify drivers of WUI change, as well as dynamics of vegetation and housing cover within stable WUI area. Moreover, I aim to assess how area burned, fire frequency and seasonality changes in relation to WUI growth. Finally, I will assess how changes in fire activity and WUI growth may affect the vegetation cover. I will address this with the following major research questions across the global Mediterranean biome:

1) Can we map WUI areas with Landsat and Sentinel-2 imagery?
2) How did WUI change between 1990-2022?
3) What drives WUI growth and losses, and how do the vegetation and impervious land cover change within stable WUI areas?
4) How did fire frequency, fire season length, and burned area change as WUI grew?
5) What is the relationship between WUI growth, fire activity, and woody to non-woody vegetation type conversions?

Study Areas

South and western Australia, California, central Chile, the Cape Province of South Africa, and the Mediterranean basin are considered as the Mediterranean climate type regions (Keeley 2012). The climate is characterized by hot and dry summers and cool and moist (wet) winters, due to the seasonal poleward-equatorward variations of temperatures that move the large subtropical high-pressure ocean cells towards the respective hemisphere. Predictable disturbance regimes exist in the Mediterranean climate regions because of the semi-arid biogeographic conditions that promote vegetation growth in winter and support flammable fuel conditions during summer (Chuvieco 2009; Keeley et al. 2011a; Médail 2008).

The Mediterranean biosphere is among the most biologically diverse with many endemic species and dominated by evergreen sclerophyllous-leaved shrublands, semi-deciduous scrubs, and woodlands, that are adapted to predictable disturbance events of drought and fires (Keeley and Pausas 2022; Keeley et al. 2011a). Plants have developed different adaptive traits in response to disturbance regimes (Keeley et al. 2011a; Médail 2008). Natural fire return intervals of the native shrublands are usually between 10-60 years, for example, the *fynbos* in South Africa, the *mallee* in South Australia, the *maquis* in Portugal, or the *chaparral* in California, while the *matorral* in Chile is considered fire-free (Médail 2008). Post-fire resprouting is a common trait due to fertile soil conditions in California and Portugal, while in South Australia and South Africa, post-fire seeding is widespread due to nutrient-poor soils (Keeley 2012). Unlike the other Mediterranean climate ecosystems, natural fire regimes existed in the Tertiary in central Chile. With the rise of the Andes in the Miocene, the natural fire regimes diminished because the Andes reduced summer lightning storms and natural ignition (Keeley et al. 2011a). This may have limited the evolution of post-fire pulse of seedlings and serotiny, which are common fire adaptive traits in all other Mediterranean climate ecosystems (Keeley et al. 2011a; Keeley et al. 2011b; Syphard et al. 2009) while resprouting after fires has been also observed in woody shrublands in Chile.

I will focus on the WUI growth in southern California, southern South Australia, Portugal, central Chile, and southern South Africa which are WUI hotspots within a Mediterranean climate ecosystem (Schug et al. in review). Here, residential development took place in the fringes of the metropolitan centers of Adelaide (Liu and Robinson 2016), San Diego (Radeloff et al. 2018), Lisbon (Pereira et al. 2018), Santiago de Chile (Miranda et al. 2020), and Cape Town (Christ et al. 2022), due to population growth, tourism, housing affordability, flexible work opportunities, and car-centered lifestyles (Jia et al. 2022; Radeloff et al. 2018; Underwood et al. 2009). The increase in settlements poses a substantial challenge for fire management (Keeley and Pausas 2019; Syphard et al. 2009). Fire risk increases due to increased human-caused ignition near human dwellings and metropolitan centers increases fire frequency at intermediate population densities (Cattau et al. 2020; Syphard et al. 2009). Especially, the expansion of the WUI is a major concern, because here residential developments overlap with fuel load in wildland vegetation landscapes (Buxton et al. 2011; Price and Bradstock 2014; Radeloff et al. 2018). This has negative consequences for the safety of people and threatens ecosystems (Keeley et al. 2011a; Keeley and Pausas 2019; Syphard et al. 2009).

Additionally, many non-native species, such as coniferous trees (i.e., *Pinus*, *Acacia*, *Eucalyptus* (Langdon et al. 2023)), or invasive grass species (i.e., *Cheatgrass* (Balch et al. 2013;

Syphard et al. 2019)), have been introduced into Mediterranean landscapes for commercial, cultural, or aesthetic purposes, which have negative impacts for the ecosystems. These invasive species tend to outcompete the native vegetation, degrade ecosystems, and change soil nutrient cycles (D'Antonio and Vitousek 1992; Mack and D'Antonio 1998). For example, several European grass species have been introduced to different countries for livestock forage or to prevent soil erosion (Porqueddu et al. 2016). Exotic grasses are highly competitive spreaders and promoted higher fire frequency that supports their persistence (Balch et al. 2013; D'Antonio and Vitousek 1992; Syphard et al. 2019). Exotic coniferous species form dense thickets that may increase fuel load and connectivity and changes the fire behavior (Brooks et al. 2004; Langdon et al. 2023; van Wilgen 2009). In summary, invasive species threaten the native vegetation because they alter nutrient cycling and disturbance regime such as type, frequency, and intensity (D'Antonio and Vitousek 1992; Mack and D'Antonio 1998). Therefore, I will investigate the WUI growth in these regions and changes in fire characteristics and vegetation compositions between 1990-2022.

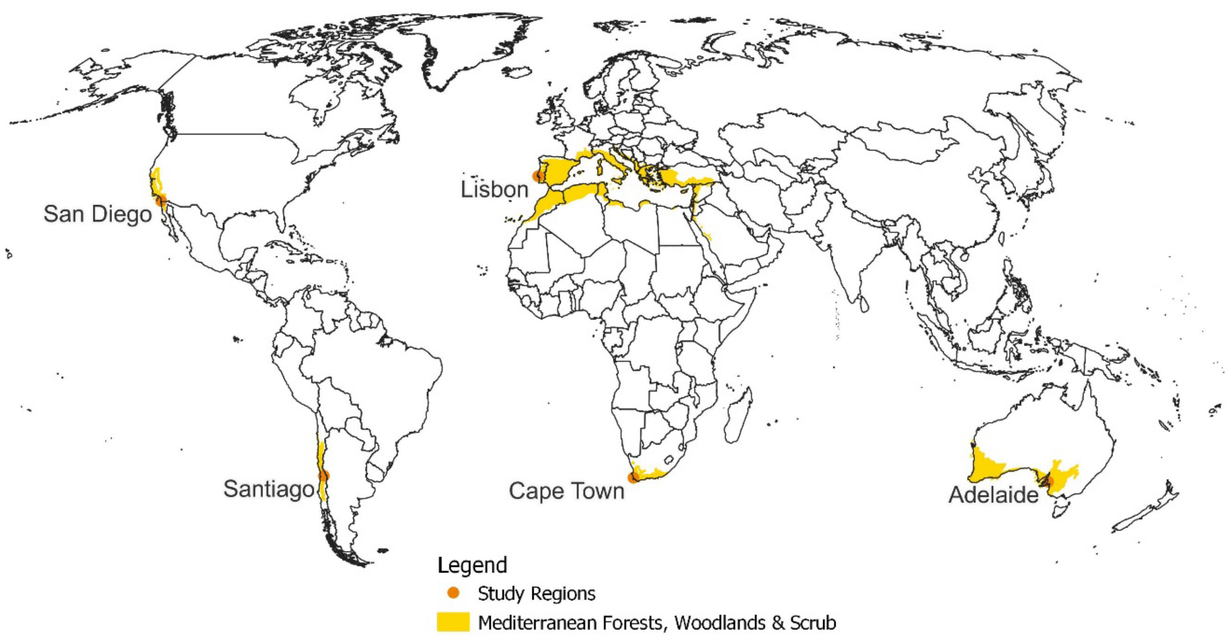

Figure 1: Overview of the Mediterranean climate ecosystems (Dinerstein et al., 2017) and the selected study region.

Chapter 1: Mapping the Wildland-Urban Interface by spectral unmixing of Landsat and Sentinel-2 imagery in Mediterranean climate landscapes.

1.1 Introduction

The Wildland-Urban Interface (WUI), where housing development meets or intermingles with wildland vegetation, is a focal point for land cover change and environmental problems (Radeloff et al. 2018). The WUI concept specifies two categories: the *intermix WUI* describes the area where settlements intermingle with wildland vegetation, and the *interface WUI* describes settlements in close proximity to wildland vegetation (Stewart et al. 2007). WUI growth has many implications on biotic and abiotic components and processes of ecosystems, such as through fragmentation and habitat loss (Theobald and Romme 2007), declining biodiversity (Gavier-Pizarro et al. 2010; Mockrin et al. 2022), the introduction of invasive species (McKinney 2002; Soulé 1991), and changes in fire regimes (Bar-Massada et al. 2014; Radeloff et al. 2018; Syphard and Keeley 2015).

Maps of the WUI have been created across the globe, but research is geographically biased toward North America, Europe, and Australia (Bento-Gonçalves and Vieira 2020). Additionally, WUI maps were created with different purposes in mind, such as fire risk assessment or conservation, resulting in various definitions and algorithms (Bento-Gonçalves and Vieira 2020; Carlson et al. 2022; Stewart et al. 2009). WUI maps are mainly created based on land cover maps and building density information (Bar-Massada 2021), and the availability of these datasets determines where and for what time periods the WUI can be mapped. I aim to develop a WUI mapping approach based on Landsat and Sentinel-2 imagery, from which information on vegetation and settlement density can be extracted to map WUI flexibly for different regions and years. I will focus particularly on WUI mapping for fire-prone Mediterranean climate ecosystems because increasing human-environmental interaction causes fragmentation, habitat loss, and changing fire activity in these biodiverse ecosystems (Bar-Massada et al. 2014; Syphard et al. 2009; Underwood et al. 2009).

The assessment of the WUI requires information on vegetation and settlement structure. I will build on a definition previously established in WUI research in the United States (Radeloff et al. 2018; Stewart et al. 2007). The *intermix WUI* is defined by a building density of > 6.17 per

km^2 and a vegetation cover of > 50% within a 500m radius. The *interface WUI* is described by an area with a building density > 6.17 per km^2 within a 500 m radius and a vegetation patch of > 5 km^2 located within a 2.4 km radius (USDI & USDA 2001). Zonal housing density information (i.e., census blocks) and information on wildland vegetation have been used to map interface and intermix WUI areas in the conterminous United States (Radeloff et al. 2005; Radeloff et al. 2018). However, zonal housing density information often varies in size and shape, and therefore, has biased estimations of WUI area (Bar-Massada et al. 2013). An alternative to census-based mapping uses individual housing locations together with a vegetation land cover dataset, also referred to as point-based WUI mapping (Bar-Massada et al. 2014; Carlson et al. 2022). Datasets on exact building locations are nearly globally available (i.e., Microsoft Building Footprint), but these datasets cannot be easily created for past years because high-resolution data availability is limited (Kasraee et al. 2023).

I propose to map the WUI using building density and vegetation cover information derived from freely available Landsat and Sentinel-2 satellite data. The approach circumvents the limitations of previously described approaches. The Landsat program provides the longest time series of globally consistent optical Earth Observation data (Wulder et al. 2019; Zhu et al. 2019) and allows me to quantify and characterize the WUI at a spatial resolution of 30 m, which is high enough to provide locally important information, and low enough to be used across large areas without excessive data storage and processing requirements (Hansen and Loveland 2012; Woodcock et al. 2020; Zhu and Woodcock 2014). Landsat imagery has been widely applied for mapping land cover changes and seems to provide sufficient spatial, spectral, and temporal resolution for observing objectively human impact on the land over time (Taubenböck et al. 2012; Wulder et al. 2015). Additionally, I will also map the WUI area with the Sentinel-2 from ESA’s Copernicus program, because the imagery has a higher spatial, spectral, and temporal resolution than Landsat (Drusch et al. 2012; Xian et al. 2019; Xu et al. 2022). Yet, the Sentinel-2 data archive is rather short since the first satellite was only in orbit in June 2015. Since both types of satellites are well established in terms of land cover mapping and monitoring the human impact on the land over time (Xu et al. 2022; Zhang et al. 2022), I will develop and test a WUI mapping approach with both, Landsat and Sentinel-2. I will approximate housing density via impervious fractions because I cannot assess individual buildings within a Landsat or Sentinel-2 pixels (Schug et al. 2022; Schug et al. 2020). Also, Landsat and Sentinel-2 images provide an advantage over very high-resolution images, because they have shortwave infrared bands that provides important for vegetation fraction mapping. Additionally, very high-resolution data often have an irregular temporal resolution (Chuvieco 2016).

Spectral unmixing mitigates a major challenge of medium spatial resolution, namely the abundance of mixed pixels in complex urban environments and vegetated landscapes (Okujeni et al. 2013; Roberts et al. 1998; van der Linden et al. 2019). While classification approaches simplify land cover complexity by assigning a pixel to one land cover category, (Griffiths et al. 2010; Reba and Seto 2020; Sousa and Small 2018), spectral unmixing quantifies land cover proportions within a pixel, and therefore assesses vegetation cover and build-up area fractions where both land cover types overlap (Okujeni et al. 2013; Schug et al. 2020). Spectral Mixture Analysis (SMA) and Multiple Endmember Spectral Mixture Analysis (MESMA) are techniques to systematically decompose mixed pixels and assess land cover proportions within pixels (Roberts et al. 1998; Small 2005; Small and Sousa 2016). Regression-based unmixing together with synthetic training datasets is advantageous (Miller et al. 2022; Okujeni et al. 2021; Wang et al. 2021) because it is an efficient strategy to improve complex urban mapping (Okujeni et al. 2017; Okujeni et al. 2013; Schug et al. 2018) and monitoring vegetation canopy parameters, disturbance and management (Kowalski et al. 2022; Senf et al. 2020), that works well in Mediterranean landscapes (Cooper et al. 2020; Okujeni et al. 2021; Suess et al. 2018). Using the combined information on vegetation cover fractions and imperviousness may enable to develop a novel WUI mapping approach.

I will develop a method to map the WUI with Landsat and Sentinel-2 data. I will test and evaluate my WUI mapping approach for five selected study areas located within the Mediterranean climate type regions. I will assess settlement and vegetation land cover information using spectral unmixing of Landsat and Sentine-2 imagery, and then map the WUI land use using a mowing window. Specifically, I will address the following research questions:

(I) How accurately can the Wildland-Urban Interface be mapped using spectral unmixing of Landsat and Sentinel-2 imagery in Mediterranean climate type landscapes?

1.2 Methods and Materials

1.2.1 Study areas

I will select five Landsat WRS-2 footprint that covers the metropolitan areas of San Diego (USA), Lisbon (Portugal), Adelaide (Australia), Santiago de Chile (Chile), and Cape Town (South Africa) to develop and test the Landsat and Sentinel-2 based WUI mapping approach. These regions are WUI hotspots, where settlements have expanded into wildland vegetation areas on the fringes of larger metropolitan centers (Christ et al. 2022; Liu and Robinson 2016; Miranda et al. 2020; Pereira et al. 2018; Radeloff et al. 2018). The expansion of the WUI has increased the risk of wildfires, which are a major threat to biodiversity, natural resources, human life and property, as well as cause challenges for fire management (Bowman et al. 2020; Syphard et al. 2009).

1.2.2 Data

Landsat and Sentinel-2 data

I will analyze multi-spectral Landsat and Sentinel-2 satellite data to map the WUI in Mediterranean climate type landscapes for 2020. I will download all available Landsat and Sentinel-2 image acquisitions with a cloud cover of ≤ 70% for five WRS-2 footprints (to be selected) covering the five study areas. I will pre-process downloaded Level-1 data using the Framework for Operational Radiometric Correction for Environmental monitoring (FORCE) environment (Frantz 2019). Pre-processing in FORCE includes cloud and cloud shadow masking as well as topographic and atmospheric correction and produces analysis-ready data.

Reference data

Training

I will use the Microsoft Building footprint and national land cover products for each study region in reference to develop a fractional threshold to map the WUI with Landsat and Sentinel-2. Based on these datasets, I will also create WUI maps, that I will compare to the Landsat and Sentinel-2 WUI maps.

Aerial high-resolution imagery

I will use very high-resolution reference (i.e., Google Earth and aerial images) images for validating the Landsat and Sentinel-2-based WUI maps. I will create a stratified random sample to assess the WUI criteria visually from VHR data. For this, I will create a 500-m buffer and a

2400-m buffer to assess visually if the intermix WUI, interface WUI, and non-WUI has been correctly identified.

1.2.3 Methods

My Landsat and Sentinel-2 WUI mapping approach is based on the assessment of pixel-based land cover fraction, which allows gathering combined information on vegetation cover and settlement density to map the WUI.

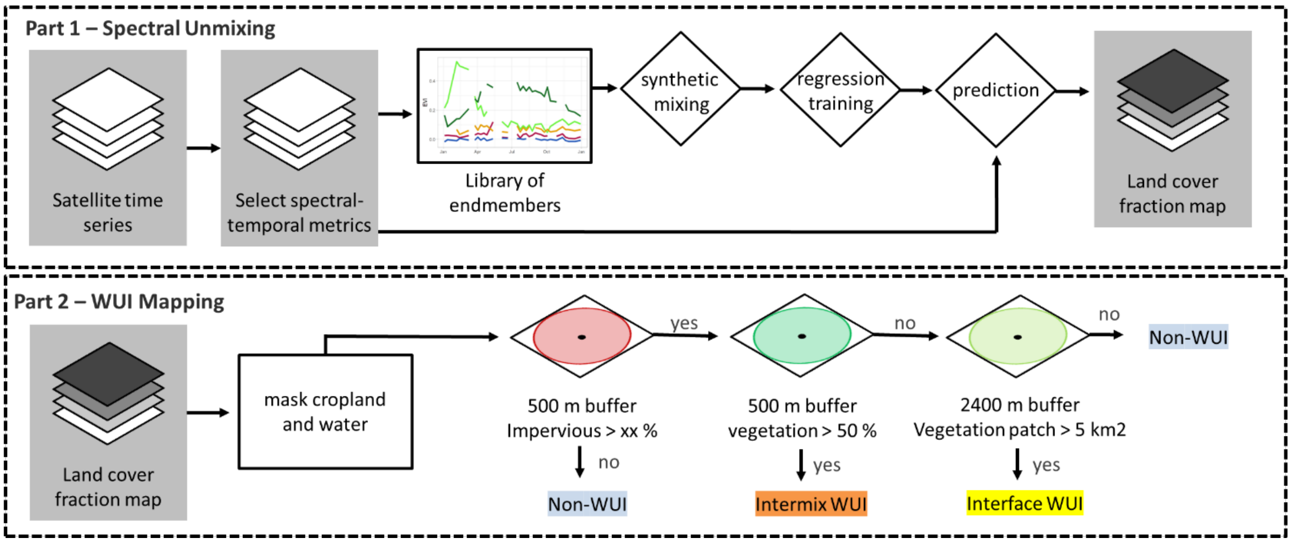

Figure 2: Flow Chart of the WUI mapping approach with Landsat and Sentinel-2 data. Part 1 shows the workflow for generating image fraction of vegetation and imperviousness, while part 2 described the process to assess the WUI based on the land cover fraction.

Spectral Unmixing

I will use spectral unmixing to derive land surface characteristics and the abundance of specific materials. For each study area, I will create a spectral library to represent pure spectral characteristics (endmembers): (1) woody vegetation, (2) non-woody vegetation, (3) impervious, (4) bare soil, and (5) water. For WUI mapping, my target classes are impervious as a proxy for settlement density, and woody and non-woody vegetation for the wildland vegetation cover criterion. I include water and soil as background classes.

I will generate synthetic mixed training data from spectral libraries to quantify land cover fractions for each study area based on derived spectral temporal metrics of the Landsat and Sentinel-2 time series. Synthetic mixed training data are training data that consists of pure original library spectra and multiple-binary mixed spectra representing a range of mixing fractions between 0-100% of the target category (Okujeni et al. 2013). Mixed spectra are constructed as linear combinations based on two or more randomly selected endmembers and provide direct means to train empirical regression models for subpixel mapping (Okujeni et al. 2017). I will use spectral temporal metrics based on Landsat and Sentinel-2 bands and indices (Okujeni et al. 2021). I will also include a temporal and phenological component that will help to separate the land cover classes, and woody and non-woody vegetation can be separated by its phenological differences across the Mediterranean climate type landscapes (Cooper et al. 2020; Kuemmerle et al. 2006; Viana-Soto et al. 2022).

I will train a regression-based unmixing model for each study area that captures the relationship between the spectral features of the corresponding fractions of a single target class (Frantz 2020; Okujeni et al. 2013; Pham et al. in review). I will then apply the regression models and predict the image fraction of each land cover category with a model output range between 0-100%.

The spectral ambiguity between bare soil, rocky, and impervious surface is a problem in the spectral unmixing analysis (Herold et al. 2003; Okujeni et al. 2013; Schug et al. 2020). I will likely encounter difficulties in separating these land surfaces and possibly overestimate imperviousness in rocky mountainous regions. The problem is that building materials often come from the surrounding area and therefore appear spectrally similar (Franke et al. 2009; Herold et al. 2004; van der Linden et al. 2019). This is why I am considering using radar data or slope data to improve this.

I will validate land cover fraction maps with high-resolution imagery, where reference data is created based on the proportion of different land cover types within a pixel. These reference proportions are generated by visually interpreting and classifying land cover for several points within the pixel. For the validation, I will compare the predicted and reference pixel fraction within a scatterplot and include the regression line and report statistical estimates of slope and intercept (eq. 1.1), R^2 (eq. 1.2), Mean Absolute Error (MAE, eq 1.3), and Root Mean Squared Error (RMSE, eq 1.3).

$$y = \beta_0 + \beta_1 x \qquad (1.1)$$

$$R^2 = \frac{\left(\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})\right)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2} \qquad (1.2)$$

I will use the coefficient of determination (R^2) to evaluate the goodness of fit between the model fraction (y_i) and the reference (x_i), where $\bar{y}$ and $\bar{x}$ represent the means of the modeled and reference fractions.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - x_i| \quad (1.3)$$

I will use MAE and RMSE to measure the prediction accuracy, which are calculated from predictions (y_i) and reference fractions (x_i), while n represents the number of validation samples.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2} \quad (1.4)$$

Masking agricultural vegetation with Spectral-Temporal Metrics

Since the WUI definition refers mainly to semi-natural and natural vegetation in combination with settlements, I will need to identify agricultural vegetation and exclude it from the WUI mapping process. I will use differences in phenology, represented by intra-annual spectral-temporal metrics, such as greenness mean, maximum, minimum, median, range, and standard deviation to distinguish cropland from semi-natural and natural vegetation types. Phenological indicators can distinguish spectrally similar managed from unmanaged vegetated land cover (Müller et al. 2015; Okujeni et al. 2021; Senf et al. 2015). I will test the usage of the spectral temporal metrics for Tasseled Cap Greenness (Crist and Cicone 1984; Kauth and Thomas 1976), the Normalized Difference Vegetation Index (NDVI) (Tucker 1979), or Enhanced Vegetation Index (EVI) (Huete et al. 2002) to develop a suitable masking approach.

In Mediterranean climate ecosystems, there can be considerable variation in seasonal shares of non-photosynthetic active vegetation and green vegetation (Gordo and Sanz 2010; Okujeni et al. 2021; Suess et al. 2018). These phenological variations are driven by the wet season (winter) and the dry season (summer). In principle, I expect a lower standard deviation and lower maximum greenness for evergreen natural vegetation (Keeley et al. 2022; Montenegro 1987), while the seasonal pattern of deciduous natural vegetation, scrubland, or grasslands follows the seasonal pattern of the year with a more pronounced minimum and maximum greenness (Bart et al. 2017; Hess et al. 2022; Milla et al. 2010). For highly managed (i.e., irrigated and fertilized) croplands, I expect a higher maximum and lower minimum of greenness, as well as a larger range or standard deviation, as there are different growth stages, management, and harvesting cycles (Müller et al. 2015). Therefore, cropland may also show higher green vegetation signals during the dry season. However, I assume that via the differences in phenology, I will be able to exclude highly managed, non-natural cropland vegetation.

WUI Mapping Approach

The WUI is mapped based on the information on vegetation cover and settlement density surrounding the pixel. Since I cannot count the number of building structures within a 10-30 m Landsat or Sentinel-2 pixel, I will develop and test an impervious fraction threshold based on the Microsoft building footprint dataset[1]. Similarly, I will test the > 50 % wildland vegetation threshold for the vegetation fractions within a 500 m radius. However, since I derive fractions of woody and non-woody vegetation, I might adjust the threshold for the Landsat versus the Sentinel-2-based WUI mapping approach in reference to national land cover maps. Additionally, I will cluster vegetation cover based on a certain fraction threshold to derive larger vegetation patches (> 500 km^2). I will need that information to determine if larger vegetation patches are within a 2400-m radius of settlements to assess the interface WUI. For the WUI classification, I will first evaluate the criterion for imperviousness and vegetation cover within a 500-m radius. When the criteria are met, I will classify the pixel as intermix WUI. Otherwise, I will check for the interface WUI criterion, and check if there is a 5-km^2 vegetation patch within 2.4 km. If none of the criteria are met, I will assign the non-WUI category.

WUI mapping Validation

I will perform validation with very high-resolution images to verify the accuracy of the Landsat and Sentinel-2-based WUI maps. I will select a stratified random sample with an equal number of points for each WUI class, i.e., interface WUI and intermix WUI, as well as for non-WUI. I will determine the number of samples per study area following the suggestions of Olofsson et al. (2014). Then, I will use visual evaluation of very high-resolution (i.e., Google Earth and orthophotos) data to determine if the intermix or interface WUI criteria apply. For this, I will draw a 500-m and 2400-m buffer around the validation point to assess the wildland vegetation cover and building density.

I will summarize the accuracy by reporting the overall accuracy, omission and commission error, and the error matrix with the class-wise accuracy of intermix WUI, interface WUI, and non-WUI. Because I expect unequally distributed classes within each study area, I will apply an area adjustment in terms of proportions of classes per area to better represent the spatial agreement and disagreement between the map and reference (Olofsson et al. 2014; Olofsson et al. 2013).

---

[1] https://www.microsoft.com/en-us/maps/building-footprints

I am considering comparing my Landsat and Sentinel-2-based WUI maps to point-based WUI maps (Microsoft Building Footprint & national land cover map based WUI maps) or the global WUI map for 2020 has been created based on the European Space Agency World Cover dataset and the Joint Research Center building footprint and has also been validated (Schug et al. in review). However, the products have different strengths and varying accuracy of land cover classes, and therefore, I consider it useful to perform a validation with high-resolution imagery first.

I will visually examine and compare the maps, as well as estimate and graphically display the area shares of intermix and interface WUI per study area. I will use the Jaccard index (Jaccard 1901) to assess the similarities between two sets S and T (eq. 1.6), where the size of the intersection is divided by the size of the union, and J(S,T)=1 if $|S \cup T|=0$ (Fletcher and Islam 2018).

$$J(S,T) = \frac{S \cap T}{S \cup T} \tag{1.6}$$

1.3 Expected Results

Evaluation of the Spectral Unmixing results

I will display scatterplots showing the predicted fractions (x-axis) versus reference fractions (y-axis), and report the slope and intercept, R^2, MAE, and RMSE as statistical evaluation of model fit and error. I expect the quality of land cover fraction mapping to be comparable to previous studies (i.e., RMSE of ~ 20 % (Okujeni et al. 2013; Schug et al. 2020)), but with a potentially higher variation between land cover classes because of the particularities and complexity of Mediterranean climate type landscapes.

Wildland-Urban Interface Maps

I will map the WUI for my five selected study areas. I will show WUI maps for each study area displaying the resulting WUI area based on Landsat and Sentinel-2 data. Additionally, I will report and display as a bar chart the estimated class-wise proportion of intermix and interface WUI for all three maps. For the evaluation and comparison of the three maps, I will report the overall accuracy, and omission and commission errors. I will display the results of the accuracy measures and error matrix as a table for intermix WUI, interface WUI, and non-WUI.

Overall, I expect to be able to map WUI relatively well along the coastline of Mediterranean climate type landscapes with vegetation cover. However, I will potentially encounter difficulties in overestimating imperviousness in bare and rocky mountainous regions with low vegetation cover, which might limit the ability to assess accurate imperviousness for example in very dry, desert-like mountain regions.

1.4 Significance and contributions

I will develop a novel WUI mapping method based on Landsat and Sentinel-2 data to assess the detailed spatial distribution of the interface and intermix WUI area. WUI maps are useful for understanding where human-environmental conflicts are most likely and are particularly important in the Mediterranean climate type landscapes since here settlements intersect with flammable vegetation fuel. Human activity increases ignition potential and fire frequency. Therefore, WUI detection supports the identification of areas with high fire risk and may help to mitigate fire damage.

Using Landsat and Sentinel-2 data will allow me a precise assessment of WUI for different temporal and spatial scales across the Mediterranean climate ecosystems. My Landsat and Sentine-2-based WUI mapping approach will assess WUI criteria of vegetation cover and settlement density without the need for land cover products and exact building locations. This is advantageous because it allows me to map WUI for a chosen region independently of other available datasets.

WUI maps are a fundamental tool for decision-making, land-use planning, and policies, fire hazard protection and prevention, and conservation management. Knowing the spatial extent of the WUI in the landscape is of interest because anthropogenic changes in the environment cause issues related to biotic and abiotic factors, as well as ecosystem functions and processes. Especially in fire-prone landscapes of the Mediterranean climate ecosystems, changes in fuel accumulation, and higher ignition potential caused by human activity increases fire hazard risk with negative consequences for humans and the environment.

Chapter 2: The growth of the Wildland Urban Interface in Mediterranean climate type landscapes

2.1 Introduction

The Wildland-Urban Interface (WUI) is a global phenomenon (Schug et al. in review), causing many environmental problems, such as fragmentation, loss of habitats (Theobald et al. 1997), declining biodiversity, spread of invasive species (McKinney 2002; Soulé 1991), and changes in fire regimes (Bar-Massada et al. 2014; Radeloff et al. 2018; Underwood et al. 2009). Humans are a dominant driver of land use changes through expanding agricultural use, deforestation, and urban development (Güneralp et al. 2020; Hansen et al. 2013). The assessment of WUI growth is important in the context of fire risk and management, as increasing settlements overlap with landscapes of high fuel load (Caton et al. 2017; Cohen 2010; Radeloff et al. 2018). Destructive fires in WUI areas cause losses of property and lives in many countries (Bento-Gonçalves and Vieira 2020; Gill et al. 2013; Moritz et al. 2014). Also, the WUI is a dominant and widespread implication for land resources and conversation (Güneralp et al. 2020; Mockrin et al. 2022; Schug et al. in review). Therefore, it is important to assess rates of WUI expansion and its associated impacts on natural ecosystem function and services (Bar-Massada et al. 2014; Carlson et al. 2022; Mockrin et al. 2022).

WUI growth is strong in the United States (Radeloff et al. 2018; Radeloff et al. 2022), Australia (Buxton et al. 2011; Gonzalez-Mathiesen et al. 2021), Europe (Bar-Massada et al. 2023; Modugno et al. 2016; Pereira et al. 2018), Chile (Miranda et al. 2020), Argentina (Godoy et al. 2019; Godoy et al. 2022), and South Africa (Christ et al. 2022). In the conterminous US, WUI was the fastest growing land use type between 1990-2010 (Martinuzzi et al. 2015; Radeloff et al. 2018). However, the data availability of zonal housing density information or building locations limits the ability to capture precise WUI growth. For example, census data only allows for decadal WUI assessments in the US (Radeloff et al. 2018; Radeloff et al. 2022). In other regions, such data are not available, and therefore WUI growth cannot be assessed (Bar-Massada 2021; Bar-Massada et al. 2013). Capturing WUI growth with Landsat data might allow tracing WUI growth more precisely. Landsat imagery provides consistent spatial, spectral, and temporal data, which have been successfully used to monitor land-use and land cover changes, and human activity (Wulder et al. 2015; Wulder et al. 2019; Zhu and Woodcock 2014).

WUI growth creates changes within semi-natural ecosystems causing conservation concerns (Bar-Massada et al. 2014), increases fire risk, and spread of invasive species (Keeley et al. 2011a; Keeley and Pausas 2019; Syphard et al. 2009), and the assessment of WUI changes can support land use planners to manage fire risk zones effectively and provide conservation strategies (Lampin-Maillet et al. 2009; Radeloff et al. 2018). Severe fire hazards occurred frequently, for example in Australia (2019-2020), California (2020), South Africa (2021), Chile (2017), and southern Europe (2021) (Bowman et al. 2020; Bowman et al. 2019). Fire risk is particularly high in the WUI because of the amount of vegetation fuel that intersects with human settlements (Bento-Gonçalves and Vieira 2020). Also, ignition frequency tends to increase with the number of people living in an area (Syphard and Keeley 2015; Syphard et al. 2009). The Mediterranean climate ecosystems are characterized by hot, dry summers and cool, moist (wet) winters, and therefore are prone to drought and fire (Keeley et al. 2011a). Here, human-induced changes may shorten fire return intervals and reduce the regeneration and reproductive capacity of some woody or shrubby ecosystems (Bowman et al. 2020; Falk et al. 2022; Syphard et al. 2011). Therefore, mapping long-term WUI growth is necessary to study growing human-environmental interactions and conflicts (Lampin-Maillet et al. 2009; Radeloff et al. 2018; Syphard et al. 2009), such as shifts in species composition (Falk et al. 2022; Keeley and Pausas 2019; Syphard et al. 2022), fuel load, and connectivity to prepare humans living within the WUI for fire risk (Theobald and Romme 2007).

I will address the research question:

(I) How much did WUI grow from 1990 to 2022 in Mediterranean landscapes in southern California, southern South Australia, Portugal, central Chile, and southern South Africa?

2.2 Methods and Materials

2.2.1 Study areas

I will assess WUI growth for the select Landsat WRS-2 footprint that covers the metropolitan areas of San Diego (USA), Lisbon (Portugal), Adelaide (Australia), Santiago de Chile (Chile), and Cape Town (South Africa). The study regions are WUI hotspots within a Mediterranean climate type regions and the expansion of human settlement into the WUI has resulted in an increase in the number of homes, businesses, and infrastructure in these areas (Abrams et al. 2012; Bento-Gonçalves and Vieira 2020; Underwood et al. 2009). Especially in

Mediterranean climate type regions, the increasing number of people living within the WUI expanded the fire risk zones and cause a significant challenge for environmental protection (Bento-Gonçalves and Vieira 2020; Syphard et al. 2009; Underwood et al. 2009). This has led to greater risks to life and property from wildfires, as well as increased pressure on natural resources and ecosystems (Gill et al. 2013; Moritz et al. 2014). Efforts to mitigate the risks associated with WUI growth across these regions require accurate maps of WUI (Caggiano et al. 2020).

2.2.2 Data

Landsat Time Series

I will use 30-m Landsat time series (TM, ETM+, and OLI) between 1990-2022 to map WUI growth in Mediterranean landscapes. Landsat data provide high-quality data with sufficient temporal (between 8 to 16-day revisits), spatial and spectral resolution to potentially quantify WUI growth (Woodcock et al. 2008; Wulder et al. 2015; Zhu et al. 2019). Similar to my first chapter, I will download Landsat data with a cloud cover of ≤ 70% and pre-process these using FORCE (Frantz 2019).

2.2.3 Methods

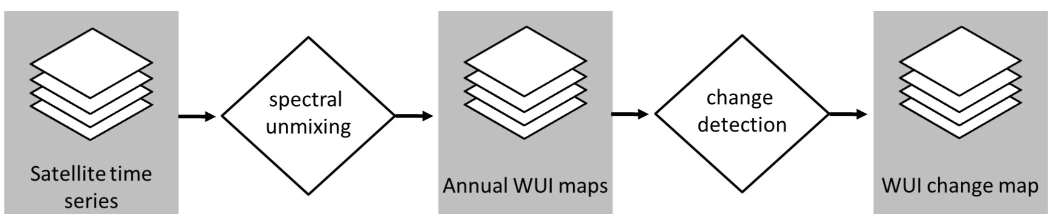

Figure 3: Flow chart of the WUI growth assessment

Multi-year WUI change detection

I will apply the WUI classification approach from chapter 1 to the Landsat time series of each of the study areas for southern California (San Diego), southern South Australia (Adelaide), Portugal (Lisbon), central Chile (Santiago de Chile), and southern South Africa (Cape Town) to assess WUI growth in my study regions. I will create annual WUI maps based on the spectrally unmixed land cover fractions of vegetation and impervious, and then apply a context-based classification approach. Next, I will assess WUI change based on my time series of annual WUI maps with three classes (intermix WUI, interface WUI, and non-WUI). I will use post-classification change detection to detect WUI changes between 1990-2022. The post-classification change detection corresponds to a comparison of independently derived land cover information from different timesteps. A true change classification (multi-temporal change detection) is based on combined data analysis, which captures the change directly based on the time series but it is complex and more feasible for detecting changes directly from 2–3-time steps (Singh 1989). Therefore, I decided to apply the simpler post-classification change detection.

Housing development or wildland vegetation cover variation are both gradual changes, and unlikely to show high year-to-year fluctuations. Therefore, I will implement and apply a temporal majority vote or ruleset to detect persistent WUI change. For instance, if I observe mainly intermix WUI throughout the time series for one pixel and only once non-WUI, it seems more reasonable that there is stable intermix WUI. Non-WUI may have been misclassified due to inter-annual variation in phenology. Therefore, I will develop a ruleset to smoothen pixels with highly variable WUI classes, and to reduce misclassifying changes based on the inter-annual variation of vegetation cover. I will only apply a temporal filter since the WUI classification already incorporates the surrounding area to determine a pixel's class, and it seems less useful to apply another spatial filter. Finally, I will flag very inconsistent pixels, and perhaps, estimate some kind of confidence measure for the detected pixel change.

Evaluation of the Landsat-based WUI change detection

To verify the accuracy of my WUI change map, I plan to compare my Landsat-based WUI change map to orthophotos or Google Earth imagery and to existing or building-location-based WUI maps. Due to limited WUI maps and high-resolution reference datasets, I cannot validate the entire time series of WUI change. However, I will be able to cross-check and validate certain points in time. I plan to use a stratified random sample with an area adjustment (Olofsson et al. 2014) for which I will estimate interface WUI, intermix WUI, or non-WUI. I will use high-resolution images (i.e., Google Earth or orthophotos) and draw a 500-m and a 2400-m buffer around each validation point. I will then visually assess the wildland vegetation cover and building density to label the points as intermix WUI, interface WUI, or non-WUI.

2.3 Expected Results

Landsat-based WUI change detection results

I will quantify WUI growth across the different study areas between 1990-2022. I expect to detect WUI growth at the fringes of large metropolitan centers across all study areas. To visualize the results, I will create maps of WUI change for each of the selected study areas. The maps will show changes in total WUI area between 1990-2022, as well as the change of interface and intermix WUI. Additionally, I will show bar charts showing the total WUI area and shares of intermix and interface WUI for each year of the 33-year time series. This provides a general overview of trend of WUI growth between the selected study regions, as well as total WUI area per year. Based on these estimates, I will assess the mean WUI growth trend, as well as identify key years of higher and lower WUI growth rates. These numbers and results will be shown in the respective bar charts of each study area.

I expect to detect WUI growth and losses in terms of gradual changes of non-WUI pixels to intermix and interface WUI. For example, I might observe that non-WUI areas with a lot of wildland vegetation cover will gradually experience housing development and change to intermix or interface WUI. Land abandonment may result in increasing intermix WUI or turning other areas into interface WUI, while urban densification may cause WUI loss, due to losses of wildland vegetation cover. However, I expect the increase in buildings within the landscape to be the dominant driver of WUI changes for all study areas, and vegetation cover increases only to matter in Portugal and Chile.

Evaluation of the Landsat-based WUI change detection

For the evaluation, I will report the accuracy of the WUI change maps for the study regions. I will compare the detected Landsat-based WUI growth to visually assessed WUI changes based on high-resolution images. However, I do not know if I can validate the complete time series from 1990-2022. I will likely assess the accuracy of WUI growth for certain periods of the time series, for which I have reference data available. Still, this will provide a good approximation of the overall accuracy. I will show the results of the error matrix and accuracies in table form and will report the overall, user and producer accuracy.

2.4 Significance and contributions

The growth rate and pattern of the Wildland-Urban Interface across the Mediterranean climate ecosystems have not been investigated. Data availability has been an important limiting factor for the assessment of WUI growth. My new Landsat-based WUI mapping approach combined with a change detection method makes it possible to investigate the growth of the WUI. This helps to investigate growing human-environment conflict, as well as the identification of areas with high fire risk and the need for fire prevention management. The analysis across different regions of the fire-prone Mediterranean climate ecosystems supports an understanding of where WUI is a dominant driver for implication for fire risk, fragmentation, and ecosystem services.

Precise WUI growth has not been assessed with Landsat time series. The Landsat Archive provides valuable data for monitoring land-use and land cover changes. This enables a precise WUI growth, and where WUI is on a trajectory to continue growing in the near future. My mapping approach is advantageous because it provides a flexible and precise assessment.

WUI growth has important implications for ecosystem function, ecosystem services, conservation concerns, and fire activity. So far, very little information has been assessed on the rate and extent of how much the WUI area has been growing. Therefore, this chapter contributes to assessing the growing human-environmental implications of the WUI that may support strategic land-use planning, conservation, and fire hazard prevention.

Chapter 3: Vegetation and housing as driver of WUI change

3.1 Introduction

The Wildland-Urban Interface is a fast-growing land use, where houses increase within wildland vegetation landscapes is an important driver of WUI growth (Buxton et al. 2011; Godoy et al. 2019; Radeloff et al. 2018). Growing residential areas are often a consequence of population growth, socioeconomic and cultural development, environmental and geographic factors, as well as spatial planning and development policies (Bar-Massada et al. 2023; Güneralp et al. 2020; Liu and Robinson 2016). Housing development is a major factor contributing to WUI growth in the US (Radeloff et al. 2005; Radeloff et al. 2018; Radeloff et al. 2010), Australia (Gill et al. 2014), and South Africa (Christ et al. 2022), caused by both push and pull factors (Gabbe et al. 2020; Jia et al. 2022) and facilitated by remote work opportunities or car-ownership (Abrams et al. 2012; Gosnell and Abrams 2011; Hammer et al. 2009). In the periphery of metropolitan areas, such as San Diego (Jia et al. 2022) or Cape Town (Christ et al. 2022), housing can be more affordable and make living close to wildland vegetation a necessity for many. High population influx to these areas can lead to uncontrolled urban sprawl, creating unorganized WUI (Bardsley et al. 2015; Buxton et al. 2011; Christ et al. 2022). In contrast, natural amenities also attract people to live in less densely settled areas, creating wide-ranging WUI surrounding cities (Abrams et al. 2012; Argent et al. 2007; Godoy et al. 2019).

WUI growth is often associated with new buildings that reduce wildland vegetation cover (Radeloff et al. 2010). Wildland vegetation is an inherent part of the WUI, where depopulation and land abandonment of rural areas may contribute to long-term vegetation regrowth, and hence, to WUI growth (Gómez-González et al. 2018; Pereira et al. 2018; Tedim et al. 2018). This occurred in some regions within Portugal and Poland, where economic and policy changes caused the abandonment of agricultural land and reduction of the population (Kaim et al. 2018; Pereira et al. 2018). Expanding forest plantations near settlements increase the fuel load and connectivity, causing higher fire hazard risks in WUI areas in Portugal (Gómez-González et al. 2018; Pereira et al. 2018) and Chile (González et al. 2018; Miranda et al. 2020). Additionally, urban densification contributes to losses of the WUI, because the vegetation criteria are no longer met, such as in Cape Town (Christ et al. 2022).

It is still unclear how vegetation and building density have changed in stable WUI areas across the five Mediterranean climate type study regions. One scenario might show that vegetation cover decreases during the establishment phase of the WUI. When new houses are built, vegetation cover often decreases due to clearings for the construction of houses and infrastructure. As people move into the landscape and arrange their homes and gardens (Buxton et al. 2011; Gavier-Pizarro et al. 2010), vegetation cover increases over time, as new trees or shrubs and other plants are planted and grow (Lampin-Maillet et al. 2009; Lampin-Maillet et al. 2011). Increasing vegetation cover may raise fire risk within the WUI (Bardsley et al. 2015; Bowman et al. 2020; Gómez-González et al. 2018). Alternatively, vegetation cover may gradually decline or stabilize at a lower level, when for example unorganized WUI development takes place, depending on how people transform and use the land (Bar-Massada et al. 2014; Moreira et al. 2020). Housing densification in intermix WUI can shift the WUI type, for example, to interface WUI land use, because high vegetation cover can be found nearby but no longer intermingles with buildings (Christ et al. 2022).

In my 3rd Chapter, I will investigate what causes WUI growth in my five Mediterranean climate type study regions across the globe. I will address the following research questions:

(I) What is the main driver of WUI growth (vegetation or buildings) in different Mediterranean climate type study sites?

(II) How did land cover change within newly created WUI areas change compared to stable WUI areas?

I hypothesize that the increase in buildings is the main driver of WUI growth, since globally, population densities are declining (Güneralp et al. 2020) but increasing residential development have been observed across the Mediterranean (Bento-Gonçalves and Vieira 2020), while vegetation increase due to land abandonment and forest plantations may contribute as a minor driver in central Chile and Portugal (Gómez-González et al. 2018).

Also, I hypothesize that new WUI areas may have more buildings and less vegetation cover at first, but over time vegetation cover may increase due to the establishment of gardens and vegetation clearance during the building construction phase, except for a few areas of unorganized WUI growth in South Africa. Additionally, I predict gradual densification processes in some areas, for instance, near urban centers, which underlines the need for a gradual WUI assessment instead of discrete classes.

3.2 Methods and Materials

3.2.1 Study area

I will investigate drivers of WUI growth in different Mediterranean climate type regions across the globe: San Diego (USA), Lisbon (Portugal), Adelaide (Australia), Santiago de Chile (Chile), and Cape Town (South Africa). In all these metropolitan areas, residential development took place in the natural and semi-natural periphery, which is associated with population growth, tourism, housing affordability, flexible work opportunities, and car-centered lifestyles (Bar-Massada et al. 2023; Jia et al. 2022; Johnston et al. 2019; Radeloff et al. 2018). In contrast, agricultural land abandonment and conversion to invasive, highly flammable forest plantations consisting took place in rural inland areas of Portugal and central Chile (Gómez-González et al. 2018; McWethy et al. 2018; Nunes et al. 2019), which may also affect WUI growth.

3.2.2 Data

I will analyze the annual time series of impervious and vegetation fractions and the detected WUI change between 1990 to 2022 from my second chapter to investigate the drivers of WUI growth and losses, as well as the dynamics within stable WUI areas. As reference information for stable WUI areas between 1990-2022, I will use the assessed stable WUI area from the change detection map of the second chapter.

3.2.3 Methods

Counterfactual scenarios: identifying drivers of WUI growth and loss

I will use the counterfactual scenarios for my pixel-based analysis of the main drivers of WUI growth and losses, as investigated by Kaim et al. (2018). For this, I will use the settlement structure information from 1990 and the vegetation cover from 2022 to create a WUI map, and vice versa (*scenario 1*: 1990 impervious and 2022 vegetation, and *scenario 2*: 2022 impervious and 1990 vegetation). Then, I will compare these results with the original WUI maps for 2022 and identify whether changes in vegetation or housing density are driving WUI growth and losses. I will use the Jaccard index (eq. 1.6, chapter 1) to assess the two counterfactual scenarios and the original WUI maps of 1990 or 2022 and evaluate if increasing impervious surfaces are the main cause of WUI growth and losses across all study regions between 1990-2022.

Trend in stable WUI areas with RemotePARTS

In a second step, I will investigate trends in vegetation and impervious fraction in stable WUI areas with RemotePARTS (Ives et al. 2021). RemotePARTS is a tool that can test map-scale statistical hypotheses, while accounting for both spatial and temporal autocorrelation (Ives et al. 2021). For my analysis, I will assess trends (in each pixel) for the time series of vegetation and imperviousness between 1990-2022. I will conduct the trend analysis for the overall stable WUI area, and for intermix and interface separately. I will report the resulting F-test and T-test from remotePARTS, to evaluate the significance level of the trends.

3.3 Expected Results

The drivers of WUI growth and losses

I will show the main driver of WUI growth and losses from the counterfactual analysis (*scenario 1*: 1990 impervious and 2022 vegetation, and *scenario 2*: 2022 impervious and 1990 vegetation) and the WUI maps of 1990 and 2022 in all study sites. I will also show the maps with the original WUI area and the two counterfactual scenarios next to the WUI maps. Also, I will present the estimation of the similarity of two sets (WUI map of 1990/2022 and *scenario 1/2*) via the Jaccard index. I expect to see a greater impact of increasing imperviousness as the dominant driver of WUI growth across all sites, while I expect only slightly positive trends in vegetation cover for Portugal and Chile. I also assume building densification processes and urban expansion in Cape Town and Adelaide cause WUI loss.

Land cover dynamics within the WUI

I will present the trends in vegetation and impervious fractions within the stable WUI area, as well as for intermix and interface WUI, for each study area. For this, I will create plots showing the annual shares of vegetation and imperviousness within stable WUI areas. I will report the statistical metrics, such as slope and intercept, standard deviation, the F-test and T-test and their p-value, of the remotePARTS analysis as a table. The results will indicate how vegetation or imperviousness have changed in association with stable overall, intermix and interface WUI. I expect to observe trends of increasing vegetation cover due to the way WUI is constructed, people settle and design their gardens in San Diego and Adelaide, while land abandonment and forest plantation increased in rural inland Portugal and central Chile. In contrast, in areas of unorganized WUI growth in South Africa, vegetation cover may decrease. Additionally, I expect also trends of more stable vegetation cover in some areas of extensive fuel treatment and prescribed burning, for example in San Diego, Adelaide, and Cape Town.

3.4 Significance and contributions

Across the different regions, I will identify what drives WUI growth and losses. The drivers provide useful insights into the pattern and dynamics that reflect on human-environmental conflicts, social-economic changes, population growth and prosperity, and policies. In addition, the analysis of the land cover dynamics within the WUI provides information on the trends of the structure and composition of the WUI and its fuel load. Increasing vegetation cover may increase the risk of fire hazards, and causes concern for the safety of people, which is important for land use planners, conservation, policy, and fire risk management across the Mediterranean climate ecosystems.

Mine will be the first study to investigate why and how WUI has changed using optical remote sensing Landsat data. The consistent Landsat Archive data provide the opportunity to assess trends in vegetation and impervious cover in relation to WUI change and its dynamics. The combined analysis of the counterfactual scenarios and remotePARTS will allow me to identify the drivers of the WUI and monitor trends of land cover dynamics within the WUI between 1990-2022.

Growing human-environmental conflicts are especially apparent in the WUI. Therefore, assessing the drivers and dynamics of the WUI provides information on where these conflicts are present, expanding, or causing issues related to ecosystem function and processes, and fire risk. The expanding fire risk zones of WUI growth and existing WUI areas through fuel load increases are important to assess for mitigating wildfire hazards and to ensure the safety of people.

Chapter 4: Changing fire activity in relation to WUI growth across Mediterranean climate type landscapes

4.1 Introduction

Severe fires have occurred in many regions across the world, especially in Mediterranean climate type landscapes, including in Australia (2019-2020), California (2020), South Africa (2021), Chile (2017, 2023), and southern Europe (2021). Wildfires kill people (Alexandre et al. 2015; Buxton et al. 2011; Collins et al. 2021), impacted ecosystem resilience (Guiterman et al. 2022; Syphard et al. 2019), wildlife habitat (Barro and Conard 1991Theobald, 1997 #44; Carlson et al. 2022) and destroyed property and homes (Alexandre et al. 2016; Bowman et al. 2020; Buxton et al. 2011). WUI growth expands the area of wildfire risk (Radeloff et al. 2018) because human activity increases the fuel exposed to fire (Alexandre et al. 2016; Lampin-Maillet et al. 2011; Nunes et al. 2019), introduces and promotes the spread of invasive species (Bar-Massada et al. 2014; Gavier-Pizarro et al. 2010; Keeley et al. 2022), and increases ignitions (Balch et al. 2017; Syphard et al. 2017; Syphard et al. 2009).

Fire regimes depend on the interactions between climate and weather, fuel availability, connectivity, soil and vegetation moisture content, as well as ignitions (Bowman et al. 2011; McColl-Gausden et al. 2022; Seidl and Turner 2022). Changing fire activity and disturbance regimes occur when one of these parameters' changes (Davis et al. 2019; Turner 2010). The presence of human activity is a major determinant of the location and timing of fires (Balch et al. 2017; Bowman et al. 2011), and fire ignition frequency increases with population density (Balch et al. 2017; Syphard et al. 2009). For example, in Australia, human colonization by Aboriginals and later European settlers were associated with increased burning (Archibald 2016; Miller et al. 2005). The trend towards longer fire seasons and more frequent and larger fires due to increase human-caused ignition occured in the USA (Balch et al. 2017; Cattau et al. 2020; Westerling et al. 2006), Chile (Miranda et al. 2017; Montenegro et al. 2004), Portugal (Moreira et al. 2009; Nunes et al. 2016), South Australia (Abram et al. 2021; Price and Bradstock 2014), and South Africa

(Christ et al. 2022; Kahanji et al. 2019). Fire management efforts in the US have resulted in extensive and costly fuel management (Baylis and Boomhower 2023; Keeley 2012; Reinhardt et al. 2008). However, due to more frequent extreme fire weather conditions, fire risk and the rate of losses and damage costs are still increasing (Kramer et al. 2019; Kramer et al. 2018). Although higher population density is often associated with higher fire frequency, human presence may also prevent and suppress fire activities (Abatzoglou and Williams 2016; Alexandre et al. 2016; Baylis and Boomhower 2023). Fire suppression is a problem in dry coniferous forests ecosystems with frequent surface fires because fuel accumulates (Bowman et al. 2011; Hagmann et al. 2021; van Wagtendonk 2007) and can lead to destructive fire events in the future, posing a threat to humans (Buxton et al. 2011; Collins et al. 2021) and deteriorates ecosystems (Falk et al. 2022; Keeley et al. 1999; Syphard et al. 2009).

In the five regions of San Diego, Adelaide, Lisbon, Santiago, and Cape Town, fire risk in the vicinity of human dwellings and metropolitan centers with highly flammable vegetation poses a significant challenge for fire management (Bowman et al. 2020; Syphard et al. 2009). Semi-arid biogeographic conditions shape these landscapes and promote vegetation growth and fuel availability during the wet-winter season, while the dry-summer season supports easily flammable fuels (Chuvieco 2009; Keeley et al. 2011a; Rundel et al. 1998). The vegetation consists of many fire-adapted or fire-dependent, endemic species, such as evergreen sclerophyllous-leaved shrublands, semi-deciduous scrubs, and woodlands, that need persistent predictable disturbances (Keeley 2012; Keeley et al. 2011b; Syphard et al. 2009). However, changing characteristics of fire disturbances threaten these ecosystems due to increasing or decreasing fire frequency and intensity (Keeley et al. 2011a; Keeley et al. 2011b; Pausas 2022).

Across Mediterranean climate ecosystems, human activity has increased fire ignition in the landscape (Bowman et al. 2020; Pausas and Keeley 2021). Increased fire ignition frequency and seasonality (earlier & later fires) occur especially around human settlements bordering wildland vegetation (Bowman et al. 2020; Keeley and Pausas 2019; Syphard et al. 2009). Also, the fire season has lengthened due to human ignition (Balch et al. 2017; Cattau et al. 2020; Pausas and Keeley 2021). Often, higher ignition rates are non-linearly related with higher population density (Balch et al. 2017; Syphard et al. 2009). However, it is unknown how WUI growth across the five-study region has contributed to increasing fire frequency, area burnt, and fire seasonality changes between 1990-2022. Therefore, I will focus on:

(I) Did the area burned due to wildfire increase as WUI grew across the five study regions within the Mediterranean climate type region around the globe?

(II) Did wildfire frequency increase as WUI grew?

(III) Did the wildfire seasons lengthen as WUI grew?

I hypothesize that WUI growth has increased fire frequency, area burned, and lengthened the fire season due to more buildings and people that cause higher ignitions within wildland vegetation landscapes.

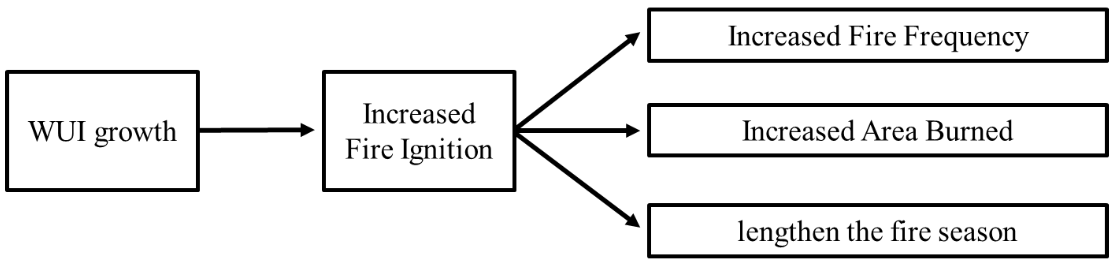

Figure 4: Potential WUI growth effects on fire activity across the Mediterranean climate ecosystem.

4.2 Methods and Materials

4.2.1 Study area

San Diego (USA) (Keeley and Syphard 2019; Syphard et al. 2021), Adelaide (Australia) (Adachi and Li 2023; Gill et al. 2014), Lisbon (Portugal) (Chergui et al. 2018; Moreira et al. 2020; Moreira et al. 2011), Santiago de Chile (Chile) (Gómez-González et al. 2018; Soto et al. 2015), and Cape Town (South Africa) (Christ et al. 2022; Liu et al. 2023) all are experiencing increasing population in or near a drying, fire-prone environment (Bowman et al. 2020; Jones et al. 2022; Pausas and Keeley 2021; Underwood et al. 2009). These regions are dominated by evergreen, sclerophyllous-leaved shrublands, semi-deciduous scrub, and woodlands plant communities that have developed different adaptive traits in response to predictable disturbance regimes (Keeley 2012; Keeley et al. 2011b). Natural fire return intervals of the shrubby vegetation communities across the global Mediterranean biome is usually 10-60 years (Médail 2008). However, humans determine the location and time of fire and disrupt the natural fire regimes, which threatens ecosystems where plants are not adapted to fire activity (Abatzoglou and Williams 2016; Bowman et al. 2011; Keeley et al. 2011b). WUI growth increases the ignition potential and wildfire risk (Balch et al. 2017; Syphard et al. 2009), and recent wildfires in these regions have caused significant damage to homes, businesses, infrastructure, and ecosystems in the past (Alexandre et al. 2016; Bowman et al. 2020; Gill and Stephens 2009).

4.2.2 Data

WUI Map

I will use the WUI change map from my second chapter to underline how WUI change affects fire regime potentials (see chapter 2).

4.2.3 Methods

Landsat-based burned area mapping (1990-2022)

I will apply the Landsat Burned Area algorithm (Hawbaker et al. 2017; Hawbaker et al. 2020) to the Landsat time series for each study region to map the area burned, fire frequency, and fire seasonality. This method is useful, because it captures fire activity for the same time period as for the WUI change detection, while the MODIS burned area product (Giglio et al. 2018) information only goes back to 2001 and has coarser resolution. The Landsat burned area algorithm has been successfully tested across ecosystems within the United States and is able to accurately identify burned areas between 1984-2018 (Hawbaker et al. 2020; Teske et al. 2021; Vanderhoof et al. 2017). However, it has not been tested for Australia, Chile, Portugal, and South Africa. Still, the approach seems promising to assess pixel-level burn probabilities and I will test it for my selected study regions. Therefore, I will validate the scene-level burned area products for regions outside of the US using high-resolution imagery and perhaps cross-check with the MODIS Burned Area product (Boschetti et al. 2019; Giglio et al. 2018). Similar to Hawbaker et al. (2020), I will report the error of omission and error of commission as validation metrics.

The algorithm uses Landsat-derived, pixel-wise spectral indices, thresholding, machine learning, and image segmentation to assess burn probabilities and a scene-level burn classification. The Landsat burn probability approach assesses the maximum burn probability across all images in a year, the number of times a pixel was classified as burned across all images in a year, the time since the last burn in years, the longest fire-free interval, and the day of the year (seasonality) of the first image pixel was classified as burned (Hawbaker et al. 2017; Hawbaker et al. 2020).

Statistical analysis

I will quantify if the area burned, fire frequency, and fire season length increases as WUI grew for each study region. I will explore the data by computing histograms, scatterplots, boxplots, and numerical summaries (i.e., mean, median, …). Then, I will use remotePARTS for each study region to investigate if there are trends in the burned area, fire seasonality, or fire frequency in association with WUI growth. I will report the F-test, T-test, R^2, estimates, and p-values. This will provide an overview of if there is a trend or relation, how strong the association is, and how significant these are, as well as how much of the variation of the response variables (y) can be explained by the predictor variables (x).

I will aggregate the data and test different sizes of hexagons (500 m, 1 km, 5 km, 20 km) to balance meaningful spatial detail and frequency of observations. I will test if WUI growth increased fire frequency, area burned, and fire season (earlier & later fires). My time series (1990-2022) may not be long enough to detect a pixel-wise change in fire frequency, and therefore, data aggregation can help. Additionally, hexagons are a useful unit of analysis because they are an evenly spaced grid with almost circular shapes, which reduces edge effects (Birch et al. 2007).

4.3 Expected Results

Statistical analysis and Model evaluation

I will quantify fire frequency, area burned, and fire season length. I will show plots and numerical summaries to present the results for each study region. I expect to observe that WUI growth is positively associated with higher fire frequency, area burned, and longer fire seasons. However, I suspect that WUI growth may not explain all variation in the data, as fluctuations in climate, temperature, precipitation, fuel moisture, and other factors also affect year-to-year fire activity. Still, I expect higher fire frequency, area burned, and longer fire season in association with WUI growth across all study regions, because WUI expansion contributes to land use changes, increasing the population density and thus higher ignition potential within landscapes of high fuel load that will have a considerable influence on fire activity.

4.4. Significance and contributions

Mediterranean climate ecosystems are undergoing rapid changes due to increasing human activity. Expanding WUI within vegetated, fire-prone landscapes causes declining biodiversity, ecosystem services, and poses risks to people and their homes. My research will determine if there are considerable feedbacks between WUI expansion and fire activity between 1990-2022 for selected study areas in Australia, California, Portugal, Chile, and South Africa. RemotePARTS will support me to determine the relationship between WUI and changing fire characteristics over 33 years. These models will show how the effect of expanding WUI area within wildland vegetation landscapes relates fire frequency, fire seasonality, and area burned in association with growing human settlements across the Mediterranean climate ecosystems.

Identifying where burned areas, fire frequency, and season have increased is an important aspect of assessing wildfire risk in the WUI and the consequences for natural ecosystems that depend on specific fire regimes. This information is particularly important for land use planning, fire management, and conservation efforts, especially in so far undeveloped land with a lot of natural vegetation that experiences housing development.

Chapter 5: Vegetation Type Conversion in Mediterranean climate type landscapes due to WUI growth and changing fire activity

5.1 Introduction

Humans have modified fire activity leading to more severe and frequent fires that have negatively impacted many ecosystems (Bowman et al. 2020; Pausas and Keeley 2021; Shuman et al. 2022). Variations in climate, wildfire, drought, invasive species, climate, and other disturbances drive widespread changes in species composition (Falk et al. 2022; McDowell et al. 2020; van Mantgem et al. 2020). Resilient ecosystems are able to recover after disturbances and the pre-disturbance species community persists, while reorganization occurs when the ecosystem fails to reestablish the pre-disturbed species community (Falk et al. 2022). Species composition can shift gradually in relation to changing environmental conditions (i.e., global warming or fire disturbance suppression), or abruptly in response to interacting, compound, or high-severity disturbances (Diez et al. 2012; Falk et al. 2022). Vegetation type conversion describes an abrupt transformation in vegetation communities that is either transitional or persistent (Guiterman et al. 2022; Syphard et al. 2022; van Mantgem et al. 2020).

In southern California, widespread vegetation type conversion is occurring. Invasive grasses are replacing native chaparral because of increased human-caused fire ignition and frequency (Syphard et al. 2019; Syphard et al. 2022). Chaparral is sensitive to shorter fire return intervals, as increased fire frequency reduces its regeneration and reproductive capacity, and makes it less competitive (Syphard et al. 2022). Cheatgrass (*Bromus tectorum*) can tolerate a higher fire frequency and severity and replaces chaparral. Cheatgrass also contributes to the spread of highly flammable fuel and promotes short fire return intervals (Balch et al. 2013; Keeley and Pausas 2022; Syphard et al. 2022). Therefore, increasing settlements and population growth within wildland vegetation areas in southern California causes conservation concern and threaten ecologically valuable areas (Balch et al. 2017; Syphard et al. 2009; Syphard et al. 2007).

In Mediterranean climate ecosystems, many vegetation communities have evolved adaptative traits to recover from fire disturbance (Keeley and Pausas 2022; Keeley 2012; Keeley et al. 2011a). Therefore, growing WUI areas in close proximity to natural ecosystems threaten the resilience and may cause vegetation type conversion. The native vegetation cannot adapt to human-caused fires and this causes changes in species composition, promotes biotic invasion, and increases the risk of erosion, landslides, and contamination of water and soil (Keeley et al. 2011b; Pausas 2022; Shuman et al. 2022).

In this chapter, I will investigate the trend in woody and non-woody vegetation in relation to WUI growth. Specifically, I ask:

(I) Did the five study areas experience vegetation type conversion from woody to non-woody vegetation between 1990-2022?

(II) Does WUI growth result in higher fire frequency and area burned and ultimately vegetation type conversion?

I hypothesize that with expanding WUI area, vegetation type conversions also occur in other regions across the Mediterranean climate ecosystems. With higher human-caused ignition, fire return intervals shorten and reduce the resilience of native woody species. Therefore, I expect an increasing conversion of non-woody vegetation type conversion. This might further change fire characteristics; however, I am not confident that in my analysis, if I will be able to link back changes in fire frequency to vegetation type conversion between 1990-2022.

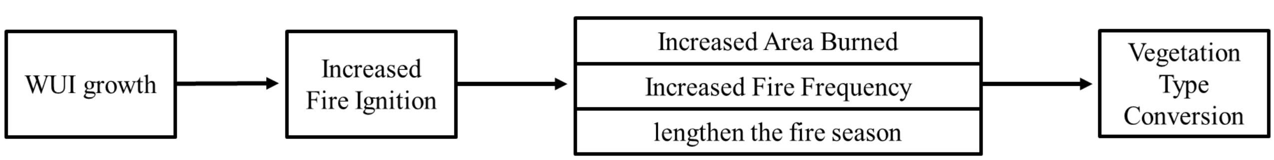

Figure 5 Vegetation Type Conversion (woody to non-woody) because of WUI growth and increased fire activity

5.2 Methods

5.2.1 Study area

The shrubland plant communities' *fynbos* in South Africa, the *mallee* in South Australia, the *maquis* in Portugal, the *chaparral* in California, and the *matorral* in Chile (Médail 2008) are dominated by evergreen sclerophyllous-leaved shrublands, semi-deciduous scrub, and woodlands that are prone to predictable disturbances (Keeley 2012; Keeley et al. 2011a). The increase in population densities and urban areas (Underwood et al. 2009) and higher human-caused ignition changes natural disturbance regimes and reduces the resilience of natural species. Additionally, exotic and invasive species are introduced for commercial (i.e., forestry and livestock forage), cultural or aesthetic purposes (gardens), and outcompete native plant species, reducing biodiversity and changing the composition of the local ecosystem (Brooks et al. 2004; D'Antonio and Vitousek 1992; Richardson and Rejmánek 2011).

The *chaparral* is threatened by increasing human-caused fire ignition that threatens native species (Syphard et al. 2009) and allows for the spread of invasive grasses, such as cheatgrass (*Bromus tectorum*), which has a rapid life cycle and can tolerate high fire frequencies (Balch et al. 2013; Brooks et al. 2004). Invasion of exotic tree species (Gill et al. 2014) and competitive grasses (i.e., African lovegrass (*Eragrostis curvula*) (Firn 2009)) are creating a higher fire risk and degrade the *mallee* ecosystems. The *matorral* is threatened by extensive afforestation of invasive, flammable forest plantations (Castillo et al. 2020; Langdon et al. 2023), while non-native, invasive grass species (i.e., cogon grass (*Imperata cylindrica*) (MacDonald 2004)) form dense, flammable stands that displace native vegetation and can increase the risk of wildfires. The Mediterranean *maquis* is replaced by invasive, flammable forest plantations (i.e., Eucalyptus (Nunes et al. 2019)) and invasive grasses (i.e., pampas grass (*Cortaderia selloana*) and fountain grass (*Pennisetum setaceum*)), that are invading a wide range of habitats, alter soil nutrient cycling and increase the risk of wildfires (Brunel et al. 2010; Marchante et al. 2017; Roy et al. 2019). The *fynbos* is under threat of *Pinus, Acacias,* and *Eucalyptus* (Nel et al. 2004; van Wilgen 2010; van Wilgen et al. 2012), and several highly competitive European grasses have been introduced (D'Antonio and Vitousek 1992) that form dense mats, displace native vegetation, alter soil nutrient cycling, and increase the risk of wildfires (Brooks et al. 2004; Nel et al. 2004).

5.2.2 Data

I will use the Landsat-based time series of the fractions of woody and non-woody from chapter 1. In addition, I will use the WUI change map from chapter 2, and assess fire frequency and area burned from chapter 4.

5.2.3 Methods: Assessing Vegetation Type Conversion

I will investigate vegetation type conversion from woody to non-woody vegetation cover across the study areas. Typically, chaparral vegetation type conversion occurs as a gradual transition from woody to non-woody vegetation dominance (Syphard et al. 2019). I am considering using the Normalized Difference Fraction Index (NDFI, eq. 5.1) (Souza et al. 2005) to map vegetation type conversion. The index highlights the difference between disturbed (thinned or cleared) and non-disturbed forest pixels by using input spectral mixture analysis derived fractions of green vegetation (GV), non-photosynthetic active vegetation (NPV), Shade, and Soil. Souza et al. (2005) and Bullock et al. (2020) used the NDFI to identify selectively logged forests, since in degraded forests the shade fraction is higher than in intact forests, which have higher GV and lower Soil and NPV fractions.

$$NDFI = \frac{GV_{Shade} - (NPV + Ssoil)}{GV_{Shade} + NPV + Soil} \qquad (5.1)$$

Viana-Soto et al. (2022) used a modified version of the index to contrast fractions of tree and shrub cover to analyze post-fire vegetation shifts in Mediterranean pine forests. I will assess shifts in vegetation cover, however, from vegetation type conversion from woody to non-woody vegetation across different Mediterranean-climate type study regions. Therefore, I propose a modified version of the NDFI (eq. 5.2) to compare and contrast the woody cover (f_{woody}) relative to the non-woody ($f_{nonwoody}$) cover fraction.

$$NDFI = \frac{f_{woody} - f_{nonwoody}}{f_{woody} + f_{nonwoody}} \qquad (5.2)$$

I will apply the index to quantify annual vegetation cover dominance between 1990-2022, where a positive index value indicates predominant woody and a negative non-woody. I will evaluate the pixel-wise trend of the index with remotePARTS (Ives et al. 2021). This will allow me to examine if there are significant trends in shifts of woody to non-woody vegetation cover, and potential vegetation type conversion. Additionally, I will cross-check some of the detected areas with significant trends in the gain of non-woody vegetation with high-resolution Google Earth TM or aerial photos.

5.3 Expected Results

Vegetation type conversion

I will assess if the five study regions have experienced vegetation type conversion from woody to non-woody vegetation between 1990-2022. I will present my results as maps highlighting the areas where vegetation type conversion occurred. I will also show a map of estimated trends in woody and non-woody vegetation fractions estimated via remotePARTS. Additionally, I will report the model result and inspect the F-test and T-test p-values ($p < 0.05$). I will report also on the observed trends of vegetation type conversion in relation to high-resolution Google Earth data to confirm trends. I expect to detect vegetation type conversion in all study regions. However, I assume the effect to be less pronounced, in Portugal and Chile, where large forest plantations have been increasing but also land abandonment tool place (Nunes et al. 2019; Pereira et al. 2018). Still, I may observe a transition from wood to non-woody vegetation, for example, on abandoned land in association with higher fire frequency near the WUI. In South Africa and South Australia, I expect to detect vegetation type conversion in areas with increased fire frequency, while an opposite effect may also occur where invasive coniferous species increase the woody fuel load in the landscape (Bowman et al. 2020; Brooks et al. 2004; Langdon et al. 2023).

Additionally, I will assess if WUI growth results in higher fire frequency and area burned and ultimately vegetation type conversion from woody to non-woody vegetation. For this, I will present how much variance in vegetation type conversion is explained by WUI growth, fire frequency, and area burned. I expect high fire frequency to have the greatest influence on vegetation type conversion from woody to non-woody vegetation, because this has been described as a significant factor influencing the resilience of native woody species (Balch et al. 2013; Syphard et al. 2009), while the amount of area burned might play a role in combination with higher fire frequency.

5.4 Significance and contributions

The growth of the Wildland-Urban Interface affects species communities of the wildland vegetation landscapes. Natural ecosystems in the Mediterranean climate ecosystems are threatened by higher fire ignition and frequency, that is caused by increasing human settlements within wildland vegetation landscapes. The analysis of vegetation type conversion of woody vegetation to non-woody ecosystems in relation to WUI growth is important for assessing the extent of changed fuel settings and the replacement of natural vegetation across different regions. Since vegetation type conversion from woody to non-woody vegetation often forms species communities that promote higher fire frequency, while other invasive coniferous tree species may increase the fuel load. Therefore, fire management efforts are important for increasing humans living within the WUI and a fire-prone landscape.

I will monitor vegetation type conversion with the fractions of dense Landsat time series. Long-term trends of the woody and non-woody fractions reflect on persistent or transitional shifts in vegetation composition and loss of biodiversity. Therefore, I will test the hypothesis of whether non-woody vegetation increases significantly. These changes can be detected and investigated using remotePARTS and determine the changes that occur in relation to WUI growth and changes in fire frequency and area burned.

WUI growth has important implications for ecosystem composition and natural vegetation communities. Vegetation type conversion is a consequence of changes in disturbance regimes that threaten natural ecosystems and reduce the recovery and reproduction of native species. In southern California, vegetation type conversion from woody to non-woody vegetation has been observed, where chaparral is replaced by invasive grasses. Since WUI growth is a global phenomenon, it is likely that these effects will also occur in other regions. However, in other WUI hotspot regions across the Mediterranean climate ecosystems, vegetation type conversion from woody to non-woody has not been studied. Therefore, this chapter will contribute to assessing the effect of vegetation type conversion across the five study regions in relation to WUI growth and increased fire activity.

Overall Significance

Mediterranean climate type regions are undergoing rapid changes due to increasing human activity. Expanding settlement within vegetated, fire-prone landscapes causes severe declines in biodiversity, undermines ecosystem services, and poses risk to people and their homes. Human activity is a major driver of changing fire activity because it increases ignition frequency and biomass burning and lengthen the fire season. Also, humans modify the terrestrial surface, change vegetation fuel and continuity, and introduce invasive species. This influences fire characteristics and is a reason for the observed severe damage and losses of past wildfires in WUI areas across Mediterranean climate ecosystems. My research will determine if there are significant feedbacks between WUI growth, fire, and vegetation characteristics within Mediterranean climate ecosystems. I will accomplish this by first quantifying trends in WUI area expansion and its drivers between 1990-2022, and then investigating trends in recurring fire activity, and vegetation cover changes in association with WUI development for selected study regions.

The WUI is a fast-growing settlement type in close proximity to wildland vegetation cover. Growing WUI across Mediterranean climate ecosystems causes reduction and fragmentation of the natural environment, as well as shifts in species composition, biodiversity, ecosystem services, and fire hazards. In particular, WUI maps are a useful tool for understanding where human-environmental conflicts are most likely. WUI growth has mainly been mapped in the conterminous US, while in other regions, the assessment of WUI growth was constrained due to limited datasets on detailed building locations over time. Therefore, my new Landsat and Sentinel-2-based WUI mapping approach contributes to a flexible assessment of WUI distribution and patterns of human development between 1990-2022 across different regions within the Mediterranean climate ecosystems. Also, assessing the trends of fire activity and associated vegetation type conversion in relation to WUI is critical for finding appropriate prevention efforts to reduce losses of life, properties, and ecosystems.

Mapping the WUI with Landsat and Sentinel-2 data is advantageous since the satellite data are consistent and freely available. This new method provides a basis for a flexible WUI assessment independent of census blocks or building footprints. I will be able to retrieve the WUI criteria of vegetation cover characteristics and housing density via land cover fractions using spectral unmixing. Also, I can conduct a change analysis of WUI using this approach and the long-time series available from Landsat imagery. This enables the detailed assessment of WUI growth and losses between 1990-2022 and provides substantial information on how WUI has evolved in different regions across Mediterranean climate ecosystems. In addition, fire activity and vegetation characteristics can be derived to identify important human-induced changes in the landscape.

Maps are useful tools for decision-making, land-use planning and policies, fire risk assessment, fire hazard prevention, and conservation management. Humans modify the land cover, vegetation canopy and connectivity, and increase ignition that raises the overall fire risk. This is especially important in the WUI across Mediterranean climate ecosystems, where human settlements overlap with vegetated, fire-prone landscapes. In Mediterranean climate ecosystems, many species have adaptive traits to recurring fire characteristics but are not per se adapted to fires. Therefore, increasing or decreasing fire activity causes conservation concerns caused by WUI growth, where settlements often spread into undeveloped, wildland vegetation landscapes. The WUI fragments the landscape and promotes biotic invasion that further threatens the natural ecosystems, and possibly leads to cascading effects and feedbacks on fire risk and regimes.

WUI growth affects ecosystems within the Mediterranean climate type regions. The Mediterranean climate ecosystems are highly diverse and have many endemic species with special adaptations to predictable disturbance. Expanding settlements into wildland vegetation landscapes threatens these species because WUI growth causes habitat loss, fragmentation, and increasing fire ignition and frequency. This reduces the resilience of ecosystems, promotes biotic invasion, and may increase severe fire hazards in the future. Especially in the last 5 years, heavy fires have occurred in WUI areas in Australia (2019-2020), California (2020), South Africa (2021), Chile (2017, 2023), and southern Europe (2021), which are related to the human modifications in the landscape, higher ignition potential, and anthropogenic climate change.

In conclusion, the WUI across Mediterranean ecosystems presents a complex and ongoing social-ecological challenge, seeking to balance human development with ecological conservation. Effective management strategies are needed to enhance the resilience of these dynamic and valuable ecosystems and to create safe and more sustainable communities in the landscape.

References

Abatzoglou, J.T., & Williams, A.P. (2016). Impact of anthropogenic climate change on wildfire across western US forests. *Proceedings of the National Academy of Sciences, 113*, 11770

Abram, N.J., Henley, B.J., Sen Gupta, A., Lippmann, T.J.R., Clarke, H., Dowdy, A.J., Sharples, J.J., Nolan, R.H., Zhang, T., Wooster, M.J., Wurtzel, J.B., Meissner, K.J., Pitman, A.J., Ukkola, A.M., Murphy, B.P., Tapper, N.J., & Boer, M.M. (2021). Connections of climate change and variability to large and extreme forest fires in southeast Australia. *Communications Earth & Environment, 2*, 8

Abrams, J.B., Gosnell, H., Gill, N.J., & Klepeis, P.J. (2012). Re-creating the rural, reconstructing nature: An international literature review of the environmental implications of amenity migration. *Conservation and society, 10*, 270-284

Adachi, J.K., & Li, L. (2023). The impact of wildfire on property prices: An analysis of the 2015 Sampson Flat Bushfire in South Australia. *Cities, 136*, 104255

Alexandre, P.M., Mockrin, M.H., Stewart, S.I., Hammer, R.B., & Radeloff, V.C. (2015). Rebuilding and new housing development after wildfire. *International Journal of Wildland Fire, 24*, 138-149

Alexandre, P.M., Stewart, S.I., Keuler, N.S., Clayton, M.K., Mockrin, M.H., Bar-Massada, A., Syphard, A.D., & Radeloff, V.C. (2016). Factors related to building loss due to wildfires in the conterminous United States. *Ecological Applications, 26*, 2323-2338

Archibald, S. (2016). Managing the human component of fire regimes: lessons from Africa. *Philosophical Transactions of the Royal Society B: Biological Sciences, 371*, 20150346

Argent, N., Smailes, P., & Griffin, T. (2007). The Amenity Complex: Towards a Framework for Analysing and Predicting the Emergence of a Multifunctional Countryside in Australia. *Geographical Research, 45*, 217-232

Balch, J.K., Bradley, B.A., Abatzoglou, J.T., Nagy, R.C., Fusco, E.J., & Mahood, A.L. (2017). Human-started wildfires expand the fire niche across the United States. *Proceedings of the National Academy of Sciences, 114*, 2946

Balch, J.K., Bradley, B.A., D'Antonio, C.M., & Gómez-Dans, J. (2013). Introduced annual grass increases regional fire activity across the arid western USA (1980–2009). *Global Change Biology, 19*, 173-183

Bar-Massada, A. (2021). A Comparative Analysis of Two Major Approaches for Mapping the Wildland-Urban Interface: A Case Study in California. *Land, 10*, 679

Bar-Massada, A., Alcasena, F., Schug, F., & Radeloff, V.C. (2023). The wildland – urban interface in Europe: Spatial patterns and associations with socioeconomic and demographic variables. *Landscape and Urban Planning, 235*, 104759

Bar-Massada, A., Radeloff, V.C., & Stewart, S.I. (2014). Biotic and abiotic effects of human settlements in the wildland-urban interface. *BioScience, 64*, 429-437

Bar-Massada, A., Stewart, S.I., Hammer, R.B., Mockrin, M.H., & Radeloff, V.C. (2013). Using structure locations as a basis for mapping the wildland urban interface. *Journal of Environmental Management, 128*, 540-547

Bardsley, D.K., Weber, D., Robinson, G.M., Moskwa, E., & Bardsley, A.M. (2015). Wildfire risk, biodiversity and peri-urban planning in the Mt Lofty Ranges, South Australia. *Applied Geography, 63*, 155-165

Barro, S.C., & Conard, S.G. (1991). Fire effects on California chaparral systems: an overview. *Environment International, 17*, 135-149

Bart, R.R., Tague, C.L., & Dennison, P.E. (2017). Modeling annual grassland phenology along the central coast of California. *Ecosphere, 8*, e01875

Baylis, P., & Boomhower, J. (2023). The economic incidence of wildfire suppression in the United States. *American Economic Journal: Applied Economics, 15*, 442-473

Bento-Gonçalves, A., & Vieira, A. (2020). Wildfires in the wildland-urban interface: Key concepts and evaluation methodologies. *Science of The Total Environment, 707*, 135592

Birch, C.P., Oom, S.P., & Beecham, J.A. (2007). Rectangular and hexagonal grids used for observation, experiment and simulation in ecology. *Ecological Modelling, 206*, 347-359

Boschetti, L., Roy, D.P., Giglio, L., Huang, H., Zubkova, M., & Humber, M.L. (2019). Global validation of the collection 6 MODIS burned area product. *Remote Sensing of Environment, 235*, 111490

Bowman, D.M.J.S., Balch, J., Artaxo, P., Bond, W.J., Cochrane, M.A., D'Antonio, C.M., DeFries, R., Johnston, F.H., Keeley, J.E., Krawchuk, M.A., Kull, C.A., Mack, M., Moritz, M.A., Pyne, S., Roos, C.I., Scott, A.C., Sodhi, N.S., & Swetnam, T.W. (2011). The human dimension of fire regimes on Earth. *Journal of Biogeography, 38*, 2223-2236

Bowman, D.M.J.S., Kolden, C.A., Abatzoglou, J.T., Johnston, F.H., van der Werf, G.R., & Flannigan, M. (2020). Vegetation fires in the Anthropocene. *Nature Reviews Earth & Environment, 1*, 500-515

Bowman, D.M.J.S., Moreira-Muñoz, A., Kolden, C.A., Chávez, R.O., Muñoz, A.A., Salinas, F., González-Reyes, Á., Rocco, R., de la Barrera, F., Williamson, G.J., Borchers, N., Cifuentes, L.A., Abatzoglou, J.T., & Johnston, F.H. (2019). Human–environmental drivers and impacts of the globally extreme 2017 Chilean fires. *Ambio, 48*, 350-362

Brooks, M.L., D'Antonio, C.M., Richardson, D.M., Grace, J.B., Keeley, J.E., DiTomaso, J.M., Hobbs, R.J., Pellant, M., & Pyke, D. (2004). Effects of Invasive Alien Plants on Fire Regimes. *BioScience, 54*, 677-688

Brunel, S., Schrader, G., Brundu, G., & Fried, G. (2010). Emerging invasive alien plants for the Mediterranean Basin. *EPPO Bulletin, 40*, 219-238

Bullock, E.L., Woodcock, C.E., & Olofsson, P. (2020). Monitoring tropical forest degradation using spectral unmixing and Landsat time series analysis. *Remote Sensing of Environment, 238*, 110968

Buxton, M., Haynes, R., Mercer, D., & Butt, A. (2011). Vulnerability to Bushfire Risk at Melbourne's Urban Fringe: The Failure of Regulatory Land Use Planning. *Geographical Research, 49*, 1-12

Caggiano, M.D., Hawbaker, T.J., Gannon, B.M., & Hoffman, C.M. (2020). Building loss in WUI disasters: evaluating the core components of the wildland–urban interface definition. *Fire, 3*, 73

Carlson, A.R., Helmers, D.P., Hawbaker, T.J., Mockrin, M.H., & Radeloff, V.C. (2022). The wildland-urban interface in the United States based on 125 million building locations. *Ecological Applications, n/a*, e2597

Carlson, A.R., Radeloff, V.C., Helmers, D.P., Mockrin, M.H., Hawbaker, T.J., & Pidgeon, A. (2023). Proportions of wildland vegetation in proximity to buildings: Assessments for the conterminous United States, National Forests lands, and private inholdings

Castillo, M., Plaza, Á., & Garfias, R. (2020). A recent review of fire behavior and fire effects on native vegetation in Central Chile. *Global Ecology and Conservation, 24*, e01210

Caton, S.E., Hakes, R.S.P., Gorham, D.J., Zhou, A., & Gollner, M.J. (2017). Review of Pathways for Building Fire Spread in the Wildland Urban Interface Part I: Exposure Conditions. *Fire Technology, 53*, 429-473

Cattau, M.E., Wessman, C., Mahood, A., & Balch, J.K. (2020). Anthropogenic and lightning-started fires are becoming larger and more frequent over a longer season length in the U.S.A. *Global Ecology and Biogeography, 29*, 668-681

Chergui, B., Fahd, S., Santos, X., & Pausas, J.G. (2018). Socioeconomic Factors Drive Fire-Regime Variability in the Mediterranean Basin. *Ecosystems, 21*, 619-628

Christ, S., Schwarz, N., & Sliuzas, R. (2022). Wildland urban interface of the City of Cape Town 1990–2019. *Geographical Research, n/a*

Chuvieco, E. (2009). *Earth Observation of Wildland Fires in Mediterranean Ecosystems*.

Chuvieco, E. (2016). *Fundamentals of satellite remote sensing: An environmental approach*. CRC press

Cohen, J. (2010). The wildland-urban interface fire problem. *Fremontia, 38*, 3

Collins, L., Bradstock, R.A., Clarke, H., Clarke, M.F., Nolan, R.H., & Penman, T.D. (2021). The 2019/2020 mega-fires exposed Australian ecosystems to an unprecedented extent of high-severity fire. *Environmental Research Letters, 16*, 044029

Cooper, S., Okujeni, A., Jänicke, C., Clark, M., van der Linden, S., & Hostert, P. (2020). Disentangling fractional vegetation cover: Regression-based unmixing of simulated spaceborne imaging spectroscopy data. *Remote Sensing of Environment, 246*, 111856

Crist, E.P., & Cicone, R.C. (1984). A Physically-Based Transformation of Thematic Mapper Data--The TM Tasseled Cap. *IEEE Transactions on Geoscience and Remote Sensing, GE-22*, 256-263

D'Antonio, C.M., & Vitousek, P.M. (1992). Biological invasions by exotic grasses, the grass/fire cycle, and global change. *Annual review of ecology and systematics, 23*, 63-87

Davis, K.T., Dobrowski, S.Z., Higuera, P.E., Holden, Z.A., Veblen, T.T., Rother, M.T., Parks, S.A., Sala, A., & Maneta, M.P. (2019). Wildfires and climate change push low-elevation forests across a critical climate threshold for tree regeneration. *Proceedings of the National Academy of Sciences, 116*, 6193-6198

Diez, J.M., D'Antonio, C.M., Dukes, J.S., Grosholz, E.D., Olden, J.D., Sorte, C.J.B., Blumenthal, D.M., Bradley, B.A., Early, R., Ibáñez, I., Jones, S.J., Lawler, J.J., & Miller, L.P. (2012). Will extreme climatic events facilitate biological invasions? *Frontiers in Ecology and the Environment, 10*, 249-257

Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gascon, F., Hoersch, B., Isola, C., Laberinti, P., Martimort, P., Meygret, A., Spoto, F., Sy, O., Marchese, F., & Bargellini, P. (2012). Sentinel-2: ESA's Optical High-Resolution Mission for GMES Operational Services. *Remote Sensing of Environment, 120*, 25-36

Falk, D.A., van Mantgem, P.J., Keeley, J.E., Gregg, R.M., Guiterman, C.H., Tepley, A.J., Jn Young, D., & Marshall, L.A. (2022). Mechanisms of forest resilience. *Forest Ecology and Management, 512*, 120129

Firn, J. (2009). African lovegrass in Australia: a valuable pasture species or embarrassing invader? *TG: Tropical Grasslands, 43*, 86

Fletcher, S., & Islam, M.Z. (2018). Comparing sets of patterns with the Jaccard index. *Australasian Journal of Information Systems, 22*

Franke, J., Roberts, D.A., Halligan, K., & Menz, G. (2009). Hierarchical Multiple Endmember Spectral Mixture Analysis (MESMA) of hyperspectral imagery for urban environments. *Remote Sensing of Environment, 113*, 1712-1723

Frantz, D. (2019). FORCE—Landsat + Sentinel-2 Analysis Ready Data and Beyond. *Remote Sensing, 11*, 1124

Frantz, D. (2020). FORCE: Framework for Operational Radiometric Correction for Environmental monitoring. In

Gabbe, C.J., Pierce, G., & Oxlaj, E. (2020). Subsidized Households and Wildfire Hazards in California. *Environmental Management, 66*, 873-883

Gavier-Pizarro, G., Radeloff, V., Stewart, S., Huebner, C., & Keuler, N. (2010). Housing is positively associated with invasive exotic plant species richness in New England, USA. *Ecological applications : a publication of the Ecological Society of America, 20*, 1913-1925

Giglio, L., Boschetti, L., Roy, D.P., Humber, M.L., & Justice, C.O. (2018). The Collection 6 MODIS burned area mapping algorithm and product. *Remote Sensing of Environment, 217*, 72-85

Gill, A.M., McKenna, D.J., & Wouters, M.A. (2014). Landscape Fire, Biodiversity Decline and a Rapidly Changing Milieu: A Microcosm of Global Issues in an Australian Biodiversity Hotspot. *Land, 3*, 1091-1136

Gill, A.M., & Stephens, S.L. (2009). Scientific and social challenges for the management of fire-prone wildland–urban interfaces. *Environmental Research Letters, 4*, 034014

Gill, A.M., Stephens, S.L., & Cary, G.J. (2013). The worldwide “wildfire” problem. *Ecological Applications, 23*, 438-454

Godoy, M.M., Martinuzzi, S., Kramer, H.A., Defossé, G.E., Argañaraz, J., & Radeloff, V.C. (2019). Rapid WUI growth in a natural amenity-rich region in central-western Patagonia, Argentina. *International Journal of Wildland Fire, 28*, 473-484

Godoy, M.M., Martinuzzi, S., Masera, P., & Defossé, G.E. (2022). Forty Years of Wildland Urban Interface Growth and Its Relation With Wildfires in Central-Western Chubut, Argentina. *Frontiers in Forests and Global Change, 5*

Gómez-González, S., Ojeda, F., & Fernandes, P.M. (2018). Portugal and Chile: Longing for sustainable forestry while rising from the ashes. *Environmental Science & Policy, 81*, 104-107

Gonzalez-Mathiesen, C., Ruane, S., & March, A. (2021). Integrating wildfire risk management and spatial planning – A historical review of two Australian planning systems. *International Journal of Disaster Risk Reduction, 53*, 101984

González, M.E., Gómez-González, S., Lara, A., Garreaud, R., & Díaz-Hormazábal, I. (2018). The 2010–2015 Megadrought and its influence on the fire regime in central and south-central Chile. *Ecosphere, 9*, e02300

Gordo, O., & Sanz, J.J. (2010). Impact of climate change on plant phenology in Mediterranean ecosystems. *Global Change Biology, 16*, 1082-1106

Gosnell, H., & Abrams, J. (2011). Amenity migration: diverse conceptualizations of drivers, socioeconomic dimensions, and emerging challenges. *GeoJournal, 76*, 303-322

Griffiths, P., Hostert, P., Gruebner, O., & der Linden, S.v. (2010). Mapping megacity growth with multi-sensor data. *Remote Sensing of Environment, 114*, 426-439

Guiterman, C.H., Gregg, R.M., Marshall, L.A.E., Beckmann, J.J., van Mantgem, P.J., Falk, D.A., Keeley, J.E., Caprio, A.C., Coop, J.D., Fornwalt, P.J., Haffey, C., Hagmann, R.K., Jackson, S.T., Lynch, A.M., Margolis, E.Q., Marks, C., Meyer, M.D., Safford, H., Syphard, A.D., Taylor, A., Wilcox, C., Carril, D., Enquist, C.A.F., Huffman, D., Iniguez, J., Molinari, N.A., Restaino, C., & Stevens, J.T. (2022). Vegetation type conversion in the US Southwest: frontline observations and management responses. *Fire Ecology, 18*, 6

Güneralp, B., Reba, M., Hales, B.U., Wentz, E.A., & Seto, K.C. (2020). Trends in urban land expansion, density, and land transitions from 1970 to 2010: a global synthesis. *Environmental Research Letters, 15*, 044015

Hagmann, R.K., Hessburg, P.F., Prichard, S.J., Povak, N.A., Brown, P.M., Fulé, P.Z., Keane, R.E., Knapp, E.E., Lydersen, J.M., Metlen, K.L., Reilly, M.J., Sánchez Meador, A.J., Stephens, S.L., Stevens, J.T., Taylor, A.H., Yocom, L.L., Battaglia, M.A., Churchill, D.J., Daniels, L.D., Falk, D.A., Henson, P., Johnston, J.D., Krawchuk, M.A., Levine, C.R., Meigs, G.W., Merschel, A.G., North, M.P., Safford, H.D., Swetnam, T.W., & Waltz, A.E.M. (2021). Evidence for widespread changes in the structure, composition, and fire regimes of western North American forests. *Ecological Applications, 31*, e02431

Hammer, R.B., Stewart, S.I., & Radeloff, V.C. (2009). Demographic Trends, the Wildland–Urban Interface, and Wildfire Management. *Society & Natural Resources, 22*, 777-782

Hansen, M.C., & Loveland, T.R. (2012). A review of large area monitoring of land cover change using Landsat data. *Remote Sensing of Environment, 122*, 66-74

Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S.V., Goetz, S.J., Loveland, T.R., Kommareddy, A., Egorov, A., Chini, L., Justice, C.O., & Townshend, J.R.G. (2013). High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science, 342*, 850-853

Hawbaker, T.J., Vanderhoof, M.K., Beal, Y.-J., Takacs, J.D., Schmidt, G.L., Falgout, J.T., Williams, B., Fairaux, N.M., Caldwell, M.K., Picotte, J.J., Howard, S.M., Stitt, S., & Dwyer, J.L. (2017). Mapping burned areas using dense time-series of Landsat data. *Remote Sensing of Environment, 198*, 504-522

Hawbaker, T.J., Vanderhoof, M.K., Schmidt, G.L., Beal, Y.-J., Picotte, J.J., Takacs, J.D., Falgout, J.T., & Dwyer, J.L. (2020). The Landsat Burned Area algorithm and products for the conterminous United States. *Remote Sensing of Environment, 244*, 111801

Herold, M., Gardner, M.E., & Roberts, D.A. (2003). Spectral resolution requirements for mapping urban areas. *IEEE Transactions on Geoscience and Remote Sensing, 41*, 1907-1919

Herold, M., Roberts, D.A., Gardner, M.E., & Dennison, P.E. (2004). Spectrometry for urban area remote sensing—Development and analysis of a spectral library from 350 to 2400 nm. *Remote Sensing of Environment, 91*, 304-319

Hess, M.C.M., Gómez-Ruiz, P.A., Morellato, L.P.C., & Buisson, E. (2022). Phenological patterns of herbaceous Mediterranean plant communities in spring: is there a difference between native and formerly-cultivated grasslands? *Plant Ecology and Evolution, 155*, 207-220

Huete, A., Didan, K., Miura, T., Rodriguez, E.P., Gao, X., & Ferreira, L.G. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment, 83*, 195-213

Ives, A.R., Zhu, L., Wang, F., Zhu, J., Morrow, C.J., & Radeloff, V.C. (2021). Statistical inference for trends in spatiotemporal data. *Remote Sensing of Environment, 266*, 112678

Jaccard, P. (1901). Étude comparative de la distribution florale dans une portion des Alpes et des Jura. *Bull Soc Vaudoise Sci Nat, 37*, 547-579

Jia, S., Lazeweski, S., Viner, J., Ho, W., & Hoover, B. (2022). High spatial and temporal resolution census data reveal communities at risk along the wildland-urban interface (WUI) in California, USA. In R.E. Keane, M. Jolly, R. Parsons, & K. Riley (Eds.), *Proceedings for the Fire and Climate Conference*. Pasadena, CA. Missoula, MT: International Association of Wildland Fire

Johnston, L., Blanchi, R., & Jappiot, M. (2019). Wildland-Urban Interface. In S.L. Manzello (Ed.), *Encyclopedia of Wildfires and Wildland-Urban Interface (WUI) Fires* (pp. 1-13). Cham: Springer International Publishing

Jones, M.W., Abatzoglou, J.T., Veraverbeke, S., Andela, N., Lasslop, G., Forkel, M., Smith, A.J.P., Burton, C., Betts, R.A., van der Werf, G.R., Sitch, S., Canadell, J.G., Santín, C., Kolden, C., Doerr, S.H., & Le Quéré, C. (2022). Global and Regional Trends and Drivers of Fire Under Climate Change. *Reviews of Geophysics, 60*, e2020RG000726

Kahanji, C., Walls, R.S., & Cicione, A. (2019). Fire spread analysis for the 2017 Imizamo Yethu informal settlement conflagration in South Africa. *International Journal of Disaster Risk Reduction, 39*, 101146

Kaim, D., Radeloff, V.C., Szwagrzyk, M., Dobosz, M., & Ostafin, K. (2018). Long-Term Changes of the Wildland–Urban Interface in the Polish Carpathians. *ISPRS International Journal of Geo-Information, 7*, 137

Kasraee, N.K., Hawbaker, T., & Radeloff, V.C. (2023). Identifying building locations in the wildland–urban interface before and after fires with convolutional neural networks. *International Journal of Wildland Fire*

Kauth, R.J., & Thomas, G. (1976). The tasselled cap--a graphic description of the spectral-temporal development of agricultural crops as seen by Landsat. In, *LARS symposia* (p. 159)

Keeley, J., & Pausas, J. (2022). Evolutionary Ecology of Fire. *Annual Review of Ecology, Evolution, and Systematics, 53*

Keeley, J.E. (2012). Fire in mediterranean climate ecosystems—a comparative overview. *Israel Journal of Ecology and Evolution, 58*, 123-135

Keeley, J.E., Bond, W.J., Bradstock, R.A., Pausas, J.G., & Rundel, P.W. (2011a). *Fire in Mediterranean Ecosystems: Ecology, Evolution and Management*. Cambridge: Cambridge University Press

Keeley, J.E., Brennan, T.J., & Syphard, A.D. (2022). The effects of prolonged drought on vegetation dieback and megafires in southern California chaparral. *Ecosphere, 13*, e4203

Keeley, J.E., Fotheringham, C.J., & Morais, M. (1999). Reexamining Fire Suppression Impacts on Brushland Fire Regimes. *Science, 284*, 1829-1832

Keeley, J.E., & Pausas, J.G. (2019). Distinguishing disturbance from perturbations in fire-prone ecosystems. *International Journal of Wildland Fire, 28*, 282-287

Keeley, J.E., Pausas, J.G., Rundel, P.W., Bond, W.J., & Bradstock, R.A. (2011b). Fire as an evolutionary pressure shaping plant traits. *Trends in Plant Science, 16*, 406-411

Keeley, J.E., & Syphard, A.D. (2019). Twenty-first century California, USA, wildfires: fuel-dominated vs. wind-dominated fires. *Fire Ecology, 15*, 24

Kowalski, K., Okujeni, A., Brell, M., & Hostert, P. (2022). Quantifying drought effects in Central European grasslands through regression-based unmixing of intra-annual Sentinel-2 time series. *Remote Sensing of Environment, 268*, 112781

Kramer, H.A., Mockrin, M.H., Alexandre, P.M., & Radeloff, V.C. (2019). High wildfire damage in interface communities in California. *International Journal of Wildland Fire, 28*, 641-650

Kramer, H.A., Mockrin, M.H., Alexandre, P.M., Stewart, S.I., & Radeloff, V.C. (2018). Where wildfires destroy buildings in the US relative to the wildland–urban interface and national fire outreach programs. *International Journal of Wildland Fire, 27*, 329-341

Kuemmerle, T., Röder, A., & Hill, J. (2006). Separating grassland and shrub vegetation by multidate pixel-adaptive spectral mixture analysis. *International Journal of Remote Sensing, 27*, 3251-3271

Lampin-Maillet, C., Jappiot, M., Long-Fournel, M., Bouillon, C., Morge, D., & Ferrier, J.-P. (2009). Mapping wildland-urban interfaces at large scales integrating housing density and vegetation aggregation for fire prevention in the South of France. *Journal of Environmental Management, 91*, 732-741

Lampin-Maillet, C., Long-Fournel, M., Ganteaume, A., Jappiot, M., & Ferrier, J.P. (2011). Land cover analysis in wildland–urban interfaces according to wildfire risk: A case study in the South of France. *Forest Ecology and Management, 261*, 2200-2213

Langdon, B., Pauchard, A., & Bustamante, R.O. (2023). Habitat suitability of five commonly planted non-native trees in Chile: Implications for an invasion process. *Forest Ecology and Management, 529*, 120726

Liu, Z., Eden, J.M., Dieppois, B., Conradie, W.S., & Blackett, M. (2023). The April 2021 Cape Town Wildfire: Has Anthropogenic Climate Change Altered the Likelihood of Extreme Fire Weather? *Bulletin of the American Meteorological Society, 104*, E298-E304

Liu, Z., & Robinson, G.M. (2016). Residential development in the peri-urban fringe: The example of Adelaide, South Australia. *Land Use Policy, 57*, 179-192

MacDonald, G.E. (2004). Cogongrass (Imperata cylindrica)—Biology, Ecology, and Management. *Critical Reviews in Plant Sciences, 23*, 367-380

Mack, M.C., & D'Antonio, C.M. (1998). Impacts of biological invasions on disturbance regimes. *Trends in Ecology & Evolution, 13*, 195-198

Marchante, H., Morais, M.C., Gamela, A., & Marchante, E. (2017). Using a WebMapping Platform to Engage Volunteers to Collect Data on Invasive Plants Distribution. *Transactions in GIS, 21*, 238-252

Martinuzzi, S., Helmers, D.P., & Radeloff, V.C. (2015). The 2010 Wildland-Urban Interface of the Conterminous United States. In USDA (Ed.)

McColl-Gausden, S.C., Bennett, L.T., Clarke, H.G., Ababei, D.A., & Penman, T.D. (2022). The fuel–climate–fire conundrum: How will fire regimes change in temperate eucalypt forests under climate change? *Global Change Biology, 28*, 5211-5226

McDowell, N.G., Allen, C.D., Anderson-Teixeira, K., Aukema, B.H., Bond-Lamberty, B., Chini, L., Clark, J.S., Dietze, M., Grossiord, C., & Hanbury-Brown, A. (2020). Pervasive shifts in forest dynamics in a changing world. *Science, 368*, eaaz9463

McKinney, M.L. (2002). Urbanization, Biodiversity, and Conservation: The impacts of urbanization on native species are poorly studied, but educating a highly urbanized human population about these impacts can greatly improve species conservation in all ecosystems. *BioScience, 52*, 883-890

McWethy, D.B., Pauchard, A., García, R.A., Holz, A., González, M.E., Veblen, T.T., Stahl, J., & Currey, B. (2018). Landscape drivers of recent fire activity (2001-2017) in south-central Chile. *PLOS ONE, 13*, e0201195

Médail, F. (2008). Mediterranean. In S.E. Jørgensen, & B.D. Fath (Eds.), *Encyclopedia of Ecology* (pp. 2296-2308). Oxford: Academic Press

Milla, R., Castro-Díez, P., & Montserrat-Martí, G. (2010). Phenology of Mediterranean woody plants from NE Spain: Synchrony, seasonality, and relationships among phenophases. *Flora - Morphology, Distribution, Functional Ecology of Plants, 205*, 190-199

Miller, D.L., Wetherley, E.B., Roberts, D.A., Tague, C.L., & McFadden, J.P. (2022). Vegetation cover change during a multi-year drought in Los Angeles. *Urban Climate, 43*, 101157

Miller, G.H., Fogel, M.L., Magee, J.W., Gagan, M.K., Clarke, S.J., & Johnson, B.J. (2005). Ecosystem Collapse in Pleistocene Australia and a Human Role in Megafaunal Extinction. *Science, 309*, 287-290

Miranda, A., Altamirano, A., Cayuela, L., Lara, A., & González, M. (2017). Native forest loss in the Chilean biodiversity hotspot: revealing the evidence. *Regional Environmental Change, 17*, 285-297

Miranda, A., Carrasco, J., González, M., Pais, C., Lara, A., Altamirano, A., Weintraub, A., & Syphard, A.D. (2020). Evidence-based mapping of the wildland-urban interface to better identify human communities threatened by wildfires. *Environmental Research Letters, 15*, 094069

Mockrin, M.H., Helmers, D., Martinuzzi, S., Hawbaker, T.J., & Radeloff, V.C. (2022). Growth of the wildland-urban interface within and around U.S. National Forests and Grasslands, 1990–2010. *Landscape and Urban Planning, 218*, 104283

Modugno, S., Balzter, H., Cole, B., & Borrelli, P. (2016). Mapping regional patterns of large forest fires in Wildland–Urban Interface areas in Europe. *Journal of Environmental Management, 172*, 112-126

Montenegro, G. (1987). Quantification of mediterranean plant phenology and growth. In J.D. Tenhunen, F.M. Catarino, O.L. Lange, & W.C. Oechel (Eds.), *Plant Response to Stress* (pp. 469-488). Berlin, Heidelberg: Springer Berlin Heidelberg

Montenegro, G., Ginocchio, R., Segura, A., Keely, J., & Gomez, M. (2004). Fire regimes and vegetation responses in two Mediterranean-climate regions. *Revista Chilena De Historia Natural - REV CHIL HIST NAT, 77*

Moreira, F., Ascoli, D., Safford, H., Adams, M.A., Moreno, J.M., Pereira, J.M., Catry, F.X., Armesto, J., Bond, W., & González, M.E. (2020). Wildfire management in Mediterranean-type regions: paradigm change needed. *Environmental Research Letters, 15*, 011001

Moreira, F., Vaz, P., Catry, F., & Silva, J.S. (2009). Regional variations in wildfire susceptibility of land-cover types in Portugal: implications for landscape management to minimize fire hazard. *International Journal of Wildland Fire, 18*, 563-574

Moreira, F., Viedma, O., Arianoutsou, M., Curt, T., Koutsias, N., Rigolot, E., Barbati, A., Corona, P., Vaz, P., Xanthopoulos, G., Mouillot, F., & Bilgili, E. (2011). Landscape – wildfire interactions in southern Europe: Implications for landscape management. *Journal of Environmental Management, 92*, 2389-2402

Moritz, M.A., Batllori, E., Bradstock, R.A., Gill, A.M., Handmer, J., Hessburg, P.F., Leonard, J., McCaffrey, S., Odion, D.C., Schoennagel, T., & Syphard, A.D. (2014). Learning to coexist with wildfire. *Nature, 515*, 58-66

Müller, H., Rufin, P., Griffiths, P., Barros Siqueira, A.J., & Hostert, P. (2015). Mining dense Landsat time series for separating cropland and pasture in a heterogeneous Brazilian savanna landscape. *Remote Sensing of Environment, 156*, 490-499

Nel, J., Richardson, D., Rouget, M., Mgidi, T., Mdzeke, N., Le Maitre, D.C., Van Wilgen, B., Schonegevel, L., Henderson, L., & Neser, S. (2004). A proposed classification of invasive alien plant species in South Africa: towards prioritizing species and areas for management action: working for water. *South African Journal of Science, 100*, 53-64

Nunes, A.N., Lourenço, L., & Meira, A.C.C. (2016). Exploring spatial patterns and drivers of forest fires in Portugal (1980–2014). *Science of The Total Environment, 573*, 1190-1202

Nunes, L.J.R., Meireles, C.I.R., Pinto Gomes, C.J., & Almeida Ribeiro, N.M.C. (2019). Historical Development of the Portuguese Forest: The Introduction of Invasive Species. In, *Forests*

Okujeni, A., Jänicke, C., Cooper, S., Frantz, D., Hostert, P., Clark, M., Segl, K., & van der Linden, S. (2021). Multi-season unmixing of vegetation class fractions across diverse Californian ecoregions using simulated spaceborne imaging spectroscopy data. *Remote Sensing of Environment, 264*, 112558

Okujeni, A., Linden, S.v.d., Suess, S., & Hostert, P. (2017). Ensemble Learning From Synthetically Mixed Training Data for Quantifying Urban Land Cover With Support Vector Regression. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 10*, 1640-1650

Okujeni, A., van der Linden, S., Tits, L., Somers, B., & Hostert, P. (2013). Support vector regression and synthetically mixed training data for quantifying urban land cover. *Remote Sensing of Environment, 137*, 184-197

Olofsson, P., Foody, G.M., Herold, M., Stehman, S.V., Woodcock, C.E., & Wulder, M.A. (2014). Good practices for estimating area and assessing accuracy of land change. *Remote Sensing of Environment, 148*, 42-57

Olofsson, P., Foody, G.M., Stehman, S.V., & Woodcock, C.E. (2013). Making better use of accuracy data in land change studies: Estimating accuracy and area and quantifying uncertainty using stratified estimation. *Remote Sensing of Environment, 129*, 122-131

Pausas, J.G. (2022). Pyrogeography across the western Palaearctic: A diversity of fire regimes. *Global Ecology and Biogeography, n/a*

Pausas, J.G., & Keeley, J.E. (2021). Wildfires and global change. *Frontiers in Ecology and the Environment, 19*, 387-395

Pereira, J., Alexandre, P., Campagnolo, M., Bar-Massada, A., Radeloff, V., & Silva, P. (2018). *Defining and Mapping the Wildland-Urban Interface in Portugal*.

Pham, V.-D., Thiel, F., Frantz, D., Okujeni, A., Schug, F., & van der Linden, S. (in review). Learning the variations in annual spectral temporal metrics to enhance the transferability of regression models for land cover fraction monitoring

Porqueddu, C., Ates, S., Louhaichi, M., Kyriazopoulos, A.P., Moreno, G., del Pozo, A., Ovalle, C., Ewing, M.A., & Nichols, P.G.H. (2016). Grasslands in 'Old World' and 'New World' Mediterranean-climate zones: past trends, current status and future research priorities. *Grass and Forage Science, 71*, 1-35

Price, O., & Bradstock, R. (2014). Countervailing effects of urbanization and vegetation extent on fire frequency on the Wildland Urban Interface: Disentangling fuel and ignition effects. *Landscape and Urban Planning, 130*, 81-88

Radeloff, V.C., Hammer, R.B., Stewart, S.I., Fried, J.S., Holcomb, S.S., & McKeefry, J.F. (2005). The Wildland-Urban Interface in the United States. *Ecological Applications, 15*, 799-805

Radeloff, V.C., Helmers, D.P., Kramer, H.A., Mockrin, M.H., Alexandre, P.M., Bar-Massada, A., Butsic, V., Hawbaker, T.J., Martinuzzi, S., Syphard, A.D., & Stewart, S.I. (2018). Rapid growth of the US wildland-urban interface raises wildfire risk. *Proceedings of the National Academy of Sciences, 115*, 3314

Radeloff, V.C., Helmers, D.P., Mockrin, M.H., Carlson, A.R., Hawbaker, T.J., & Martinuzzi, S. (2022). The 1990-2020 wildland-urban interface of the conterminous United States - geospatial data (3rd Edition) In F.S.R.D. Archive (Ed.)

Radeloff, V.C., Stewart, S.I., Hawbaker, T.J., Gimmi, U., Pidgeon, A.M., Flather, C.H., Hammer, R.B., & Helmers, D.P. (2010). Housing growth in and near United States protected areas limits their conservation value. *Proceedings of the National Academy of Sciences of the United States of America, 107*, 940-945

Reba, M., & Seto, K.C. (2020). A systematic review and assessment of algorithms to detect, characterize, and monitor urban land change. *Remote Sensing of Environment, 242*, 111739

Reinhardt, E.D., Keane, R.E., Calkin, D.E., & Cohen, J.D. (2008). Objectives and considerations for wildland fuel treatment in forested ecosystems of the interior western United States. *Forest Ecology and Management, 256*, 1997-2006

Richardson, D.M., & Rejmánek, M. (2011). Trees and shrubs as invasive alien species – a global review. *Diversity and Distributions, 17*, 788-809

Roberts, D.A., Gardner, M., Church, R., Ustin, S., Scheer, G., & Green, R.O. (1998). Mapping Chaparral in the Santa Monica Mountains Using Multiple Endmember Spectral Mixture Models. *Remote Sensing of Environment, 65*, 267-279

Roy, H.E., Bacher, S., Essl, F., Adriaens, T., Aldridge, D.C., Bishop, J.D.D., Blackburn, T.M., Branquart, E., Brodie, J., Carboneras, C., Cottier-Cook, E.J., Copp, G.H., Dean, H.J., Eilenberg, J., Gallardo, B., Garcia, M., García-Berthou, E., Genovesi, P., Hulme, P.E., Kenis, M., Kerckhof, F., Kettunen, M., Minchin, D., Nentwig, W., Nieto, A., Pergl, J., Pescott, O.L., M. Peyton, J., Preda, C., Roques, A., Rorke, S.L., Scalera, R., Schindler, S., Schönrogge, K., Sewell, J., Solarz, W., Stewart, A.J.A., Tricarico, E., Vanderhoeven, S., van der Velde, G., Vilà, M., Wood, C.A., Zenetos, A., & Rabitsch, W. (2019). Developing a list of invasive alien species likely to threaten biodiversity and ecosystems in the European Union. *Global Change Biology, 25*, 1032-1048

Rundel, P., Montenegro, G., & Jaksic, F. (1998). *Landscape disturbance and biodiversity in mediterranean-type ecosystems. Springer-Verlag, Heidelberg, xxv + 447 pp*.

Schug, F., Bar-Massada, A., Carlson, A., Cox, H., Hawbaker, T., Helmers, D., Hostert, P., Kaim, D., Kasraee, N., Martinuzzi, S., Mockrin, M., Pfoch, K., & Radeloff, V. (in review). The global Wildland-Urban Interface and associated wildfire risk to people

Schug, F., Frantz, D., Okujeni, A., & Hostert, P. (2022). Sub-pixel building area mapping based on synthetic training data and regression-based unmixing using Sentinel-1 and -2 data. *Remote Sensing Letters, 13*, 822-832

Schug, F., Frantz, D., Okujeni, A., van der Linden, S., & Hostert, P. (2020). Mapping urban-rural gradients of settlements and vegetation at national scale using Sentinel-2 spectral-temporal metrics and regression-based unmixing with synthetic training data. *Remote Sensing of Environment, 246*, 111810

Schug, F., Okujeni, A., Hauer, J., Hostert, P., Nielsen, J.Ø., & van der Linden, S. (2018). Mapping patterns of urban development in Ouagadougou, Burkina Faso, using machine learning regression modeling with bi-seasonal Landsat time series. *Remote Sensing of Environment, 210*, 217-228

Seidl, R., & Turner, M.G. (2022). Post-disturbance reorganization of forest ecosystems in a changing world. *Proceedings of the National Academy of Sciences, 119*, e2202190119

Senf, C., Laštovička, J., Okujeni, A., Heurich, M., & van der Linden, S. (2020). A generalized regression-based unmixing model for mapping forest cover fractions throughout three decades of Landsat data. *Remote Sensing of Environment, 240*, 111691

Senf, C., Leitão, P.J., Pflugmacher, D., van der Linden, S., & Hostert, P. (2015). Mapping land cover in complex Mediterranean landscapes using Landsat: Improved classification accuracies from integrating multi-seasonal and synthetic imagery. *Remote Sensing of Environment, 156*, 527-536

Shuman, J.K., Balch, J.K., Barnes, R.T., Higuera, P.E., Roos, C.I., Schwilk, D.W., Stavros, E.N., Banerjee, T., Bela, M.M., Bendix, J., Bertolino, S., Bililign, S., Bladon, K.D., Brando, P., Breidenthal, R.E., Buma, B., Calhoun, D., Carvalho, L.M.V., Cattau, M.E., Cawley, K.M., Chandra, S., Chipman, M.L., Cobian-Iñiguez, J., Conlisk, E., Coop, J.D., Cullen, A., Davis, K.T., Dayalu, A., De Sales, F., Dolman, M., Ellsworth, L.M., Franklin, S., Guiterman, C.H., Hamilton, M., Hanan, E.J., Hansen, W.D., Hantson, S., Harvey, B.J., Holz, A., Huang, T., Hurteau, M.D., Ilangakoon, N.T., Jennings, M., Jones, C., Klimaszewski-Patterson, A., Kobziar, L.N., Kominoski, J., Kosovic, B., Krawchuk, M.A., Laris, P., Leonard, J., Loria-Salazar, S.M., Lucash, M., Mahmoud, H., Margolis, E., Maxwell, T., McCarty, J.L., McWethy, D.B., Meyer, R.S., Miesel, J.R., Moser, W.K., Nagy, R.C., Niyogi, D., Palmer, H.M., Pellegrini, A., Poulter, B., Robertson, K., Rocha, A.V., Sadegh, M., Santos, F., Scordo, F., Sexton, J.O., Sharma, A.S., Smith, A.M.S., Soja, A.J., Still, C., Swetnam, T., Syphard, A.D., Tingley, M.W., Tohidi, A., Trugman, A.T., Turetsky, M., Varner, J.M., Wang, Y., Whitman, T., Yelenik, S., & Zhang, X. (2022). Reimagine fire science for the anthropocene. *PNAS Nexus*

Singh, A. (1989). Review Article Digital change detection techniques using remotely-sensed data. *International Journal of Remote Sensing, 10*, 989-1003

Small, C. (2005). A global analysis of urban reflectance. *International Journal of Remote Sensing, 26*, 661-681

Small, C., & Sousa, D. (2016). Humans on Earth: Global extents of anthropogenic land cover from remote sensing. *Anthropocene, 14*, 1-33

Soto, M.C., Julio-Alvear, G., & Salinas, R.G. (2015). Chapter 4 - Current Wildfire Risk Status and Forecast in Chile: Progress and Future Challenges. In J.F. Shroder, & D. Paton (Eds.), *Wildfire Hazards, Risks and Disasters* (pp. 59-75). Oxford: Elsevier

Soulé, M.E. (1991). Land Use Planning and Wildlife Maintenance: Guidelines for Conserving Wildlife in an Urban Landscape. *Journal of the American Planning Association, 57*, 313-323

Sousa, D., & Small, C. (2018). Spectral Mixture Analysis as a Unified Framework for the Remote Sensing of Evapotranspiration. *Remote Sensing, 10*, 1961

Souza, C.M., Roberts, D.A., & Cochrane, M.A. (2005). Combining spectral and spatial information to map canopy damage from selective logging and forest fires. *Remote Sensing of Environment, 98*, 329-343

Stewart, S., Radeloff, V., Hammer, R., & Hawbaker, T. (2007). Defining the Wildland-Urban Interface. *Journal of Forestry, 105*

Stewart, S., Wilmer, B., Hammer, R., Aplet, G., Hawbaker, T., Miller, C., & Radeloff, V. (2009). Wildland-Urban Interface Maps Vary with Purpose and Context. *Journal of Forestry, 107*, 78-83

Suess, S., van der Linden, S., Okujeni, A., Griffiths, P., Leitão, P.J., Schwieder, M., & Hostert, P. (2018). Characterizing 32 years of shrub cover dynamics in southern Portugal using annual Landsat composites and machine learning regression modeling. *Remote Sensing of Environment, 219*, 353-364

Syphard, A.D., Brennan, T.J., & Keeley, J.E. (2019). Drivers of chaparral type conversion to herbaceous vegetation in coastal Southern California. *Diversity and Distributions, 25*, 90-101

Syphard, A.D., Brennan, T.J., Rustigian-Romsos, H., & Keeley, J.E. (2022). Fire-driven vegetation type conversion in Southern California. *Ecological Applications, 32*, e2626

Syphard, A.D., & Keeley, J.E. (2015). Location, timing and extent of wildfire vary by cause of ignition. *International Journal of Wildland Fire, 24*, 37-47

Syphard, A.D., Keeley, J.E., & Brennan, T.J. (2011). Comparing the role of fuel breaks across southern California national forests. *Forest Ecology and Management, 261*, 2038-2048

Syphard, A.D., Keeley, J.E., Pfaff, A.H., & Ferschweiler, K. (2017). Human presence diminishes the importance of climate in driving fire activity across the United States. *Proceedings of the National Academy of Sciences, 114*, 13750-13755

Syphard, A.D., Radeloff, V.C., Hawbaker, T.J., & Stewart, S.I. (2009). Conservation Threats Due to Human-Caused Increases in Fire Frequency in Mediterranean-Climate Ecosystems. *Conservation Biology, 23*, 758-769

Syphard, A.D., Radeloff, V.C., Keeley, J.E., Hawbaker, T.J., Clayton, M.K., Stewart, S.I., & Hammer, R.B. (2007). HUMAN INFLUENCE ON CALIFORNIA FIRE REGIMES. *Ecological Applications, 17*, 1388-1402

Syphard, A.D., Rustigian-Romsos, H., & Keeley, J.E. (2021). Multiple-scale relationships between vegetation, the wildland–urban interface, and structure loss to wildfire in California. *Fire, 4*, 12

Taubenböck, H., Esch, T., Felbier, A., Wiesner, M., Roth, A., & Dech, S. (2012). Monitoring urbanization in mega cities from space. *Remote Sensing of Environment, 117*, 162-176

Tedim, F., Leone, V., Amraoui, M., Bouillon, C., Coughlan, M.R., Delogu, G.M., Fernandes, P.M., Ferreira, C., McCaffrey, S., & McGee, T.K. (2018). Defining extreme wildfire events: Difficulties, challenges, and impacts. *Fire, 1*, 9

Teske, C., Vanderhoof, M.K., Hawbaker, T.J., Noble, J., & Hiers, J.K. (2021). Using the Landsat burned area products to derive fire history relevant for fire management and conservation in the state of Florida, southeastern USA. *Fire, 4*, 26

Theobald, D.M., Miller, J.R., & Hobbs, N.T. (1997). Estimating the cumulative effects of development on wildlife habitat. *Landscape and Urban Planning, 39*, 25-36

Theobald, D.M., & Romme, W.H. (2007). Expansion of the US wildland–urban interface. *Landscape and Urban Planning, 83*, 340-354

Tucker, C.J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment, 8*, 127-150

Turner, M.G. (2010). Disturbance and landscape dynamics in a changing world. *Ecology, 91*, 2833-2849

Underwood, E.C., Viers, J.H., Klausmeyer, K.R., Cox, R.L., & Shaw, M.R. (2009). Threats and biodiversity in the mediterranean biome. *Diversity and Distributions, 15*, 188-197

USDI & USDA (2001). Urban wildland interface communities within the vicinity of federal lands that are at high risk from wildfire. *Federal Register, 66*, 751-777

van der Linden, S., Okujeni, A., Canters, F., Degerickx, J., Heiden, U., Hostert, P., Priem, F., Somers, B., & Thiel, F. (2019). Imaging Spectroscopy of Urban Environments. *Surveys in Geophysics, 40*, 471-488

van Mantgem, E., van Mantgem, P., Falk, D., & Keeley, J. (2020). Linking diverse terminology to vegetation type-conversion, a complex emergent property. *California Fire Science Consortium*

van Wagtendonk, J.W. (2007). The History and Evolution of Wildland Fire Use. *Fire Ecology, 3*, 3-17

van Wilgen, B. (2009). The evolution of fire and invasive alien plant management practices in fynbos. *South African Journal of Science, 105*

van Wilgen, B.W. (2010). The evolution of fire and invasive alien plant management practices in fynbos. *South African Journal of Science, 105*, 335

van Wilgen, B.W., Forsyth, G.G., & Prins, P. (2012). The Management of Fire-Adapted Ecosystems in an Urban Setting: the Case of Table Mountain National Park, South Africa. *Ecology and Society, 17*

Vanderhoof, M.K., Fairaux, N., Beal, Y.-J.G., & Hawbaker, T.J. (2017). Validation of the USGS Landsat Burned Area Essential Climate Variable (BAECV) across the conterminous United States. *Remote Sensing of Environment, 198*, 393-406

Viana-Soto, A., Okujeni, A., Pflugmacher, D., García, M., Aguado, I., & Hostert, P. (2022). Quantifying post-fire shifts in woody-vegetation cover composition in Mediterranean pine forests using Landsat time series and regression-based unmixing. *Remote Sensing of Environment, 281*, 113239

Wang, Q., Ding, X., Tong, X., & Atkinson, P.M. (2021). Spatio-temporal spectral unmixing of time-series images. *Remote Sensing of Environment, 259*, 112407

Westerling, A.L., Hidalgo, H.G., Cayan, D.R., & Swetnam, T.W. (2006). Warming and Earlier Spring Increase Western U.S. Forest Wildfire Activity. *Science, 313*, 940-943

Woodcock, C.E., Allen, R., Anderson, M., Belward, A., Bindschadler, R., Cohen, W., Gao, F., Goward, S.N., Helder, D., Helmer, E., Nemani, R., Oreopoulos, L., Schott, J., Thenkabail, P.S., Vermote, E.F., Vogelmann, J., Wulder, M.A., & Wynne, R. (2008). Free Access to Landsat Imagery. *Science, 320*, 1011-1011

Woodcock, C.E., Loveland, T.R., Herold, M., & Bauer, M.E. (2020). Transitioning from change detection to monitoring with remote sensing: A paradigm shift. *Remote Sensing of Environment, 238*, 111558

Wulder, M.A., Hilker, T., White, J.C., Coops, N.C., Masek, J.G., Pflugmacher, D., & Crevier, Y. (2015). Virtual constellations for global terrestrial monitoring. *Remote Sensing of Environment, 170*, 62-76

Wulder, M.A., Loveland, T.R., Roy, D.P., Crawford, C.J., Masek, J.G., Woodcock, C.E., Allen, R.G., Anderson, M.C., Belward, A.S., Cohen, W.B., Dwyer, J., Erb, A., Gao, F., Griffiths, P., Helder, D., Hermosilla, T., Hipple, J.D., Hostert, P., Hughes, M.J., Huntington, J., Johnson, D.M., Kennedy, R., Kilic, A., Li, Z., Lymburner, L., McCorkel, J., Pahlevan, N., Scambos, T.A., Schaaf, C., Schott, J.R., Sheng, Y., Storey, J., Vermote, E., Vogelmann, J., White, J.C., Wynne, R.H., & Zhu, Z. (2019). Current status of Landsat program, science, and applications. *Remote Sensing of Environment, 225*, 127-147

Xian, G., Shi, H., Dewitz, J., & Wu, Z. (2019). Performances of WorldView 3, Sentinel 2, and Landsat 8 data in mapping impervious surface. *Remote Sensing Applications: Society and Environment, 15*, 100246

Xu, L., Herold, M., Tsendbazar, N.-E., Masiliūnas, D., Li, L., Lesiv, M., Fritz, S., & Verbesselt, J. (2022). Time series analysis for global land cover change monitoring: A comparison across sensors. *Remote Sensing of Environment, 271*, 112905

Zhang, Y., Woodcock, C.E., Arévalo, P., Olofsson, P., Tang, X., Stanimirova, R., Bullock, E., Tarrio, K.R., Zhu, Z., & Friedl, M.A. (2022). A Global Analysis of the Spatial and Temporal Variability of Usable Landsat Observations at the Pixel Scale. *Frontiers in Remote Sensing, 3*

Zhu, Z., & Woodcock, C.E. (2014). Continuous change detection and classification of land cover using all available Landsat data. *Remote Sensing of Environment, 144*, 152-171

Zhu, Z., Wulder, M.A., Roy, D.P., Woodcock, C.E., Hansen, M.C., Radeloff, V.C., Healey, S.P., Schaaf, C., Hostert, P., Strobl, P., Pekel, J.-F., Lymburner, L., Pahlevan, N., & Scambos, T.A. (2019). Benefits of the free and open Landsat data policy. *Remote Sensing of Environment, 224*, 382-385