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Landscape Transitions and Socioeconomic Drivers as Predictors of Fire Frequency

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LANDSCAPE TRANSITIONS AND SOCIOECONOMIC DRIVERS AS PREDICTORS OF FIRE FREQUENCY

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To my Nana

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ABSTRACT

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Fire prediction systems rely on meteorological descriptors and fuel characteristics to determine fire risk at national scales. However, at a regional scale, anthropogenic dynamics play an important role in determining fire ignition, as well as spatial and temporal distributions. Under an increasing fire activity scenario projected for the next century, Mediterranean ecosystems are particularly fragile regions. Fire variability driven by human stressors is the main threat to the native vegetation and human populations in these regions. The inclusion of anthropogenic indicators on fire prediction systems, especially within Mediterranean ecosystems, is key to developing accurate predictions and effective fire management efforts. As the relationship between human dynamics and fire is complex, it is important to first understand the landscape and socioeconomic perspectives of the human component in these regions and then to identify which specific anthropogenic indicators have the most significant effects on fire in order to include them in the fire predictions systems.

The first case study (CHAPTER 2) focuses on understanding and selecting the landscape transitions, intensity rates, and patch characteristics that have a significant effect on fire variability in Chile. Landsat eight scenes were classified based on spectral signatures to derive four land use categories between two-time intervals. The classification outputs were used to perform a change detection and intensity analysis. The second case study (CHAPTER 3) focuses on selecting the most significant socioeconomic variables that affect fire in Chile and integrates all the significant

anthropogenic descriptors into a fire prediction model. To do so, spatial analysis tools were used to understand spatial distribution patterns of fire frequencies. Furthermore, regression models were used to select the most relevant human variables affecting fire frequency change. Finally, based on the data over dispersion and zero frequency characteristics, a zero-inflated model was used to simulate fire frequency predictions. The output predictions were then compared against a climate-based prediction model to evaluate fire prediction accuracy at a regional scale.

In the first case study (CHAPTER 2), regional differences were found in land use transition and characteristics. Twenty-seven percent of the area experienced a change in land use mainly associated with decreases in agriculture and increases in forest/plantation areas. Both transitions significantly decreased the landscape homogeneity. Across space, both landscape transitions and characteristics significantly affected fire frequency changes. The highest increases in fire frequency were related to increases in landscape heterogeneity, increases in forest/plantations (patch mean area) fragmented into multiple (patch number) distant patches (patch density), and decreases in urban and bareland areas.

In the second case study (CHAPTER 3), the spatial distribution of the fire activity was clustered towards the southern regions in years with extreme fire events, categorizing the area as an oscillating hotspot. The socioeconomic variables had a significant effect on fire frequency. Increases in fire frequency were related to increases in poverty percentage and road access. Opposite socioeconomic characteristics were related to decreases in fire frequency. Furthermore, 50% of the fire frequency was explained by the integration of the socioeconomic and landscape descriptors. Furthermore, all the socioeconomic characteristics affecting the fire frequency also had a significant effect on reducing the landscape homogeneity. All the significant descriptors were incorporated into a fire prediction model (LE Social model) and the output was compared to current climate model outputs and observed fire frequency. The LE Social model had a better goodness of fit (1.52) than the climate model (1.73). The LE Social model had a higher accuracy in the predictions in regions located towards the southern areas of the country. On the other hand, the climate models had higher accuracy in regions located towards the north. Finally, the accuracy of both models was reduced when predicting extreme fire frequencies due to the reduce seasonality and spatial distribution of those events that might be explained by a different driver not included in this study.

Results from the study highlight the strong impact of landscape and socioeconomic variables on the fire frequency. At the landscape level, both intensity and transition played an important role in fire frequency change. Furthermore, sites that meet the landscape criteria described in the first case study (CHAPTER 2) have a higher susceptibility to increases in fire frequency. Therefore, those areas should be considered as priority areas for management. Furthermore, despite the previous conceptions about the relevance of climate variables on fire predictions, the second case study (CHAPTER 3) found that the accuracy of the fire predictions using climate descriptors is regional-dependent. The effectiveness of the fire prediction models was highly dependable to the socioeconomic, landscape, and climate differences but temporal dynamics (year differences) as well. Therefore, the incorporation of the internal anthropogenic characteristics on fire predictions accuracy does have an effect in areas with high landscape heterogeneity and poverty levels. These results may provide important insight to help improve current fire prediction systems.

CHAPTER 1. CLIMATE AND ANTHROPOGENIC EFFECTS ON FIRE FREQUENCY AND THEIR IMPLICATIONS FOR FIRE PREDICTION SYSTEMS IN MEDITERRANEAN ECOSYSTEMS

1.1 Fire activity worldwide

Fire activity has historically been controlled by anthropogenic and natural processes since the development of terrestrial flora (Bowman et al. 2009). Fire affects stand replacement, vegetation structure, composition changes and ecosystems productivity worldwide (Pausas and Ribeiro 2013, Pausas et al. 2017). Furthermore, fire is consistently used as a tool for anthropogenic activities that play an important role in human development (Bowman et al. 2011). However, fire has also had severe effects on natural resources, economies and human lives (Bowman et al. 2009, Chuvieco et al. 2014). Inside the United States, fire expenditures were more than $11.6 billion in 2010 (Geneva Association 2014, INE 2017). Fires have caused mortality in several countries; for example, 1890 people died in 2009 in Japan because of fire activity (Geneva Association 2014, INE 2017). The increasing number of uncontrolled fire events registered in the last decades has exceeded the capacity of the current predictions and management systems to prevent and assess fire variability (Bowman et al. 2009).

The effect of fire on vegetation depends on the ignition source (cause), frequency (seasonality and occurrence) and the intensity (fire behavior) of the event, which might improve, degrade or maintain the ecology of a site (Cochrane 2009). The combination of fire frequency, intensity, ignition source, spatial distribution, and severity comprise a fire regime (Bowman et al. 2009, Keeley 2009). Furthermore, the cause-effect relationship between fire regimes and human-environment interactions is complex, where fire regime changes can be caused by a combination of landscape dynamics related directly or indirectly to human activities (Veblen et al. 2000, Marlon et al. 2008, Bowman et al. 2011). Interchangeably, changes in fire regimes have a direct and indirect effect on ecosystems and humans (Vázquez et al. 2002). In addition to the influences of climate on fire regimes, shifting fire regime have an effect on climate, where both variables affect global warming (Bowman et al. 2009, Jolly et al. 2015). Between 1997 and 2001, burning of biomass accounted for 63% of the CO_2 global greenhouse gas emissions (Bowman et al. 2009). The current world's CO_2 emissions related to fire activity is comparable to half of the emissions released by fossil fuels (Bowman et al. 2009). The receptivity to capture the interaction between human-climate and fire activity is highly dependent on seasonal and spatial scales (Hantson et al. 2016). Effects that are captured at one particular scale can be completely missed at a different scale (Levin 1992). The complexity of fire regime interactions combined with scale-dependent processes increase the difficulty to understand the connectivity between human-climate-fire relationships and how they are affected one by the other (Bowman et al. 2011).

1.2 Climate change and fire activity

Continuous changes in climate regimes around the world have affected the severity and intensity of fire events (González et al. 2011). Asia and Latin America have been the regions with the highest increases in fire activity (Bowman et al. 2009). During the El Niño-Southern Oscillation (ENSO) of 1997-1998, South Asia spent more than $9 billion on fire management and health issues related to fire events (Bowman et al. 2009, Jolly et al. 2015). In addition, the same event in Latin America cost more than $10 billion during the same period to assess fire damages (Bowman et al. 2009). Drastic climate regimes are associated with long drought periods and shorter wet seasons. Climate seasonality can affect the fire dynamics either by drying out the biomass available for burning or by stimulating the growth of grasses that become also flammable fuel during droughts (Bowman et al. 2009, Cochrane 2009). Climate oscillations such as the ENSO are predicted to increase in frequency for the next decades (Cochrane 2009, González et al. 2011), and such weather instability has increased the uncertainty about the current systems to predict and prevent fire damage (Chuvieco 2003). However, as climate changes could increase the risk of specific locations to experience intensive fire events (Knorr et al. 2016), other factors such as ecological cycles, vegetation dynamics and human activities can also increase the risk of fire ignition (Bowman et al. 2009). At a global or local scale, fire activity is constantly interacting with social, landscape, and climate factors (Hantson et al. 2016). Historically, several countries have experienced fire frequency fluctuations outside of the average fire intervals, where climate affects the fluctuation intensity but political, economic, and social characteristics affect the ignition (Chuvieco 2003). Despite the relevance of climate dynamics, the socio-economic interactions have a major effect over the natural cycles and change the landscape shape affecting the fire regimes (Castro et al. 1998), where more than 90% of the fire events registered worldwide are related directly or indirectly to human activities (Chuvieco 2003, Jolly et al. 2015).

1.3 Socio-economic and landscape changes affect fire regimes

Anthropogenic changes are occurring all over the world from economic development and infrastructure establishment to agriculture production shifts. However, most of the rapid changes in landscape transition as in socio-economic patterns is occurring within geographical clusters (Porter 2000). These rapid growing clusters have been primarily associated with increases in population size and urbanization rates where increases in both regional growth rates produce a 50% increase in fire probability of ignition (Knorr et al. 2016). Current increases in fire activity seem to be related to rapid increases in population dynamics within dry ecosystems. Climate characteristics and anthropogenic variations have made Mediterranean ecosystems one of the most affected by fire fluctuations (Chuvieco 2003). On the other hand, within moist ecosystems, fire activity increases is mostly affected by climate changes (Knorr et al. 2016). Therefore, the understanding of both climate and human effects over fire is key to direct fire management efforts appropriately within each region.

The way that the human component interacts with fire is case specific but in general, it is associated with negligence, arson, land abandonment and conflicts within the urban-rural interface (Chuvieco 2003). However, one of the biggest challenges in trying to understand the human component is that it could be evaluated either as spatial or non-spatially explained patterns (Bowman et al. 2011). Therefore, the integration of the human component into fire management should involve economic, demographic and landscape perspectives in order to capture both direct and indirect effects (Sarmiento and Frolich 2002). The landscape perspective accounts for the social variables that have an effect on the land such as land use types, change, intensity, access (roads), structures (electric lines, buildings), etc. (Syphard et al. 2008, Moreno et al. 2011, Carmona et al. 2012). On the other hand, the economic-demographic perspective involves social variables related to population characteristics based upon location as density, poverty, profits, education, etc. (Jennings 1999). As mentioned before, the inclusion of those perspectives becomes a challenge with scale variations where "the occurrence of patterns can disappear or emerge going from one scale to other" (Koning et al. 1998). Therefore, scale selection is key to understanding the connection between socioeconomic factors and fire ignition. In addition, the differences between scales and the relative effect on the socioeconomic variables significance can efficiently focus the management forces to target specific fire drivers in each scale.

1.4 Fire risk estimation and prediction

The fire assessment at a local or global scale could be determined by analyzing the interaction between the fire hazard risk and the fire ignition vulnerability (Chuvieco 2003). The fire hazard risk describes the number of flammable sources accumulated and the fire ignition vulnerability evaluates the site susceptibility to burning (Castro et al. 1998). Despite the controversy over the use of the terms fire risk and fire danger, I refer to fire risk as the combination of the fire hazard and the fire ignition vulnerability (Castro et al. 1998, Chuvieco 2003). Multiple methods have been developed to estimate fire risk involving the integration of variables into mathematical indexes (Chuvieco 2003). All methods differ on the temporal and spatial scales selected, variables and procedures used to develop the indexes. The fire risk estimation could be classified into long-term and short-term indexes based on the type of variables that are used (Ayanz et al. 2003). The long-term indexes use variables that change over long time intervals but that do not have a significant change in shorter intervals. An example of a long-term index variable could be topography. On the other hand, short-term indexes are based on dynamic variables that constantly changing as vegetation moisture content, wind speed or temperature (Chuvieco 2003). Even inside of the same category, the long and the short-term methods could use different direct or indirect calculations of the same variables to estimate fire risk, which creates variations on the predictions when comparing different indexes (Morgan et al. 2014). Worldwide, fire risk assessment methods have been implemented in different countries (Lee et al. 2002, Chuvieco 2003, Bedia et al. 2014). A summary of some of the methods is found in Table 1.1. The methods described in the table have been modified throughout time adapting the temporal and spatial scales. Despite the continuous updating and improving of the methods, advantages and disadvantages still exist.

The relationship between anthropogenic characteristics and fire activity might involve a wide amount of indicators and perspectives to try to explain the association between them (Chuvieco 2003, Carmona et al. 2012, Andersson et al. 2016). Several studies have focused on analyzing the relevance of socioeconomic variables over fire frequency (Xavier-Viegas 1999, Chuvieco 2003, Pérez-Vermin, G., Márquez-Linares, M.A., Cortes-Ortiz, A., Salmerón-Macias 2012, Bedia et al. 2014, Chuvieco et al. 2014), but they considered a larger amount of variables and the results are not comparable between studies (Table 3). In addition, fire risk indexes decrease their applicability for management when incorporating larger numbers of variables (Ayanz et al. 2003). Consequently, integration of social variables for fire prediction requires detailed selection and preparation of variables in order to accurately explain the human interactions with fire. The current fire prediction approaches focus on the natural or vegetation causes of fire ignition and propagation by misleading the effect of human influences (Chuvieco 2003). Most of the current research and fire models have well studied fire behavior but less is known about the causality behind the fire events related to human interactions. Much research is needed to understand and implement the human-caused fire dimension on the current fire prediction systems (Chuvieco 2003).

One of the major concerns regarding the use of the current fire prediction systems is the inclusion of the human dimension, despite the multiple studies and current evidence pointing out the relevance of the anthropogenic effects over fire (Leone et al. 2003). In order to assess fire accurately, the estimates should include both, the danger and the fire vulnerability as indexes to predict fire risk. Fire danger contemplates the fire behavior characteristics as propagation potential (fuel characteristics). On the other hand, fire vulnerability focuses no ignition probability (cause), the ecological, economic, and social value of a location (Chuvieco 2003, Keeley 2009, Chuvieco et al. 2014). Most of the current fire prediction system contemplates only the fire danger aspect, focusing on the propagation characteristics overlooking the ignition probability related to human characteristics (Bowman et al. 2011). This gap of knowledge increases the differences between observed and predicted fire events especially in areas where the fire matrix is driven by human activity. Several clustered regions with rapid anthropogenic transitions show this problem (Table 1.2). According to the Institute of Forest Conservation of Honduras (ICF), in 2015, 95% of the fire events registered in this country were human related. In addition, reports from the Center for International Forestry Research (CIFOR) in 2003 reported that 44% of the fire events in Indonesia were directly associated with agricultural production and forest clearing activities. Furthermore, 85% of Chile's fire activity is driven by human interactions (CONAF 2014). Nevertheless, those are only a few examples of the countries in which the human-driven fire activity demands effective and accurate systems, which includes the anthropogenic dimension. Although temperature and precipitation variations might affect the fire regimes in different regions around the world, there is the uncertainty of the associated effects related to the human interactions on fragile habitats.

1.5 Risk of fire in Mediterranean ecosystems

Nowadays, the accelerated human population has been associated with increases in fire activity that in conjunction with the dry conditions of these regions have made the Mediterranean ecosystems one of the most affected by fire variability (Syphard et al. 2009). Mediterranean ecosystems are concentrated within five coastal regions of the world, occupying 2% of the Earth surface (Cox and Underwood 2011). Historically, these regions have been targeted for human development due to the suitable locations and environmental conditions. Over 250 million people live in the region where five important cities are located (i.e. Rome, Santiago de Chile, Cape Town, Los Angeles and Perth) (Cox and Underwood 2011). Therefore, with an increase in population, there is high pressure over the land and resources of those areas. Furthermore, anthropogenic ignitions have significantly changed the fire activity by affecting the timing and spatial distribution of fires (Syphard et al. 2009). Chile is the Mediterranean region with the highest potential for biodiversity conservation (75%) based on the natural vegetation without direct anthropogenic impact (i.e. agriculture, plantation, grasslands)(Cox and Underwood 2011). Unfortunately, repeated burns have affected the vegetation where more than half of the native forest has been lost as result of human-induced fires (Ubeda and Sarricolea 2016). Little is known about how the spatial distribution of fire is changing in the Mediterranean ecosystems of Chile due to human activity and what specific anthropogenic characteristics have the highest impacts on fire frequency changes.

1.6 Chile's case study

Historically, Chile has used prescribed fire as a tool for land clearing and agricultural purposes since the colonization period (Díaz-Hormazábal and González 2016). However, fire registries became available until 1964 as developed by the Forest Police Department (Díaz-Hormazábal and González 2016). After 1974, fire regulations changed and the National Forest Corporation of Chile (CONAF) was designated as an official fire authority to record the fire activity. Around 200,000 uncontrolled fire events have been registered since 1964, affecting more than two million hectares of agricultural and forest lands (Moreno 2000, Carmona et al. 2012, Díaz-Hormazábal and González 2016). The uncontrolled fire activity has been one of the most intensive disturbances for Chile's landscape (Castilla et al. 2016). The historical records of fire frequency in Chile show an eightfold increment of fire incidence over the last four decades (CONAF 2014). The upward tendency of fire activity was originally observed in the early 70's (6,000 fire events per year registered between 1970-1984) (Díaz-Hormazábal and González 2016). Consequently, fire frequency peaks were registered in 1990 (6,600 events), 2003 (7,500 events) (CONAF 2016). In January 27, 2017, the active fire system of NOAA registered 119 fire alerts occurring simultaneously in the country (Hansen, M. C., P. V. Potapov, R. Moore, M. Hancher, S.

A. Turubanova, A. Tyukavina, D. Thau, S. V. Stehman, S. J. Goetz, T. R. Loveland, A. Kommareddy, A. Egorov, L. Chini, C. O. Justice, 2017). The unprecedented episode highlighted the current changes in fire regimes experience in the country. Furthermore, the future fire frequency has been predicted to increase (Pechony and Shindell 2010, Díaz-Hormazábal and González 2016), and with it the uncertainty of the causes driving the unprecedented fire activity changes and possible major effects on the ecosystem, economy, and society.

Chile has undergone political, social, and economic transitions since 1930. The population growth and the increase of urbanization rates led to a rapid industrialization development, which also influenced agriculture production at the beginning of the 20th century (Robles Ortiz 2003). The production matrix of the country changed from mineral exports to agricultural products, which led to transportation development (Robles Ortiz 2003). The transitions had an effect on the landscape where the urbanization patterns and the reduction of the native Mediterranean vegetation have induced fragmentation and landscape homogenization (Aguayo et al. 2009). On the other hand, the economic diversification influenced by government policies as economical subsidies, and infrastructure trends, had a significant effect on Chile’s society (Aguayo et al. 2009, Heilmayr et al. 2016). The changes in production patterns have incentivized the instauration of the forest plantation industry (Heilmayr et al. 2016). During the last decades, forestry plantation area has expanded dramatically producing several impacts over the social, economic and landscape patterns of the country (Huber and Iroumé 2006, Andersson et al. 2016, Heilmayr et al. 2016). Those transitions might be affecting the fire regimes changes in the country but the mechanisms of how that is happening are still unknown.

Spatial analysis has reported some evidence of changes in the geographic spatial distribution of the fire hotspots in Chile possibly related to the accelerated landscape dynamics

(Heilmayr et al. 2016). Historically, most of the fire events were located in the Mediterranean ecosystems of the country, where regions from Valparaiso to Bio Bío are located (Peña-fernández and Valenzuela-palma 2004, CONAF 2016). Nowadays, the accelerated landscape transition might start to affect the fire distribution in other ecosystems but there is no evidence of those changes (Peña-Fernandez & Valenzuela-palma, 2004). Land use changes are mainly occurring between the 33° and 38° south latitudes where most of the country agriculture and wood production are located (Díaz-Hormazábal and González 2016). The effect of the accelerated landscape changes and the possible implications for shifts in fire distribution are uncertain and further research is required in order to adjust the current management approach.

The fire trends in Chile are seasonally dependent (González et al. 2011). The fire events initiate in late August and finish in early May (Díaz-Hormazábal and González 2016), with most of the ignitions occurring between December and February (CONAF 2014). Evidence has shown that 80% of the fires registered during the fire season are categorized as low-intensity events (<5ha) affecting 11% of the burned area (Díaz-Hormazábal and González 2016). On the other hand, high-intensity fires (>200ha), represent only 1% of the fire events and affect 44% of the burned land (CONAF 2014). As current changes in fire regimes can affect fire spatial distribution, fire seasonality could change as well and may be related to human and climate interactions (Pechony and Shindell 2010). The fire initiation causes vary from natural ignition (climate) to intentionally provoked activities (human). There is evidence to suggest that > 85% of fires registered in Chile are related to human activities (CONAF BIRF 1999). In some areas, reports indicate higher values such as in the Maule region where 97% of the uncontrolled fires are human-related (Díaz-Hormazábal and González 2016). Some studies have associate fire evens to transportation accidents, recreation, and production activities (Díaz-Hormazábal and González 2016) where most of the ignition fuels have been identified on grassland areas and plantations (75% of the events) (Ubeda and Sarricolea 2016), but specific landscape transitions and characteristics have not been associated with changes in fire dynamics.

The National Institute of space research (INPE) of Brazil developed the current fire prediction system (FPS) used in Chile and several other South American and Central American countries. The FPS predictions are based on the number of drought days to quantify the risk of fire occurrence in a given vegetation type (CONAF 2014). Furthermore, the FPS was developed considering climatic (Precipitation and Temperature) and vegetation (Fuel source) characteristics as the main input for fire prediction (CONAF 2014) and does not include human variables as in the other systems used worldwide. Both vegetation characteristics and climatic variations have been shown to be relevant in the understanding of fire activity in countries where most of the fires are wildfires (Chuvieco 2003, González-Ollino, D., Rodríguez-Vignoli 2004). On the other hand, in countries like Chile where most of the fire frequency is human-driven, the inclusion of anthropogenic drivers could be a key element for fire management. Despite all the related literature about this issue (Table 1.3), the inclusion of both landscape and economic-demographic perspective variables have not been adapted to current systems. In order to improve the current fire prediction systems, the incorporation of all the aspects describe above could be key in order to efficiently manage the future fire regime changes.

1.7 Justification for study

Global fire activity has changed from a climate-induced to a human-driven fire regime (Pechony and Shindell 2010). Current fire prediction systems rely on meteorological outputs and fuel characteristics to determine fire risk, not including the human dimension (Chuvieco 2003). This becomes a greater issue within areas where most of the fire variability relies on social-landscape interactions. Mediterranean ecosystems are often targeted for urban development. However, the biodiversity value of these ecosystems is severely threatened by the fire variability caused by human ignitions (Syphard et al. 2009). The accuracy of the current fire prediction system is a challenge within this particular region where fire ignition is predominantly human-based. Furthermore, the restricted geographical distribution of Mediterranean ecosystems, unprotected conservation status, and dry conditions combined with accelerated human development (Cox and Underwood 2011) increases the pressure to improve efficiency of fire risk detection within these areas. The connectivity between fire regimes and human-environment interactions is complex but the understanding of socio-economic drivers and landscape transitions is key to accurately assess the fire risk. From selection of spatial and temporal scale to evaluation of variables, multiple factors should be considered in order to capture the effect of anthropogenic variation in fire changes. Current literature has begun to move towards the understanding of the connectivity between these elements. However, more research is required to understand both direct and indirect effects of anthropogenic indicators affecting fire variability within Mediterranean regions and the inclusion of those into fire prediction systems.

1.8 Summary of objectives

The objective of this study is to analyze the effect of anthropogenic drivers on fire frequency variability and the inclusion of human indicators to improve fire frequency predictions based on two case studies in Chile. More specifically, in order to account for the complexity of the human dimension, each case study focuses on different anthropogenic perspectives. The first case study will investigate the effect of landscape transitions on the fire frequency changes. The specific questions are the following i) What are the particular transitions that are driving the landscape changes over the area. ii) What are the characteristics of the landscape changes? iii) What are the specific landscape characteristics and transitions affecting the fire frequency changes and iv) Does the speed of the transitions affects the fire frequency changes? The second case study evaluates the integration of socioeconomic descriptors into a fire prediction system while accounting for spatial distribution changes, selection of variables and prediction accuracy. The specific questions are i) Are there changes in the spatial distribution of fire activity? ii) What are the most significant socio-economic characteristics affecting fire frequency? iii) How are socioeconomic and landscape variability connected to fire frequency changes? and iv) How does the inclusion of socioeconomic and landscape indicators improve fire frequency prediction systems? Both case studies focus on a Mediterranean ecosystem, which is the targeted ecosystem to improve fire prediction systems. Results and implications of this study are described in chapter two and three. A synthesis of the results, fire management implications and future steps are described in chapter four.

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Table 1.1 Description of multiple fire prediction systems used around the world comparing variables, scales and descriptive characteristics (Adapted from Ayanz et al. 2003)

Location	**Category**	**Index name**	**Variables**	**Scale**
Europe	Long-term	Fire Probability Index	Fuel source availability Topography Socio-Economic Variables	1 km^2
		Vulnerability Index	Potential erosion: soil type, slope, and rainfall Level of protection: rareness, environmental interest Distance to settlements: number of human lives and settlements	1 km^2
	Short term	Meteorological Index	Fine dead fuel moisture content Fuel water content The initial rate of propagation Quantity of fuel Atmospheric conditions	50 km
		Vegetation stress index	Fuel moisture content Time window	16km^2
		Fire potential Index	Live-ratio (NDVI) The moisture content of dead vegetation Fuel type Meteorological variables	16 km^2
USA	Short term	National Fire Danger Rating System	Burning index Spread component Energy release component Ignition component	1 km^2
Australia	Short term	McArthur's Fire Danger System	Fine fuel Availability submodels: Drought factor: moisture status of fuel, moisture gradient in the fuel bed, the intensity of the fire, chemical and mechanical structure of fuel and the horizontal and vertical structure of the fuel Keetch drought index: soil moisture content, time since last rainfall event, maximum daily temperature, 24-hour rainfall Surface fine fuel Moisture: Ambient air temperature Relative humidity The rate of Spread: Surface fine fuel moisture Wind speed The difficulty of Suppression: Dryness of the fuel	
Canada	Short term	Canadian Forest Fire Danger Rating System	Subsystems: Forest Fire weather index: fuel type, dry bulb temperature, relative humidity, wind speed, accumulated rainfall.	

			Forest Fire Behavior Prediction: fuel type, topographic situations.	
New Zealand	Short term	Adaptation of the Canadian Forest Fire Danger Rating System	Temperature Relative Humidity Wind direction Rainfall	4 km^2
South America	Short term	Fire Risk Index	Precipitation Temperature Relative Humidity Vegetation Type	60km

Table 1.2 Comparison between the fire causality due to human and natural ignitions in several countries around the world*

Country	**Human Ignition (%)**	**Natural Ignition (%)**	**Reference**
EU		1-2%	Chuvieco et al. 2003
France		29.7%	Chuvieco et al. 2003
Spain	25%	30%	FAO 1990
Greek island		50%	Kailidis 1992
Finland		10%	Larjavara et al 2002
Canada		40%	Chuvieco et al. 2003
Turkey	59%		Chuvieco et al. 2003
Austria	50%		Chuvieco et al. 2003
Portugal	32%		Chuvieco et al. 2003
Chile	85%		CONAF 2015
Honduras	95%		ICF 2015
Indonesia	44%		CIFOR 2003

*Values apply for some regions of the country, do not necessarily extrapolate to the entire country and specific year

Table 1.3 Summary of a literature review evaluating the effect of human dimensions on fire frequency and intensity. Description of variables and effects assessed from each paper.

Paper Title	Effect	Variables	Reference
Abandonment of traditional activities in wildland/rural areas	The increase of forest fuel accumulation	Temporal evolution of agrarian active population Temporal variation of agriculture	Carvacho 1998 Chuvieco et al 1996b
Abandonment of traditional activities in wildland/rural areas in privately own forests	Lack of traditional silviculture and care of the forest	Forest area (public and private, managed and no managed, with and without commercial value)	Chou 1992 Pérez and Delgado 1995 Vega-García et al 1993, 1995
Depopulation of rural areas	Decrease of the active population in rural areas, abandonment of croplands, spontaneous natural vegetation colonization, increase in forest fuel sources	Change of forest and agricultural surface	Romero and Perry 2002
Increase use of forest as a recreational resource	The increase of visits to the forest, increase the risk of negligence fire events	Distance and accessibility to touristic areas Distance to roads and urban areas	Abhineet et al 1996, Alcazar et al 1998, Benvenuti et al 2002, Bradshaw et al 1987, Brass et al 1983b, Castro and Chuvieco 1998 Chou 1992,1993, Vega Garcia et al 1996
Human presence, population increase, and urban growth	More pressure on wild lands	The increase of the urban/wildland interface, urban/forest interface, population number and density, urban area, city lights density	Chuvieco et al 1999, Pérez and Delgado 1995, Chuvieco et al 1998, Dagorne et al 1994, Donoghue and Main 1985
Population increase in rural villages during summer holidays	More amount of waste- ignition sources	Location of rubbish's dumps	Alcazar et al 1998
Aged rural population	Traditional management methods- increase probability of propagation	Age rate	Chuvieco et al 1999
Agriculture	Fire use to eliminate harvesting wastes – an increase of propagation risk	Agricultural area and forest area interface	Chuvieco et al 1999, Pérez and Delgado 199, Milani et al 2002, Leone et al 2002b
Cattle grazing	Fire use to maintain herbaceous vegetation	The density of livestock, grassland/forest interface, distance to livestock	Chuvieco et al 1999, Leone et al 2002, Perez and Delgado 1995, Oleveira et al 2002
Electric lines	Ignition by accident	Distance to electric lines	Alcazar et al 1998, Oleveira et al 2002, Bradshaw et al 1987

Engines and Machines working in or close to the forest area	Ignition by accident	Agrarian machinery density	Chuvieco et al. 2003
Hunting Activities	Ignition by accident	Hunting licenses	Ayanz et al. 2003
Landscape structure	Fire propagation for the abandonment of plots	Fragmentation index and landscape diversity	Pérez and Delgado 1995, Romero and Perry 2002
Presence of roads, railroads, tracks, and accessibility	Human pressure- ignition by accident	Length and density of roads and railroads	Abhineet et al 1996, Milani et al 2002, Dagorne et al 1994
Military maneuvers and quarries explosions	Ignition by accident	Military areas	Ayanz et al. 2003

CHAPTER 2. EFFECT OF LANDSCAPE TRANSITIONS ON FIRE FREQUENCY IN THE CENTRAL ZONE OF CHILE

2.1 Abstract

Changes in fire regimes can be triggered by a series of factors that vary temporally. Most of these changes in fire regimes are linked to landscape structural changes that are directly or indirectly related to human activities. Chile's landscape has undergone a series of accelerated transitions throughout history, including agricultural expansion and tree plantation establishment. These changes in production dynamics and fire activity could be related to internal landscape dynamics. The goal of this study was to analyze the landscape transition patterns in the Center zone of Chile and the effect of those transitions on fire frequency between 2014-2017. Landsat 8 OLI TIRS Level 1 imagery was used to derive a change detection contingency table (CT). The CT was used to perform an intensity analysis. Overall, 27.2% of the area changed between 2014-2017. The Maule region showed the most significant rate of transition between agriculture and forest/plantation area ($P<0.001$). The majority of the change was categorized as an exchange where agriculture and urban/burned areas had active transition rates higher than the uniform intensity (>9.08%). Intensive transitions where forest/plantation area increased were related to decreases in agriculture areas (Uniform transition >3.95%). Increases in agricultural areas were related to a reduction in bare soil areas (Uniform transition >1.85%). Conversion from bare soil to forest/plantation area, categorized as a passive transition, significantly affected the fire frequency change. Transitions between agriculture to the forest, bare soil to other and forest to other ($p<0.001$) were categorized as active transitions where increases in the rates of those transitions can trigger changes in the fire frequency of the area (3.95, 1.38, and 3.47% respectively). Fire frequency is more likely to change in areas where active transitions occur and where those

transitions follow low patch density, a high number of patches and high mean patch area ($p<0.001$). These results highlight that transition intensity and landscape characteristics can increase fire risk vulnerability, whereas the inclusion of this element into fire prediction systems could improve fire risk assessment in areas with similar landscape patterns.

2.2 Introduction

2.2.1 *Fire dynamics*

Fire activity has influences on stand replacement and triggers most of the structure and composition changes over vegetation worldwide (Bowman et al. 2009, Pechony and Shindell 2010). The fire has played an important role in human development as a tool for improvement; however, the fire has also had severe effects on natural resources, economies and human lives (Bowman et al. 2009). Inside the United States, fire expenditures related to damage control were more than $11.6 billion in 2010 (Geneva Association 2014, INE 2017). The impacts of fires have also been a cause of mortality in several countries; for example, 1890 people died in 2009 in Japan because of fire activity(Geneva Association 2014, INE 2017). The increasing number of uncontrolled fire events related to human ignitions has exceeded the capacity of the current fire prediction and management systems to prevent and assess the fire damage (Bowman et al. 2009). In contrast with future projections pointing at fire regimes shifting (Pechony and Shindell 2010), that increase the uncertainty of the effectiveness of current systems, to accurately predict, prevent and monitor fire variability (Watson et al. 2005, Chuvieco et al. 2010). The effective allocation of fire resources relies on the understanding of the causes triggering the fire regime changes at the local scale (Pechony and Shindell 2010).

Fire frequency and intensity are two important concepts for use in fire risk assessment. The fire intensity is determined by the previous condition of the vegetation (Morgan et al. 2014) and is commonly used to map land use changes in order to prioritize management of areas after fire events (Chuvieco et al. 2014). Although fire intensity is a key component to understanding fire behavior, fire frequency is an important element to understanding fire ignition (Chuvieco 2003, Cochrane 2009). Both components in combination with spatial variability, severity, and seasonality determine a fire regime (Bowman et al. 2009). The understanding of fire regimes begins with understanding the stimulus behind the fire initiation (Gabban et al. 2008, Knorr et al. 2016).

The causes driving the fire activity worldwide have changed from climate to human-climate interactions (Pechony and Shindell 2010). In order to determine priority areas for fire management, most of the current Fire Prediction Systems (FPS) rely on meteorological outputs and fuel characteristics (Chuvieco et al. 2010, 2014) to determine when and where fire ignition will occur and how the fire will behave (Bowman et al. 2009). However, current patterns within Chile have observed an upward trend on fire frequencies in areas with exponential socio-economic and production transitions (Carmona et al. 2012), under covering the possible relevance of including landscape transitions on fire frequency predictions (Moreno et al. 2011) not only in Chile but also in regions where the fire initiation is driven directly or indirectly by human activity.

2.2.2 *Landscape changes*

Landscape transitions can be triggered by social, political, economic or ecological drivers (Heilmayr et al. 2016). However, transition speed and quality have strongly relied on agriculture production system changes that have an internal and external influence on the landscape dynamics of the sites involved (Foley 2005, Heilmayr et al. 2016). Chile has undergone significant landscape transition across history, combining agricultural expansion and forestry plantation establishment (Heilmayr et al. 2016). Most of the changes have been triggered by colonization, political reforms, production incentives and population redistribution (Clapp 1998). Nowadays, Chile's production system has a shift into a rapid establishment of forest plantations (1986-2001) (Heilmayr et al. 2016). Native forest areas were reduced 21% of the country surface between 1975 and 2000. Simultaneously, are of forestry plantations areas has increased from 5% to 36% over the same time interval (Echeverria et al. 2006, Heilmayr et al. 2016). Several studies have reported significant production changes along the countryside (Toro and Gessel 1999, Aguayo et al. 2009). Simultaneously, the area covered by urban settlements have doubled its size in the last 40 years as result of socioeconomic transitions occurring at the same time (Aguayo et al. 2009). Despite the short-term, long-term, local and country land use analysis that have already been done in Chile related to land use changes (Echeverria et al. 2006, Aguayo et al. 2009, Díaz-Hormazábal and González 2016, Schultz et al. 2016) the direct effect of the accelerated shift in landscape transition on the fire activity of the country have been poorly studied. Furthermore, similar patterns are occurring around the world (Turner et al. 1994, Mladenoff and Baker 1999, Moreno et al. 2011) were improving the knowledge of the speed and extent of landscape transitions could lead to a deeper understanding of the fire dynamics over those areas.

2.2.3 *Chile's Fire Activity*

The elements causing the fire regime changes vary depending on the country, from natural to accidental or intentional ignitions. The uncontrolled fire activity has been one of the most intensive threats to Chile's natural resources and population (Ubeda and Sarricolea 2016). The historical record of fire frequency has shown an increment of almost eight times the incidence of fire events over the last four decades (CONAF 2014).On January 27, 2017, the Active Fire System NOAA registered 119 fire alerts occurring simultaneously over the country (NOAA 2017). There is evidence that suggests that more than 80% of fires registered are related to human activities associated with production activities (CONAF 2014). Furthermore, the interaction between urban-wildland interface is considered one of the most important factors that have increased the fire risk in some regions (Radeloff et al. 2005, Jolly et al. 2015, Díaz-Hormazábal and González 2016). Therefore, in response to the radical increases of the fire activity and evidence highlighting the possible relevance of landscape transition over the fire frequency changes, an improved understanding of the relation between both, landscape characteristics and fire frequency changes are needed.

The aim of this study is to understand and describe the landscape transition and intensity over the central zone of Chile and to evaluate the effect of those transitions over the fire frequency changes. The specific questions we intend to answer are i) what are the particular transitions that are driving the landscape changes over the area? ii) Are those changes related to shifts or exchanges between the land uses? iii) What are the specific landscape characteristics and transitions affecting fire frequency changes over the Center Zone of Chile? and, iv) Is the speed of the transitions from passive to active (non-stationary) more likely to affect the fire frequency changes?

2.3 Materials and Methods

2.3.1 *Study area*

The analysis was conducted using the central zone of Chile as a case study for the period 2014-2017 (Figure A1). The central zone of Chile was selected based on its population, which is concentrated mostly in this area according to 2017 registries (INE 2017). Chile administrative divisions are classified as Regions, which are at the same time are conform by comunas. Within the study area, there are five major regions and 194 comunas that represent 73% of Chile's population (Table A1). A "comuna" is considered the smaller administrative division of the country, which was selected as sampling units, for a total sample size of 194 comunas. The predominant economic activities are a focus on the production of agriculture, wine yards, fruits, and timber plantations (Table A2) with annual increases in agriculture and timber plantation areas (1.1% yearly) (Schulz et al. 2010).

2.3.2 *Land Use Data*

Landsat 8 OLI TIRS Level 1 imagery for the period extended from January 2014 to January 2017 was downloaded from the Earth Explorer of USGS (Table A3). The data was selected based on the season, the quality and the availability. Time wise the data was acquired with a time separation of less than a week between scenes of the same year and between years. All data was selected for Chile's summer season, to increase the accuracy of the classification, and with less than 10% cloud cover.

All the layers from the same scene were stacked using the Erdas Imagine 2013 Software. For this case study, only bands 1-8 were selected for evaluation during the stacking process. The possible band's combinations were tested based on the differences in pixel values of the evaluated land uses and the variation along the band's pixels. The bands that showed the higher differences in pixel value and visual color differences between land uses were selected using spectral profiles and surface profiles comparisons. No differences were found between bands 1, 2, 3, 4, and 8. The band combination between 5, 6, and 7 were selected where the bands had the highest differences between each other when evaluating possible land use separation. The three bands were stacked and the scenes from similar days were mosaic and geographically corrected.

An unsupervised data classification was used to classify the imagery for this study. Detail of category descriptions is available in Table A4. The data were classified using the ISODATA classification where the classification specifications were 150 classes, 50 iterations, and 2 SD. The classification was performed using an R5-G6-B7 color adjustment where most of the color differences between land uses were visible in other to separate the land uses. The classification was then recorded into four categories relevant for this study. The classification process was performed simultaneously for all the years and dates analyzed. The four categories classification for each year was evaluated through an accuracy assessment. As there were no suitable complete reference data available for the dates selected, the accuracy assessment was developed using 800 random points (200 per category evaluated) based on the Catastro thematic maps (CONAF BIRF 1999) and Google Earth Pro data and additional reference maps from the Forest Corporation of Chile (CONAF). The accuracy assessment was based on the Kappa Statistics not accepting less than 0.8 of Kappa value (Table 2.1).

2.3.3 *Change detection analysis and Landscape Homogeneity*

The land use transitions were evaluated through time and space. First, the time evaluation was accomplished using a post-classification change detection analysis (CDA) between 2014 and 2017 classification outputs. The CDA was performed using a Matrix Union reporting the transition area per land use as a function of the pixel count and size. The change detection analysis was evaluated using the methodology of Pontius & Santacruz, 2014. In addition, post-classification techniques were used to obtain the Contingency Table (CT). The spatial characteristics of the transitions, the intensity rate and uniform intensity (UI) of them were calculated using Pontius & Santacruz, 2014; Zakaria Aldwaik & Gilmore Pontius Jr, 2012 methods.

Quantity, exchange, shift, and intensity were calculated using the CT. In addition, the table was used to derive the intensity analysis. Second, the spatial patterns of landscape characteristics were evaluated through the Shannon Evenness Index (SHEI) (Li and Reynolds 1993) (Equation 1), use to represent homogeneity based on the areas extracted from the classification process for each year separately. In addition, the land use change per year was evaluated using methods of Aguayo et al., 2009; Echeverria et al., 2006.

Equation 1 $$SHEI = (-\sum (Pi*Ln (Pi))/Ln (m))$$

In the SHEI equation, *Pi* represents the proportion of the landscape occupied by the land use and *m* represents the number of land uses evaluated. SHEI index is a value between 0 and 1 that represents the dominance of a land use over a specific area, where values close to zero represent areas that are basically covered by only one land use (e.g., as agriculture), and values close to 1 represent areas that are covered by different land uses where none of them dominate the land cover. In addition, FRAGSTATS 3.3 software was used to calculate additional patch characteristics. The parameters were selected based on Dezhkam, Jabbarian Amiri, Darvishsefat, & Sakieh, 2016 (Table A5). FRAGSTATS calculates land use categories metrics based on Shape, Area and Aggregation characteristics, which is used as a measure of landscape fragmentation (Pijanowski and Robinson 2011). The patch characteristics were calculated using the output classification with and without majority neighborhood adjustments. As no significant differences were found, the data without smoothing is presented in this chapter.

2.3.4 *Fire frequency and weather data*

The fire frequency records (2014-2017) were available at the Fire Information for Resource Management System (FIRMS) of NASA. For the studied time interval, the fire data was selected based on the fire frequency annual curve presented by CONAF (Figure A2), where fire events registered between August 1st and June 30th were selected for each year. The fire data was used to calculate the Fire frequency represented as fire counts per sample unit.

The weather stations data between August 1st and June 30th per year was available at the Climate Explorer tool of Chile. The precipitation expressed as daily average (mm) and the Average Temperature (°C) of the explorer tool was used to estimate the weather variables for the comunas were no weather stations were found. The data interpolation was accomplished using a co kriging interpolation method using as covariate the 1 km resolution elevation data (Global 30 Arc-Second Elevation GTOPO30a) available at the USGS website.

2.3.5 *Statistical Analysis*

Fire frequency was evaluated as a function of both patch characteristics and landscape transitions through multiple linear regressions models. The stepwise analysis was used in order to select the best-fitted model describing the fire frequency. In addition, the spatial autocorrelation of the sample unit was evaluated an accounted for using a weighted matrix based evaluated through a Moran's test following Bivand, Pebesma, & Gomez-Rubui, 2008; Ward & Gleditsch, 2007**.**

2.4 Results

2.4.1 *Change Detection Analysis*

Twenty-seven percent of the area experienced land use transition between 2014-2017, where the spatial distribution of the change was not homogeneous between regions and land uses. The change detection output for the period 2014-2017 is shown in Figure 2.1. Within the time step, the land use persistence was 72.74% with an average of 9.08% change per year. The regional change differences between land use and years are presented in table 2.2 and 2.3. Overall. The area had decreases in agriculture land and increases in forest/plantation areas (four out of five regions shown this trend). Valparaíso and Bio Bío are the regions that had the highest annual increment on forest/plantation (5.14% and 2.26% respectively). On the other hand, agriculture had the highest annual decrease within Maule and Bio Bío (2.61% and 5.42% respectively), where most of the observed change is clustered along the coastline of both regions. Overall, the Bio Bío Region transition the most (29.17%) compared to the other regions of the country.

2.4.2 *Transition Analysis*

At a time interval level, the land use change during 2014-2017 was classified as Exchange (23%), Shift (3%) and Quantity (2%). The overall pattern of the land use change based on the segmentation of the change between three categories is shown in Figure 2.2. Most of the transition was occurring interchangeably between two dominant categories in the same location (Exchange). In addition, a small fraction of the area was shifting between three or more categories, which highlights that the land use changes does not follow a direct transition pathway (Quantity). Furthermore, within shift areas, multiple intermediate stages happened in order to get from one land use to the other (shift) not as a sharp transition as was usually thought.

At a category level, Bareland and forest/plantation are the classes that had the largest gain in annual change area and agriculture had the largest losses. On the other hand, agriculture and urban/burned were the categories with intensity rates higher than the UI (9.08%), which classifies them as active or non-stationary (transition speed higher than average) (Figure 2.3). Therefore, all land use transitions associated with both categories are meaningful explaining changes over the area. At a transition level, figure 2.4 and 2.5 detailed each category gain and losses of area respectively, and the classes that are targeted (non-stationary) or avoided (stationary) to receive or donate land. Bareland and agriculture are the largest contributors to forest/plantations increases. Furthermore, the rate at which forest/plantations receive area from agriculture is higher than the UI (8.83%>3.95%), which categories agriculture as a targeted category to transition into forest/plantation areas (Figure 2.4). In contrast, urban/burned (4.94%>3.47%) and agriculture

(4.44%>3.47%) are targeted receivers when deforestation occurs (Figure 2.5). Bareland increases are related to a reduction in forest/plantation and urban/burned areas, where urban/burned is a targeted category for bareland conversion (20.01%>6.80%). Furthermore, agriculture (7.97%>6.56%) and urban/burned (15.93%>6.56%) are targeted categories to receive bareland, which is associated with crops rotation and construction. On the other hand, agriculture areas increased as result of bareland reductions (2.04>1.85%) also mostly associated with crops rotation seasonality; in contrast with agriculture losses associated with forest/plantations installment (3.83%>2.32%). Finally, urban/burned areas are interchangeably gaining (1.89%>1.38%) and losing (2.47%>1.48%) area from bareland.

2.4.3 *Landscape Characteristics*

There are patch characteristics heterogeneity between land uses. The forest/plantations and urban/burned categories are the ones that have the higher patch density (number of patches/100 ha). The category that comprises most of the landscape area within a patch was bareland, where lower values for the agriculture and urban/burned categories can be related to higher fragmentation. In terms of patch shape, most of the land uses are non-squared (values > 0), where bareland and forest/plantation had the most irregular shapes, which could be relevant for fire activity.

2.4.4 *Fire and landscape transitions*

Differences in patch characteristics between land uses had a significant effect on the fire frequency changes throughout space (Table 2.4) and time (Table 2.5). First, the patch characteristics and the land use transitions were analyzed as a function of the fire frequency changes between 2014-2017. The best-fitted model of the patch characteristics that had a significant effect on the fire frequency is shown in table 4 ($F_{7, 186}$=29.41, R^2= 0.507, p <0.01). First, increases in landscape heterogeneity (SHEI values close to 1) were associated to increases in fire frequency, where heterogeneity relates to the number of land use in the area, the more land uses presented the more heterogeneity. Second, increases in forest/plantation area segmented into fragmented distant patches were related to increases in fire frequency, in contrast with larger homogenous forest/plantation areas across space that were associated with a reduction in fire frequencies. On the contrary, across time, increases in landscape homogeneity towards dominance on forest/plantation had a significant effect increasing fire frequencies ($F_{1, 192}$=32.16, R^2=0.13, p < 0.01) (Data not shown). On the other hand, decreases in the number and density of urban/burned and bareland were related to increases in fire frequency (rural areas). The best-fitted model of the fire frequency change between 2014-2017 as a function of land use change is shown in table 2.5 ($F_{4, 189}$=20.79, R^2= 0.291, p <0.01). Throughout time, both increases in forest/plantation installment and urban/burned areas produced significant effect over fire frequency increases. Furthermore, reductions in bareland and agriculture areas were associated with increases in fire frequency as well.

At a regional scale, the Maule region was the one that increased the most the fire frequency between 2014-2017 (Figure 2.6), where the transition from forest/plantation to bareland had the highest increased in fire frequency in this region. On the other hand, within Bio Bío region, changes in agriculture and bareland towards forest/plantations had the highest fire frequency changes. Overall, the land use transition that is significantly associated with fire frequency changes is shown in figure 2.6. Land use change in agriculture to forest/plantation, bareland to forest/plantation, bareland to urban/burned, and forest/plantation to urban/burned had a significant effect over fire frequency changes ($F_{15, 44}$=3.53, R^2=0.392, p <0.01).

The criteria to select the most relevant transitions for fire management on the central zone of Chile was based on transitions that had both landscape significance and significant effect on fire frequency. The resulted transitions were classified as stationary and non-stationary. A stationary class refers to changes in land use that are slower than the average transition rate (transition rate < UI). In this scenario, bareland to forest/plantation was the stationary transition that had effects on fire frequency. On the other hand, the non-stationary class represents the transitions that are changing faster than the average transition rate (transition rate > UI). Agriculture to forest/plantations (>3.95%), bareland to urban/burned (1.38%), and forest/plantation to urban/burned (3.47%) are considered both actively (non-stationary) changing on the landscape and significantly affecting fire frequency when transitioning higher than the UI. Finally, when combining both active transitions with patch characteristics, transition higher than UI combine with changes in forest/plantation area towards increases in landscape heterogeneity are likely to increase fire frequency within a region.

2.5 Discussion

2.5.1 *Change detection and transition*

The central zone of Chile is experiencing an accelerated land use transition mostly associated towards reduction in agriculture areas and increases in forest/plantations. Several studies have reported similar or higher transition rates from previous time intervals from 23% (1986-2011)(Heilmayr et al. 2016), 27.4% (1999-2009)(Carmona et al. 2012) and 40% (1979-2000)(Aguayo et al. 2009). The studies related to landscape change in Chile started in 1970's (Fuentes 1979, Clapp 1998), where native forest declines were associated to an national agriculture production shift incentivizing plantation installment (Heilmayr et al. 2016). Despite previous studies reported larger native forest area conversion into tree plantation areas at the late nineties(Aguayo et al. 2009, Andersson et al. 2016, Heilmayr et al. 2016), the results of this paper highlight the transition tendency of agriculture land into forest/plantations between 2014-2017. At a local scale, increases in plantation areas have been previously associated with increases in economic challenges for farmers related market availability and water availability for irrigation (Huber and Iroumé 2006, Andersson et al. 2016) which probably explain the current agriculture reduction tendency. Other studies associate the reduction in agriculture areas as a result of increases in migration from rural to urban settlements based on the skill set required for job positions on plantations companies(Andersson et al. 2016). This argument could also support the significant increased on transition rate related to urban/burned areas moving towards possible growth in urban areas found in this paper. Historically, Chile has undergone several production transitions, especially in the coastal areas during the 70's where the production of wheat was reduced as result of soil erosion related to extensive monocultures installment, and the introduction of exotic species (*Pinus radiata*)(Fuentes 1979, Pausas and Keeley 2014). Most of the land use change observed in this study was localized within the coastline of Maule and Bio Bío regions. Both areas have showed the highest increases in forest/plantations and reduction in agriculture areas, which could be related to the high concentration of the timber industry and the highest rates of native forest deforestation (53% reduction between 1973-2000) found in both regions (Peña-fernández and Valenzuela-palma 2004, Echeverria et al. 2006, Heilmayr et al. 2016).

The high speed of the transitions driving the landscape changes is mostly associated to forest/plantations related to increases in tree plantations installment (Fuentes 1979, Nahuelhual et al. 2012, Heilmayr et al. 2016, Ubeda and Sarricolea 2016). Although transitions into forest/plantations have increased the area of this land use, at a slower rate, tree stands are also being replaced by deforestation to install agricultural plots (Chuvieco 2003). Furthermore, deforestation of tree stands is also moving towards human disturbance either through fire events (Carmona et al. 2012) or logging for firewood (Echeverria et al. 2008). In addition, a type of rotation between the tree stands and the bareland was observed in the landscape where forest/plantation areas are shifting towards bareland also observed for agriculture areas (Nahuelhual et al. 2012). Furthermore, bareland is also being replaced by human settlements as infrastructure development (Fay and Morrison 2007) or affected by disturbance events as fire (Nahuelhual et al. 2012). In terms of patch characteristics, as forest/plantations and urban/burned patches have the highest density across the landscape. High patch density could be related to the transition of native forest from homogeneous large areas into fragments as result of deforestation (Echeverria et al. 2008). But also could be related to the conversion of spread agriculture patches into tree stands across the landscape (Clapp 1998).

2.5.2 *Fire frequency vulnerability*

Changes in patch characteristics across the landscape and variations in the land transition rate have significant implications on fire frequency within sites. First, regions that presented the most accelerated shifts are more likely to present fire activity changes (Ubeda and Sarricolea 2016). Maule and Bio Bio were the regions that presented most of the changes in both landscape and fire frequencies associated with rotations between bareland and forest/plantations (Díaz-Hormazábal and González 2016). This could be related to the increase in homogeneity and large areas occupied by the same species, with similar characteristics (age) contrasted with high densities which affects the fuel matrix of the area (Peña-fernández and Valenzuela-palma 2004) Furthermore, the species that are used for tree plantations (*Pinus radiata* and *Eucalyptus globulus)* are both fast-growing species that have flammable foliage. Therefore, combined with the harvest method where most of the aerial biomass is left on site could increase fire vulnerability

(Nahuelhual et al. 2012, Heilmayr et al. 2016). In addition, across space, increases in landscape heterogeneity (transition towards forest/plantations installment) mostly at peripheral areas of cities produce fire frequency change by reducing urban-wildland interface (Kerby et al. 2007, Syphard et al. 2008). As a result, reductions in landscape connectivity from fragmentation are more likely to affect fire seasonality, distribution, and frequency because the probability of fire spread by human activity increased into patchy systems (Archibald et al. 2012). Fire selectivity move towards pine plantation patches and shrubland in presence of native forest, and crops (Barros and Pereira 2014). On the other hand, across time, rapid installment of forest/plantations patches increases landscape homogeneity (dominance by one land use) which could change fuel loading, which also increases fire vulnerability(Syphard et al. 2008).

Second, transitions between forest/plantations and urban/burned areas significantly affected fire frequency. Most of the tree stands are located surroundings human settlements where the access and susceptibility to burn increase (Mikusiński et al. 2003, Díaz-Hormazábal and González 2016, Ubeda and Sarricolea 2016). In addition, one of the main causes of fire within the central zone of Chile is the burning of arson, which increases the vulnerability of accidental fires near surrounding vegetation (Pausas and Keeley 2014). Finally, transition between agriculture and forest/plantations also increase susceptibility to fire frequency change. This study found that increases in forest/plantations were associated to decreases in agriculture areas which suggest the probability if finding tree stands surrounded by agriculture land. Increases in tree stands proximity to agriculture areas increase probability of accidental fires because prescribed fires are used as tool for vegetation clearing and grass regrowth in farmlands (Gill and Williams 1996). Furthermore, the Bio Bio region presented most of the transitions related to the increase in tree stands as the result of the conversion of agriculture land and bare soil to forest-plantation areas that have an effect on the changes in the regional fire frequency.

The results of this paper suggest that relative changes within specific landscape transitions and patch characteristics can have a significant effect on fire activity in sites with human-driven fire matrices. Similar patterns have been evaluated around the world where the integration between landscape dynamics and the urban-rural interface is key to understand fire activity (Cardille et al. 2001, Syphard et al. 2006, 2008, Parisien and Moritz 2009). Despite differences on environmental characteristics within sites, regions in Spain (Moreno et al. 2011), and California(Radeloff et al. 2005, Syphard et al. 2008) highlight the significance of landscape structure and variability to predict fire activity. Therefore, the understanding of key land use change, transition rate and patch characteristics to suggest improvement on fire management. As in this case study, specific active transitions related to increases in forest/plantations, reduction in agriculture and increases in urban/burned areas associated with specific transition rates change the local fire frequency activity.

2.6 Conclusions

Despite the previous conceptions about the effect of climate on fire frequency, this study did not find a strong effect of this variable on fire frequency in Chile. This could be related to the strong impact of landscape dynamics in countries where the fire matrix is human-driven, whereas, in countries with natural-driven matrices, climate plays an important role as an ignition source. In addition, the climate could play an important role in Chile determining fire propagation and behavior, but not frequency. Furthermore, landscape descriptors prove to be relevant in understanding the fire frequency of the center zone of Chile. This could be used as an insight for current fire prediction systems improvement. Finally, both intensity and transition play an important role on fire frequency were areas that meet the landscape criteria susceptible to fire described in this study should be considered as priority areas for management in terms of fire activities.

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Table 2.1 Accuracy assessment for the 2014 and 2017 LULC* classifications. Output-based on 800 reference points equalized distributed between classes

Year	Class Name	Producers Accuracy (%)	Users Accuracy (%)	Overall Accuracy and Kappa Statistics
2014	Forest/Plantation	84.26	91.00	Overall= 86.50
	Bareland	87.00	97.00	Kappa=0.80
	Agriculture	93.22	76.39	
	Urban/Burned	76.74	58.93	
2017	Forest/Plantation	88.83	91.96	Overall= 88.78
	Bareland	88.32	94.50	Kappa = 0.83
	Agriculture	91.80	82.96	
	Urban/Burned	80.70	70.77	

*LULC=Land use land cover

Table 2.2 Change detection analysis comparing the land use persistence and rate of change between and within the Central Zone of Chile regions and land use classes.

Region	Persistence (%)	Change (%)	Annual Change by Land Use (%) Forest/ Plantation	Bareland	Agriculture	Urban/ Burned
Maule	73.18	26.82	0.03	-0.53	-2.61	11.51
Metropolitana de Santiago	73.15	26.85	1.1	1.82	-1.59	-10.95
Libertador General Bernado O'Higgins	72.75	27.25	-0.51	-1.33	-0.09	15.71
Valparaíso	77.96	22.04	5.14	1.63	1.12	-16.78
Bio Bío	70.83	29.17	2.26	-0.4	-5.43	4.15
Total	72.74	27.26	Change Rate per Year = 9.08%			

Table 2.3 The proportion of land use change by region expressed as a percentage between 2014 and 2017. Positive values relate to increases of the land use class and negative values relate to the class decreases between years

Maule	Forest/Plantations	Bareland	Agriculture	Urban/Burned
Total 2014	36.29	43.18	15.18	5.35
Total 2017	36.31	42.50	13.99	7.20
Change (17-14)	0.08	-1.59	-7.84	34.52
Annual Change	0.03	-0.53	-2.61	11.51
Metropolitana de Santiago	Forest/Plantations	Bareland	Agriculture	Urban/Burned
Total 2014	11.46	68.75	8.43	11.37
Total 2017	11.83	72.50	8.03	7.63
Change (17-14)	3.290	5.469	-4.761	-32.853
Annual Change	1.10	1.82	-1.59	-10.95
General Bernardo O'Higgins	Forest/Plantations	Bareland	Agriculture	Urban/Burned
Total 2014	25.01	56.54	12.79	5.65
Total 2017	24.63	54.29	12.76	8.32
Change (17-14)	-1.520	-3.981	-0.256	47.127
Annual Change	-0.51	-1.33	-0.09	15.71
Valparaíso	Forest/Plantations	Bareland	Agriculture	Urban/Burned
Total 2014	8.98	75.40	5.21	10.41
Total 2017	10.36	79.08	5.39	5.17
Change (17-14)	15.423	4.879	3.363	-50.335
Annual Change	5.14	1.63	1.12	-16.78
Bio Bío	Forest/Plantations	Bareland	Agriculture	Urban/Burned
Total 2014	49.98	27.22	20.56	2.24
Total 2017	53.37	26.90	17.21	2.52
Change (17-14)	6.790	-1.194	-16.280	12.452
Annual Change	2.26	-0.40	-5.43	4.15

Table 2.4 Best-fitted model of the relationship between of the patch characteristics between land uses and fire frequency estimated as fire counts per comuna. Acronyms of the variables are described as followed: Shannon Evenness Index (SHEI), number of forest patches (NPF), number of urban/burned patches (NPUB), density of forest patches (PDF), density of bareland patches (PDBL), density of urban/burned patches (PDUB), and mean patch area of forest (PAF).

Variables	Estimate	Std. Error	T value	Pr (>|t|)
SHEI	1.460	0.852	1.714	0.088
NPF	0.000	0.000	5.628	<0.01
NPUB	-0.000	0.000	-2.451	0.015
PDF	-0.064	0.028	-2.261	0.024
PDBL	-0.074	0.034	-2.177	0.032
PDUB	-0.033	0.011	-3.040	0.002
PAF	0.053	0.002	2.638	0.009

Fire Frequency Model: $F_{4,189} = 29.41$, $R^2 = 0.507$, $P<0.01$

Table 2.5 Fire frequency changes as a function of the land use change by class. Acronyms of the variables stand for CF= Change in forest/plantation, CBL=Change in Bareland, CAG=Change in agriculture, CUB=Change in Urban/Burned area.

Variables	Estimate	Std. Error	T value	Pr (>|t|)
CF	3.196	0.957	3.337	0.001
CBL	-0.236	1.440	-0.164	0.869
CAG	-3.358	0.920	-3.647	<0.001
CUB	2.939	0.452	6.490	<0.001
Fire Frequency Change Model: $F_{4,189} = 20.79$, $R^2 = 0.290$, $P<0.01$				

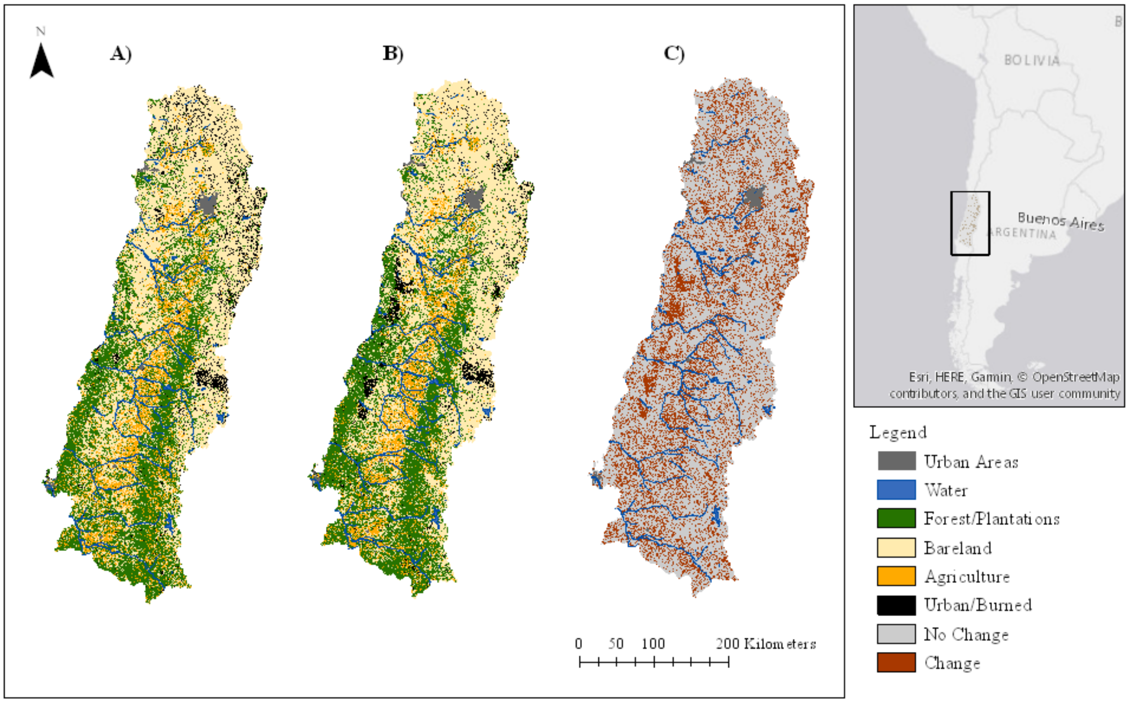


Figure 2.1 Change detection analysis for the central zone of Chile. A) LULC classification for 2014, B) LULC classification for 2017, and C) Change/No Change comparison between 2014-2017.

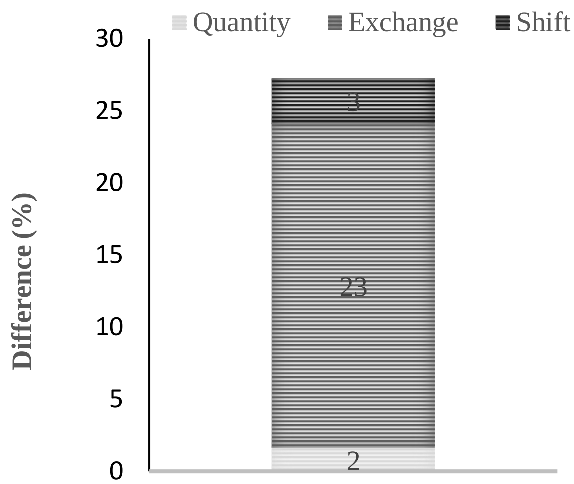


Figure 2.2 Classification of the landscape change between 2014-2017 divided as exchange, quantity, and shift.

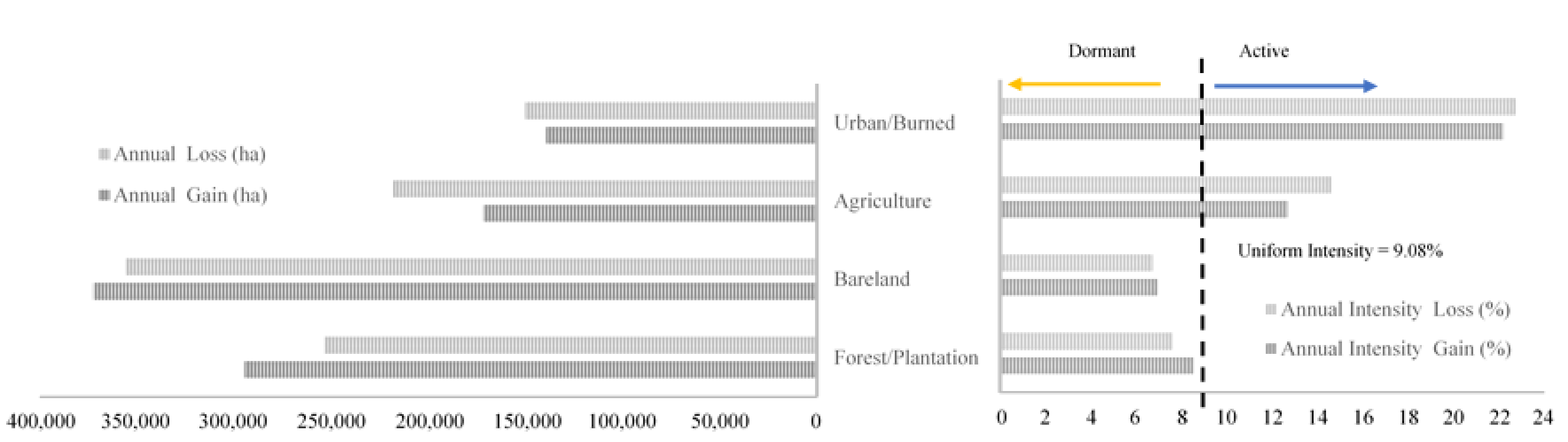


Figure 2.3 Analysis of the annual change in area and intensity between land use categories. The horizontal bars extended to the left of the zero represent the annual change area expressed as hectares lost and gain. The horizontal bars extended to the right of the zero represent the annual change intensity as a percentage. Stationary between categories is defined using a uniform intensity percentage (UIP) (pointed line) in the annual intensity change. The classes which intensity change is lower than the UIP are considered dormant categories (stationary) and the classes which values are higher than the UIP are considered active categories (non-stationary).

Figure 2.4 Analysis of gain area and intensity between categories. The bars extended to the left of the zero represent the annual transition area (ha) by category. The bars extended to the right of the zero represent the annual transition intensity (%) by category. Each transition is evaluated TO (class name listed in the upper left side of each plot considered as "land receiver") and FROM (class names listed inside the plot considered as "land donors") for each category. This process allows identifying specific land use shifts between categories. In addition, the intensity change is classified into two types: "avoid" and "targeted" using as a threshold a uniform intensity percentage (UIP) or visualize as the pointed line in the figure. The classes which intensity change is lower than the UIP are considered avoided to donate land to the receiver class, and classes with higher transition intensity than the UIP are considered targeted to shift towards the receiver class.

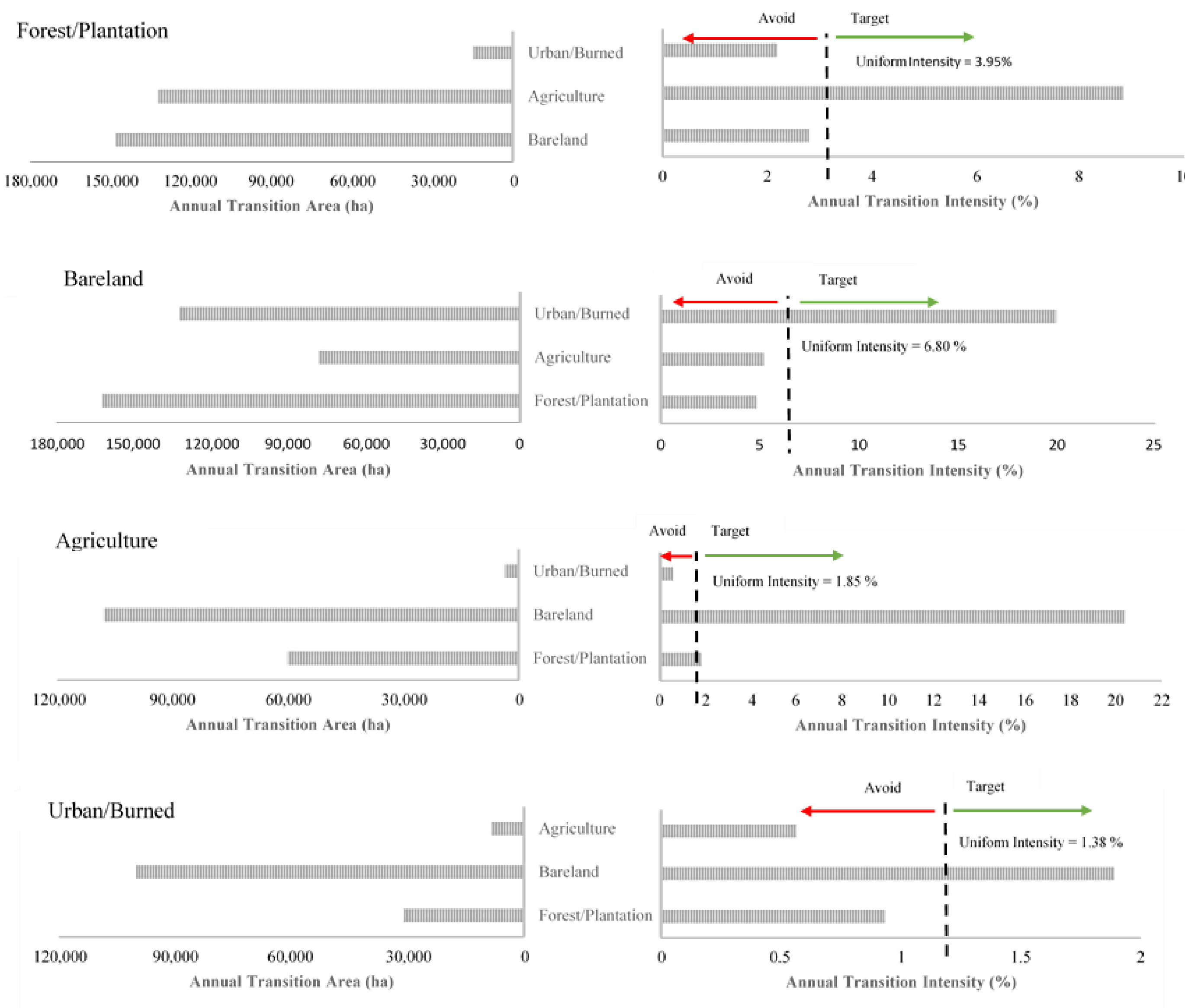
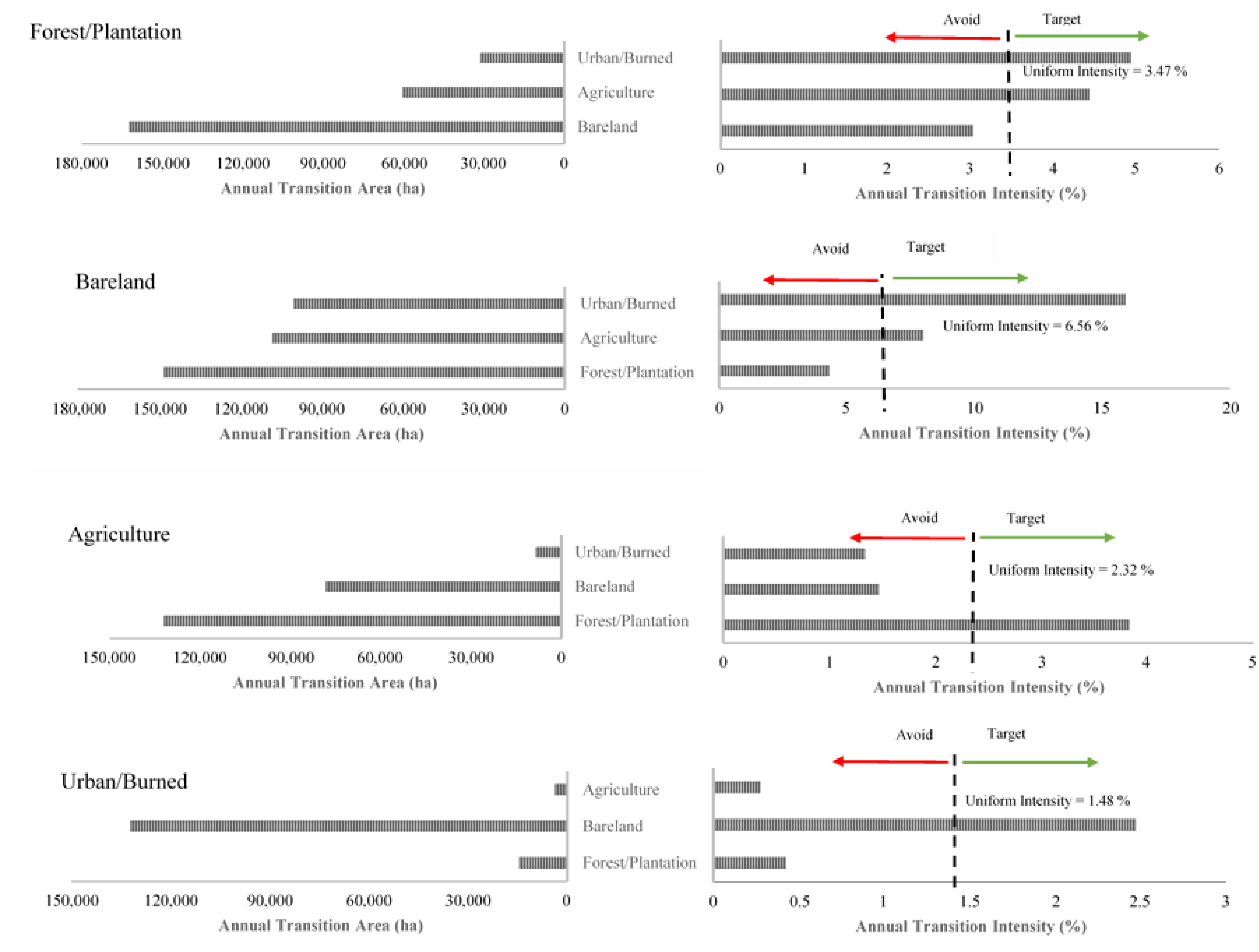

Forest/Plantation
Urban/Burned
Agriculture
Bareland
180,000 150,000 120,000 90,000 60,000 30,000 0
Annual Transition Area (ha)
Avoid
Target
Uniform Intensity = 3.95%
0 2 4 6 8 10
Annual Transition Intensity (%)
Bareland
Urban/Burned
Agriculture
Forest/Plantation
180,000 150,000 120,000 90,000 60,000 30,000 0
Annual Transition Area (ha)
Avoid
Target
Uniform Intensity = 6.80 %
0 5 10 15 20 25
Annual Transition Intensity (%)
Agriculture
Urban/Burned
Bareland
Forest/Plantation
120,000 90,000 60,000 30,000 0
Annual Transition Area (ha)
Avoid
Target
Uniform Intensity = 1.85 %
0 2 4 6 8 10 12 14 16 18 20 22
Annual Transition Intensity (%)
Urban/Burned
Agriculture
Bareland
Forest/Plantation
120,000 90,000 60,000 30,000 0
Annual Transition Area (ha)
Avoid
Target
Uniform Intensity = 1.38 %
0 0.5 1 1.5 2
Annual Transition Intensity (%)

Figure 2.5 Analysis of loss area and intensity between categories. The bars extended to the left of the zero represent the annual transition area (ha) by category. The bars extended to the right of the zero represent the annual transition intensity (%) by category. Each transition is evaluated FROM (class name listed in the upper left side of each plot considered as “land donor”) and TO (class names listed inside the plot considered as “land receivers”) for each category. This process allows identifying specific land use shifts between categories. In addition, the intensity change is classified into two types: “avoid” and “targeted” using as a threshold a uniform intensity percentage (UIP) or visualize as the pointed line in the figure. The classes which intensity change is lower than the UIP are considered avoided to receive land from the donor class, and classes with higher transition intensity than the UIP are considered targeted to receive land from the donor class.



Forest/Plantation
Urban/Burned
Agriculture
Bareland
180,000
150,000
120,000
90,000
60,000
30,000
0
Annual Transition Area (ha)
Avoid
Target
Uniform Intensity = 3.47 %
0
1
2
3
4
5
6
Annual Transition Intensity (%)
Bareland
Urban/Burned
Agriculture
Forest/Plantation
180,000
150,000
120,000
90,000
60,000
30,000
0
Annual Transition Area (ha)
Avoid
Target
Uniform Intensity = 6.56 %
0
5
10
15
20
Annual Transition Intensity (%)
Agriculture
Urban/Burned
Bareland
Forest/Plantation
150,000
120,000
90,000
60,000
30,000
0
Annual Transition Area (ha)
Avoid
Target
Uniform Intensity = 2.32 %
0
1
2
3
4
5
Annual Transition Intensity (%)
Urban/Burned
Agriculture
Bareland
Forest/Plantation
150,000
120,000
90,000
60,000
30,000
0
Annual Transition Area (ha)
Avoid
Target
Uniform Intensity = 1.48 %
0
0.5
1
1.5
2
2.5
3
Annual Transition Intensity (%)

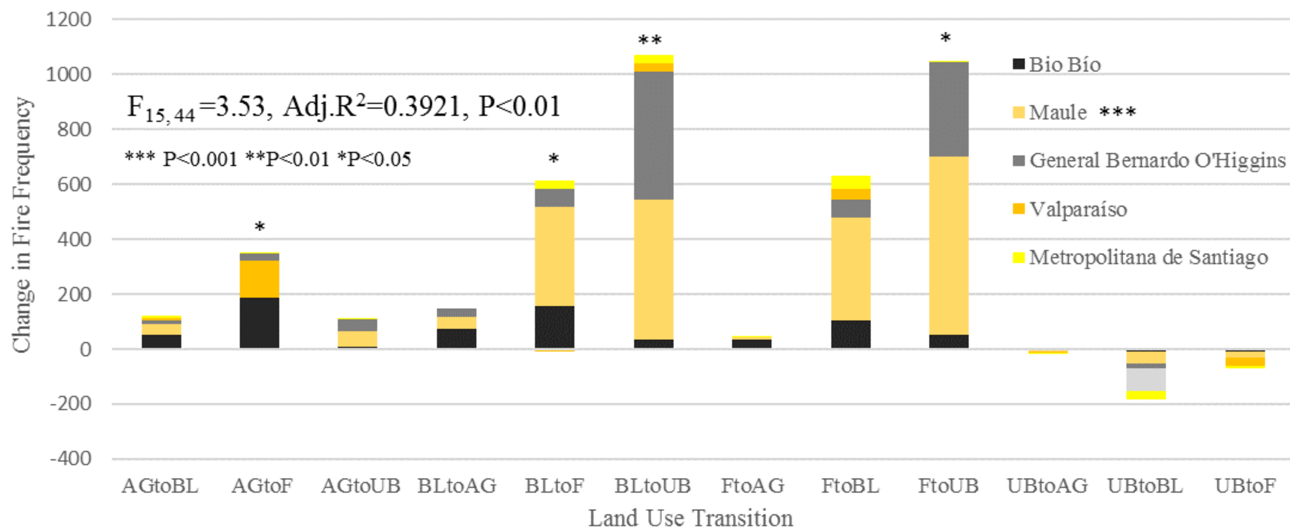


Figure 2.6. Fire frequency changes between 2014-2017 as a function of the land use transition between regions located in the central zone of Chile. Land use transition names stand for AG=Agriculture, BL=Bareland, F=Forest/Plantations, and UB=Urban/Burned.

CHAPTER 3. INTEGRATION OF SOCIO-ECONOMIC AND LANDSCAPE VARIABLES IN FIRE FREQUENCY PREDICTIONS

3.1 Abstract

Anthropogenic changes have affected the spatial and temporal distribution of fire activity worldwide. The Mediterranean ecosystems are the ones with the highest degradation due to the fire variability induced by population development. However, despite the high impact of the human component in human-driven fire regimes, most of the current fire prediction systems (FPS) do not account for them. Furthermore, the accuracy of the predictions might be reduced within regions dominated by human-driven fire matrices and continuous spatial variations of fire distribution. The aim of this study was to select and integrate socioeconomic descriptors into a fire prediction system while accounting for spatial distribution changes, selection of variables and prediction's accuracy. Spatial analysis tools were used to understand spatial distribution patterns of fire frequency. Furthermore, a combination of regression models were use to select the most relevant human variables affecting fire frequency change. Finally, a zero-inflated model was used to simulate fire frequency predictions compared against observing fire frequency and a climate model within the Mediterranean ecosystem of Chile. The fire frequency increases were significantly affected by changes in socioeconomic and landscape drivers. Changes in poverty, roads, and education level combine with highly fragmented forest explained fifty percent of the variance in fire frequency. Furthermore, the results highlight a change in the spatial distribution of the fire activity clustering from the center to the southern regions in years with the highest fire frequencies. The accuracy of fire prediction models is highly dependent on internal regional dynamics related to socio-economic, landscape and climate differences. Fire frequency predictions integrating socioeconomic and landscape had a higher overall agreement when

compared to the observed fire frequency in regions located towards the south. On the other hand, in northern regions, climate models had a higher accuracy. Both models had low accuracy when predicting extreme events. As consequence, changes in fire spatial distribution correlated with extreme fire frequencies might be mispredicted with the current systems.

3.2 Introduction

3.2.1 *Worldwide fire condition*

The causes driving fire activity worldwide have changed from climate to human-climate interactions (Pechony and Shindell 2010). Fire activity reconstructions from the last two millennials have estimated that prior 1870, fire activity was driven by climate change. After the industrial revolution, unprecedented changes in fire regimes around the world have been driven by anthropogenic causes (Marlon et al. 2008). Furthermore, fire simulations predict a 5-35% increase in fire activity for the following decades associated with population growth patterns, socio-economic development and greenhouse gas emissions (Pechony and Shindell 2010).

The social interactions have an effect on the natural cycles and change the landscape shape affecting the fire regimes (Castro et al. 1998). About 90% of the fire events registered worldwide are related directly or indirectly to human activities (Chuvieco 2003, Jolly et al. 2015). The increasing number of uncontrolled fire events related to human ignitions has exceeded the capacity of the current fire prediction and management systems to prevent and assess the fire damage (Bowman et al. 2009). Future projections pointing at shifting fire regimes (Pechony and Shindell 2010), increase the uncertainty of the current fire policies effectiveness and raise concerns over the efficiency of the current systems to accurately predict, prevent and monitor fire variability (Watson et al. 2005, Chuvieco et al. 2010).

3.2.2 *Fire Assessment*

Effective fire assessment involves the understanding of fire variability, vulnerability, and risk given a time and spatial scale (Chuvieco et al. 2010). Fire risk systems (FRS) are used as tools to predict fire initiation that rely on meteorological outputs and fuel characteristics (Chuvieco et al. 2010, 2014). FRS is used to determine planning, and monitoring activities to establish when and where fires have a higher probability of ignition (Chuvieco et al. 2014). Fire frequency and intensity are two important concepts for fire risk assessment. Fire intensity is determined by the previous condition of the vegetation and is commonly used in spatial analyses to prioritize management areas post-fire (Morgan et al. 2014). Although fire intensity is a key component to understand fire behavior, fire frequency is important for understanding fire ignition (fire initiation) (Chuvieco 2003). Both components in combination with spatial variability, severity, and seasonality determine a fire regime (Bowman et al. 2009). Fire regimes are also affected by the hazard risk or a number of flammable sources accumulated and second, the fire ignition vulnerability, which is a descriptor of a site susceptibility to burn based on human resources (Castro et al. 1998). Effective allocation of fire resources relies on the understanding of fire regimes, hazard, and vulnerability. In addition, the sensitivity of the FRS to detect the interaction between the vulnerability and hazard components is dependent upon scale (Perera et al. 2004) and the understanding of how the spatial and temporal distribution is changing at a local scale (Pechony and Shindell 2010).

The estimation of the fire risk involves the integration of variables into indexes. All indices used vary with the time and spatial scales selected, predictors and procedures used to develop the indices (Perera et al. 2004). A detailed comparison between the methods is listed in Table 1.1 Chapter 1. Different FRS have been used in different countries and have been modified by changing time and spatial scales (Chuvieco 2003, Perera et al. 2004, Chuvieco et al. 2014).

However, despite continuous updating and improvement of the methods, there still exists limitations in assessing shifting of fire regimes and spatial distributions (Chuvieco 2003). The implementations of both fire spatial distribution changes and human-climate interactions are key to effectively predict fire activity (Chuvieco et al. 2010). One of the major concerns regarding the efficiency of the current FPS is the limitation of including both components. The integrated fire risk assessment should consider the danger and vulnerability variables to accurately predict fire risk (Chuvieco et al. 2014). Fire danger, as explained before, contemplates the ignition (cause) and propagation (fuel characteristics). On the other hand, fire vulnerability is related the socio-economic value of a given location (Chuvieco 2003, Chuvieco et al. 2014). Most of the current fire prediction systems contemplate only the fire danger aspect focusing on propagation and overlooking the ignition and vulnerability components related to human-related characteristics.

3.2.3 *Mediterranean ecosystems vulnerability*

At a global or local scale, fire activity is driven by a series of social, landscape, and climate interactions (Hantson et al. 2016). Historically, several countries have experienced fire frequency fluctuations outside of the average fire intervals (Hantson et al. 2016). The patterns related to those fluctuations are linked to climate and atmospheric conditions but mostly related to political, economic, and demographic dynamics (Chuvieco 2003). Within Mediterranean ecosystems, fire temporal and spatial distribution have been associated with increases in human population (Syphard et al. 2009). Historically, these regions have been targeted for human development due to the suitable locations and environmental conditions. Mediterranean ecosystems are concentrated within five coastal regions of the world occupying 2% of the Earth surface (Cox and Underwood 2011). Over 250 million people live in the region where five important cities are located (i.e. Rome, Santiago de Chile, Cape Town, Los Angeles and Perth) (Cox and Underwood 2011). Specifically, the Mediterranean region of Chile has the highest potential for biodiversity conservation (75%) based on the natural vegetation without direct anthropogenic impact (i.e. agriculture, plantation, grasslands)(Cox and Underwood 2011). Unfortunately, repeated burns have affected the vegetation where more than half of the native forest has been lost as result of human-induced fires (Ubeda and Sarricolea 2016). Few is known on how the spatial distribution of fire is changing in these ecosystem due to the human activity and what specific anthropogenic characteristics are having the highest impacts of fire frequency changes.

3.2.4 *Anthropogenic characteristics*

Most of the current studies of fire models have emphasized fire behavior but little is known about the connectivity between fire and human interactions. Furthermore, the implementation of the connectivity within current FRS is poorly understood (Cardille et al. 2001, Chuvieco 2003, Syphard et al. 2008). The multidimensionality of the human component expressed as economic, demographic or landscape patterns increases the complexity of the inclusion of the human dimension within FRS. It is relevant to delineate the key characteristics affecting fire patterns and the spatial and temporal influence of those descriptors in fire regimes (Cardille et al. 2001, Peña-fernández and Valenzuela-palma 2004, Syphard et al. 2008, Pérez-Vermin, G., Márquez-Linares, M.A., Cortes-Ortiz, A., Salmerón-Macias 2012). Several studies have analyzed the effect of multiple social variables over fire parameters (Xavier-Viegas 1999, Chuvieco 2003, Pérez-Vermin, G., Márquez-Linares, M.A., Cortes-Ortiz, A., Salmerón-Macias 2012, Bedia et al. 2014, Chuvieco et al. 2014), but the large number of variables considered makes it difficult to compare the results across studies. On the other hand, not including the human component could affect the accuracy of the current systems in countries where the fire matrix is mainly driven by human-caused events. Moreover, the fire prediction models have less applicability in the field when incorporating larger numbers of variables. Consequently, integration of social variables for fire prediction requires prioritization of variable selection in order to efficiently explain the human interactions with fire.

The aim of this study was to evaluate the integration of multiple socio-economic descriptors into a fire prediction system while accounting for spatial distribution changes, selection of variables and prediction accuracy focusing on Mediterranean ecosystems. It is assumed that the applicability of this study is focused on areas with human-driven fire matrices. The specific questions are: where should the FRS focus the resources based on the historical fire spatial distribution patterns? What are the most significant socio-economic characteristics affecting fire frequency and how they are connected to landscape variability? Finally, how does the inclusion of those descriptors improve fire frequency prediction systems related to current approaches?

3.3 Materials and Methods

3.3.1 *Study area*

The analysis was conducted in the central zone of Chile, which was selected based on its socio-economic and demographic characteristics (INE 2017). The area has five administrative regions where 73% of the country's population is located (Table 3.1). The smallest regional administrative division, the comuna, was considered as a sample unit for this study, which included 194 comunas geographically located inside the study area. The study area is located between latitudes 32° and 38°S and longitude 70° and 73°. The central zone of Chile has a population of 13,475,550 and 115,551.1 km^2 of land area. The area has fluctuations in yearly precipitation oscillating between 100-700 mm (Falvey and Garreaud 2007). The elevation within the area varies between zero masl in the coastal areas to 5000 masl in the Andes Mountains. The area has predominantly a Mediterranean climate with drastic vegetation transitions between the coast and the steepest areas whereas aspect changes have an effect on vegetation structure and composition (Armesto and Martínez 1978). The landscape is heterogeneous across the regions where VII (Maule) has the highest cultivated land (Donoso et al. 1999). The predominant economic activities are the production of agriculture, wine yards, fruits, and timber plantations (Table 3.2) with annual increases in agriculture and timber plantation areas (1.1% yearly) (Schulz et al. 2010).

3.3.2 *Data sources and processing*

The selection of socio-economic variables was based on previous study results that highlight the relevance of those social characteristics over the area (Chuvieco 2003, Carmona et al. 2012, Andersson et al. 2016). The socioeconomic variable characteristics and sources are detailed in Table 3.3. The variables were divided into three groups based on the data characteristics (Table 3.3). The population and poverty data were extracted from the 2013 National Census. The demographic data presented a high correlation between variables within sites (0.80). To reduce the overestimation of this variable, the Poverty (%) was created representing the percentage of people in poverty in relation to the total population of a site. On the other hand, the access data was available in a shapefile format, so the variables within this group were calculated using the spatial analysis tools of ArcGIS PRO 2.0.

The landscape characteristics, land use, and weather data were extracted from Chapter 2. For each of the land uses (Forest/Plantations, Bareland, Agriculture, and Urban/Burned) based on (Schulz et al. 2010) considered in this study, the landscape characteristics (Pijanowski and Robinson 2011, Dezhkam et al. 2016) were quantified following Case study 1 methodologies (Table 3.4 and 3.5). Weather station data between August 1 and June 30 per year was available at the Climate Explorer tool of Chile. Precipitation expressed as daily average (mm) and the average daily temperature (°C) of the explorer tool (Centro del Ciencia del Clima y Resiliencia 2017) were used to estimate the weather variables for the comunas where no weather stations were found. The data interpolation was accomplished using a co kriging interpolation method using as covariate the1 km resolution elevation data (Global 30 Arc-Second Elevation GTOPO30a) (USGS n.d.).

The fire frequency records (2000-2017) were available at the Fire Information for Resource Management System (FIRMS) of NASA. For the studied time interval, the fire data was selected based on the fire frequency annual curve presented by the forest corporation of Chile (CONAF 2016), where fire events registered between August 1 and June 30 were selected. The data was available as point features. For each site, the total fire frequency was calculated using the spatial analysis tools of ArcGIS PRO 2.0. Finally, the climate data was downloaded from the climate explorer database of Chile. The two variables used to create a simulation for this model were average temperature (C) and accumulated precipitation (mm) interpolated using kriging methods available in Chapter 2.

3.3.3 *Fire Frequency Analysis*

The historic fire trends were analyzed for the interval between 2000 and 2014. First, the significant fire location across space was analyzed through an Optimized Hot Spot Analysis (OHSA). Values higher > 90% confidence interval were considered significant hot and cold spots cluster across space. The significant fire locations across time were evaluated using an Emerging Hot Spot Analysis (EHSA) based on a space-time cube created with the 15 years data considered for the OHSA, using each year as a bin step for the analysis. Both analyses were performed using ArcGIS PRO 2.0.

3.3.4 *Integration of Variables*

The relationship of variables was analyzed using multiple regression models. First, the spatial autocorrelation of the sample units was evaluated and accounted for using a weighted matrix based evaluated through a Moran's test following (Ward and Gleditsch 2007, Bivand et al. 2008). In addition, co-linearity between the variables was analyzed and transformation (log +1) was done for required variables. The stepwise model comparison was used in order to select the best-fitted model. The two relationships that were studied were the socio-economic to fire frequency (fire counts) variables and, the socio-economic to landscape variables (SHEI). The best-fitted model selection was based on the lowest AIC value of the models. Finally, a global model was created considering the effect of socio-economic and landscape variables over the fire frequency. The most significant variables of the best-fitted models were used as based predictors for constructing the fire frequency prediction model.

3.3.5 *Model Integration*

The 14 significant predictors were used in combination with the climate data to create two models: LE-Social or socio-economic landscape model and a climate model. The variables were group analyzed through a principal components analysis (PCA) to account for correlation between the variables. The PCA output did not present any significant trends in the axis so the PCs were not used. Then, a random subsample of half of the data (97 sample units) was taken in order to create and evaluate the model. The other half of the sites were used later on in the model validation process.

As the fire frequency data has a significant amount of zeros, a Zero-Inflated Negative Binomial model (ZIP-negbin) was considered. The ZIP model was divided into two sections, a Poisson count model and a logit model. The zero fire frequencies are modeled independently from the remaining values of the response variable through a logit model (Hanks et al. 2011) this is used for the Poisson count section of the model. First, the fire frequency was transformed in a binary variable (zero=fire absence, 1=fire presence) and analyzed through binomial GLM, incorporating one variable at a time to select the predictors that are more associated with the zero fire frequency. After, the models were compared based on the AIC values, selecting the model with lower AIC and less number of variables. Then, the ZIP model was created using the previously selected predictors for the log it section of the ZIP model. On the Logit model, the predictors were added one by one to select the best model with the fewest amount of variables. Finally, the model with the lowest AIC was selected after a stepwise comparison. The same procedure was follow for the climate model.

3.3.6 *Model validation*

The second subsample of the data (97 sites) was used to evaluate the model predictions. Using the predict function of the software, based on the setting “Response”, the observed fire frequency for the sites was compared to the predicted values of the model. The observed and the predicted fire frequencies were evaluated through quantitative and qualitative analysis. First, the quantitative differences were evaluated through a goodness of fit value based on the Poisson residuals of both models. The qualitative differences were evaluated through a Matrix Union analysis using overall agreement percentage (Shao et al. 1995, Wynne and Jenness 2005).

3.4 Results

The spatial distribution of the fire frequency in Chile between 2000-2014 is clustered in specific locations within the country (Figure 3.1). The hot spots are concentrated in the central zone of Chile (>95% confidence) and mainly in the regions Valparaíso, General Bernardo

O'Higgins, Metropolitana de Santiago, Maule, and Bio Bío. Throughout the time interval analyzed, there were yearly differences on the fire frequency patterns, whereas, in the years where the high frequency was recorded (99% confidence), there was a clustering tendency of the fire activity moving towards the southern regions, the Araucanía (Figure A3). On the other hand, in years with intermediate or low fire activity recorded (<95% confidence), the hot spots were clustered within central and northern regions.

The EHSA output classifies the center zone of Chile as an oscillating hotspot between 2000-2014. Oscillating hotspots are areas that have had significant fire activity clustering (99% confidence) > 70% and < 90% on the time steps analyzed. Therefore, the regions located in the central zone of Chile are the focus areas that require a deeper fire monitoring. On the other hand, areas located north or south of the central zone of Chile were classified as sporadic, intensifying or persistent cold spots. Those categories mean that cold spots were found between 70-90% of the time steps analyzed within those areas so no significant fire activity occurred there between 2000-2014. For those regions, there is no necessity to increase the grain of resolution for fire analysis. Furthermore, the OHSA output highlights that most of the significant hotspots are located along the coastlines of the Bio Bío and Maule regions. The yearly outputs of the OHSA highlight three-time steps where the fire spatial distribution shifted (2000-2002, 2008-2009, 2011) but overall, there is a significant hotspot pattern across the remaining time steps. Finally, no areas showed persistent hotspots (significant fire activity in >90% of the time steps analyzed) between 2000-2014 which explains possible fire frequency variations across time.

Fire frequency increases in the Central zone of Chile are significantly affected by changes in socio-economic and landscape drivers. Half of the fire frequency variation is explained by both groups of predictors (Table A6). The overall and individual regression analysis between the fire frequency changes and the socio-economic and landscape descriptors are presented in Figure 3.2. The best-fitted model (Table A6) that describes the overall relationship between the groups of variables explained 56% of the variation in the fire frequency ($F_{11, 182}$ = 23.28, P<0.01). Within this model, sites with higher poverty level (percentage of the population in poverty), road access, education, and forested areas (number and size of the patches) were likely to have higher fire frequencies. In addition, sites with reduced bareland (empty-land) area and low infrastructure development were also likely to present higher fire frequencies. Therefore, sites with opposite socio-economic and landscape characteristics are more likely to present lower fire activity.

Individual regression analyses between the groups of variables (Landscape Homogeneity-Socio-economic, Socio-economic-Fire Frequency, and Landscape Homogeneity-Fire Frequency) are available in Table A7, Table A8 and Chapter 2 Table 2.4. First, the relationship between landscape homogeneity and socio-economic drivers is available at Table A7. Socio-economic drivers significantly affect landscape homogeneity levels (dominated by one land use) ($F_{5, 188}$=21.63, P<0.01, Adj. R^2=0.34). Within this relationship, increases in poverty levels and road access within sites significantly increases landscape heterogeneity values (SHEI values close to 1). In addition, reduction in overall site expenses combined with low rates of education registration is related to increases in landscape heterogeneity. Therefore, sites with the opposite characteristics, such as reduced poverty levels, roads access and higher income and education levels are more likely to present more homogeneous landscapes (SHEI values close to 0). Furthermore, the relationship between landscape homogeneity and socio-economic descriptors is bidirectional ($F_{1, 192}$=65.62, R^2=0.2508, P<0.001), where sites poverty level is significantly affected by changes in landscape homogeneity.

Second, the relationship between social drivers and fire frequency is presented in Table A8. Socio-economic drivers have a significant effect on the fire frequency in the central zone of Chile ($F_{3, 190}$=42.03, Adj. R^2=0.389, P<0.01). Within this analysis, increases in poverty and road access in conjunction with reduced site expenses are associated with higher fire frequencies. Therefore, reduced poverty level and lower road access in conjunction with higher site expenses are linked to lower fire frequencies. Is important to highlight that poverty levels, road access, and expenses level affect both, directly and indirectly, landscape homogeneity and fire frequency simultaneously. Furthermore, the portion of the variance explained by the landscape descriptor on the fire frequency changes is available in table 2.4 of Chapter 2. In summary, the individual significant effect of the landscape over fire frequency increase is driven by the reduction of bareland patch area and density combined with increases in forest patch area, density and shape values. Finally, the variance partitioning between the variable groups shows that landscape characteristics have a direct effect on fire frequency (50%) than the direct effect associated to the socio-economic descriptors. Moreover, the effect of the socio-economic descriptors on the fire frequency is larger when accounting for both the direct and indirect relationship of the socio-economic variables between both fire frequency (38%) and landscape homogeneity changes (34%).

Improvements of the fire frequency predictions on the Central Zone of Chile at a regional scale are the result of the integration between the LE Social (Landscape and socio-economic variables) and the climate models (Figure 3.3). The output of the best-fitted models for both, the LE-Social and the climate models are available on the Table A9 and Table A10. When comparing both prediction models**,** the LE-social model had a better goodness of fit (goodness of fit =1.52, AIC=1328.8) than the climate model (goodness of fit=1.73, AIC=1440.56). The overall residuals distribution shows that the accuracy of both models is reduced when predicting extreme values. Therefore, accuracy increases when intermediate fire frequency values are predicted. On the other hand, when comparing the observed fire frequency with both, LE-Social and Climate models output, the climate model had a higher overall agreement (42.2%) than the LE-Social model (35.5%) (Table A11). However, at a regional scale, differences in the overall agreement between observed and predicted fire frequency by each model were found (Figure 3.3).

The results showed that regional differences in landscape, socio-economic and climate characteristics influence the model's accuracy and therefore the relevance of the selection for specific fire frequency prediction models in each region. The LE-Social model had a higher overall agreement compared to the observed fire frequency in regions located towards the southern portion of the central zone of Chile. Those regions are Maule and Bio Bío with 39.05% and 35.30% of overall agreement respectively. In contrast with the northern regions where the climate model had a higher overall agreement when comparing to the LE Social model. Those regions are Valparaíso, Metropolina de Santiago and General Bernardo O'Higgins with 56.09%, 69.73%, and 48.20% respectively.

3.5 Discussion

3.5.1 *Fire Frequency: Spatial Distribution*

The fire frequency activity in Chile is clustered within the Central Zone of the country with intermittent year oscillations towards the southern regions. Similar fire clustering trends have been found in previous time intervals (Castillo, Garfias, Julio, & Gonzalez, 2012; Peña-Fernández & Valenzuela-Palma, 2004; Ubeda & Sarricolea, 2016) that support the significance of the central zone of Chile as a predominant fire region. Historically, Chile's fire frequency have shown an upward trend between 1984-2016 (Díaz-Hormazábal & González, 2016; Peña-Fernández & Valenzuela-Palma, 2004) but previous records highlight increases since the 1970's (CONAF 2014). The Valparaiso, General Bernardo O'Higgins, Metropolitana de Santiago, Maule and Bio Bío were defined as the regions where fire activity was concentrated (Ubeda and Sarricolea 2016). However, recently there is been an observed reduction in the fire frequency for the Valparaiso and General Bernardo O'Higgins regions (Ubeda and Sarricolea 2016). The results of the OHSA in combination with previous evidence (Peña-fernández and Valenzuela-palma 2004, Aguayo et al. 2009, Castillo et al. 2012, Heilmayr et al. 2016, Ubeda and Sarricolea 2016) suggest a possible shift in focus on the spatial distribution of fire incidence on the Maule, Bio Bío, and Araucanía. As fire frequency is negatively correlated with fire intensity, simulations between 1976-2016 found that the regions in the central zone of Chile that had the lowest fire frequencies (Valparaiso and GBOH) are actually those accounting for the largest fires (Castillo et al. 2012). Therefore, further management approaches should include both, regions with higher frequency and higher fire intensity.

Similar to Chile's clustering patterns, other regions in the world have been shown to have heterogeneity on the fire distributions and shifts in the spatial distribution of fire (Brown et al. 1999, Moreno 2000, Taylor and Skinner 2003, Syphard et al. 2008). The understanding of the clustering dynamics and spatial transitions of fire is relevant to delimitate the spatial resolution and to capture fire variability within fire prediction systems (Mladenoff and Baker 1999). Current fire prediction systems are designed to analyze the overall fire activity in larger areas within a singular-sized grain at a time, where within clustered areas internal fire dynamics might be missed. Despite the deep understanding of scale relationships, the complexity of the integration of simultaneous scale systems is limited (Parisien and Moritz 2009). This result suggests the integration of fire prediction systems that combine sharp and coarse prediction resolutions simultaneously in order to capture hotspots and cold spots fire dynamics and to increase efficiency in fire resources allocation. Furthermore, the time scale is relevant when observing intermittent fire dynamics within specific regions, as in Chile's case study where oscillating regions should be accounted for fire resource *investing*.

3.5.2 *Socio-economic, landscape and fire connectivity*

More than 50% of the change in fire frequency in the central zone of Chile is explained by socio-economic and landscape factors. The predominant characteristics driving the change are related to the poverty level, transportation access, education and landscape heterogeneity increases. The connection between the three components (socio-economic, landscape and fire frequency) is complex. This study demonstrates the interconnectivity between them and highlights interspecific dynamics occurring with Chile's scenario. However, these connections are observed around the world in countries with human-driven fire matrices and changing production dynamics (Cardille and Ventura 2001, Cardille et al. 2001, Syphard et al. 2006). As the reason that the variables are connected to one another is possibly case-specific, the overall trend observed in different scenarios reinforces the connectivity between them outside the case-specific boundaries.

Multiple studies have analyzed the positive correlation between population and fire frequency (Moreno 2000, Cardille and Ventura 2001, Cardille et al. 2001). Moreover, internal local characteristics of population growth (as poverty and education) and expansion (as access) can determine fire variability and spatial distribution (Syphard et al. 2006, Parisien and Moritz 2009). In Chile, in the last decades, socio-economic dynamics have been driven by a production transition from an agriculture to a tree plantation-based economy (Castillo et al. 2012, Heilmayr et al. 2016, Ubeda and Sarricolea 2016). Despite the national economic benefit incentivized by the plantations, at a local level, several studies have reported negative social and ecological effects correlated to them (Chuvieco 2003, Huber and Iroumé 2006, Andersson et al. 2016, Ubeda and Sarricolea 2016). From a fire perspective, CONAF has reported Maule and Bio Bio as the regions with the highest proportion of fires initiated at plantations areas compared to the native forest (CONAF 2016). This paper highlights both regions as those with the highest changes in fire frequency, with most of the change within landscape transitions related to forest/plantation. More than 80% of the fire events result from accidental or intentional causes (CONAF 2016). Within Bio Bio region alone, more than 60% of the fires are categorized as intentional. These causes could be related to discrepancies between indigenous communities (Mapuche) located within this areas and the social discontent expressed by them as result of the establishment of plantations (Andersson et al. 2016, Ubeda and Sarricolea 2016). Within this context, the interconnection between economic shifts, landscape transition and social impacts at a regional level is relevant to understanding changes in fire activity. Previous studies relate increases in poverty levels linked to farmers displacement as consequence of the replacement of agriculture lands into plantation areas (Peña-fernández and Valenzuela-palma 2004, Castillo et al. 2012). Furthermore, this study found that increases in heterogeneity towards forest/plantations and specific patch characteristics are highly related to fire frequency changes. On the other hand, further characteristics related to the plantations by themselves can increase the area vulnerability to fire (i.e., fuel loading changes, species flammability, and harvesting techniques) (Ubeda and Sarricolea 2016). In this context, the combination of all the factors in contrast with urban-rural interface expansion (Moreno 2000) may increase fire vulnerability in Chile. However, case-specific scenarios in other regions in Spain (Moreno 2000), California (Syphard et al. 2006), and the Midwest US (Cardille et al. 2001) have assessed the three components over fire dynamics. The evidence suggests that the relevance of the inclusion of both socio-economic and landscape drivers within fire predictions systems is key to increase accuracy on predictions.

3.5.3 *Fire frequency predictions*

Results from the study highlight the strong impact of landscape and socioeconomic variables over the fire frequency predictions. However, the accuracy of the fire predictions using climate and anthropogenic descriptors is regional-dependent. In regions located towards the south, Landscape-Social model predictions have higher accuracy whereas, in northern regions, climate models seem to be more effective. Therefore, the predictions differences between the models highlight the relevance of both local dynamics and regional scale in areas with significant fire clusters. This results contrast with the current fire prediction system that uses the same set of descriptors to generate predictions for the entire country. Furthermore, in combination with coarser resolutions, this system might not capture the regional fire variability, therefore could mispredict the fire activity within those areas. This suggests that the possible integration between both, climate-based and anthropogenic-based models, could give a more effective and adapted prediction system.

Currently, the fire prediction system of Chile, as well as other systems in the world, focuses on climate-based descriptors to make national fire predictions (Chuvieco 2003). Furthermore, nowadays most of the research has focused on the effect of climate in fire activity (Pausas and Keeley 2014), and how climate affects the southern regions of Chile (Moreno 2000, Ubeda and Sarricolea 2016). However, the results of this study highlight those climate-based models might not be the most suitable prediction systems within fire-clustered regions (southern regions of the country). Therefore, these results integrate the idea that internal regional dynamics related to landscape and socio-economic interactions at a local level are relevant to determine fire prediction models accuracy, specifically in areas where most of the fire is occurring. Charcoal studies have described that historically, climate conditions used to drive the fire ignition and the fire spread around 13000-12200 14C yr B.P in Chile (Moreno 2000). However, this study's results suggest that fire ignition might no longer be driven by climate conditions. We suggest that climate interacting with landscape transitions (Chapter 2), and the socio-economic drivers that have shaped the landscape are the main forces for fire variability within this region.

3.6 Conclusions

This study proposed three main insights to improve fire frequency predictions and management in countries where the fire frequency variations are driven by human activities as Chile. First, fire-clustering patterns suggest the relevance of integrating multiple resolution approaches to focus fire resources and greater spatial resolution detail in areas where significant hotspots are located. Second, the fire frequency variations are significantly affected directly or indirectly by changes in socioeconomic characteristics and landscape transitions. Finally, the accuracy of fire prediction models is highly dependent on internal regional dynamics related to socio-economic, landscape, climate differences but also temporal dynamics (year differences).

3.7 References

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Table 3.1 Description of the population, area, and climate characteristics of the regions located within the central zone of Chile

Region	Population 2017	Population (%)	Area (Km^2)	Climate
Valparaiso	1,859,672	10.10	16,396.10	Temperate Mediterranean
Metropolitana	7,482,635	40.72	15,403.20	Mediterranean
LGBOH*	934,671	5.08	16,387.00	Temperate Mediterranean
Maule	1,057,533	5.75	30,296.10	Temperate Mediterranean
Bio Bio	2,141,039	11.65	37,068.70	Temperate humid and dry

*GBOH=Libertador General Bernardo O'Higgins

Table 3.2 Regional production distribution between crops in the central zone of Chile (Ministerio de Agricultura, 2007)

Region	Regional Production (%)*	Production
Valparaíso	37.7	Tree Plantations
	34.2	Fruit Plantations
	10.7	Forage Plants
Metropolitana de Santiago	35.8	Fruit Plantations
	17	Vegetables
	14.4	Forage Plants
	10.7	Cereals
	8.2	Vineyards
Libertador General Bernardo O'Higgins	38.8	Tree Plantations
	21.5	Fruit Plantations
	15.6	Cereals
	9.9	Vineyards
Maule	94	Tree plantations, cereals, fruits, forage, vineyards
Bio Bío	79	Tree Plantations

*Percentage on the total production of the region

Table 3.3 Description of the databases used to estimate socio-economic descriptors

Group	Variable	Acronyms	Units	Source
Demographics	Population	Poverty (% of the population)	# per site	The National Statistics Institute of Chile
	Poverty		# per site	The National Statistics Institute of Chile
Education	Elementary School Registration	Reg. B	# students registered	National System of Municipal Information
	Middle School Registration	Reg. M	# students registered	National System of Municipal Information
Economic	Income	Income	% of site income in relation to total income	National System of Municipal Information
	Expenses	Expenses	% of site expenses in relation to total expenses	National System of Municipal Information
Access	Roads	Roads	Total length (meters)	Chilean Congress Library
	Railroads	Railroads	Total length (meters)	Chilean Congress Library

Table 3.4 Description of the land use categories used for the unsupervised classification based on Schulz, Cayuela, Echeverria, Salas, & Rey Benayas, 2010 parameters

Forest/Plantations	Dense (>75%) canopy cover and timber plantations
Bareland	Exposed rock, and sand or dry riverbeds, dunes, cleared land and degraded areas.
Agriculture	Includes shrubland, grasslands and irrigated and non-irrigated agriculture, fruits, and vineyards
Urban/Burned	Areas with domestic or industrial infrastructure and burned areas, both categorizes as a disturbance. In addition, water and Ice represent a small fraction of this category (<10%), but based on the majority of data related to disturbance, the name of the category is based on Urban and Burned areas (>80% of category data)

Table 3.5 Description of the patch characteristics acronyms evaluated per land use (Forest/Plantations, Bareland, Agriculture, and Urban/Burned) in the Central Zone of Chile comunas based on parameters of Dezhkam et al., (2016) and Pijanowski & Robinson (2011)

SHEI	Shannon Evenness Index
NP	Number of patches
PD	The density of patches (number of patches per 100 ha)
PA	Mean patch area (m^2)
PShape	Patch Shape
LPI	Large Patch Index

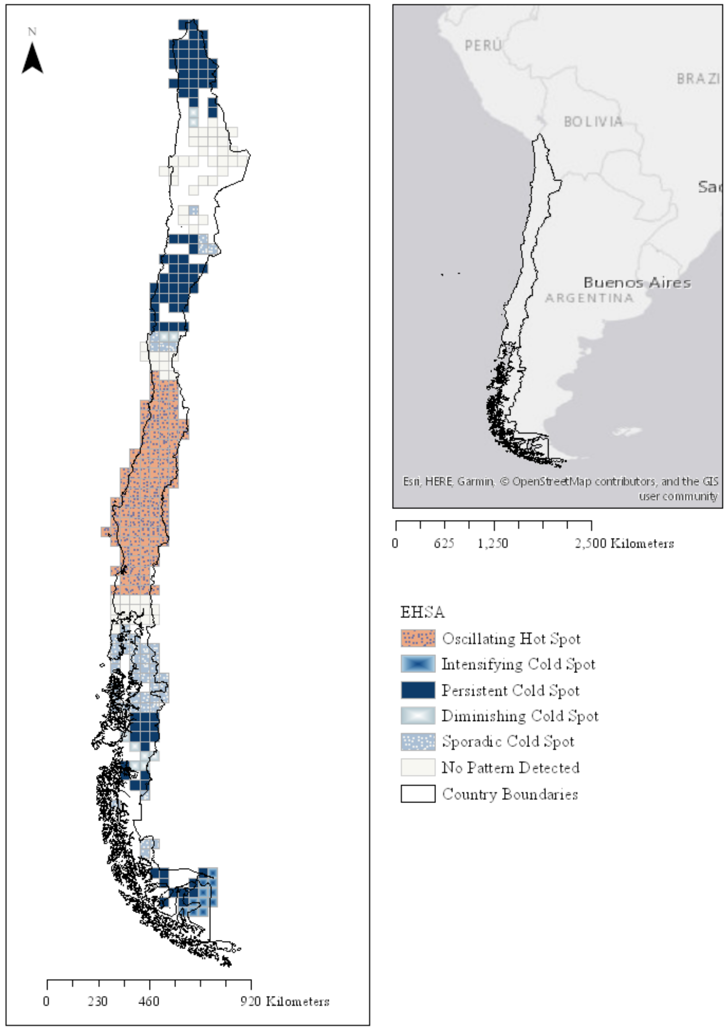

Figure 3.1 Emerging hot spot analysis output for the fire frequency events registered between 2000-2014 in Chile.

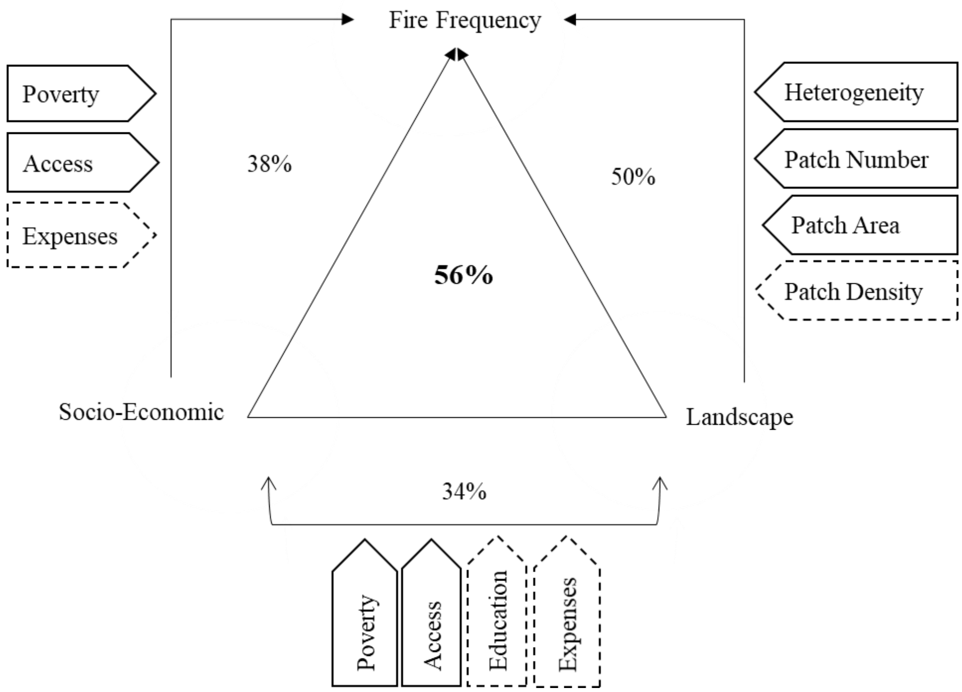

Figure 3.2 Diagram of the connectivity between fire frequency, socioeconomic, and landscape variables. Values inside and outside the triangle represent the variance (R^2) explained by individual (outside) and global (inside) regression models. The arrows represent the groups of variables involved in the individual regression analysis (socio-economic and fire frequency, socio-economic and landscape, and landscape and fire frequency) the variables within each group are listed next to the arrows. Variables that are listed within straight-line boundaries have a positive effect on the response variable (Exp. Increases in poverty produce an increase in fire frequency). On the other hand, variables listed in pointed line boundaries have a negative relationship with the response variable (exp. decreases in education produce increases in fire frequency).

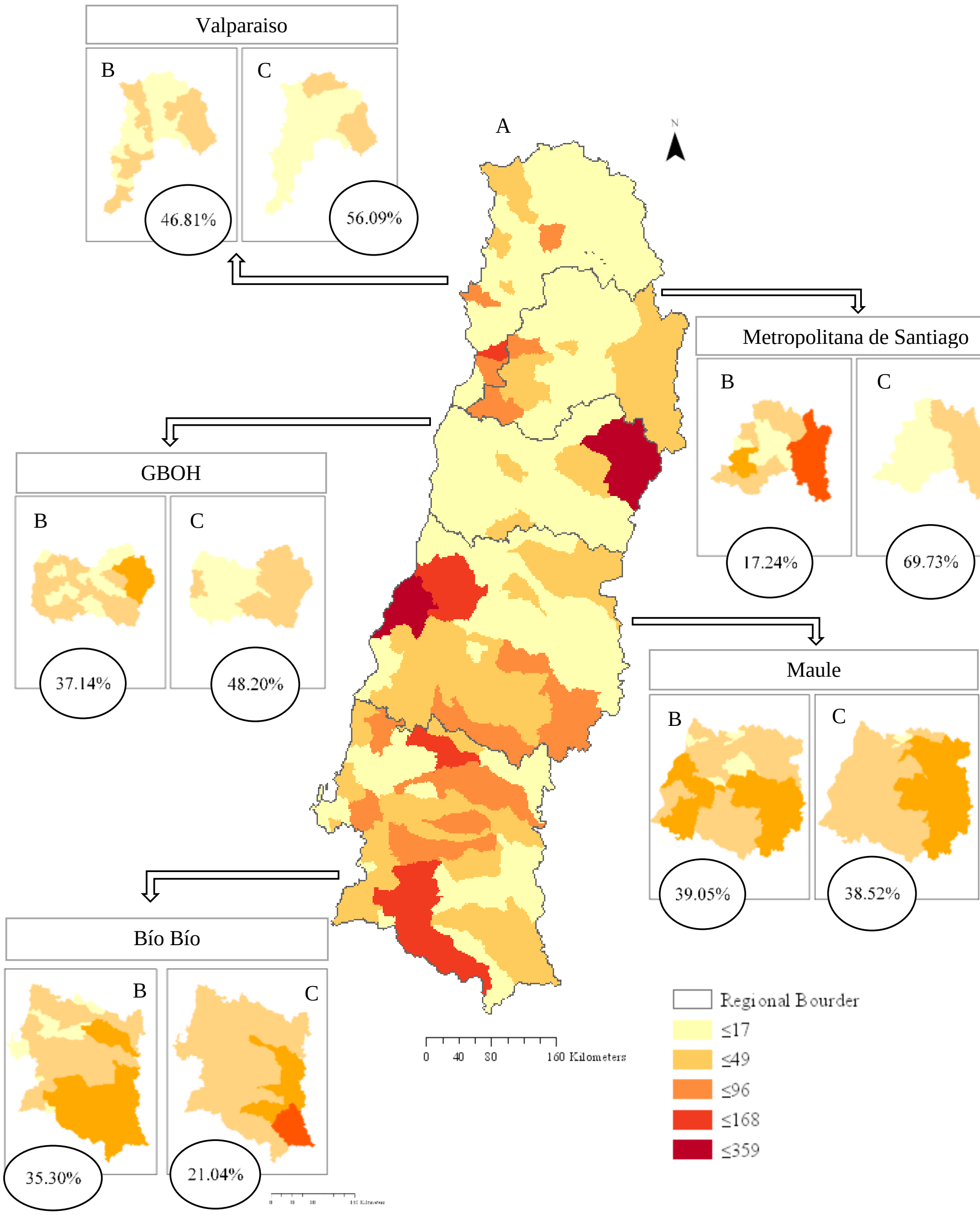

Figure 3.3 Comparison between observed and predicted fire frequency models for the central zone of Chile. A) Observed fire frequency registered in the fire season between 2013-2014. Each of the tables surrounding A represent the regions located within the central zone of Chile. B) Output fire frequency prediction using the Socio-economic-Landscape model. C) Output fire frequency prediction using the climate model. Values located within the circles represent the overall agreement percentage between fire frequencies observed and models prediction for each region.

CHAPTER 4. SYNTHESIS OF RESULTS, IMPLICATIONS FOR FIRE PREDICTION SYSTEMS AND FUTURE RESEARCH RECOMMENDATIONS

4.1 Synthesis of Results

Fire regime variability has been driven by climate changes in the last two millennials (Pechony & Shindell, 2010). However, charcoal reconstruction relates fire variations after the industrial revolution to the interaction between anthropogenic and climate activity (Bowman et al., 2011; Pechony & Shindell, 2010). Despite the relevance of climate change in future fire projections, specific locations are likely to experience intensive fire events (Knorr, Arneth, & Jiang, 2016) as a result of political, economic, landscape and demographic fluctuations (Bowman et al., 2009; Castro & Chuvieco, 1998; Chuvieco, 2003; Hantson et al., 2016). Anthropogenic stressors can directly or indirectly affect fire regimes, as 90% of the fire ignitions registered worldwide are the result of human interactions with the landscape (Bowman et al., 2011; Chuvieco, 2003; Jolly et al., 2015; Marlon et al., 2008; Veblen, Kitzberger, & Donnegan, 2000). Anthropogenic interactions can change multiple fire regime characteristics, from ignition and frequency to seasonality and spatial distribution (Syphard, Radeloff, Hawbaker, & Stewart, 2009). Furthermore, the complexity of this relationship is scale-dependent which increase the difficulty to understand the connectivity between human-climate-fire (Bowman et al., 2011).

Fire management agencies use fire prediction systems (FPS) to understand fire activity. FPS rely on meteorological descriptors and fuel characteristics to predict fire probability of ignitions. Despite the multiple studies and current evidence pointing out the relevance of the anthropogenic effects on fire (Leone, Koutsias, Martínez, Vega-García, & Allgower, 2003), the FPS do not consider anthropogenic factors as an indicator for the predictions. At a regional scale, anthropogenic dynamics play an important role in determining fire ignition, as well as spatial and temporal distributions (Balch et al., 2017). The accuracy of the current fire prediction system is challenged within regions where fire ignition is predominantly human-based, as is the case for Mediterranean ecosystems (Syphard et al., 2009). Mediterranean ecosystems are high biodiversity areas with a restricted geographical distribution covering less than 5% or the Earth surface (Cox & Underwood, 2011). The environmental suitability of Mediterranean ecosystems makes this region particularly susceptible to anthropogenic pressures. Furthermore, the biodiversity value of these ecosystems is severely threatened by the fire variability caused by human ignitions (Syphard et al., 2009).

Chile is the Mediterranean region with the highest potential for biodiversity conservation (75%) based on the natural vegetation without direct anthropogenic impact (i.e. agriculture, plantation, grasslands) (Cox & Underwood, 2011). Unfortunately, repeated burns have affected the vegetation where more than half of the native forest has been lost as result of human-induced fires (Ubeda & Sarricolea, 2016). The inclusion of anthropogenic indicators on fire prediction systems, especially within Mediterranean ecosystems, is key for developing accurate predictions and effective fire management efforts. As the relationship between human dynamics and fire is complex, it is important to understand first the landscape and socioeconomic perspectives of the human component in these regions and then to identify which specific anthropogenic indicators have the most significant effects on fire in order to include them in the fire predictions systems.

The purpose of this study was to analyze the effect of anthropogenic drivers on fire frequency variability and the inclusion of human indicators to improve fire frequency predictions using Chile's Mediterranean ecosystem as a study area. In order to account for the complexity of the anthropogenic stressors, each case study focused on different perspectives of the human component. The landscape perspective accounts for the social variables that have an effect on the land such as land use types, change, and intensity, etc. (Carmona, González, Nahuelhual, & Silva, 2012; J. M. Moreno, Viedma, Zavala, & Luna, 2011; Syphard et al., 2008). On the other hand, the economic-demographic perspective involves social variables related to population characteristics based on location as density, poverty, profits, education, transportation access etc. (Jennings, 1999). The first case study focused on understanding the landscape transitions, intensity rates, and patch characteristics and selecting the landscape indicators that have a significant effect on fire variability (Chapter 2). The second case study focused on selecting the most significant socioeconomic variables that affect fire ignition. In addition, this case study integrated all significant anthropogenic descriptors in multiple fire prediction models (GLM, ZIP, and ZINB), selected the most suitable model to predict fire, and compared the model predictions against the observed fire frequency and climate models outputs (Chapter 3).

4.1.1 *Landscape transitions*

The spatial distribution of the land use transition speed and characteristics was not homogeneous across the regions within the study area (Figure 2.1, Chapter 2). Twenty-seven percent of the land went through a land use change mainly associated with decreases in agriculture areas and increases in forest/plantations (Table 2.2, 2.3, Chapter 2). Most of the land use transition was dominated by two active or non-stationary (i.e. transition speed higher than average) categories (23% exchange) affecting the landscape (Figure 2.2, Chapter 2). Those categories were agriculture and urban/burned, with an intensity rate higher than the uniform intensity (UI) of 9.08% (Figure 2.3, Chapter 2). However, a small fraction of the area was categorized as shifting between three or more categories (3% shift). At a transition level, reductions in bareland and agriculture are the target contributors to forest/plantations increases at a rate higher than 3.95%. In contrast, urban/burned and agriculture are the target categories to receive area from forest/plantations when deforestation occurs (>3.47% UI) (Figure 2.4, 2.5, Chapter 2).

4.1.2 *Fire frequency changes*

There were significant differences in the patch characteristics between land use transitions, and the differences between them had a significant effect on the fire frequency changes throughout space (Table 2.4, Chapter 2) and time (Table 2.5, Chapter 2). Increases in landscape heterogeneity (SHEI values close to one) produced a significant effect in fire frequency. Across space, increases in forest/plantations fragmentation were related to increases in fire frequency as well. The fire probability of ignition by human activity increased with reductions in landscape connectivity from the fragmentation that also affected the fire seasonality, distribution, and frequency (Archibald, Staver, & Levin, 2012). However, across time, landscape homogeneity dominated by forest/plantations installment significantly increased fire frequency where fire selectivity moves towards pine plantations (dominant production activity in the area) (Barros & Pereira, 2014). Landscape transitions both, stationary and non-stationary, had a significant effect on the fire frequency change (Figure 2.6, Chapter 2). A stationary class refers to changes in land use that are slower than the average transition rate (transition rate < UI). In this scenario, bareland to forest/plantation was the stationary transition that had effects on fire frequency. On the other hand, the non-stationary class represents the transitions that are changing faster than the average transition rate. Agriculture to forest/plantations, bareland to urban/burned, and forest/plantation to urban/burned are considered both actively changing the landscape and significantly affecting fire frequency. Finally, sites that present both active transitions and significant patch characteristics are likely to have an increase in fire frequency. The results of this study suggest that relative changes within specific landscape transitions and patch characteristics can have a significant effect on fire activity in sites with human-driven fire matrices. Similar patterns have been evaluated around the world where the integration between landscape dynamics and the urban-rural interface is key to understanding fire activity (Cardille, Ventura, & Turner, 2001; Parisien & Moritz, 2009; Syphard et al., 2008; Syphard, Franklin, Keeley, & Keeley3, 2006). Despite differences in environmental characteristics within sites, regions in Spain (Moreno et al., 2011), and California (Radeloff et al., 2005; Syphard et al., 2008) highlight the significance of landscape structure and variability in predicting fire activity.

4.1.3 *Fire spatial distribution and socioeconomic effects*

The spatial distribution of the fire activity is clustered within the central zone of the country with intermittent year oscillations (Figure 3.1, Chapter 3). In years with high fire frequency, however, there was a tendency of the fire clusters moving towards the southern regions (Figure A3). Previous studies support the significance of this area as a fire activity hotspot throughout history (Castillo, Garfias, Julio, & Gonzalez, 2012; Peña-Fernández & Valenzuela-Palma, 2004; Ubeda & Sarricolea, 2016); therefore, this area should be prioritized for management efforts. Socioeconomic and landscape descriptors had a significant effect on fire frequency changes, explaining >50% of the fire variance. The predominant characteristics driving the change were poverty level, transportation access, education and landscape heterogeneity increases (Figure 3.2, Chapter 3, Table A6, and A8). Socioeconomic drivers significantly affected landscape homogeneity levels (SHEI) whereby increases in poverty levels and road access within sites significantly increase landscape heterogeneity values (SHEI values close to 1) and fire activity. In addition, reduction in overall site expenses combined with low rates of education registration was related to increases in landscape heterogeneity (Table A7). It is important to highlight that poverty levels, road access, and expenses level affect both, directly and indirectly, landscape homogeneity and fire frequency simultaneously. Finally, the variance partitioning between the variable groups shows that landscape characteristics have a more direct effect on fire frequency (50%) than the direct effect associated with the socio-economic descriptors. Moreover, the effect of the socio-economic descriptors on the fire frequency is larger when accounting for both the direct and indirect relationship of the socio-economic variables between both fire frequency (38%) and landscape homogeneity changes (34%). Furthermore, the connection between socioeconomic, landscape and fire regimes changes have been observed in other Mediterranean regions of the world (P. I. Moreno, 2000; Syphard et al., 2006). Despite the background, processes driving the socioeconomic and landscape changes are different; the overall trend observed in different scenarios reinforces the connectivity between them outside the case-specific boundaries (Cardille & Ventura, 2001; Cardille et al., 2001; Syphard et al., 2006).

4.1.4 *Fire prediction model*

The integration of socioeconomic and landscape characteristics into fire prediction systems increase fire prediction accuracy for areas with high landscape heterogeneity and high poverty and access level. Regional differences were found when comparing the climate and the LE-Social model's accuracy (Table A9, A10). Evidence suggests that the relevance of the inclusion of both socioeconomic and landscape drivers within fire predictions systems is key to increasing accuracy of predictions. Therefore, the prediction differences between the models highlight the relevance of both local dynamics and regional scale in areas with significant fire clusters (Figure 3.3, Chapter 3). However, this study's results suggest that fire ignition might no longer be driven by climate conditions in regions located towards the south of the central zone of Chile; whereas in the northern regions, use of climate conditions might be accurate enough. We suggest that climate interacting with landscape transitions (Chapter 2), and the socioeconomic drivers that have shaped the landscape are the main forces for fire variability within this region (Chapter 3).

Results from Chapter 2 indicate that landscape transition, speed, and characteristics had a significant effect on fire frequency increases. In particular, within the Mediterranean ecosystem of Chile, transitions faster than the uniform intensity rate from agriculture to forest/plantation and increases in urban/burned area as result from deforestation or bareland reduction significantly affected fire activity. Furthermore, changes related to tree stands rotations between bareland and forest/plantations increased fire vulnerability when combined with large patch area fragmented into multiple (patch number) distant patches (patch density), in areas with low urban and bareland. Areas that meet the landscape transition criteria should be considered as a priority for fire management. Findings from Chapter 3 highlight the relevance of socioeconomic and landscape characteristics on fire frequency predictions in areas with human-driven fire activity. Furthermore, despite the previous conceptions about the relevance of climate variables on fire predictions, the results prove that the accuracy of the fire predictions using climate descriptors is regional-dependent. These results suggest that because the regional internal dynamics determine the model's accuracy, the climate and LE-Social models should be integrated into one index to improve fire prediction systems to account for both climate and human-driven dynamics. Furthermore, as is the case for Chile's FPS, other regions in the world are relying on climate-based models to make national predictions and determine fire management resources. However, these results indicate that climate-based models alone might not be the most suitable models to predict fire within fire clusters experiencing the large landscape and socioeconomic dynamics. As the Mediterranean regions are experiencing similar fire fluctuations as Chile's case study, this result gives particular insights for variables selection and model comparisons to improve FPS in these regions. This could possibly change the current climate-based approach to predict fire, to a human-climate integration.

4.2 Implications for fire prediction models and future research

The spatial distribution of the fire activity has changed within years with high fire frequency in the central zone of Chile. As northern regions might experience a reduction in fire incidence, southern regions might be exposed to higher fire frequencies (Díaz-Hormazábal & González, 2016). The understanding of the spatial fire variability is relevant to delimitate areas for investing fire resources. Because changes in the spatial distribution of fire are occurring, increased focus should be on the relevance of areas that are now experiencing higher fire frequencies. In addition, as fire activity is likely to change related to future projections (Pechony & Shindell, 2010) and continuous landscape transitions (Peña-Fernandez & Valenzuela-palma, 2004), fire seasonality and further changes in spatial distribution might occur as well. Therefore, fire distribution (space and time) should be constantly monitored. So far, the central zone of Chile is considered the fire hotspot where the fire predictions systems now require a higher accuracy and sharper resolution in order to give effective predictions.

Landscape characteristics and transitions have a significant effect on fire frequency. As specific land use changes and transition rates have been identified as the main drivers of the fire change in the central zone of Chile, management agencies should consider corresponding areas that are vulnerable to fire increases as priority areas for management. Furthermore, regulations should focus towards transition speed and yearly transitioned area. On the other hand, as areas experiencing land use rotation from bareland to forest/plantation had a significant increase in fire activity, harvesting techniques, and species flammability could be managed in order to reduce the fuel available for burning. Chile's silvicultural approach in *Pinus radiata* plantations focuses mainly on clearcuts leaving aerial biomass on the ground when harvesting, for the next rotation (Salas et al., 2016). This can affect fuel loading and increase the risk of fire (Ubeda & Sarricolea, 2016), so regulation agencies can also consider alternative harvesting methods that reduce fuel loading.

Poverty level and access had a significant effect on fire variability. Sites that fit these criteria are dominantly located within the urban-wildlife interface, surrounding the periphery of urban centers. In contrast to the accelerated land use conversion in this interface from agriculture towards forest/plantations, these are highly vulnerable areas. Fire resources should be available at these locations, and as fires are dominantly human-ignited, environmental education and research within these areas are relevant to understand people perspective related to the fire. As there is a high interconnectivity between socioeconomic and landscape changes where education, transportation, production dynamics, and poverty have a significant role in fire variability, regional management should focus on these characteristics in fire campaigns efforts.

The integration of landscape and socioeconomic characteristics improve fire predictions accuracy in the southern regions of the central zone of Chile. As the climate model proved to be relevant for the northern regions, the integration of both models should be considered in order to address fire variability in the entire region. Despite our findings, both models had reduced accuracy in predicting extreme fire activity. Considering fire projections (Pechony & Shindell, 2010) that fire extremes are more likely to occur, improvements for both models are still needed to address this issue. In addition, there is no differentiation between coast-valley-mountain areas that can affect the fire activity as they have different dynamics, as most of the change in the landscape was observed in the coastal area. In addition, future research should aim to understand seasonal variability caused by anthropogenic stressors.

We found the most significant indicators in both socioeconomic and landscape settings that influence fire variability, and we were able to integrate the anthropogenic stressors into a fire prediction model. Furthermore, we found a suitable statistical model to use for fire predictions and were able to understand accuracy differentiation of model predictions depending on regional dynamics. Those characteristics were not identified for the central zone of Chile before. However, there is still work to be done on integrating both climate and landscape-social models into fire predictions. Furthermore, as mentioned before, the inclusion of those perspectives becomes a challenge with scale variations where "the occurrence of patterns can disappear or emerge going from one scale to other" (Koning, Veldkamp, & Fresco, 1998). Therefore, scale selection is key to understanding the connection between socioeconomic factors and fire ignition. In addition, the differences between scales and the relative effect on the socioeconomic variables significance can efficiently focus the management forces to target specific fire drivers in each scale. Although the effects of temporal and spatial scales on model accuracy was out of the scope of this study, further research should integrate this analysis in order to find a suitable resolution to capture the effect of both climate and anthropogenic activity on fire ignitions.

Although the results of this study were focused on the Mediterranean ecosystem of Chile, other Mediterranean regions are experiencing the same trends in fire variability and anthropogenic stressors. However, despite the background, dynamics driving the fire activity are possibly case-specific for each region; the overall trend observed in different scenarios reinforces the connectivity between landscape-socioeconomic drivers outside the case-specific boundaries. Therefore, these study results give particular insights for variable and model selection and integration on the accuracy of fire prediction systems in other Mediterranean regions.

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APPENDIX

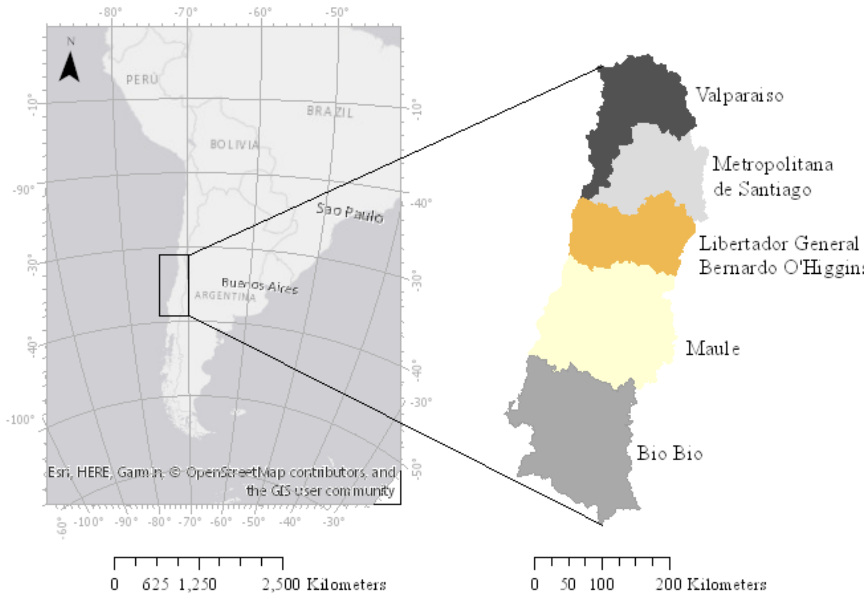

Figure A 1 Central Zone of Chile- Location of the study A) Chile, B) Zoom of the regions located in the Central Zone of Chile.

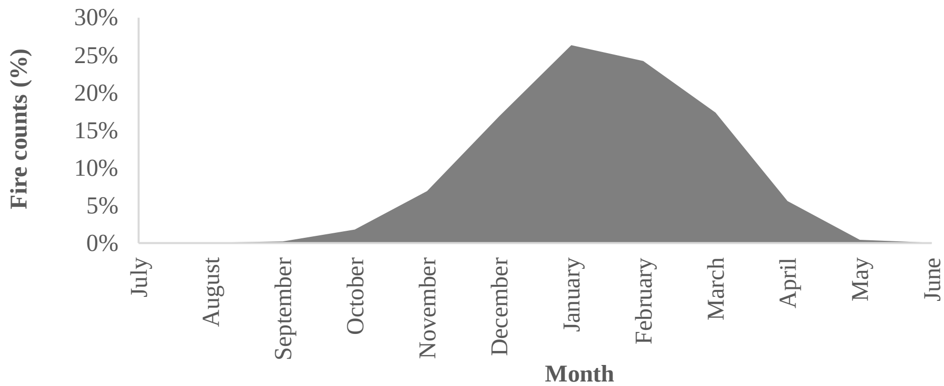

Figure A 2 Fire annual seasonal distribution for the Center Zone of Chile (CONAF 2015).

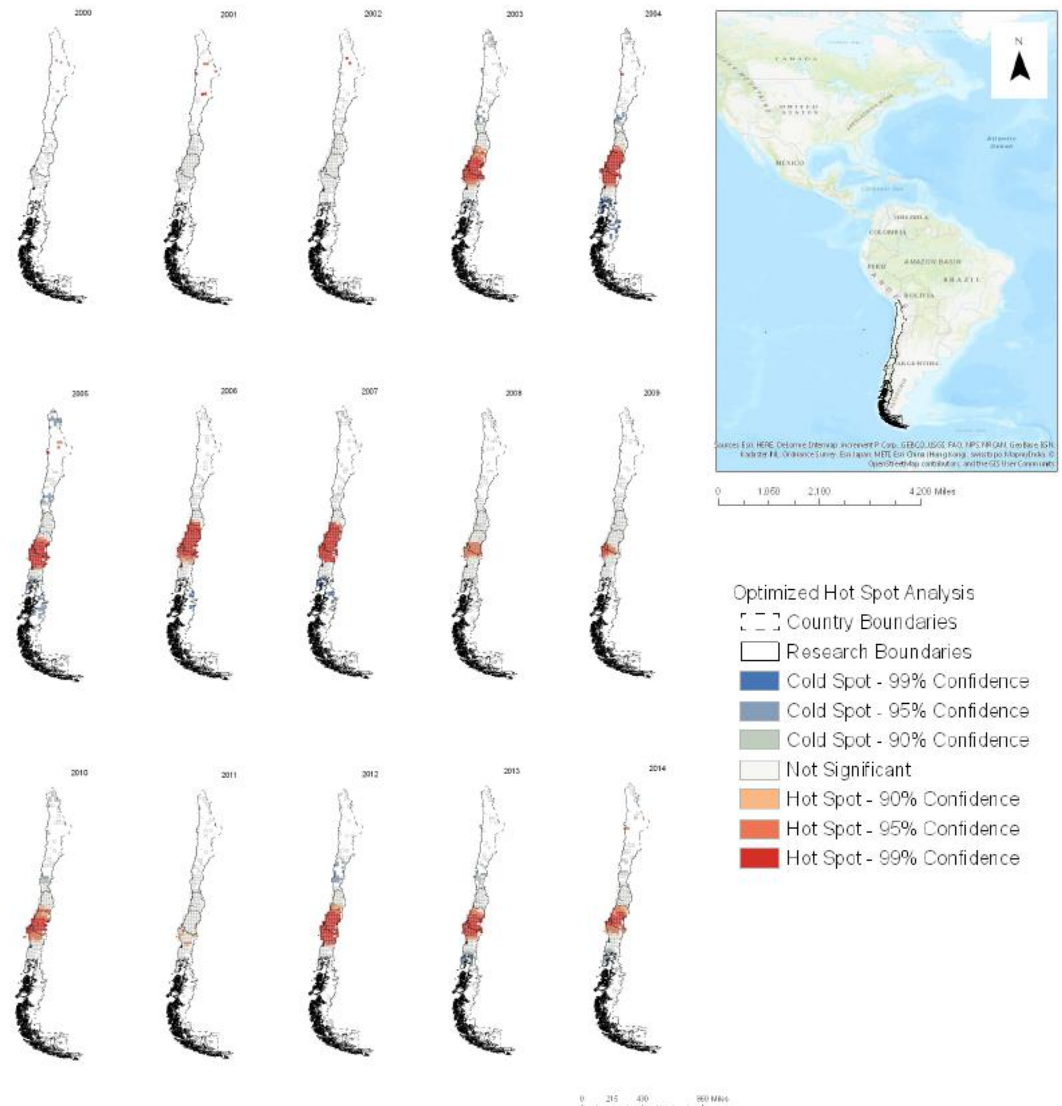

Figure A 3 Historical fire frequency clusters between 2000-2014 in Chile based on an Optimized Hot Spot Analysis

Table A 1 Description of the population, area, and climate characteristics of the regions located within the central zone of Chile.

Region	Population 2017	%Population	Area (Km^2)	Climate
Valparaiso	1,859,672	10.10	16,396.10	Temperate Mediterranean
Metropolitana	7,482,635	40.72	15,403.20	Mediterranean
LGBOH*	934,671	5.08	16,387.00	Temperate Mediterranean
Maule	1,057,533	5.75	30,296.10	Temperate Mediterranean
Bio Bio	2,141,039	11.65	37,068.70	Temperate humid and dry

*GBOH=Libertador General Bernardo O'Higgins

Table A 2 Regional production distribution between crops in the central zone of Chile (Ministerio de Agricultura, 2007).

Region	Regional Production (%)*	Production
Valparaíso	37.7	Tree Plantations
	34.2	Fruit Plantations
	10.7	Forage Plants
Metropolitana de Santiago	35.8	Fruit Plantations
	17	Vegetables
	14.4	Forage Plants
	10.7	Cereals
	8.2	Vineyards
Libertador General Bernardo O'Higgins	38.8	Tree Plantations
	21.5	Fruit Plantations
	15.6	Cereals
	9.9	Vineyards
Maule	94	Tree plantations, cereals, fruits, forage, vineyards
Bio Bío	79	Tree Plantations

*Percentage on the total production of the region

Table A 3 Description of the Landsat 8 OLI TIRS Level 1 scenes used for the unsupervised classification. Map projection UTM Zone 18-19, Datum WGS84 (cell size = panchromatic 15m, reflective and thermal 30 m)

Dataset scene	Acquisition Date	Path	Row	Scene Cloud Cover (%)
LC82330832014025LGN00	01/25/2014	233	83	3.32
LC82330872014025LGN00	01/25/2014	233	87	6.49
LC82330852014025LGN00	01/25/2014	233	85	0.56
LC82330842014025LGN00	01/25/2014	233	84	3.51
LC82330822014025LGN00	01/25/2014	233	82	0.69
LC82330862014025LGN00	01/25/2014	233	86	0.25
LC80010852014032LGN00	02/01/2014	1	85	0.02
LC80010842014032LGN00	02/01/2014	1	84	0.01
LC82330862017017LGN00	01/17/2017	233	86	1.14
LC82330832017017LGN00	01/17/2017	233	83	0.68
LC82330852017017LGN00	01/17/2017	233	85	0.12
LC82330842017017LGN00	01/17/2017	233	84	0.49
LC82330872017017LGN00	01/17/2017	233	87	5.13
LC82330822017017LGN00	01/17/2017	233	82	0.95
LC80010852017024LGN00	01/24/2017	1	85	5.33
LC80010842017024LGN00	01/24/2017	1	84	0.61

Table A 4 Description of the land use categories used for the unsupervised classification based on (Schulz et al. 2010) parameters

Forest/Plantations	Dense (>75%) canopy cover and timber plantations
Bareland	Exposed rock, and sand or dry riverbeds, dunes, cleared land and degraded areas.
Agriculture	Includes shrubland, grasslands and irrigated and non-irrigated agriculture, fruits, and vineyards
Urban/Burned	Areas with domestic or industrial infrastructure and burned areas, both categorizes as a disturbance. In addition, water and Ice represent a small fraction of this category (<10%), but based on the majority of data related to disturbance, the name of the category is based on Urban and Burned areas (>80% of category data)

Table A 5 Description of the patch characteristics acronyms evaluated per land use (Forest/Plantations, Bareland, Agriculture, and Urban/Burned) in the Central Zone of Chile comunas based on (Pijanowski and Robinson 2011, Dezhkam et al. 2016) parameters.

SHEI	Shannon Evenness Index
NP	Number of patches
PD	The density of patches (number of patches per 100 ha)
PA	Mean patch area (m^2)
PShape	Patch Shape
LPI	Large Patch Index

Table A 6 Best fitted model of the relationship between socio-economic, landscape descriptors and fire frequency (fire counts as response variable)

Variables	Estimate	Std. Error	T value	Pr(>|t|)
Poverty	$2.745e^{-02}$	$1.021e^{-02}$	2.690	0.007
Roads	$7.873e^{-07}$	$3.794e^{-07}$	2.075	0.039
Reg. M	$4.853e^{-05}$	$1.618e^{-05}$	3.000	0.003
BL	$-9.256e^{-06}$	$4.259e^{-06}$	-2.173	0.031
NPF	$1.500e^{-04}$	$3.493e^{-05}$	4.294	$2.85e^{-05}$
PDF	$-5.479e^{-02}$	$2.830e^{-02}$	-1.936	0.054
PDBL	$-4.590e^{-02}$	$2.872e^{-02}$	-1.598	0.111
PDUB	$-5.279e^{-02}$	$9.952e^{-03}$	-5.304	$3.26e^{-07}$
PAF	$1.073e^{-01}$	$4.095e^{-02}$	2.620	0.009
PShapeBL	$4.671e^{-02}$	$3.036e^{-02}$	1.539	0.125
LPIF	$-2.176e^{-02}$	$1.152e^{-02}$	-1.889	0.060

Fire Frequency Model (Log+1) : $F_{11,182}=23.38$, $R^2=0.561$, $P<0.01$

Table A 7 Best fitted model of the relationship between socio-economic descriptors and landscape homogeneity (SHEI).

Variables	Estimate	Std. Error	T value	Pr(>|t|)
Poverty	$8.356e^{-03}$	$1.655e^{-03}$	5.048	$1.05e^{-06}$
Roads	$2.364e^{-07}$	$5.682e^{-08}$	4.161	$4.82e^{-05}$
Railroads	$1.283e^{-06}$	$6.149e^{-07}$	2.086	0.0383
Expenses	$-2.311e^{-03}$	$1.145e^{-03}$	-2.019	0.0449
Reg. B	$-2.778e^{-06}$	$1.433e^{-06}$	-1.939	0.0540

Landscape homogeneity model: $F_{5, 188}$=21.63, R^2= 0.348, P<0.01

Table A 8 Best fitted model of the relationship between socio-economic descriptors and fire frequency (fire counts).

Variables	Estimate	Std. Error	T value	Pr(>|t|)
Poverty	$5.648e^{-02}$	$1.019e^{-02}$	5.545	$9.76e^{-08}$
Roads	$2.430e^{-06}$	$3.747e^{-07}$	6.487	$7.41e^{-10}$
Expenses	$-1.147e^{-02}$	$7.740e^{-03}$	-1.482	0.140
Fire frequency model (Log+1): $F_{3,190}$=42.03, R^2=0.389, P<0.01				

Table A 9 Zero-inflated negative binomial output of the landscape-socio-economic descriptors and fire frequency.

Variables	Coef	Std. Error	z	P>|z|
Negative Binomial				
Poverty	0.011	0.012	0.949	0.342
Log-NPF	0.802	0.103	7.771	$7.77e^{-15}$
Log-LPIF	-0.787	0.188	-4.177	$2.95e^{-05}$
Log- PAF	1.619	0.328	4.928	$8.30e^{-07}$
Log (Theta)	-0.238	0.114	-2.081	0.037
Zero-Inflated				
Poverty	0.023	0.156	0.148	0.883
Log-NPF	4.426	3.167	1.397	0.162
Log-LPIF	-6.523	4.264	-1.530	0.126
Log- PAF	2.719	1.990	1.366	0.172
	AIC= 1328.89	Theta= 0.787		

Table A 10 Zero-inflated negative binomial model for the climate descriptors as a function of fire frequency.

Variables	Coef	Std. Error	z	P>|z|
Negative Binomial				
Temperature	-0.110	0.039	-2.798	0.0051
Precipitation	0.0009	0.0003	2.786	0.0053
Log (Theta)	-0.562	0.128	-4.384	$1.16e^{-05}$
Zero-Inflated				
Precipitation	-0.007	0.002	-3.222	0.0012
	AIC=1440.56	Theta= 0.569		

Table A 11 Comparison between the landscape-socio-economic model and the climate model values as a function of the observed fire frequency represent as overall agreement.

Region	Overall Agreement (%)	
	Climate Model	LE-Social Model
Valparaíso	56.09	46.81
Metropolitana	69.73	17.24
LGBOH**	48.20	37.14
Maule	38.52	39.05
Bio Bío	21.04	35.30
Total*	42.20	35.77

*The total value represents the overall agreement for the entire area as a function of the observe fire frequency.
** LGBOH= Libertador General Bernardo O'Higgins