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From Flames to Safety: Understanding and Mitigating Megafire Risk in Curacaví, Chile: A Fire Behaviour and Eco-DRR Perspective

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Zusammenfassung

Diese Studie untersucht die wichtigsten Umweltfaktoren, die das Risiko von Megabränden in Curacaví, Chile, beeinflussen, und bewertet die Wirksamkeit von ökosystembasierten Strategien zur Katastrophenvorsorge (Eco-DRR) zur Eindämmung der Feuerverbreitung. Die Ergebnisse bestätigen, dass niedrige relative Luftfeuchtigkeit der Haupttreiber für die Feuerverbreitung ist, gefolgt von Windgeschwindigkeit, Windrichtung und Temperatur. Die Analyse des schlimmsten Szenarios zeigte, dass bei extremen meteorologischen Bedingungen Feuer unkontrollierbar wird, was die Notwendigkeit eines integrierten Brandmanagements unterstreicht.

Unter den getesteten Minderungsstrategien erwiesen sich die Reduzierung der Vegetationsdichte und das Kraftstoffmanagement als am effektivsten, da sie die Brandwahrscheinlichkeit von 22.5 % (schlimmstes Szenario) auf 3,5 % senkten. Allein eingesetzte Brandschutzstreifen boten eine mäßige Minderung, aber in Kombination mit Vegetationsmanagement wurde das Feuerrisiko erheblich reduziert und das Auftreten von Megabränden verhindert. Diese Ergebnisse unterstützen die Notwendigkeit eines proaktiven Landschaftsmanagements anstelle einer reaktiven Brandbekämpfung und zeigen, dass die Priorisierung von Brennstoffreduzierung und gezielter Minderung in Hochrisikogebieten für die Feuerprävention in Curacaví entscheidend ist.

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Abstract

This study investigates the key environmental factors influencing megafire risk in Curacaví, Chile, and evaluates the effectiveness of Ecosystem-based Disaster Risk Reduction (Eco-DRR) strategies in mitigating fire spread. The results confirm that low relative humidity is the primary driver of fire propagation, followed by wind speed, wind direction, and temperature. The worst-case scenario analysis showed that when extreme meteorological factors align, fire spreads uncontrollably, emphasizing the need for integrated fire management.

Among the mitigation strategies, thinning vegetation and fuel management were the most effective, reducing burn probability from 22.5% (worst-case scenario) to 3.5%. Firebreaks alone provided moderate mitigation, but when combined with vegetation management, fire risk was significantly reduced, eliminating megafire occurrences. These findings support the need for proactive landscape management over reactive fire suppression and suggest that prioritizing fuel reduction and targeted mitigation in high-risk areas is essential for fire prevention in Curacaví.

Resumen

Este estudio analiza los factores ambientales clave que influyen en el riesgo de megaincendios en Curacaví, Chile, y evalúa la eficacia de las estrategias de Reducción del Riesgo de Desastres basadas en Ecosistemas (Eco-DRR) para mitigar la propagación del fuego. Los resultados confirman que la baja humedad relativa es el principal factor impulsor de la propagación del fuego, seguido por la velocidad del viento, la dirección del viento y la temperatura. El análisis del peor escenario mostró que cuando los factores meteorológicos extremos se alinean, el fuego se propaga de manera incontrolable, destacando la necesidad de una gestión integrada del fuego.

Entre las estrategias de mitigación, el adelgazamiento de la vegetación y la gestión del combustible fueron las más efectivas, reduciendo la probabilidad de incendio del 22.5% (peor escenario) al 3,5%. Los cortafuegos por sí solos proporcionaron una mitigación moderada, pero cuando se combinaron con la gestión de la vegetación, el riesgo de incendio se redujo significativamente, eliminando la ocurrencia de megaincendios. Estos hallazgos refuerzan la necesidad de una gestión proactiva del paisaje en lugar de una supresión reactiva del fuego y sugieren que la reducción del combustible y la mitigación dirigida en áreas de alto riesgo son esenciales para la prevención de incendios en Curacaví.

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List of abbreviations

BP	Burn probability.
CR2	Centre for Climate and Resilience Research.
CCA	Climate Change Adaptation.
CONAF	National Forestry Corporation.
DEM	Digital Elevation Model.
DMC	Meteorological Directorate of Chile.
DRR	Disaster Risk Reduction.
Eco-DRR	Ecosystem-based Disaster Risk Reduction.
FBP	Canadian Fire Behaviour Prediction.
IFM	Integrated Fire Management.
HBP	High busto al arbole.
LFW	Low integrante fil.
SENAPRED	National Disaster Prevention and Response Service.
SDGs	Sustainable Development Goals.
WUI	Wildland-urban interface.

1. Introduction

Over the last few decades, humankind has been experiencing a warming climate, and an explosive population increase in urban areas. This has led to a higher risk of, inter alia, wildfires, compromising more people year over year living in the wildland-urban interface (WUI).

Following that, the term megafires has emerged to describe large and severe wildfires, which are becoming a common phenomenon rather than an infrequent one, especially in the past two decades due to human activities and climate change combined effects (Breton et al., 2022; G. Neary, 2022; Linley et al., 2022). Among the impacts of megafires are not only soil erosion, ecosystem damage, air pollution and carbon dioxide emissions, which contribute to global warming (Barrera et al., 2018; Fidelis et al., 2018; Mancilla-Ruiz et al., 2021; Pandey & Ghosh, 2018; Sağlam et al., 2008), but also, loss of human lives, migration, trauma and damage in infrastructure (Linley et al., 2022; Nel et al., 2014; Sarricolea et al., 2020; Varga et al., 2022).

Megafires are especially affecting Mediterranean landscapes, such as Australia, California in The United States, Portugal and Chile (Azócar de la Cruz et al., 2022; Barrera et al., 2018; Leite et al., 2015). The latter has experienced a marked increase in wildfire frequency and severity over the last few decades, particularly in the central and southern regions. The 2017 and 2023 fire seasons were among the most severe, with millions of hectares burned and significant loss of life and property (Cordero et al., 2024; Hayasaka, 2024).

According to the findings of the Centre for Climate and Resilience Research (CR2) (2020), between 2008 and 2018, an average of approximately 116,000 hectares burned annually in Chile. This includes around 46,000 hectares of exotic forest plantations, 19,000 hectares of native forest, and 43,000 hectares of grasslands and shrubs. However, only in the megafires of 2017, nearly of 570,200 hectares were burned, causing significant social, economic, and environmental impacts (for example, the CO2 emissions from the 2017 megafires were comparable to 23 years of CO2 emissions from all light passenger vehicles in the Santiago Metropolitan Region), with direct costs to the state amounting to around 243,000 million Chilean pesos.

In general terms, wildfires play a fundamental role in ecosystem dynamics, acting as natural regulators and even benefiting biodiversity, especially in fire-adapted communities (Barrera et al., 2018; Breton et al., 2022; Leite et al., 2015). However, in the current climate change scenario, where fires tend to be larger, more frequent and unpredictable, high-severity events are increasing, making it harder to expect positive feedback from wildfires due to their the frequency and magnitude (Barrera et al., 2018).

The increase in global temperatures, droughts, heat waves and decreasing precipitation are some of the factors that, while not causing a wildfire, provide suitable conditions for increased spread and magnitude, raising the risk of wildfires (Azócar de la Cruz et al., 2022; Barrera et al., 2018; Leite et al., 2015). In addition to warming climate conditions, human activities and land-use changes pose a higher risk in the WUI, where natural conditions, climate and anthropogenic sets interact and are enhanced (Azócar de la Cruz et al., 2022). According to Barrera (2018), the combined effects of human-induced climate change and land-use changes have led to more frequent, severe, and large wildfires worldwide. Thus, these fires could significantly affect land and communities in the near future.

Furthermore, climate change is expected to increase the frequency, extent, and intensity of wildfires in Chile due to rising temperatures and changing humidity levels. This will likely exacerbate the impacts on natural ecosystems and human well-being (González, M.E. et al., 2020). Human activities are also responsible for nearly 90% of wildfires in Chile, with socio-economic factors such as population density, road access, and land cover changes playing a significant role in the spatiotemporal distribution of wildfire (Pozo et al., 2022). Likewise, the expansion of agricultural lands and exotic tree plantations, such as Pinus radiata and Eucaliptus spp., has altered the landscape, increasing the risk and severity of wildfires (Olmedo et al., 2023). Thus, megafires will likely persist in Chile, particularly if unfavourable meteorological conditions combine with inadequate planning and weak regulations on intensive exotic forest plantations (Barrera et al., 2018).

Therefore, there is a need for comprehensive wildfire mitigation management, particularly in native forest, to address the increasing frequency and severity of wildfires driven by both climatic and human factors, considering the complex interplay of these features with local environmental conditions (Duarte et al., 2024; Hayasaka, 2024). Chilean scientists are actively developing wildfire prediction models to mitigate the impact of these events. Examples include several fire simulators development, such as Cell2Fire (Pais et al., 2021) which cluster multiple methods to simulate fire behaviour and will serve as the primary methodology for this research.

Given the escalating severity of wildfires, effective mitigation strategies are crucial. One promising approach is Ecosystem-based Disaster Risk Reduction (Eco-DRR), which UNDRR (2020) defines as a subset of Nature-based solutions (NbS), focusing on leveraging ecosystem functions to mitigate natural hazards such as floods, landslides, tsunamis and wildfires through the preservation of natural ecosystems. Furthermore, an Eco-DRR approach has been demonstrated to be a sustainable and economically convenient option to reduce these and other types of risk. Meanwhile, Eco-DRR is described as suitable management, conservation and restoration of ecosystems to reduce disaster risk, aiming to achieve sustainability and resilient development (Sudmeier-Rieux et al., 2021). Hence, it is possible to imply that implementing more Eco-DRR interventions could serve as new conservation strategies and tools to mitigate biodiversity loss and promote ecosystem recovery to cope the increase in frequency and magnitude of megafires and their effects (Nimmo, Andersen, et al., 2022).

For this thesis, Curacaví was selected as the study area due to its recurrent wildfire activity, its location in a high-risk region in central Chile, and its susceptibility to extreme fire weather conditions such as strong winds, low humidity and prolonged drought (Municipalidad de Curacaví, 2023).

Considering the aforementioned, the research question to be answered by this master's thesis is: **How do Eco-DRR strategies impact megafire probability and fire behaviour in Curacaví, Chile, under worst-case meteorological conditions?**

To answer that, two main objectives are given to be addressed with their specific objectives:

1. To assess the spatial distribution of megafire-prone areas and evaluate the key environmental factors influencing fire behaviour in Curacaví.
    - To analyse the spatial distribution of megafire-prone areas in Curacaví based on environmental and fire history variables.
    - To determine the key meteorological factors influencing megafire propagation under worst-case conditions.
2. To evaluate the effectiveness of different Eco-DRR strategies in reducing megafire probability and spread through predictive wildfire simulations.
    - To assess the effectiveness of different Eco-DRR strategies in reducing megafire probability.
    - To compare megafire spread behaviour under different mitigation scenarios and determine which strategies provide the greatest reduction in fire spread.

2. Theoretical background

2.1 Megafires Risk and Their Drivers

2.1.1 Definition and Characteristics of Megafires

Megafires are large, high-severity wildfires that persist spatially and temporally, typically exceeding 10,000 hectares (Ha) in size. These fires are characterized by extreme and unpredictable behaviour, including rapid spread rates, high-intensity flames, and resistance to suppression efforts, resulting in significant ecological and social impacts (Campos et al., 2023; Coen et al., 2018; Linley et al., 2022). While the scientific community lacks a universally agreed-upon definition, megafires are commonly distinguished by their extreme fire behaviour and the difficulty of containment rather than solely by their size (Lindley et al., 2019; Linley et al., 2022; Nimmo, Jolly, et al., 2022) .

Unlike low-intensity wildfires, megafires exceed suppression capabilities, affecting ecosystems, human settlements and infrastructure, particularly in the wildland-urban interface (WUI) (Mancilla-Ruiz et al., 2021). They are strongly associated with extreme weather conditions such as heat waves, prolonged droughts, and strong winds, exacerbated by climate change (Leite et al., 2015). Additionally, megafires can generate their own weather systems through pyro-convection, leading to the formation of pyro-cumulus or pyro-cumulonimbus clouds, intensifying fire spread through fire-generated winds and atmospheric instability (Campos et al., 2023; Coen et al., 2018).

Megafires pose a significant threat to the WUI, defined as the area where human settlements meet or intermingle with undeveloped wildland vegetation, creating a zone of interaction between human habitation and natural environments (Azócar de la Cruz et al., 2022; Ferreira et al., 2023). This WUI is particularly vulnerable due to the proximity of structures to flammable vegetation, creating an environment where wildfires can transition rapidly from wildland to settlements. This vulnerability is exacerbated by factors such as housing density, fuel continuity and inadequate fire-resistant building designs (Carlson et al., 2022; Kumar et al., 2022). Structural vulnerabilities, including combustible material and poor urban planning, further contribute to fire spread and damage (Vacca et al., 2020).

The expansion of WUI areas is driven by climate change, historical land management practices, and increasing human settlement in fire-prone regions. These factors have led to a rise in the frequency and severity of WUI fires (Harries et al., 2022). According to Chen (2024) the global WUI area is estimated at 6.62 million km2, with 3.83 million people living within a 2,400-meter buffer zone of wildfire threats. In Chile, WUI expansion is particularly critical in metropolitan areas such as Valparaíso and Concepción, where urban growth near wildland areas has heightened wildfire risk (Jaque Castillo et al., 2021; Severino et al., 2022). The increasing WUI trend, combined with intensifying climate change effects, underscores the urgent need for integrated wildfire management strategies incorporating both ecological and urban planning solutions (Wadhwani et al., 2019; Wang et al., 2020).

As previously discussed, megafires have profound environmental, societal, and economic consequences. They can inject massive smoke plumes into the stratosphere, where particles persist for months, affecting atmospheric conditions and contributing to global climate change (Guimond et al., 2023). Other significant environmental impacts include soil erosion, long-term ecosystem degradation, biodiversity loss, and the release of large amounts of carbon dioxide, exacerbating global warming (Barrera et al., 2018; Fidelis et al., 2018; Mancilla-Ruiz et al., 2021; Pandey & Ghosh, 2018; Sağlam et al., 2008). Hydrological disturbances also follow megafires, with increased sediment and nutrient fluxes altering watershed dynamics, as observed in post-fire studies in Utah (Lindley et al., 2019).

The 2019-2020 Australian megafire season exemplifies the devastating impacts of megafires, with estimates suggesting that billions of animals were affected, and ecosystem recovery remains uncertain despite many vertebrates' fire-adaptive behaviours (Nimmo, Jolly, et al., 2022). Beyond ecological damage, megafires displace communities, destroy homes, and inflict severe mental health consequences due to trauma and loss (Linley et al., 2022; Nel et al., 2014; Sarricolea et al., 2020; Varga et al., 2022). Economically, megafires lead to extensive losses, including destruction of wood plantations, firefighting costs, damage to infrastructure, disruptions in tourism and agriculture, and reduced land productivity (Handke, 2020; Makumbura et al., 2024; Sağlam et al., 2008). Given these wide-ranging impacts, long-term fire management strategies are needed, incorporating both preventive ecosystem management and post-fire restoration efforts to support species recovery and ecosystem resilience (Ward et al., 2022).

2.1.2 Drivers Increasing Megafire Risk

The probability of megafires is influenced by multiple interacting factors, including climate change, altered fire regimes, high fuel availability, urbanization, and topography. The complexity of terrain (slope, elevation, and surface roughness) further complicates suppression efforts, making fire more difficult to control (Chen et al., 2024; Kumar et al., 2022).

In literature, the “megafire triangle” is a framework that highlights three primary drivers increasing the probability and intensity of megafires: climate change, fire exclusion and antecedent disturbance (Lindley et al., 2019; Morais et al., 2011; Stephens et al., 2014).

- **Climate change** intensifies fire conditions by increasing temperatures, altering precipitation patterns and extending fire seasons, thereby creating more opportunities for fire to ignite and spread (Lindley et al., 2019; Stephens et al., 2014). Increased aridity and extreme weather conditions such as heatwaves and strong winds exacerbate fire behaviour (Chen et al., 2024; Fidelis et al., 2018)

- **Fire exclusion** is a practice to prevent fires, which have led to unnatural fuel accumulation, making forest more susceptible to severe wildfires when they do occur (Morais et al., 2011; Stephens et al., 2014)
- **Antecedent disturbances**, such as insect infestations, droughts and previous fires, can weaken vegetation and create additional dry fuel that enhances fire spread. (Lindley et al., 2019; Stephens et al., 2014).

Climate and weather play a fundamental role in megafire likelihood by influencing fuel moisture, ignition probability, and fire spread dynamics. For instance, high **temperature** accelerate fuel drying, making vegetation more flammable. Climate change-driven warming has intensified fire behaviour by reducing relative humidity and increasing fine fuel availability (Varga et al., 2022). Land-use changes, including urbanization and rural abandonment, contribute to fragmented landscapes with continuous fuel loads, exacerbating fire spread (Ayala-Carrillo et al., 2022; Fiorini et al., 2022). **Wind** is also a critical factor in fire spread, influencing flame angle, heat transfer, and ember transport, leading to spot fires that accelerate fire expansion (Moon et al., 2013; Simpson et al., 2013). Winds patterns interact with topography, leading to complex fire behaviours such as channelling on shielded slopes, lateral fire spread, and pyro-cumulonimbus storms (Fendell & Wolff, 2001; Shen et al., 2022). Likewise, **low humidity** accelerates fuel drying, making ignition more likely, and drought conditions further exacerbate fire risk by reducing live fuel moisture content, increasing the probability of large-scale wildfires (Martin-StPaul et al., 2020; Suzuki et al., 1988).

Historically, ecosystems experienced frequent, low- to moderate- intensity fires that regulated fuel loads and maintained biodiversity (Hoffman et al., 2019; Knapp et al., 2004). However, decades of fire suppression have led to excessive fuel accumulation, increasing the probability of high-severity fires (Harris & Taylor, 2015). Simulations of extreme wildfires, such as the King Fire in California, highlight how accumulated fuels and fire-induced winds contribute to megafire expansion (Coen et al., 2018). Therefore, prescribed burns and management fire regimes have been shown to mitigate these risks by reducing fuel loads, although their effectiveness depend on local environmental conditions (Hoffman et al., 2019; Stephens et al., 2014).

Finally, past disturbances, including insect outbreaks, windstorms, and previous fires, alter forest structure and fuel composition, increasing fire susceptibility (Buma & Wessman, 2011). Multiple disturbances can lead to ecosystem instability, affecting biochemical cycles and nutrient fluxes (Crandall et al., 2021). Then, over time the likelihood of fire increases as fuel loads accumulate, reinforcing the long-term impact of antecedent disturbance (Clark, 1989).

The expansion of the WUI is also an important driver to increase megafire probability of occurrence by placing more people and infrastructure next to fire-prone landscapes. This expansion leads to: **increased ignitions** due to human activities which contribute to nearly 90% of wildfire in some regions (Calviño-Cancela et al., 2014; Chen et al., 2024); **flammable building material** and **urban fuel loads**, because many structures in WUI areas use highly flammable materials, increasing fire spread potential (Aguirre et al., 2024; Purnomo et al., 2024); and **limited fire suppression capacity**, due to urban expansion into fire-prone areas that complicates suppression efforts and increases the need for proactive mitigation strategies (Dondi, 2022; Kumar et al., 2022).

To mitigate the increasing risk in WUI zones, proactive strategies such as modifying urban fuel loads and using fire-resistant vegetation can be considered. For example, in Portugal, replacing flammable vegetation with broadleaf forest has significantly reduced fire intensity and spread (Oliveira et al., 2023). For this reason, wildfire spread models incorporating urban and agricultural fuel loads provide valuable insights for assessing wildfire risk in WUI communities (Dondi, 2022).

2.2 Eco-DRR Principles and Strategies in Fire Management

2.2.1 Definition and Principles of Eco-DRR

According to the United Nations Office for Disaster Risk Reduction (2021) ecosystem-based Disaster Risk Reduction (Eco-DRR) is a key component of Nature-based solutions (NbS). It overlaps with Ecosystem-based adaptation (EbA), which leverages ecosystem services to help communities cope with climate change (Sudmeier-Rieux et al., 2019). Then, Eco-DRR aims to reduce the risk and impact of natural hazards by preserving natural ecosystems, taking into account both non-climate hazards, like earthquakes, tsunamis or technological accidents, and climate-related hazards like hurricanes and heat waves, during all stages of DRR. Moreover, as mentioned by Gupta and Nair (2012), Eco-DRR also involves merging disaster risk reduction (DRR) and climate change adaptation (CCA), aiming to decrease the risk based on local knowledge and historical data. Furthermore, through sustainable management, conservation and restoration of ecosystems, Eco-DRR aims to manage the environment to build communities' resilience (Klein et al., 2019; Santos et al., 2021; Sudmeier-Rieux, 2015).

Other authors also claim that Eco-DRR refers to networks of different actors working alongside to reduce disaster risk, including the communities to reduce their vulnerability, combining scientific knowledge and political strategies to manage ecosystems (Gupta & Nair, 2012; Kautsar & Mulyono, 2021; Santos et al., 2021). Thus, the solutions provided by Eco-DRR bring benefits to both people and biodiversity (Matthews & Dela Cruz, 2022). This integration between ecosystem management and human activities, including land use planning, creates a balanced approach that supports environmental sustainability, providing sustainable livelihoods, by maintaining ecosystem services, and disaster risk reduction (Chen et al., 2024; Sudmeier-Rieux et al., 2019).

Regarding Eco-DRR principles, those vary throughout the authors. Nevertheless, in line with the UNDRR (2021), Eco-DRR principles could be split into four categories: Building resilience and enhancing adaptive capacity; Ensuring inclusivity and equity in planning and implementation; Achieving Eco-DRR in multiple scales; and Effectiveness and efficiency.

Building resilience of socio-ecological systems and enhancing adaptive capacity, not only reduces environmental degradation and biodiversity loss but also decreases vulnerability to disasters (United Nations Office for Disaster Risk Reduction, 2021) through leveraging the protective functions of natural ecosystems such as forests, wetlands and mangroves to reduce the risk of different hazards, for instance, planting trees in flood-prone areas (Santos et al., 2021; Sudmeier-Rieux, 2015; United Nations Office for Disaster Risk Reduction, 2021). In addition to that, it integrates disaster and climate risk into local development plans or ensures that infrastructure and livelihood have better tools to be prepared for extreme events (United Nations Office for Disaster Risk Reduction, 2021). In this way, it is possible to build resilience in communities, through education, training and capacity-building activities (Klein et al., 2019; Santos et al., 2021; Sudmeier-Rieux, 2015).

As with any Disaster Risk Reduction strategy, Eco-DRR must address **inclusivity and equity principles**, considering the communities potentially affected by disasters, especially vulnerable groups such as women, children, the elderly and Indigenous people (Klein et al., 2019; United Nations Office for Disaster Risk Reduction, 2021). Furthermore, according to the same authors, local, indigenous and traditional knowledge are important inputs to join with scientific research. This practice allows being more culturally appropriate and grow their involvement in local governance and decision-making processes (Chabba et al., 2022).

Achieving Eco-DRR in **multiple scales** refers not only to spatial and temporal ones, meaning that Eco-DRR benefits are observable at larger spatial scales and at longer timeframes, but also to the global and local integration of DRR strategies (United Nations Office for Disaster Risk Reduction, 2021). This includes elements such as Early Warning Systems (EWS), disaster preparedness and response through strengthening relationships between different actors (government agencies, NGOs, private companies and scientists), ensuring that local communities are actively involved in decision-making (Kautsar & Mulyono, 2021; Klein et al., 2019; Santos et al., 2021; Sudmeier-Rieux, 2015).

According to UNDRR (2021), Eco-DRR interventions must be **effective and efficient**, evidence-based, and be evaluated constantly by continuous monitoring to spot and reduce limitations that could happen in the study area. Moreover, Eco-DRR addresses multiple problems as well, focusing on solving them altogether, such as technical (difficulty of detecting and extinguishing fire in remote areas), socio-economic (identifying people exposed and their economic necessities), and law-enforcement (e.g. against the illegal practice of slash-and-burn agriculture) (Gupta & Nair, 2012; Kautsar & Mulyono, 2021; United Nations Office for Disaster Risk Reduction, 2021). On the other hand, Eco-DRR is known for being more cost-effective compared to traditional engineering solutions, due to the use of natural processes to mitigate disasters and less maintenance required (United Nations Office for Disaster Risk Reduction, 2021). Eco-DRR interventions also create and provide new jobs among the community involved, improving their economic situation (Klein et al., 2019).

Furthermore, Eco-DRR plays a fundamental role in biodiversity conservation and restorations, by protecting a vast amount of flora and fauna (Klein et al., 2019), and from its side, biodiversity could protect communities against natural hazards by acting as natural protective barriers and maintaining healthy ecosystems, which in turn, regulate the climate and provide ecosystem services, such as water purification and soil fertility, improving human well-being and their survival rate (Gupta & Nair, 2012; Klein et al., 2019; Santos et al., 2021).

2.2.2 Role of ecosystems in mitigating natural hazards and reducing disaster risk

One of the most important benefits of Eco-DRR for this research is its role in reducing disaster risk through sustainable environmental management. To achieve this goal, different interventions can be implemented depending on the specific disaster risk being addressed. Biodiversity conservation plays a fundamental role in DRR by acting as a natural barrier against various hazards. For example, forests prevent landslides by stabilizing slopes, mangroves reduce storm surge impacts, coral reef dissipate wave energy, and wetlands help absorb floodwater (Chabba et al., 2022; Gupta & Nair, 2012; Klein et al., 2019; Sudmeier-Rieux et al., 2019). Moreover, healthy and diverse ecosystems are more resilient to environmental changes and extreme events, offering more protection to communities and enhancing their capacity to adapt (Sudmeier-Rieux et al., 2019).

In wildfire-prone landscapes, ecosystems provide critical regulatory functions that mitigate fire risk. Native fire-adapted forest can act as natural firebreak, slowing down the spread of wildfires and reducing their severity. Additionally, wetlands and riparian zones help maintain higher humidity levels, limiting fire ignition and intensity (Sudmeier-Rieux et al., 2019). Studies suggest that fire-resilient landscapes, such as Mediterranean woodlands, can reduce wildfire risks by supporting native species that regenerate quickly post-fire and maintaining soil stability to prevent erosion (Hülsen et al., 2023). These ecosystems also help moderate extreme temperatures and wind speeds, two major contributors to megafire behaviour (Sudmeier-Rieux et al., 2021).

While healthy ecosystems provide essential protective functions, degraded landscapes significantly increase vulnerability to disasters. For example, deforested or burned areas are more prone to landslides and flash floods, which can exacerbate post-fire impacts on human settlements (Sudmeier-Rieux et al., 2019). Loss of vegetation cover reduces soil stability, increasing sediment runoff into water bodies and compounding the ecological damage caused by megafires (Balzer et al., 2023). In addition, the loss of tree canopy and undergrowth vegetation can lead to higher local temperatures and lower humidity, making landscapes more prone to frequent and intense wildfires.

Beyond direct hazard mitigation, Eco-DRR also reduces vulnerability in exposed communities by enhancing essential ecosystem services such as water retention, food security, and sustainable land use, which support local livelihoods and overall well-being (Sudmeier-Rieux et al., 2019). Protecting, managing, and restoring ecosystems is crucial to maintaining these benefits, as studies highlight the role of reforestation and wetland restoration in improving climate resilience and reducing disaster exposure (Hülsen et al., 2023). The integration of Eco-DRR into developed agendas, land-use planning, and post-disaster recovery strategies is essential to leverage nature's protective functions and reduce disaster vulnerability (Wickramasinghe, 2021).

Furthermore, Eco-DRR not only mitigates hazards but also provides socio-economic benefits, including job creation, sustainable agriculture, and long-term economic resilience. Large-scale ecosystem restoration projects have been shown to boost local economies by providing employment opportunities in reforestation, land rehabilitation, and agroforestry sectors (Wickramasinghe, 2021). In wildfire-prone regions, managing vegetation through sustainable forestry and fuel reduction strategies creates safer landscapes while supporting rural economies (Sudmeier-Rieux et al., 2021).

2.2.3 Integrated Fire Management

Within the Eco-DRR, Integrated Fire Management (IFM) is an approach that combines ecological, social, and technological strategies to manage fire regimes and mitigate risks while enhancing ecosystem resilience and community safety (Castro Rego et al., 2021). Unlike conventional fire suppression, IFM recognises fire as a natural and essential ecological process, moving away from the zero-fire perspective that seeks to eliminate fire entirely from ecosystems (Barradas et al., 2020; Castro Rego et al., 2021). Instead, IFM integrates adaptive fire management strategies that balance fire risk reduction with ecosystem restoration and biodiversity conservation.

IFM is particularly relevant in fire-prone regiones, such as Mediterranean landscapes, where climate change and historical fire suppression have exacerbated fire severity and frequency (Baudena et al., 2023; Costa Freitas et al., 2017; D'Evelyn et al., 2022). By implementing controlled burns, fuel reduction treatment, and landscape-scale forest management, IFM proactively reduces wildfire hazards while maintaining the health of the ecosystem (Moore, 2019; Pinho & Mateus, 2018).

One notable example of IFM in action is the Kenow wildfire case, occurred in Canada, where prescribed burns were employed to control aspen encroachment and preserve native grassland. However, the effectiveness of these burns depends on timing, scale, and local ecological conditions, highlighting the importance of site-specific adaptive fire management (Eisenberg et al., 2019).

Additionally, IFM promotes fuel reduction treatments, such as the introduction of fire-resilient species (e.g., resprouting plants), which increase ecosystem stability and mitigate fire occurrence under diverse climate scenarios (Baudena et al., 2023).

A key strength of IFM is its reliance on participatory decision-making, which includes local stakeholders, scientist, policymakers, and fire management professionals. This collaborative approach fosters transparency, adaptability, and community resilience, ensuring that fire management strategies are socially acceptable and ecologically sound (Cocuccioni et al., 2022).

Moreover, technological advancements play a crucial role in modern IFM strategies. Remote sensing, satellite imagery, and fire simulation models allow for real-time monitoring of fire regimes, enabling early intervention and improved predictive capabilities (Marcos et al., 2022). Models such as Cell2Fire and PHOENIX RapidFire simulate wildfire spread dynamics by integrating fuel type, wind conditions, and topography, supporting evidence-based fire management planning. (Pais et al., 2021)

By incorporating scientific knowledge, traditional fire practices, and emerging technologies, IFM balances wildfire risk with ecological restoration. This approach is essential for addressing the complex interactions between land-use change, vegetation dynamics, and climate variability (Goldammer, 2022).

Furthermore, capacity-building initiatives at local and national levels strengthen fire preparedness and response efforts, ensuring that IFM strategies remain adaptive to evolving fire regimes (Castro Rego et al., 2021; D'Evelyn et al., 2022). The global perspective in IFM underscores the importance of shifting away from reactive fire suppression towards proactive, ecosystem-based fire management, which is cost-effective, socially inclusive, and ecologically sustainable (Costa Freitas et al., 2017; Pinho & Mateus, 2018).

2.3 Fire simulators

Fire simulators are computational tools that predict wildfire behaviour under various environmental conditions. They assist in real-time decision-making for emergency response, long-term wildfire management, and risk assessment. Given their role in IFM, these simulators are crucial for predicting fire spread, optimizing suppression strategies, and enhancing public safety measures (Fox-Hughes et al., 2024).

Several fire simulators are used globally, each with specific strengths and applications. In Australia, fire agencies utilise models such as Australis, Phoenix, Prometheus, and Spart to predict wildland fire spread. A comparative evaluation using spatial metrics and visual aids found that no single simulator is universally superior; rather each excels under different conditions (Fox-Hughes et al., 2024). Fire simulators are particularly valuable in emergency response training, offering immersive, risk-free environments where firefighters can practice responding to diverse wildfire scenarios (Sun et al., 2024).

According to Jevtic (2015), fire simulators such as PrysoSim predict potential fire scenarios by modelling fire development and spread. These tools help researchers and emergency responders understand fire dynamics, including temperature distribution, smoke flow, and thermal radiation, which are crucial for designing effective fire safety measures. Simulators are also used in evacuation planning, helping to determine the most effective evacuation routes, reducing evacuation time and improving safety during fire emergencies (Tang et al., 2022). The Web-based Wildfire Simulator (WWS), for instance, demonstrated real-time utility during the 2021 Sardinia fires in Italy (Arca et al., 2022).

On the other hand, fire simulators employ a variety of methodologies to enhance prediction accuracy in high-risk areas, integrating advanced computational techniques and data-driven models. Firstly, Cellular Automata (CA) models are used to simulate wildfire spread by capturing interactions between neighbouring cells and incorporating factors, such as wind direction, speed, and vegetation density. These models use probabilistic transitions to mirror real-world fire behaviour, enhancing prediction accuracy by accounting for spotting and terrain effects (Ghosh et al., 2024). These probabilistic models incorporate uncertainty in weather, fuel loading, and model physics parameters. This approach provides information on the most likely forecast scenario and confidence levels, improving the interpretability and reliability of predictions (Coen et al., 2024).

Secondly, deep learning models, such as Convolutional Neural Networks-Ling Short-Term Memory Networks (CNN-LSTM), are employed to predict wildfire risk by integrating diverse datasets, including satellite imagery and meteorological data. These models enhance prediction accuracy by incorporating channel and spatial attention mechanisms, which refine high-risk prevention areas and reduce false alarms

(He et al., 2023). Also, machine learning techniques, such as the Vector-Quantized Variation Autoencoders (VQ-VAE), generate spatial-temporal sequences to predict wildfire progression. These models are effective in producing realistic fire scenarios by incorporating geophysical factors like vegetation and terrain slope (Cheng & Arcucci, 2024). Furthermore, the use of a double weighted naïve Bayes with compensation coefficient (DWCNB) method improves prediction accuracy by weighting fire characteristic attributes and compensating for prior probability, resulting in higher accuracy compared to traditional naïve Bayes methods (Shu et al., 2021).

Thirdly, environmental models that predict fuel hazards based on environmental variables excel traditional models that rely on time since fire. These models account for live and dead vegetation components influenced by environmental factors, leading to more accurate predictions of fire behaviour and risk estimation (Penman et al., 2022).

Finally, combining machine learning with physical-based simulations allows for rapid, high-fidelity predictions. Techniques such as dimensionality reduction and deep learning provide full-fields predictions significantly faster than traditional computational fluid dynamics (CFD) simulations, though further work is needed to improve accuracy (Lattimer et al., 2020).

A notable example of a Cellular Automata (CA)-based approach is the Cell2Fire simulator (Woodruff et al., 2019), used in Chile. It models wildfire spread by simulating interaction between neighbouring cells, allowing for detailed representation of fire dynamics. Key factors influencing fire spread within Cell2Fire include wind direction, wind speed, vegetation density, and spatial data, which are crucial for mapping and analysing fire risk in specific geographic areas (Ghosh et al., 2024).

Cell2Fire is designed to be highly flexible, supporting both individual fire event prediction, and integration into larger landscape management simulation models. Its adaptability makes it suitable for application ranging from tactical firefighting to strategic wildfire planning (Pais et al., 2021). By incorporating Cell2Fire into Eco-DRR and IFM strategies, Chilean wildfire management efforts can benefit from improved fire behaviour modelling, better risk assessment, and more effective fore mitigation planning.

While fire simulators provide valuable insights into wildfire behaviour, their strengths and limitation vary. For example, deep learning-based models enhance prediction accuracy by integrating satellite and meteorological data, but they require extensive training dataset and high computational power (He et al., 2023). CCA models, such as Cell2Fire, offer fast processing speeds and are cost-effective, but they may lack the precision of physics-based fire models (Pais et al., 2021). Finally, probabilistic models account for uncertainties in fire spread, making them highly useful for forecasting under variable conditions, but they may be less effective in complex landscapes with irregular terrain (Coen et al., 2024)

2.4 Context of Chile

2.4.1 CONAF, Protection Plans Against Wildfires and SENAPRED

The National Forestry Corporation (CONAF) is the primary governmental agency responsible for the management, conservation, and protection of Chile’s forest ecosystems. Operating under the Ministry of Agriculture, CONAF plays a crucial role in wildfire prevention, suppression, and post-fire recovery, particularly in fire-prone areas such as the WUI (CONAF, 2024b). Its main strategies focus on fuel management, controlled burns, public education campaigns, and community involvement to mitigate wildfire risk.

CONAF operates under several legal frameworks and strategy plans that define its responsibilities in wildfire management:

- **Forest Law N°20,283 (2008)**, where the agency is tasked to promote sustainable forest management, requiring measures to prevent and control wildfires, protect native forest, and ensure ecosystem conservation (Biblioteca del Congreso Nacional, 2008).
- **Supreme Decree N°276 (1980) - modified by Supreme Decree N°34 (2016)**, which establishes regulations for forest fire prevention and control, granting CONAF authority to impose fines on individual or companies that engage in illegal burning or negligence leading to wildfires.
- **Law N°20,653 (2013),** which strengthens CONAF's firefighting and prevention capabilities, allowing for increased funding, aerial firefighting support, and international collaboration in extreme fire events (Biblioteca del Congreso Nacional, 2013).

Regarding official documents and strategic plans, there are two crucial ones associated to wildfire prevention and ecosystem conservation:

- **National Strategy on Climate Change and Vegetation Resources : 2017-2025** (2016), which integrates wildfire risk reduction with broader efforts to conserve biodiversity and restore damaged ecosystems post-fires, which are responsibilities overseen by CONAF, and emphasized the role of climate adaptation, afforestation, and sustainable land-use planning to mitigate fire risk.
- **National Forest Fire Protection Plan**, which provides a framework for wildfire risk assessments, mitigation measures, and emergency response coordination at national, regional, and local levels. Likewise, encourages community participation, capacity-building, and landowner involvement in fire prevention initiatives (CONAF, n.d.).

As part of the National Forest Fire Protection Plan, CONAF developed local-level strategies called Communal Protection Plans (CCP), which aimed at preventing and managing wildfires within municipalities in Chile, particularly those located in high-risk areas, such as the WUI. These plans are created in collaboration with local governments and communities, integrating national wildfire protection efforts with local actions to enhance fire prevention and preparedness in vulnerable areas. Key components of CCPs include:

- **Risk Assessment and Zoning**, identifying fire-prone areas based on vegetation type, topography, and historical fire occurrences.
- **Prevention Measures**, like fuel management or implementing controlled burns, strategic thinning, and buffer zones to reduce fire spread potential.
- **Community Involvement and Education**, through conducting public awareness campaigns and emergency preparedness drills to strengthen local response capacity.
- **Public and Private Sector Collaboration**, engaging municipalities, businesses, and landowners in coordinated fire prevention strategies.

Even though Curacaví does not have a CPP by CONAF, the National Disaster Preparedness and Response Service (SENAPRED) plays a critical role in wildfire response by collaborating with CONAF, local municipalities, and emergency response teams. SENAPRED supports the design, coordination, and implementation of DRR plans in Chile. Curacaví approved in November 2024 the DRR Plan of the commune (Municipalidad de Curacaví, 2024b), aiming to enhance resilience at the communal level by identifying and addressing disaster risk through strategic actions. It includes measures for disaster prevention, preparedness, and response, involving various local authorities and community organizations. The plan also emphasizes the importance of community involvement and the development of human and social capital to effectively manage disaster risks. The plan details the roles and responsibilities of different stakeholders and provides a comprehensive overview of the disaster risk landscape in Curacaví, including natural and anthropogenic hazards. Regarding wildfires, the plan documented the need for community involvement in wildfire prevention and mitigation, including the removal of fine fuel, proper waste disposal, and the implementation of firebreaks.

Likewise, SENAPRED provides tools to every municipality to create their Emergency Communal Plan (Municipalidad de Curacaví, 2024a). These are focused on risk assessment, prevention measures, response strategies community education, and resource allocation. Particularly in the case of wildfire in Curacaví, the plan identifies wildfires as a significant risk, especially during the dry summer months. It highlights the areas most vulnerable to wildfires, such as those with dense vegetation and complex terrain. Furthermore, the plan emphasizes the importance of community education about wildfire risk and prevention measures, including public awareness campaigns, training programs, and community drills to ensure residents are prepared for wildfire emergencies.

2.4.2 Silvicultural Preventive Strategies

Silviculture preventive strategies are essential for reducing wildfire risk in Chile, aiming to manage forest fuels, enhance ecosystem resilience, and mitigate fire severity. These strategies encompass fuel treatments, prescribed burning, thinning, and firebreak, which have been globally recognised for lowering fire intensity by reducing vegetation density and fue loads (Zong et al., 2024). However, their effectiveness depends on site-specific conditions, fire regimes, and climate variability.

In Central Chile, controlling invasive shrubs as Teline monspessulana, Ulex europaeus, and Rubus ulmifolius has proven to significantly decrease fire intensity, flame length, and heat release per unit area. Additionally, biomass from these shrub has been repurposed for pellet production, offering both an energy alternative and wildfire risk reduction strategy (Espinoza-Monje et al., 2023).

While fuel reduction treatments generally lower wildfire risk, their implementation faces challenges under extreme drought conditions. Research highlights that drought intensify wildfire risk by drying out fuels, making even well-managed forest susceptible to large-scale fire events (Duarte et al., 2024). Therefore, adaptive silviculture is necessary, incorporating selection of fire-resistant and drought-adapted species in reforestation programs; ecosystem-based fire management, including riparian buffer zones to retain soil moisture; and improved hydrological interventions to counteract declining water availability are needed.

Chile’s forestry policies have historically played a significant role in shaping wildfire risk. The DL701 law, which subsidised afforestation, led to 13% increase in forested areas compared to non-subsidised scenarios (España et al., 2022). However, this policy has been criticised for promoting large-scale monoculture plantations of flammable exotic species, such as Pinus radiata and Eucalyptus spp., which may have contributed to increased wildfire hazards (Pérez & Simonetti, 2022). Without appropriate land-use planning and fuel management, such plantations can become high-risk fire corridors rather than wildfire mitigation tools.

Given Chile’s increasingly severe fire seasons, it is crucial to integrate continuous monitoring, adaptive management, and fire prediction technologies into silvicultural strategies. Remote sensing tools and fire simulations models (e.g., Cell2Fire) can help assess fuel loads, predict fire spread, and refine forest management plans. Additionally, strengthening CONAF’s regulatory oversight and ensuring fire-adaptive reforestation efforts will be key to mitigating future megafires.

3. Study Area

Curacaví, located in the Metropolitan Region of Chile, is a commune with a complex topography, consisting of valleys, hills, and steep slopes ranging from 250 to 700 meters of elevation (figure 1). This terrain plays a crucial role in wildfire dynamics, as fires tend to spread more rapidly uphill due to pre-heating effects (Morandini et al., 2018), making fire control efforts more challenging in elevated areas.

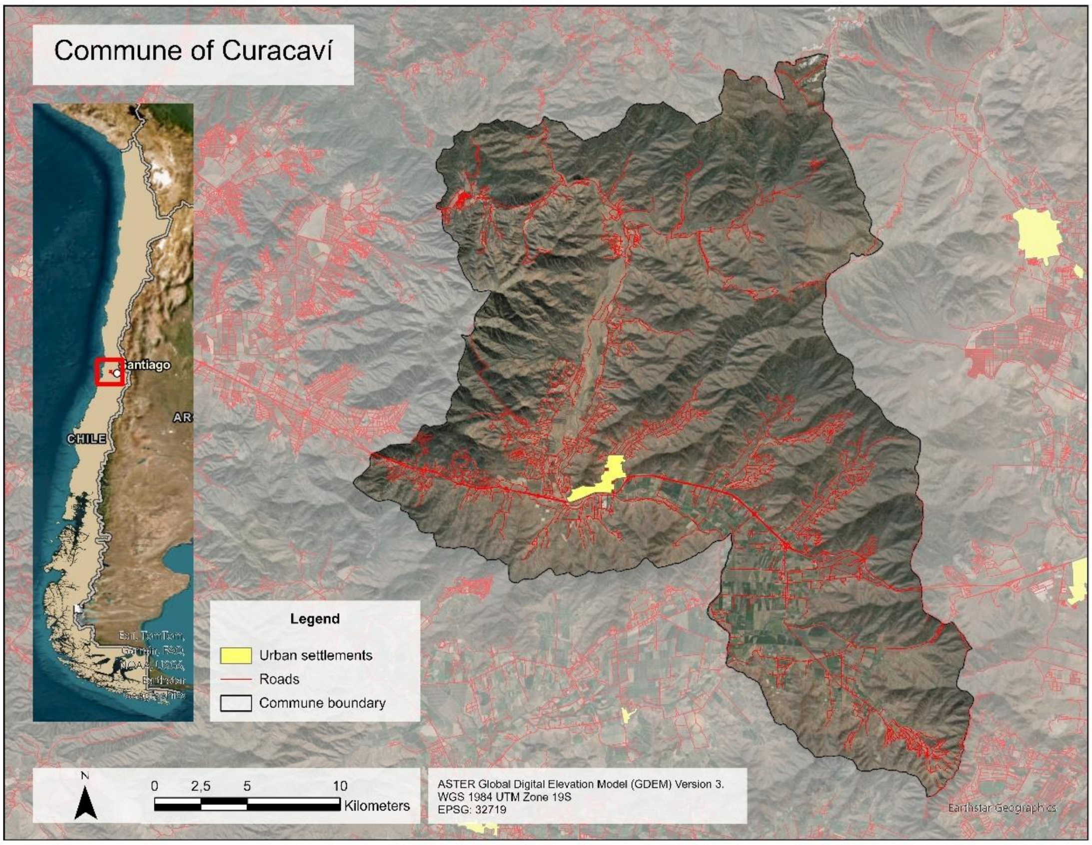

Figure 1: Curacaví commune location. Prepared by the author based on data from the Library of the National Congress.

The slope map below (figure 2) based on the Digital Elevation Model (DEM) from ASTER GDEM version 3, taken from 2000-03-01 to 2013-11-30 and updated on 2019-08-05, shows the significant variation in slope within Curacaví, suggesting a mix of valleys and hills. The central areas of Curacaví have mostly gentler slopes, while steeper slopes are found along the edges.

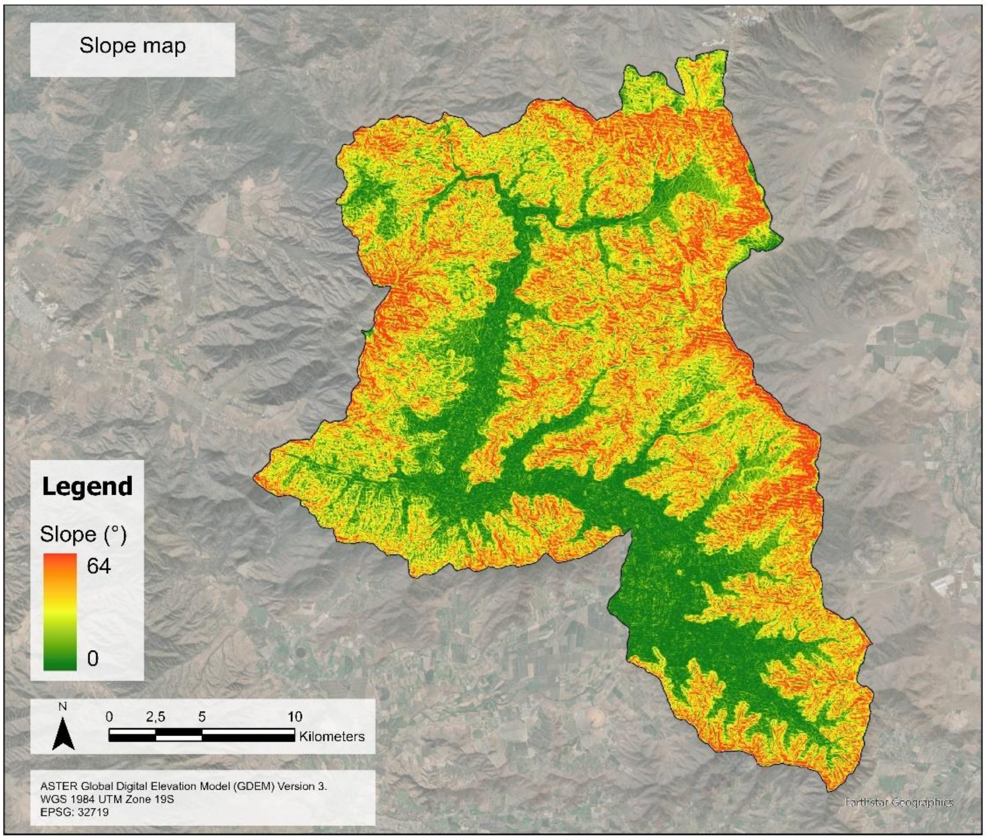

Figure 2: Curacaví slope map. Prepared by the author based on ASTER GDEM data.

Overall, steeper slopes can accelerate the upward spread of fire, considering as critical slope angle over 20°, due to dominance of convective heat transfer rather than radiative heat transfer (Sánchez-Monroy et al., 2019). On the other hand, the gentler slopes may allow slower rate of spread but could still pose a risk, especially in high fuel load areas.

3.1 Meteorological settings

Regarding climate, Curacaví experiences Mediterranean climate, with hot, dry summers and mild, wet winters (Meteorological Directorate of Chile, 2024). The fire season in Chile aligns with the hottest months, peaking between December and March, when temperatures frequently exceed 35°C, relative humidity drops, and strong wind facilitates fire spread.

Regarding historical climate trends (Meteorological Directorate of Chile, 2024) Curacaví shows record high temperatures over 38°C, increasing wildfire probability (table 1). Average summer temperatures frequently exceed 30°C, with minimal precipitation. In contrast, winter months (June to August) bring most of the annual rainfall, which supports vegetation growth that later becomes dry fuel. This seasonal climate pattern results in dry vegetation during summer months, making it highly flammable and increasing the risk of wildfires.

According to the Meteorological Directorate of Chile (DMC), in terms of temperature, the hottest period is concentrated between November and March, contributing to highly flammable vegetation, increasing the risk of wildfires. Moreover, January, February, and December consistently show the highest temperatures (table 1), often exceeding 35°C, with January 2019 recording a high of 38.7°C.

Table 1: Maximum temperature recorded by month between October 2015 and October 2024. Prepared by the author based on DMC data.

Year	January	February	March	April	May	June	July	August	September	October	November	December	Monthly maximum per year
2015	N/D	N/D	N/D	N/D	N/D	N/D	N/D	N/D	N/D	25.1	32.3	34.3	**34.3**
2016	35.1	35	35.1	26.2	26.6	21.9	22.1	24.7	31.6	31.5	36.4	37.9	**37.9**
2017	38.4	35.5	35.5	32.8	22.7	20	23.8	24.1	30.5	28.6	33	35.8	**38.4**
2018	35.7	37.8	33.7	28.6	28	23.8	22.2	26.1	29.5	28.6	35.2	31.2	**37.8**
2019	38.7	37.2	32.8	33.6	27.6	23	27.4	30.3	27.5	34.4	35.2	37.2	**38.7**
2020	35.6	35.6	36.1	N/D	29	18.6	N/D	25.6	23	29.8	33.9	34.3	**36.1**
2021	30.8	N/D	34.6	31.7	27.7	26.1	25.6	26.7	31.4	31.6	N/D	N/D	**34.6**
2022	N/D	34.1	32.4	31.2	27.7	17.8	21.3	28.8	27.3	31.5	34.5	37.5	**37.5**
2023	35.5	36.3	35.5	33.7	30.2	24	25.8	26.6	26.8	29.2	33	35.2	**36.3**
2024	38.1	37.1	33.6	33.1	21.8	21.6	24	23.7	28.2	31.7	33.9	35.6	**38.1**

Based on DMC records (Meteorological Directorate of Chile, 2024) the years 2017, 2019 and 2024 show particularly high summer temperatures, with multiple months exceeding 35°C, indicating intense summer heat. Furthermore, 2024 shows some similarities with 2019, in terms of maximal temperatures recorded, not only in January and February, but also in March and April. There is a clear annual variability, with some years showing slightly cooler or warmer trends. For instance, 2023 and 2024 indicate rising maximum temperatures, particularly in January and February, suggesting recent warmer years.

Regarding precipitation, rainfall is concentrated in winter months, between June and August, while summers are typically dry and prone to droughts. Throughout the years, the Meteorological Directorate of Chile (DMC) (2024) has recorded a decline in precipitation from 2016 until 2019, followed by a gradual increase, culminating in an abrupt rise in 2024 due to heavy rainfall period that affected the central zone of Chile in winter (figure 4).

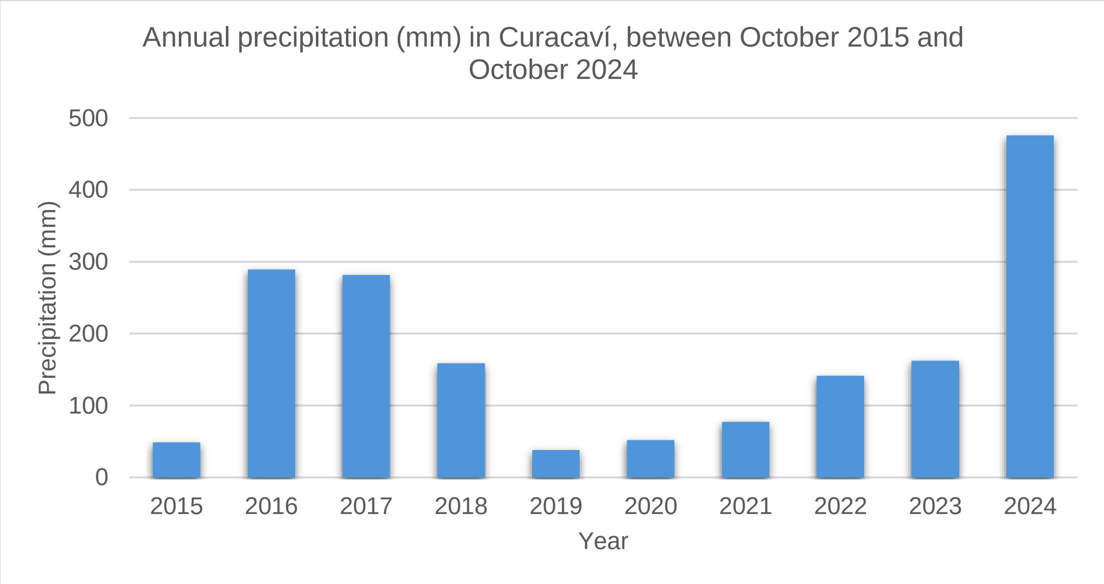

Figure 3: Annual precipitation records between October 2015 and October 2024. Prepared by the author based on DMC data.

There is a significant variability in annual precipitation throughout the years. Heavy rainfall records include 2016, 2017 and 2024, the latest showing a major increase. In contrast, 2019 and 2020 recorded very low precipitation, barely reaching 50 mm. Prolonged periods of low rainfall from 2018 to 2021 contributed to drier vegetation and higher wildfire risk due to the accumulated dry conditions. This low precipitation period likely increased fire risk as vegetation became more flammable due to lack of moisture. Conversely, high precipitation years, such as 2024, can lead to an increase in vegetation growth, which may serve later as additional fuel if followed by dry years.

Additionally, the terrain diversity influences wind patterns and can exacerbate fire spread in dry conditions. Based on DMC (2024) dataset, wind speed has remained relatively stable, ranging between 12 and 14 km/h except for 2021, when the average wind speed drop to 4 km/h (figure 5). Wind direction is predominantly westward (W) in most years, except in 2021, when it shifted to northwest (NW). This stable westward wind pattern generally influences fire behaviour by promoting fire spread in an eastward direction. The change to a NW direction in 2021 may have affected fire dynamics, potentially pushing fires towards different areas.

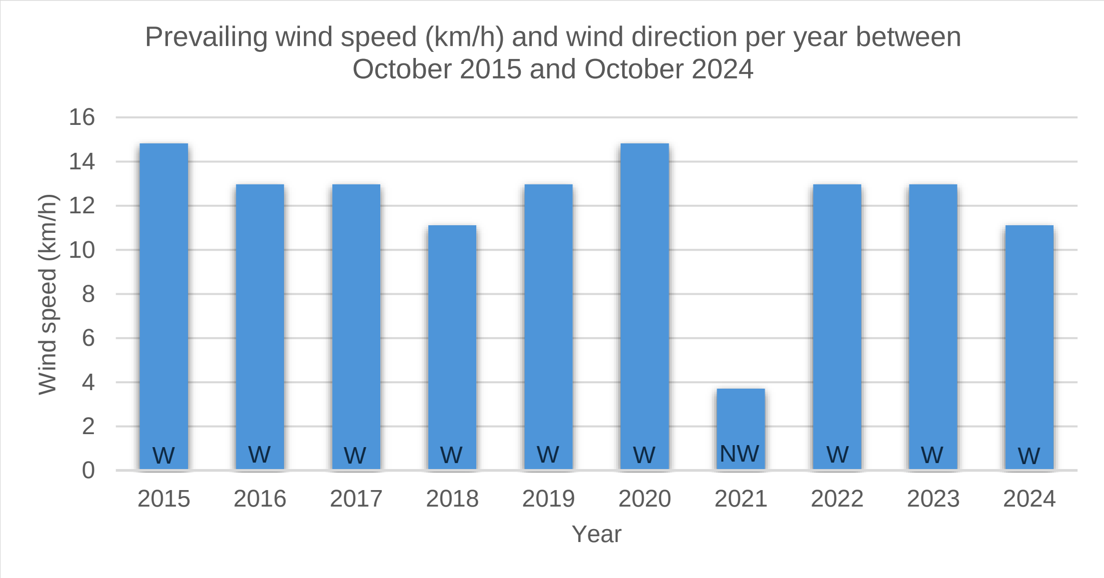

Figure 4: Wind patterns per year between October 2015 and October 2024 in Curacaví. Prepared by the author based on DMC data.

In terms of relative humidity, DMC recorded seasonal variation between October 2015 and December 2024 (table 2), when lower humidity has prevailed in November, December, January, and February, when humidity levels drop often below 35%.

Table 2: Monthly minimum relative humidity percentages (%) in Curacaví from October 2015 to December 2024. Prepared by the author based on DMC data.

Year	January	February	March	April	May	June	July	August	September	October	November	December	Monthly minimum per year
2015	31.8	42.8	35.8	48	61	77	75.3	69.3	62.8	47.3	39.5	37	**31.8**
2016	45	37.8	45.3	61.5	76.8	79.3	69.5	74	59	47.8	25.3	31.3	**25.3**
2017	31.8	42.8	35.8	48	61	77	75.3	69.3	62.8	47.3	39.5	37	**31.8**
2018	34.8	32.5	41	64	52.6	59.4	73.4	68.9	57.7	46.3	32.9	48.3	**32.5**
2019	37.9	38.9	36.3	46.1	43.6	59.7	73	58.2	39.6	27.7	37.3	26.1	**26.1**
2020	34.9	31.9	40.9	N/D	46.9	76.7	N/D	51.9	70.2	46.9	32.6	27.9	**27.9**
2021	45.2	N/D	49.7	54.7	55.4	63.6	51.4	53.9	43.7	39.3	39.3	N/D	**39.3**
2022	N/D	41.4	30.1	38.9	66.7	73.2	77.8	72.1	62.2	33.3	29.2	31.5	**29.2**
2023	35	35.9	35.2	35.9	63.2	N/D	N/D	70.9	67.2	54	45.8	39.2	**35**
2024	36.9	39.3	36.4	40.5	70.9	73.7	73.6	68.8	57.5	51	35.2	38.9	**35.2**

In particular, the years in 2016, 2019, 2020 and 2022 recorded consistently very low annual humidity averages (25.3%, 26.1%, 27.9% and 29.2%, respectively), suggesting drier conditions overall. These years correspond to periods of potentially higher fire risk due to less moisture in the air and vegetation.

3.2 Biodiversity settings

As a mediterranean landscape, Curacaví is especially affected by wildfires, particularly when weather conditions favour them with fast wind, high temperature and low humidity (Barrera et al., 2018). Therefore, megafires have a high probability of occurrence, endangering inhabited urban areas, especially under extreme weather linked to climate change (Azócar de la Cruz et al., 2022; Ferreira-Leite et al. 2015).

According to CONAF and CIREN (2019), the vegetation of the region includes native sclerophyll forest and mediterranean shrubland, as well as areas of eucalyptus plantations (figure 6). These introduced species are highly flammable and contribute to increased fire intensity and spread (Pettinari & Chuvieco, 2016). The fuel load of Curacaví consists of a mix of natural and planted vegetation, providing substantial biomass that can fuel large wildfires. Furthermore, the diversity of vegetation types, from low shrubs to dense plantations, makes fuel load management crucial for fire risk reduction.

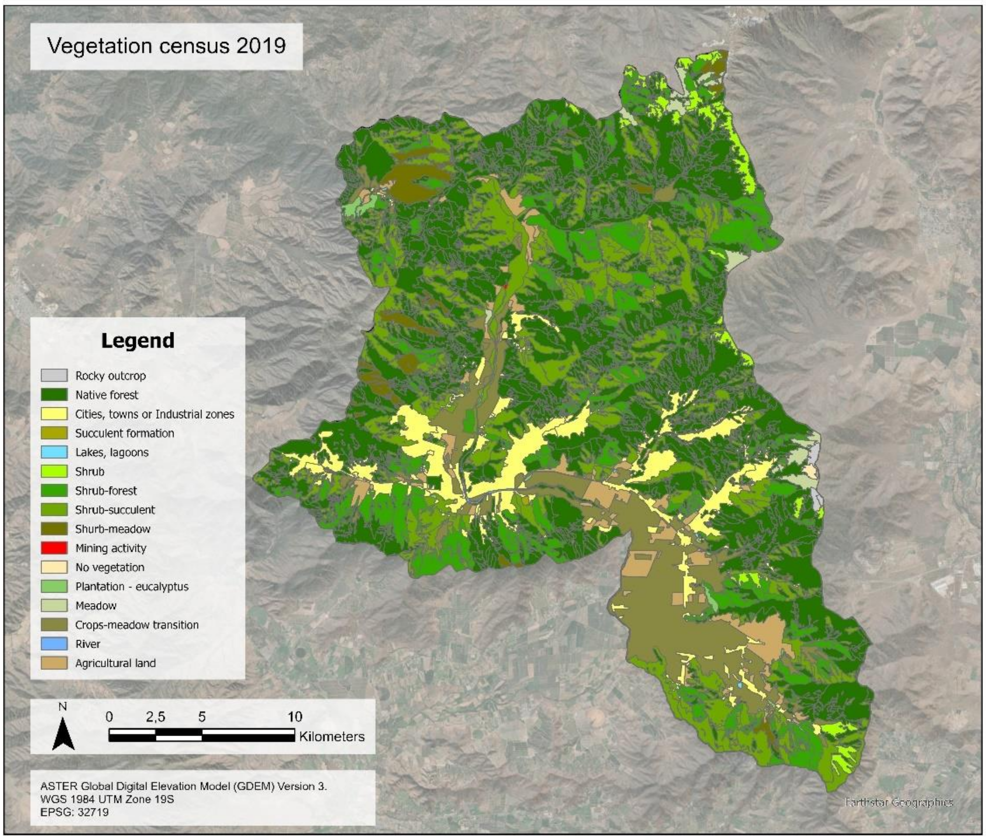

Figure 5: Vegetation census map of Curacaví. Prepared by the author based on 2019 CONAF data and CC BY 4.0 CIREN.

The 2019 Vegetation Census by CONAF and CIREN (2019) indicates a diversity of native vegetation, including sclerophyll forest, hawthorn, frangel, peumo, quillay, and litre. These species are common in Mediterranean ecosystems and known for their adaptability to dry conditions, dominating the landscape, particularly in the northern and central areas of Curacaví.

On the other hand, there are significant areas of eucalyptus plantations, particularly towards the southern (S) part of Curacaví. This type of tree is highly flammable due to their oily leaves and bark, which can intensify fires and increase the spread rate (Guerrero et al., 2022).

Based on the Global Fuelbed Dataset (Pettinari & Chuvieco, 2016), different types of vegetation and land cover had high levels of flammability, that is possible to find in Curacaví, represented in figure 7. For instance, **shrubs and sparse vegetation** are highly flammable especially under dry conditions; **grasses** are especially prone to ignition and rapid fire spread due to their fine structure and high surface-to-volume ratio; **crops**, typically present a lower fire risk compared to natural vegetation. However, dry agricultural lands at the end of the growing season can still ignite and contribute to fire spread; **broadleaf evergreen and deciduous trees** have a higher moisture content compared to shrubs and grasses, making them less flammable under normal conditions but becoming risky during drought periods.

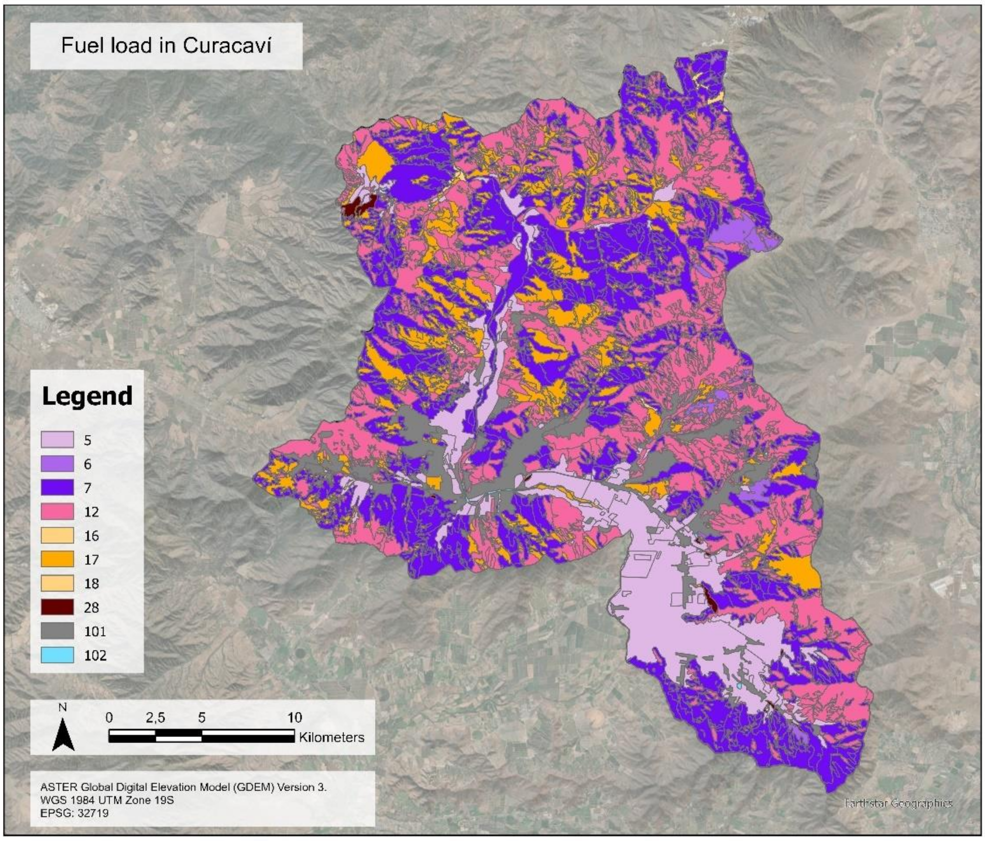

Figure 6: Fuel types in Curacaví. Prepared by the author based on CONAF Vegetation Census and Kitral Fuel Load classification, see table 4 for more details of fuel code.

Additionally, urban expansion in Curacaví has increased WUI zones (figure 7), heightening fire risk (Municipalidad de Curacaví, 2023). These areas are particularly vulnerable to wildfires due to the proximity of home and infrastructure to flammable vegetation. The land use in Curacaví includes a combination of agricultural lands, residential areas, industrial zones, and recreational spaces, which not only contribute to fire ignition risks but also complicate fire management (Municipalidad de Curacaví, 2023).

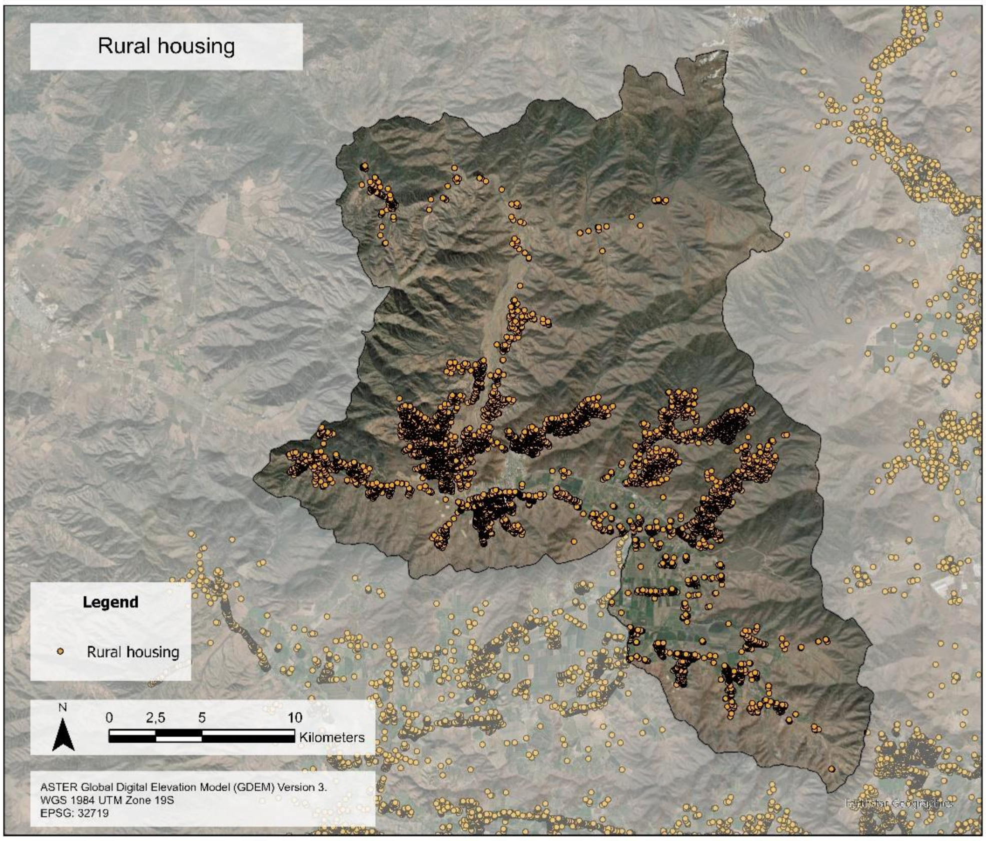

Figure 7: Expansion of WUI zones in Curacaví, through georeferenced rural housing. Prepared by the author based on demographic data from Census 2017.

3.3 Fire history

Curacaví has a documented history of seasonal wildfires (figure 8), with significant fire events recorded over the past decades (CONAF, 2024a). Major fires have burned extensive areas, driven by high fuel loads, dry summer conditions, and strong winds. The historical fire data highlights patterns of fire occurrence and spread, underscoring the need for effective fire management and Eco-DRR strategies in the commune.

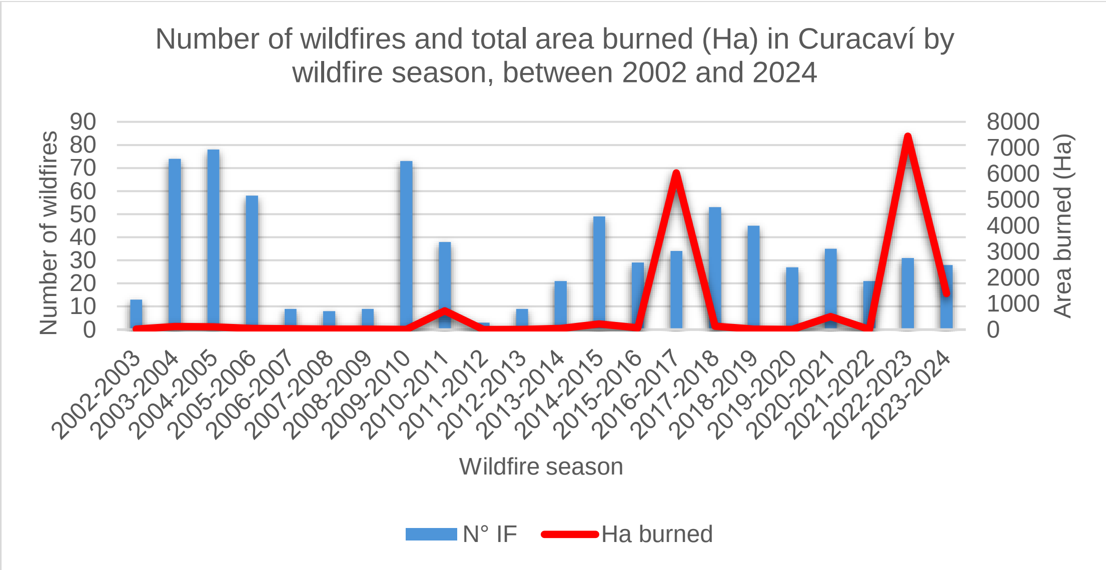

Figure 8: Number of wildfires and total area burned (Ha) in Curacaví by wildfire season, between 2002 and 2024. Prepared by the author based on CONAF data.

Based on CONAF data from 2002 to October 2024, the fire history of Curacaví includes detailed records of wildfires occurrences over 1 Ha, covering fire frequency, burned area, location, and meteorological conditions at the time of ignition.

Over this period, wildfire occurrence in Curacaví has shown cyclical peaks, particularly during the 2003-2006 and 2009-2011 fire seasons. After these periods, fire frequency stabilised, but an increasing trend in burned area was observed (figure 9).

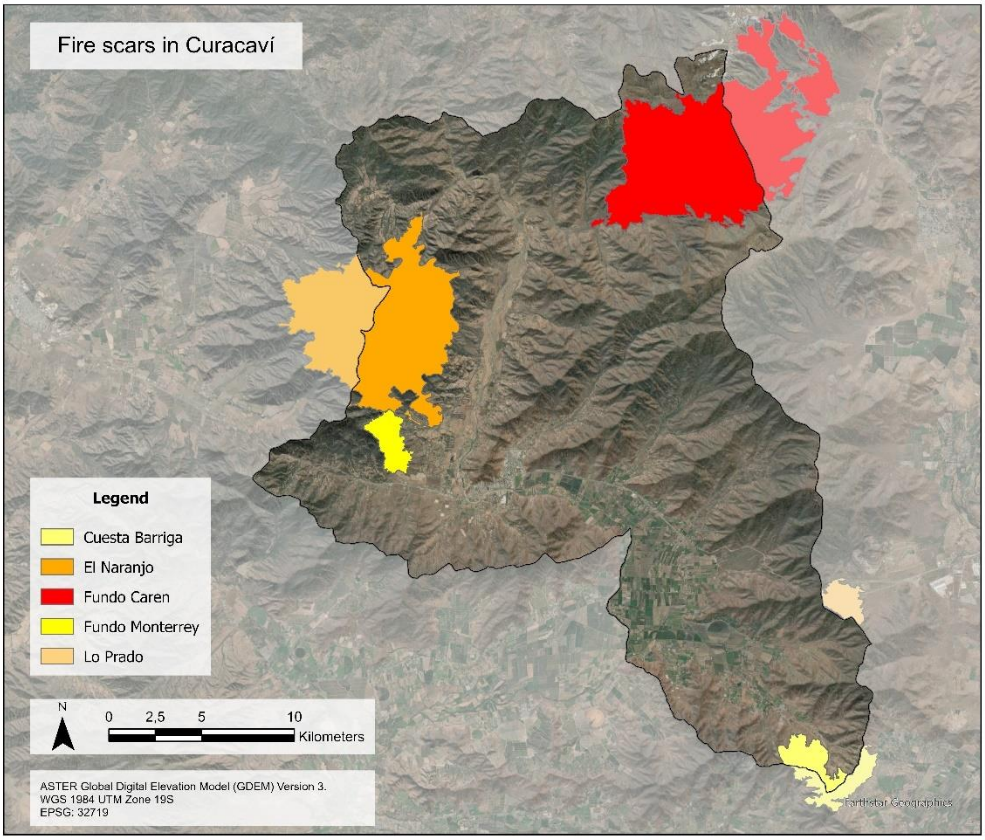

Figure 9: Fire history in Curacaví between 2002 to 2024, including ignition points and fire scars of the most relevant, recorded fires. Prepared by the author based on CONAF data.

Although Curacaví is not typically characterised by frequent large-scale fires, high-magnitude wildfires have become more common in recent years (table 3). The burned area has increased over the study period, with two major peaks occurring in the 2016-2017 and 2022-2023 fire seasons. The largest wildfire recorded was the Fundo Caren fire (2022), which burned 7,364.71 Ha, followed by El Naranjo (2017), which affected 5,904.90 Ha.

Table 3: Top big wildfires in Curacaví between 2022 and 2023, and their meteorological parameters. Prepared by the author based on CONAF data.

Date	Name	Hectares burned	Temperature (°C)	Relative humidity (%)	Wind speed (km/h)	Wind direction
14/12/2022	Fundo Caren	7,364.71	26	37	13	NW
18/01/2017	El Naranjo	5,904.90	26	31	13	W
19/12/2023	Cuesta Barriga	1,004.38	24	25	16	W
28/02/2021	Fundo Monterrey	483.7	30.6	18	15	SW
24/01/2024	Cuesta Lo Prado	367.21	29	26	8	W
02/04/2011	Hacienda Caren	350	11	78	N/D	N/D
03/01/2011	Cerro Bustamante	270	26	34	6	N/D

Interestingly, these large wildfires did not occur under extreme meteorological conditions, suggesting that other factor, such as fuel accumulation, land-use pattern, and human activity may play a more significant role in wildfire risk in Curacaví.

The geographic distribution of wildfires in Curacaví (figure 10) indicates that ignition points between 2002 and 2024 are concentrated in the western and central regions, particularly near the WUI.

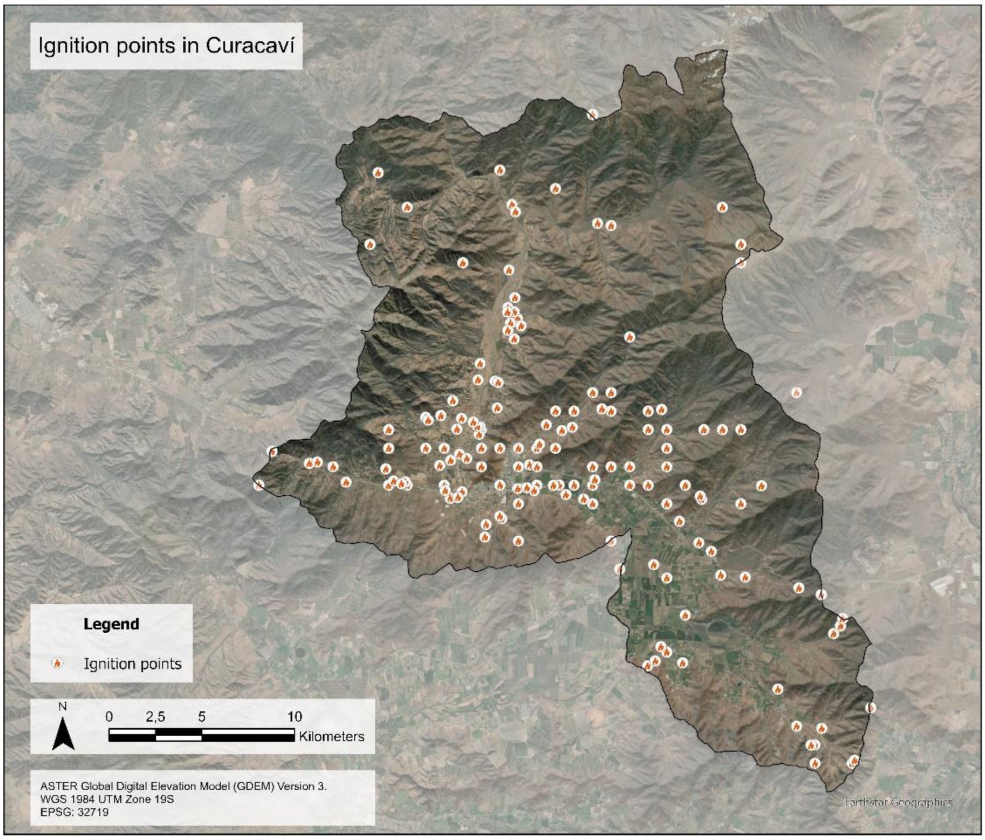

Figure 10: Ignitions points of wildfires beyond 1 hectare occurred in Curacaví from 2002 to 2024. Prepared by the author based on CONAF dataset.

4. Methodology

4.1 Data collection and preparation

This study employs a multi-faceted methodology to assess wildfire risk, the effectiveness of Eco-DRR strategies, and fire behaviour simulations in Curacaví, Chile. The methodology is structured into four main components: Data collection, Spatial analysis and fire risk assessment, Fire behaviour simulation using Cell2Fire, and Evaluation of Eco-DRR strategies.

4.1.1 Data Collection

Meteorological data

Meteorological data were obtained from the Meteorological Directorate of Chile (DMC), retrieved on October 27th, 2024. The dataset includes historical precipitation records, relative humidity, wind speed and wind direction levels of Curacaví, from the meteorological station number 330121 “Curacaví Ad.”, which have been registering data from October 2015 until October 2024 and so on. These meteorological variables are essential for understanding fire seasonality and identifying trend in extreme weather conditions that contribute to increase wildfire risk.

Fuel load data

The fuel load of Curacaví was created based on the Vegetation Census (CONAF & CIREN, 2019), retrieved on October 29th, 2024 and linked to the surface load model of Kitral classification (table 4), included in Cell2Fire simulator.

Table 4: Surface load model of Kitral and load fuel in Curacaví highlighted, retrieved from Cell2Fire (2021).

Code	Fuel Type	Name
1	PCH1	Pastizales Mesomorficos Densos
2	PCH2	Pastizales Mesoomorficos Ralos
3	PCH3	Pastizales Higromorficos Densos
4	PCH4	Pastizales Higromorficos Ralos
5	PCH5	Chacareria. Vinedos y Frutales
6	MT01	Matorrales y Arbustos Mesomorficos Densos
7	MT02	Matorrales y Arbustos Mesomorficos Medios y Ralos
8	MT03	Matorrales y Arbustos Higromorficos Densos
9	MT04	Matorrales y Arbustos Higromorificos Medios y Ralos
10	MT05	Formaciones con predominancia de Chuesquea spp
11	MT06	Formaciones con predominancia de Ulex spp
12	MT07	Renovales Nativos diferentes al Tipo Siempreverde
13	MT08	Renovales Nativos del Tipo Siempreverde
14	BN01	Formaciones con predominancia de Alerzales
15	BN02	Formaciones con predominancia de Araucaria
16	BN03	Arbolado Nativo Denso
17	BN04	Arbolado Nativo de Densidad Media
18	BN05	Arbolado Nativo de Densidad Baja
19	PL01	Plantaciones Coniferas Nuevas (0-3) sin Manejo
20	PL02	Plantaciones Coniferas Jovenes (4-11) sin Manejo
21	PL03	Plantaciones Coniferas Adultas (12-17) sin Manejo
22	PL04	Plantaciones Coniferas Mayores (>17) sin Manejo
23	PL05	Plantaciones Coniferas Jovenes (4-11) con Manejo
24	PL06	Plantaciones Coniferas Adultas (12-17) con Manejo
25	PL07	Plantaciones Coniferas Mayores (>17) sin Manejo
26	PL08	Plantaciones Eucaliptos Nuevas (0-3)
27	PL09	Plantaciones Eucaliptos Jovenes (4-10)
28	PL10	Plantaciones Eucalipto Adultas (>10)
29	PL11	Plantaciones Latifoliadas y Mixtas
30	DX01	Desechos Explotacion a Tala Rasa de Plantaciones
31	DX02	Desechos Explotacion a Tala Rasa de Bosque Nativo
100	Non-fuel	Not Available
101	Non-fuel	Non-fuel
102	Non-fuel	Water
103	Non-fuel	Unknown
104	Non-fuel	Unclassified
105	Non-fuel	Vegetated Non-Fuel

Topography data

To obtain topography data imagery from ASTER was downloaded, started on March 1st, 2000, ended on November 30th, 2013, and updated on August 5th, 2019. This data was retrieved from Earth Explorer by USGS on October 29th, 2024.

Historical Fire Data

Data on historical fire ignition in Curacaví was collected from CONAF (National Forestry Corporation, 2024) considering a period from 2002-2003 to 2023-2024 fire seasons. That information contains date, time, name, location, hectares burned, firefighting days, type of vegetation burned and meteorological data of every fire over 1 hectare occurred in Curacaví. This was retrieved on October 16th, 2024, in point and polygon feature shapefile. Besides, the most relevant fires in terms of burned area were compiled using the same dataset. This information allows the identification of high-risk areas and fire-prone periods, informing both fire simulation and risk assessment.

4.2 Fire hazard assessment

A fire risk model was developed by integrating meteorological, topographic, and vegetation-related variables using QGIS spatial analysis. The model evaluates fire **ignition probability** based on historical fire ignition and scar locations, **fire spread potential** considering slope (table 5) and wind exposure (table 6), and **fire severity hazard**, determined by fuel loads and climatic trends.

Through this Digital Elevation Model (DEM), Slope and Aspect were created using raster terrain analysis and reclassify process to set megafire probability levels where 3 is low and 1 is high probability.

Table 5: Slope categorisation and their assigned hazard level of megafires, made by the author.

Inclination (°)	Category	Megafire probability
0 – 10	Gentle	**3**
10 – 20	Moderate	**2**
20 – 30	Steep	**1**
30 >	Very steep	**1**

Table 6: Aspect categorisation and their assigned megafire probability, made by the author.

Degree (°)	Cardinal point	Megafire probability
0 – 22.5	North (N)	0
22.5 – 67.5	Northeast (NE)	1
67.5 – 112.5	East (E)	1
112.5 – 157.5	Southeast (SE)	0
157.5 – 202.5	South (S)	0
202.5 – 247.5	Southwest (SW)	0
247.5 – 292.5	West (W)	0
292.5 – 337.5	Northwest (NW)	0
337.5 - 360	North (N)	0

In the case of aspect, due to this research it was possible to identify that the prevailing wind direction in Curacaví is west (W). Therefore, for the purpose of this work only east (E) and northeast (NE) were considered into the simulation.

Likewise, using raster and reclassify tool to select only fuel present in Curacaví and fit it with the supported model in Cell2Fire, the criteria to consider megafire probability from 3 (low) to 1 (high) is shown in table 7.

Table 7: Fuel load data of Curacaví, made by the author based on Vegetation Census (CONAF, 2019) and Kitral fuel load model.

Code	Fuel Type	Name	Name (English)	Megafire probability
5	PCH5	Chacareria. Vinedos y Frutales	Farming, Vineyards and Fruit Trees	**2**
6	MT01	Matorrales y Arbustos Mesomorficos Densos	Dense Mesomorphic Shrubs and Bushes	**1**
7	MT02	Matorrales y Arbustos Mesomorficos Medios y Ralos	Medium and Rare Mesomorphic Shrubs and Bushes	**2**
12	MT07	Renovales Nativos diferentes al Tipo Siempreverde	Native Non-Evergreen Renewals	**2**
16	BN03	Arbolado Nativo Denso	Dense Native Trees	**2**
17	BN04	Arbolado Nativo de Densidad Media	Medium Density Native Trees	**3**
18	BN05	Arbolado Nativo de Densidad Baja	Low Density Native Trees	**3**

28	PL10	Plantaciones Eucalipto Adultas (>10)	Adult Eucalyptus plantations (>10)	**1**
101	Non-fuel	Non-fuel	Non-fuel	**0**
102	Non-fuel	Water	Water	**0**

Finally, the probability map was created through raster calculator using the proportion defined in table 8, in which fuel load was considered as primary driver with 40% due its influencing in both intensity and spread of wildfires. High fuel loads provide more material for combustion, increasing the likelihood of a fire escalating into a megafire (Gray et al., 2018; Parks et al., 2012). Followed by slope giving it 25%, and taking into account the topography in Curacaví, which affects the rate of fire spread, with steeper slopes facilitating faster fire movement due to preheating of fuel upslope (Conedera et al., 2024; Parks et al., 2012). Aspect and Fire scars were next with 15%, because aspect influences microclimatic conditions such as sunlight exposure and wind patterns, although it depends directly on fuel moisture (Nyman et al., 2015) and fire scars influence on fire probability is less significant compared to other factors (Jaafari et al., 2019). Finally, ignition points were assigned 5% since their influence on the probability of fire becoming a megafire is minor compared to the other variables (Parks et al., 2012).

Table 8: Weight defined to each variable to create the probability map of megafire occurrence, made by the author.

Variable	Weight (%)
Fuel load	40
Slope	25
Aspect	15
Fire scars	15
Ignition point buffers	5

Using these inputs, a probability map was generated to visualise high-probability zones and identify priority areas for mitigation strategies. This map indicates where a megafire is likely to ignite and spread more easily as an input for the simulation that follows, high probability areas for megafires spread provided a foundation for the predictive model.

4.3 Predictive model using Cell2Fire

4.3.1 Cell2Fire fire simulator

In Chile, a variety of advanced technologies is employed in its fire simulators to enhance the accuracy and efficiency of wildfire prediction and management. One of the most renowned is the KITRAL System, developed by the Forest Fire Laboratory at the University of Chile, which uses statistical validation to compare simulated fire with real events, achieving high levels of accuracy for larger fires (Castillo Soto & Garfias Salinas, 2014).

Furthermore, open-source frameworks are being developed to facilitate numerical simulations in Chilean wildfires, incorporating partial differential equations. One of those open sources is called Cell2Fire, which is a sophisticated, cell-based wildland fire growth simulator designed to integrate data-driven decision-making models, particularly useful for forest and wildland landscape management in Chile and beyond (Pais et al., 2021). The simulator partitions the landscape into numerous cells, each characterized by specific attributes such as fuel, weather, moisture, and topography, allowing for detailed and accurate modelling of fire environments (*Cell2Fire*, 2021).

Cell2Fire requires several key inputs to function effectively, including forest raster data that details the geographical coordinates and attributes of each cell, such as fuel type and topography. It also utilizes a fuel-type dictionary aligned with the Canadian Fire Behaviour Prediction (FBP) System, ignition points for fire initiation, and weather data streams from nearby fire weather stations (*Cell2Fire*, 2021).

The outputs of the simulator are used to inform forest management decisions, such as harvesting and fuel treatment plans, by evaluating the impact of these interventions on fire behaviour (*Cell2Fire*, 2021). Furthermore, Cell2Fire has been used in comparative studies with other fire simulation models, such as Prometheus, to validate its accuracy and reliability in simulating fire growth across different landscape conditions, the results showed that Cell2Fire could accurately predict the growth of both real and hypothetical fires, demonstrating its reliability, offering insight into fire behaviour and management strategies that can help mitigate the impact of wildfires on forest ecosystems (Pais et al., 2021).

These days, Cell2Fire (2021) has been integrated into QGIS through the Fire Analytics Toolbox plugin, which allows users to simulate wildfires and analyse several risk metrics with a user-friendly interface. The simulator supports three behaviour models such as Scott & Burgan, which is primarily used in Australia; Kitral, mostly used in Chile; and the Canadian Forest Fire Behaviour Prediction System, used in Canada. Their outputs simulated fire spread with scar and growth propagation tree, together with risk metrics such as Burn Probability (BP), which was used in the present research.

Key features of Cell2Fire are parallel computation, utilising parallel processing to handle large-scale simulations effectively; QGIS integration, offering a graphical interface within QGIS for setting up simulation, running analyses, and visualizing results. However, the first step to run simulations is the preparation of the input data, obtaining or creating the necessary input data, which include fuel type, elevation data and weather information.

4.3.2 Scenario 1: Baseline condition for megafire likelihood and spread

To perform the simulation by Cell2Fire every georeferenced data was set in WGS 84 / UTM zone 19S EPSG: 32719 and resampled them to the same cell size (26.8 and -26.8) and dimension (X: 1244 Y: 1489).

The simulator is split into three sections to input parameters. The first one, named Landscape Section, was necessary to select the surface fuel model. In this case, the

Kitral model was chosen, developed by the Faculty of Forestry and Nature Conservation Sciences of the University of Chile in the middle of the 90's, whose algorithm is still used in modern predictive models such as Cell2Fire. Likewise, surface fuel model previously created and elevation data from Digital Elevation Model are selected.

Next, the second section corresponds to Ignition, where 200 simulations were set and the generation mode selected is the probability map that was created.

Finally, the third section is Weather, where weather scenarios were set. For this purpose, five scenarios were created based on meteorological data of DMC dataset intensifying minimal or maximal values of one variable per scenario, considering Wind speed (WS) (table 9), Wind direction (WD) (table 10), Temperature (TMP) (table 11), and Relative Humidity (RH) (table 12), keeping the rest of variables in normal to no beneficial values for wildfire ignition and spread, and one last scenario which considers the worst case with the extreme values of every variable put all together (table 13). These scenarios are set in periods of 14 hours, each hour represented by one row.

Table 9: Scenario with fast wind speed (WS), keeping wind direction (WD), temperature (TMP) and relative humidity (RH) in values that do not trigger wildfires in Curacaví, made by the author based on DMC dataset.

Scenario	WS	WD	TMP	RH
WS	**10.7**	134	10.3	56.3
WS	**11.8**	149	12.4	54.7
WS	**12.6**	124	13.7	47.9
WS	**14.8**	118	14.8	42.8
WS	**16.1**	250	19.5	45.7
WS	**10.5**	145	22.1	46.8
WS	**12.3**	173	23.1	47.7
WS	**12.7**	134	22.4	41.5
WS	**13.7**	179	20.6	48.6
WS	**15.9**	165	18.4	49.9
WS	**16.8**	137	15.9	54.7
WS	**12.5**	185	12.7	63.6
WS	**13.7**	150	11.9	79.1
WS	**13.5**	183	8.3	87.3

Table 10: Scenario with wind direction E and NE, keeping wind speed (WS), temperature (TMP) and relative humidity (RH) in values that do not trigger wildfires in Curacaví, made by the author based on DMC dataset.

Scenario	WS	WD	TMP	RH
WD	5.3	**25.7**	10.3	56.3
WD	5.9	**46.8**	12.4	54.7
WD	7.9	**67.4**	13.7	47.9
WD	8.1	**78.3**	14.8	42.8
WD	7.5	**68.4**	19.5	45.7
WD	8.7	**78.3**	22.1	46.8
WD	9.2	**110.2**	23.1	47.7
WD	9.7	**53.1**	22.4	41.5
WD	6.4	**89**	20.6	48.6
WD	3.8	**75.3**	18.4	49.9
WD	6.2	**100.1**	15.9	54.7
WD	9.6	**49.9**	12.7	63.6
WD	10	**37.2**	11.9	79.1
WD	6.8	**99.1**	8.3	87.3

Table 11: Scenario with high temperatures (TMP), keeping wind direction (WD), wind speed (WS) and relative humidity (RH) in values that do not trigger wildfires in Curacaví, made by the author based on DMC dataset.

Scenario	WS	WD	TMP	RH
TMP	5.3	134	**28.2**	56.3
TMP	5.9	149	**29.7**	54.7
TMP	7.9	124	**30.3**	47.9
TMP	8.1	118	**32.8**	42.8
TMP	7.5	250	**35.8**	45.7
TMP	8.7	145	**38.7**	46.8
TMP	9.2	173	**37.9**	47.7
TMP	9.7	134	**37.8**	41.5
TMP	6.4	179	**35.4**	48.6
TMP	3.8	165	**31.1**	49.9
TMP	6.2	137	**26.5**	54.7
TMP	9.6	185	**24.2**	63.6
TMP	10	150	**22.5**	79.1
TMP	6.8	183	**20.7**	87.3

Table 12: Scenario with low relative humidity (RH), keeping wind direction (WD), wind speed (WS) and temperatures (TMP) in values that do not trigger wildfires in Curacaví, made by the author based on DMC dataset.

Scenario	WS	WD	TMP	RH
RH	5.3	134	10.3	**35.1**
RH	5.9	149	12.4	**33.6**
RH	7.9	124	13.7	**30.5**
RH	8.1	118	14.8	**28.3**
RH	7.5	250	19.5	**27.5**
RH	8.7	145	22.1	**26.8**
RH	9.2	173	23.1	**25.1**
RH	9.7	134	22.4	**26.7**
RH	6.4	179	20.6	**28.1**
RH	3.8	165	18.4	**28.6**
RH	6.2	137	15.9	**29.7**
RH	9.6	185	12.7	**30.2**
RH	10	150	11.9	**33.2**
RH	6.8	183	8.3	**35.8**

Table 13: Worst-case scenario, in which relative humidity (RH), wind direction (WD), wind speed (WS) and temperatures (TMP) get values that trigger wildfires in Curacaví, made by the author based on DMC dataset.

Scenario	WS	WD	TMP	RH
WORST	10.7	25.7	28.2	35.1
WORST	11.8	46.8	29.7	33.6
WORST	12.6	67.4	30.3	30.5
WORST	14.8	78.3	32.8	28.3
WORST	16.1	68.4	35.8	27.5
WORST	10.5	78.3	38.7	26.8
WORST	12.3	110.2	37.9	25.1
WORST	12.7	53.1	37.8	26.7
WORST	13.7	89	35.4	28.1
WORST	15.9	75.3	31.1	28.6
WORST	16.8	100.1	26.5	29.7
WORST	12.5	49.9	24.2	30.2
WORST	13.7	37.2	22.5	33.2
WORST	13.5	99.1	20.7	35.8

Based on these inputs, four results were generated, utilizing each meteorological variable in order to determine which one is more relevant for ignition and spread of megafires. However, only the worst-case scenario was considered to analyse the impact of Eco-DRR mitigation strategies.

4.3.3 Scenario 2: impact of Eco-DRR interventions on Fire Spread

Eco-DRR integrates strategies such as firebreaks and fuel management (including thinning vegetation). To firebreaks setting it was used burn propagation map of the worst-case scenario named previously, to position them in high-risk areas near to rural settlements or in zones where burn probability was high.

In case of fuel management, there were two modifications incorporated to the fuel data. Thinning dense mesomorphic shrubs and bushes for medium and rare mesomorphic shrubs and bushes to reduce fuel loads, and fuel management, replacing native non-evergreen renewals with low-density native trees, reducing hierarchy fuels and creating discontinuities in vegetation. These adjustments are registered in the table 14.

Table 14: Modified fuel load to include Eco-DRR strategies in Curacaví, made by the author based on Vegetation Census (CONAF, 2019) and Kitral fuel load model.

Code	Fuel Type	Name	Name (English)	Original Risk level	Eco-DRR risk level
5	PCH5	Chacareria. Vinedos y Frutales	Farming, Vineyards and Fruit Trees	**2**	**2**
6	MT01	Matorrales y Arbustos Mesomorficos Densos	Dense Mesomorphic Shrubs and Bushes	**1**	**2**
7	MT02	Matorrales y Arbustos Mesomorficos Medios y Ralos	Medium and Rare Mesomorphic Shrubs and Bushes	**2**	**2**
12	MT07	Renovales Nativos diferentes al Tipo Siempreverde	Native Non-Evergreen Renewals	**2**	**3**
16	BN03	Arbolado Nativo Denso	Dense Native Trees	**2**	**2**
17	BN04	Arbolado Nativo de Densidad Media	Medium Density Native Trees	**3**	**3**
18	BN05	Arbolado Nativo de Densidad Baja	Low Density Native Trees	**3**	**3**
28	PL10	Plantaciones Eucalipto Adultas (>10)	Adult Eucalyptus plantations (>10)	**1**	**1**
101	Non-fuel	Non-fuel	Non-fuel	**0**	**0**
102	Non-fuel	Water	Water	**0**	**0**

5. Results

This chapter presents the results of the analysis on fire behaviour and the effectiveness of Eco-DRR strategies.

5.1 Megafire probability areas

The megafire probability model incorporates multiple fire risk variables, each contributing to wildfires spread dynamics: **aspect**, including northeast (NE) and east (E) facing slopes due their increased solar exposure in the morning, leading to vegetation drying faster and higher ignition risk, especially under dry and windy conditions; **slope**, considering steep (20-30°) and very steep (>30°) slopes as they accelerate fire spread due to increased preheating and convective heat transfer. These areas are primarily found along ridges, valley edges, and mountainous regions; **fire scars** of three major wildfires. These fires mainly occurred in hilly regions, where topography likely influenced fire spread; **fuel types** based on vegetation reclassified by flammability according to table 7; and **ignition points** with 10 km buffer of wildfires between 2002 and 2024.

The result is the following map (figure 11) representing the probability of megafire occurrence in Curacaví, generated using QGIS raster analysis that integrated key fire risk variables. The colours scale represents the probability of megafire occurrence, ranging from low probability (green) to high probability (red).

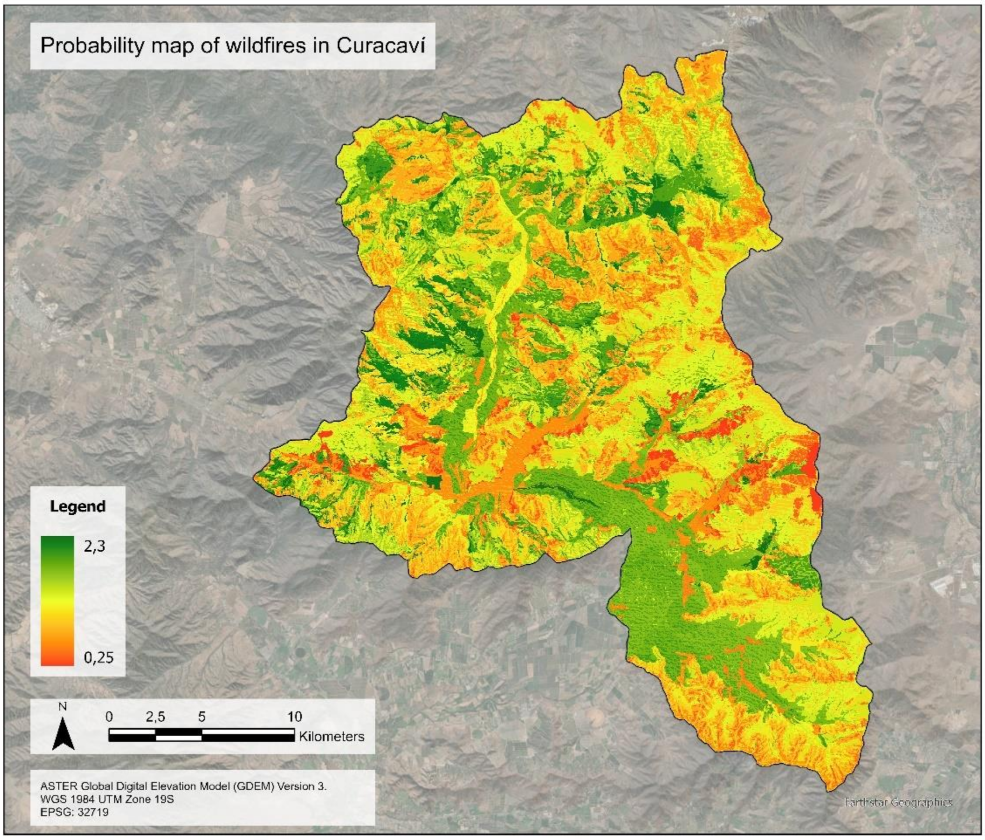

Figure 11: Probability of wildfire occurrence in Curacaví, based on high temperature, low relative humidity, strong wind and prone wind direction. Prepared by the author based on DMC dataset.

The high-probability areas are concentrated in the northern (N) and eastern (E) areas of Curacaví, as well as along major ridges and valleys. These areas are characterised by high fuel loads, steep slopes and aspect orientation that promote fire spread through increased solar radiation or prevailing wind exposure.

The moderate-probability areas are found on gentler slopes with moderate fuel loads, while low-probability areas are primarily found in the southern (S) and central valley regions, as well as urbanised zones, where vegetation is sparse, actively managed through agricultural or limited by urbanised zones.

These insights highlight the importance of proactive fire management, particularly in high-probability zones, to mitigate potential megafires events in Curacaví.

5.2 Model validation

The megafire probability model was validated by comparing the simulated fire spread results with historical fire occurrence data. Specifically, the high-probability areas identified in the model closely align with previously recorded fire scars in Curacaví. This spatial correlation suggests that the model accurately captures key environmental and topographic conditions that contribute to wildfire spread.

The validation process involved overlaying historical fire scars (recorded by CONAF between 2002 and 2024) with the predicted high-probability zones. The results indicate that areas classified as high probability in the model correspond to past wildfire events, particularly in regions with high fuel loads, steep slopes, and favourable aspect orientation. Additionally, ignition points from historical data were predominantly within or near these high-probability areas, reinforcing the predictive reliability of the model.

While the model effectively reflects historical fire patterns, further refinement could incorporate real-time fire spread dynamics and ignition probability under varying meteorological conditions. Future validation efforts could involve testing the model against recent or ongoing fire events to assess its predictive accuracy under different climatic scenarios.

5.3 Baseline Megafire probability

After running 200 wildfire simulation in Curacaví under extreme meteorological conditions (isolated or combined) to assess megafire probability, the results are displayed by variable and for a worst-case scenario, in which all the meteorological factors reach their more triggering recorded values since 2015, based on DMC dataset.

5.3.1 Relative humidity

Among the meteorological variables analysed, relative humidity (RH) plays a key role in fire behaviour. The following section presents the RH-based burn probability distribution across Curacaví.

Burn probability under low RH conditions is concentrated in the northern and central regions of Curacaví, where steep terrain with high fuel loads dominates. This pattern suggests that low RH significantly increases fire ignition and spread, especially in densely areas.

The colour gradient in figure 12 represents a burn probability, with red areas reaching up to 18% and green zones indicating probabilities as low as 0.5%. The spatial distribution of burn probability under low RH conditions aligns with previous fire-prone areas, with high burn probability (HPB) zones concentrated in steep terrains with dense vegetation, particularly near the Fundo Caren fire scar. Conversely, low burn probability (LBP) is concentrated in southern and valley areas, where flatter terrain, sparse vegetation and agricultural or urban land use act as natural fire buffers.

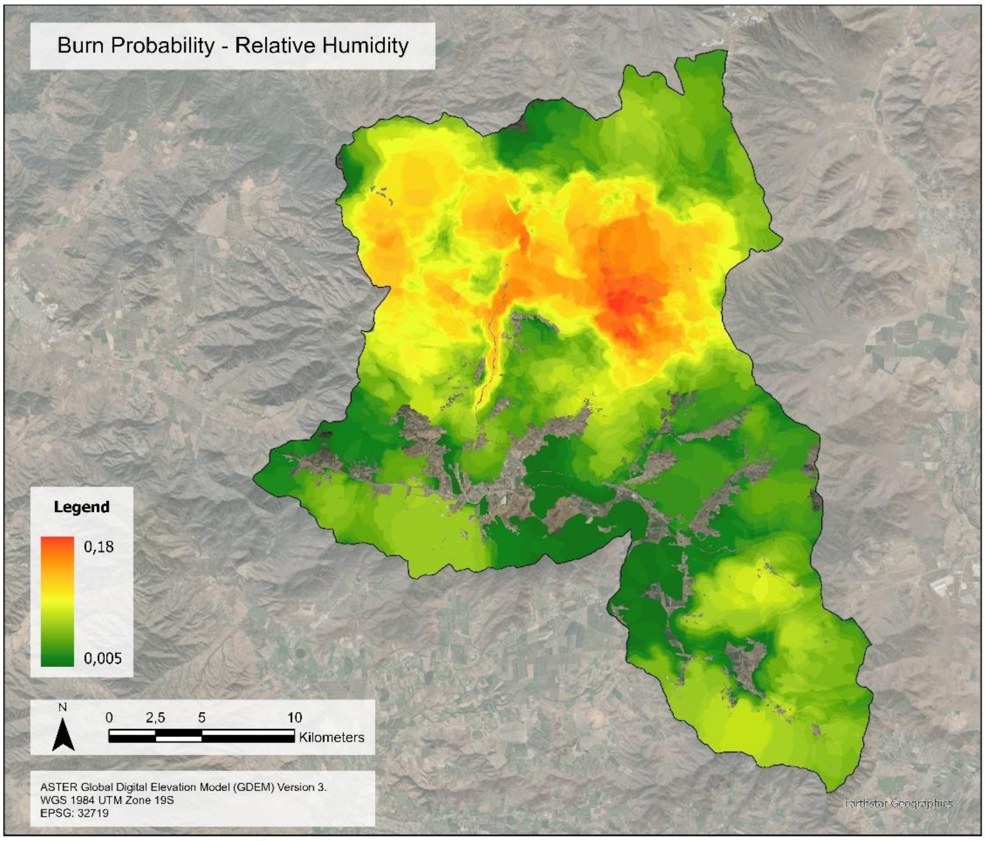

Figure 12: Result of simulation: Burn probability of isolated low relative humidity. Prepared by the author

These results underscore the importance of considering RH in fire risk assessment, particularly in high-fuel, steep-slope regions where fire suppression efforts may be more challenging.

5.3.2 Temperature

To assess the influence of high temperatures on megafire probability, the model was adjusted to isolate temperature as the primary variable. The results indicate that HBP areas are concentrated in the north-central part of Curacaví (figure 13). However, the affected area is significantly smaller compared to RH scenario.

Likewise, the burn probability in this scenario is lower than in the previous simulations, with high probability areas reaching only 3%. This suggests that while high temperatures contribute to wildfire risk, their impact is not as pronounced in isolation as other factors like fuel load, which reached high probability of 18%. LBP areas are widespread across the entire study area, reinforcing the idea that temperature alone is not the dominant driver of megafire probability but rather acts in conjunction with other environmental variables.

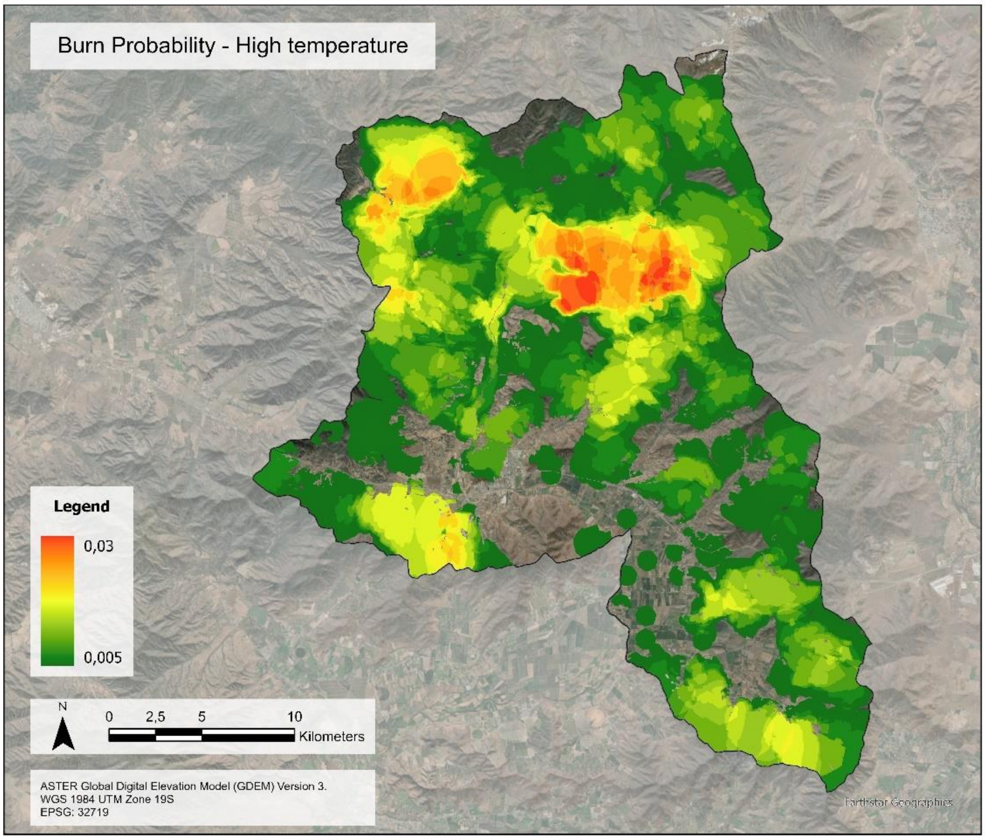

Figure 13: Result of simulation: Burn probability of isolated high temperature. Prepared by the author

5.3.3 Wind direction

When isolating wind direction (WD), HBP areas are concentrated in the northern-central part of Curacaví. However, their extent is smaller compared to RH scenario, with a maximum burn probability of 7.5% (figure 14).

Once again, HBP is concentrated in areas with steep slopes, suggesting that specific wind direction aligns with topography and fuel availability to enhance fire spread potential.

Moderate burn probability (MBP) is less extensive than in the low RH and high temperature scenarios, reinforcing the idea that wind direction alone has a limited impact on fire spread.

Finally, LBP dominates most of the study area, particularly in valleys and lower elevation where vegetation is less flammable. The widespread presence of low burn probability areas indicates that, without high wind speeds, extreme temperatures, or low humidity, wind direction alone has minimal influence on fire ignition and spread.

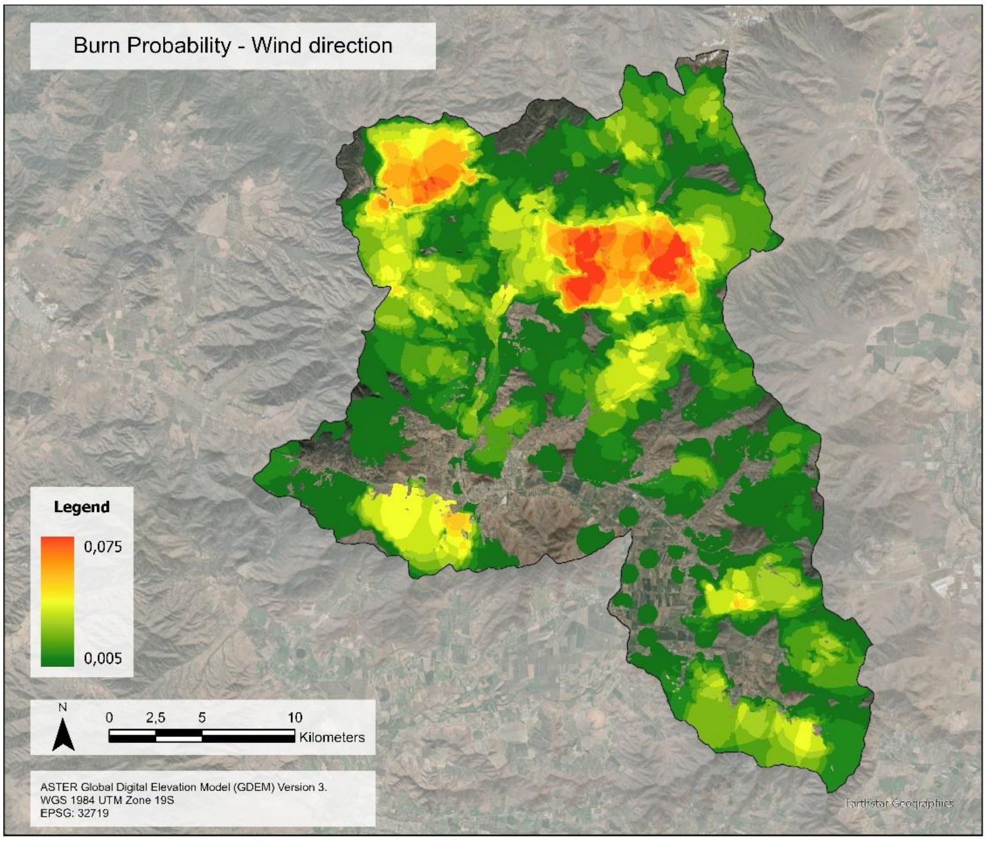

Figure 14: Result of simulation: Burn probability of isolated wind direction. Prepared by the author.

5.3.4 Wind speed

Isolating wind speed from wind direction, temperature and relative humidity reveals HBP concentrated in the northern-central and northwestern areas of Curacaví (figure 15). This suggests that wind speed enhances fire propagation when specific terrain and fuel conditions are met, but its impact is less pronounced compared to low RH. The results indicate that wind speed alone does not significantly trigger megafire risk unless compounded by other factors such as high temperature and low RH.

MBP appears in specific corridors, likely where fuel loads and topographic features facilitate wind-drive fire spread, particularly along ridges and valleys. However, low burn probability dominates most of the study area, particularly in valleys, lower slopes, and fragmented vegetation zones. The scattered distribution of LBP areas suggests that fuel availability and topography act as limiting factors, reducing the extent of wind-driven fire spread. This confirms that while wind speed influences fire behaviour, it does not independently generate widespread megafire risk without additional environmental stressors.

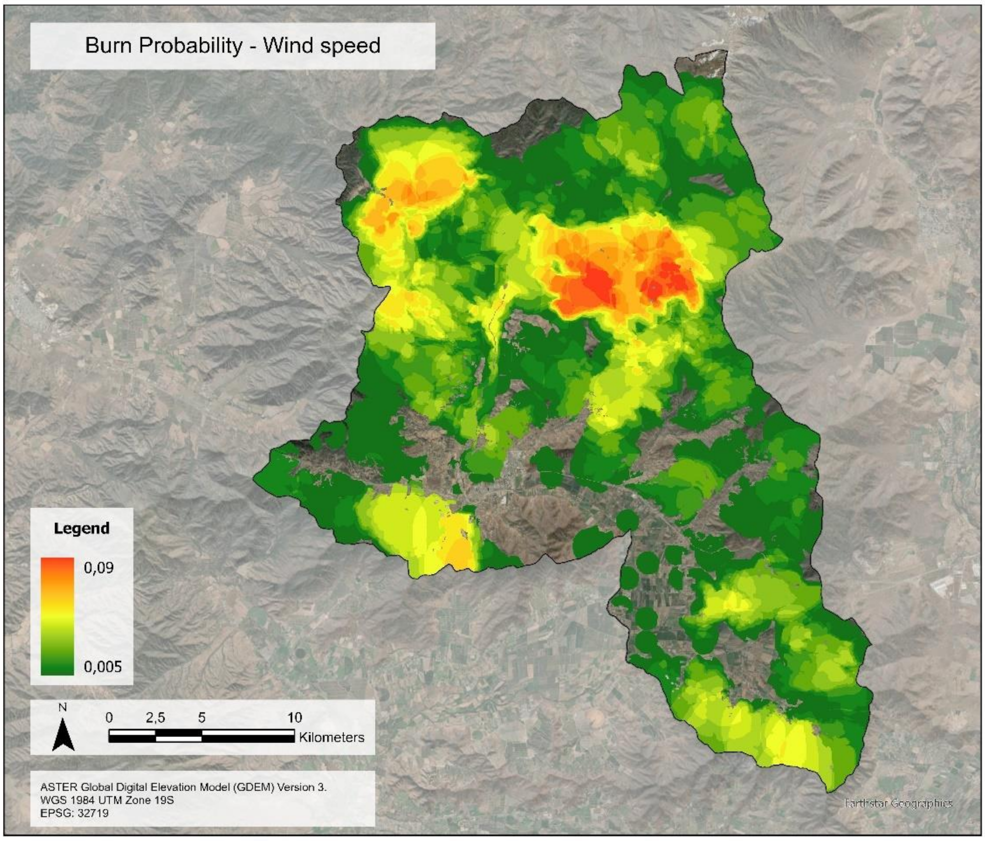

Figure 15: Result of simulation: Burn probability of isolated strong wind speed. Prepared by the author.

5.3.5 Worst-case scenario

The worst-case scenario was built considering low relative humidity, high temperatures, northeast and east wind direction and high wind speed. HBP is concentrated in the Northern and central areas of Curacaví, where the terrain, fuel load, and wind alignment create conditions for rapid and intense fire spread (figure 16). The expansion of HBP zones compared to individual variable simulation confirms that megafire behaviour is a product of multiple compounding factors. The strongest burn probability values are found in areas with dense vegetation, steep slopes and wind corridors. MBP, represented by yellow colours, is found in transitional regiones, particularly near valley edges and mixed terrain. These areas show a moderate likelihood of fire spread due to variable fuel loads and wind effects. Finally, LBP is concentrated in valleys, urbanized areas, and sparsely vegetated lands, where fuel availability is lower, wind exposure is less direct and natural or humanmade firebreaks reduce spread potential.

With a maximum burn probability of 22.5%, this scenario confirms that fire risk is significantly amplified when multiple factors align. Compared to the low RH scenario, where the highest burn probabilities reach 18%, this map suggests that while humidity is the most dominant factor alone, wind and temperature further intensity fire spread. Compared to the wind direction and wind speed (maximum 9% burn probability each), this map confirms that wind effects alone are not as critical as their interaction with fuel moisture and temperature.

In terms of megafire occurrences in Curacaví, out of 2,800 total wildfires simulated, 30 cases resulted in megafires (fires exceeding 10,000 hectares). Although megafires account for only 1.07% of total fire occurrences, their large-scale destruction dominates the overall fire risk landscape. This aligns with the concept of fire regimes shifts, where a small fraction of fires causes disproportionately high environmental and socio-economic damage.

In the worst-case scenario, the smallest megafire recorded is 10,299 hectares, while the largest reaches 12,301 ha, confirming large-scales fires characteristics of megafires. The average megafire size is approximately 11,000 Ha, demonstrating a high baseline fire risk without mitigation measures. These values indicate that once a fire surpasses the megafire threshold, it continues expanding rapidly, suggesting that fire suppression becomes nearly impossible under these conditions.

Multiple simulations show similar results, meaning that under worst-case conditions, fire spread dynamics are consistently extreme. The recurrence of megafires across multiple simulations (e.g., runs 6, 44, 74, 85, 113, 135, 144, 154, 162 and 191) highlights that, in the absence of Eco-DRR strategies, the landscape and weather conditions make these fires inevitable.

The fire perimeters range between 76,000 and 196,000 meters, indicating large fire fronts that would be challenging for fire suppression efforts. Fires with perimeters exceeding 100,000 meters are particularly difficult to contain, requiring extensive resources and strategic suppression tactics. The propagation shows that megafires cover an extensive portion of the central and northern study area. The central region of the study area experiences the highest fire density, with overlapping fire scars from different simulations. This confirms that certain zones are more prone to megafires, making them priority areas for fire mitigation strategies.

While only 1,07% of wildfires become megafires based on this scenario in Curacaví, these few events dominate fire management challenges. Fire prevention and management strategies should prioritize reducing the likelihood of megafires, as stopping every small fire is not feasible.

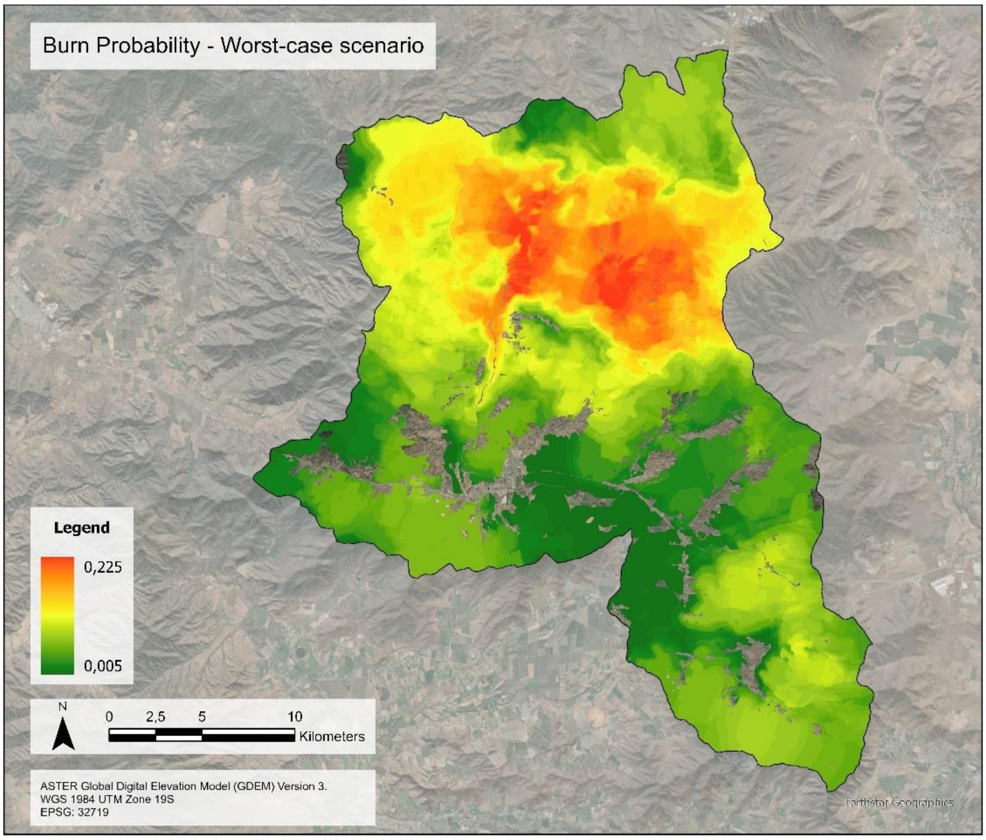

Figure 16: Result of simulation: Burn probability enhancing look have never. Prepared by the author.

5.4 Eco-DRR mitigation scenario

The Eco-DRR strategies implemented in these scenarios include vegetation thinning, targeted vegetation management and firebreaks. **Thinning** was applied by replacing dense mesomorphic shrubs and bushes with medium and rare mesomorphic shrubs and bushes to reduce fuel loads; **vegetation management,** involved replacing native non-evergreen renewals with low-density native trees, which act as natural firebreaks by reducing ladder fuels and creating discontinuities in vegetation; and 1 km **firebreaks** were located based on high burn probability areas from the worst-case scenario without Eco-DRR overlap with rural settlements.

These strategies reduce the likelihood of horizontal spread of surface fires. Particularly in areas with steep topography where fire spread is naturally accelerated.

By implementing these Eco-DRR strategies, the fire spread and burn probability are expected to decrease in high burn probability areas, particularly those with historically high fire recurrence.

5.4.1 Firebreaks

This scenario includes low relative humidity, high temperatures, NE and E wind direction and high wind speed, resulting in the following map (figure 17) showing strategically placed firebreaks, primarily in high-risk corridors, where historical fire patterns suggest high fire spread probability. These firebreaks physically disrupt the continuity of fuel, reducing fire expansion (Crotteau et al., 2020). In the burn probability map, areas near the firebreaks show lower burn probability compared to the previous worst-case scenario without firebreak.

In terms of reduction of HBP, the north-central region still exhibits it, but the extent of red zones has decreased, indicating that firebreaks successfully slowed fire spread in key areas. The highest burn probability in this scenario is 20.5%, lower than the worst-case scenario without Eco-DRR measures, where it reaches 22.5% of burn probability, confirming a moderate reduction in megafire burn probability.

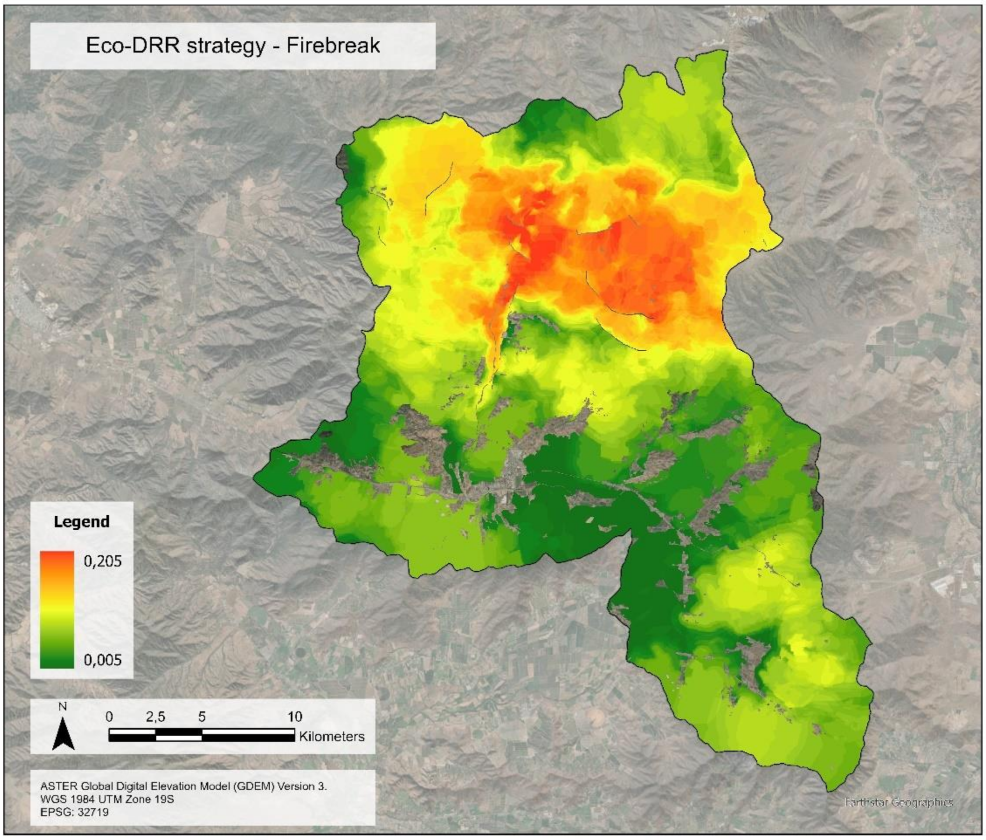

Figure 17: Result of simulation incorporating Eco-DRR strategies: Burn probability of megafires occurrence containment by Firebreaks. Prepared by the author.

The transition zones between high and low probability areas have expanded, suggesting that while firebreaks reduce fire spread, some areas remain vulnerable. This confirms that firebreaks alone do not eliminate fire risk but significantly reduce the probability of large-scale fire spread.

Finally, the southern and western areas show increased green areas, meaning firebreaks have effectively limited the fire's reach in these regions. The greatest reduction in fire probability in seen near and downstream on the firebreaks, highlighting their role in containing and redirecting fire movement.

Firebreaks act as physical barriers that disrupt fire continuity, forcing the fire to slow down or change direction. They are especially effective in areas where terrain and wind patterns accelerate fire spread. The burn probability reduction is less than what was observed in the thin vegetation and vegetation management scenario. Firebreaks alone are not as effective as fuel reduction strategies but work well in combination with vegetation management.

Considering firebreak as the only Eco-DRR mitigation strategy, only 13 out of 2,800 simulations (0.46%) resulted in megafires, compared to 30 cases (1.07%) in the worst-case scenario without Eco-DRR strategies. This represents a decrease of 57% in the occurrence of megafires. Therefore, firebreaks have successfully limited the number of extreme fire events, confirming their role in fire containment.

The minimum fire size recorded is 10,115 Ha, and the largest is 11,799 Ha. In contrast, in the worst-case scenario without firebreaks, fire sizes reached up to 12,301 Ha. This means that firebreaks have helped in reducing fire growth by disrupting fire spread patterns. The fire perimeters range between 100,00 and 135,000 meters, showing that even with firebreaks, fire still has large and complex boundaries. This suggests that firebreaks slow down fire growth but do not necessarily stop fire spread entirely, especially under extreme conditions.

However, with only 13 megafires compared to 30 in the worst-case scenario, firebreaks have been effective in lowering the likelihood of catastrophic fires. They act as barriers that limit fire expansion, preventing individual fires from merging into massive fire complexes.

Although fire sizes are slightly smaller and less frequent, the high perimeters and spread indicate that firebreaks alone cannot fully control fire expansion. The remaining megafires suggest that certain fire corridors remain unprotected. Firebreaks may need to be expanded or repositioned to target the highest-risk fire pathways.

5.4.2 Fuel management and thinning vegetation

Compared to the previous worst-case scenarios without Eco-DRR, the extent of HBP areas has significantly decreased. The north-central region still shows high burn probability, but the overall intensity and extent of high burn probability zones have been reduced. Additionally, fire spread potential has shifted toward MBP levels, indicating a positive impact of vegetation management. The reduction in fuel loads has weakened fire continuity, making it harder for megafire to sustain rapid spread. Due to Eco-DRR mitigation strategies, more areas now exhibit LBP, particularly in managed vegetation regions. The southern and western sections of the study area show significant reductions in burn probability, further demonstrating the effectiveness of Eco-DRR interventions.

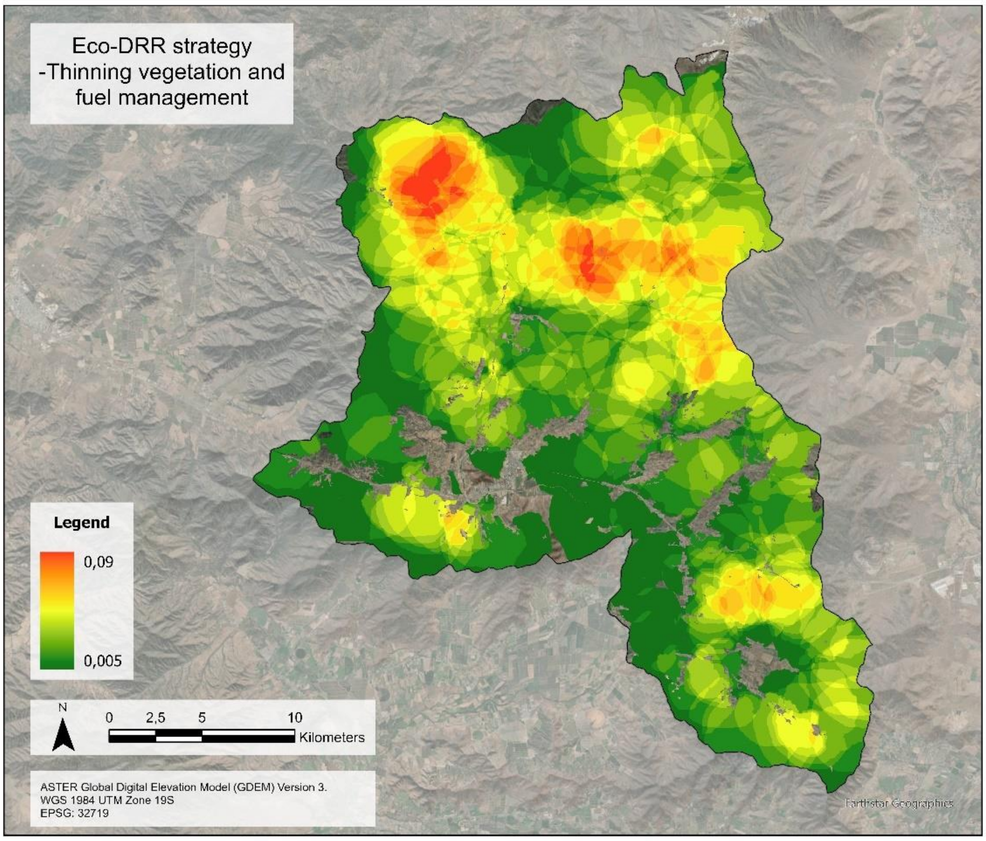

Figure 18: Result of simulation incorporating Eco-DRR strategies: Burn probability of megafires occurrence containment by Fuel management. Prepared by the author.

Thinning vegetation and vegetation management are effective because they reduce fuel continuity (Crotteau et al., 2020; Stephens et al., 2020). These strategies limit fire intensity and spread potential by transforming dense and highly flammable vegetation into lower-flammability plant species. Specifically, dense mesomorphic shrubs and bushes were replaced with medium and rare mesomorphic shrubs, which exhibit lower volatile oil content and slower combustion rates. Additionally, native non-evergreen renewals were replaced with low-density native tress, which act as natural firebreaks by reducing ladder fuels, increasing moisture retention, and creating vegetation discontinuities that disrupt fire progression.

The maximum burn probability, being 9% in this scenario versus 22.5% in the original worst-case scenario confirms a substantial reduction in fire risk. This indicates that fuel structure modifications alone can mitigate extreme fire conditions, though HBP zones remain where fuel loads and wind effects persist.

Thinning vegetation and vegetation management seems to be more effective that firebreaks, since from 2,800 wildfires simulated, the largest recorded had 2923.19 Ha, suggesting a further decrease in extreme fire events, confirming that thinning vegetation and fuel management significantly lower the probability of megafires by reducing fire intensity and continuity. Fire scars present in this scenario suggest that fire is more fragmented rather than forming large, continuous burns. This strategy effectively reduces fuel availability, preventing fires from reaching extreme sizes as frequently as in the worst-case scenario without mitigation.

Additionally, fire perimeters in this scenario appear generally smaller than in the other scenarios. This suggests that thinning vegetation and fuel management reduce the erratic and extreme fire spread patterns, likely by creating fewer flammable zones and breaking fire continuity. Unlike firebreaks, which only limit fire movement, fuel management and thinning vegetation reduce fire intensity, making suppression efforts more feasible.

While these strategies effectively reduce fire severity, they do not completely prevent large wildfires (over 1,000 Ha), hence, combining thinning vegetation and fuel management with firebreaks may further reduce fire probability and spread.

Moreover, the feasibility of large-scale implementation should be considered. Thinning and vegetation management require sustained effort and investment, but they can be more cost effective than traditional fire suppression by preventing large-scale fires before they start. Future studies could explore the economic viability and long-term benefits of integrating Eco-DRR strategies into regional fire management policies.

5.4.3 Combined Eco-DRR

The final scenario combines all previous Eco-DRR strategies, firebreaks, which interrupts fuel continuity to slow fire spread; thinning fuel, replacing dense mesomorphic shrubs and bushes with medium and rare shrubs to reduce fuel load; and vegetation management, transforming native non-evergreen renewals into low-density native trees to create natural fire-resistant landscapes.

Compared to the previous worst-case scenario without Eco-DRR, which had a burn probability of 22.5%, this simulation shows a major decrease in fire spread likelihood, up to 3.5%. The extensive presence of green areas (low burn probability) confirms that the combination of firebreak, thinning fuel, and vegetation management is highly effective in reducing fire risk. Therefore, only a few small red zones remain, mainly in the northwestern and central areas, where fire spread potential is still slightly elevated due to terrain or residual fuel concentrations. The elimination of large contiguous HBP zones, as seen in previous maps, confirms that these strategies disrupt fire corridors and reduce extreme fire behaviour.

The majority of Curacaví area now falls within the LBP range, from 0.05% to 3.5%, highlighting the success of Eco-DRR measures in fire risk mitigation (figure 19). Furthermore, rural and urban areas within the WUI show significantly reduced fire exposure, which has strong implications for community safety.

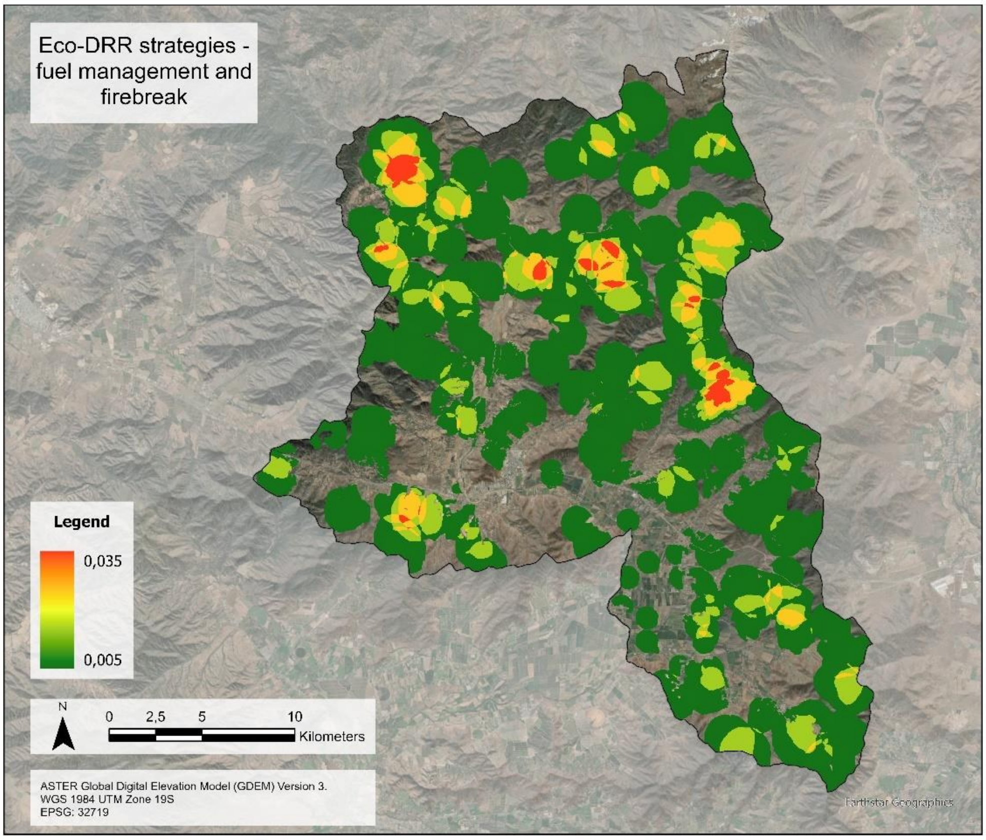

Figure 19: Probability map including Eco-DRR strategies confide. Prepared by the author.

Overall, worst-case scenario without Eco-DRR reach up to 22.5% of burn probability, with extensive fire spread across the study area. The scenario with only firebreaks reduced BP to 19.5%, but still leaving vulnerable areas. Finally, thinning fuel and vegetation management further reduced BP to 8.5%, indicating a substantial decrease of fire risk.

Together, these strategies reduce BP up to 3.5%, being a drastic reduction compared to previous scenarios. Eco-DRR strategies maximize fire prevention by combining strategic containment (firebreaks) with reduced ignition potential (vegetation management). The combined approach demonstrates that Eco-DRR can be a powerful alternative or complement to traditional fire suppression efforts. The results suggest that firebreaks should be strategically placed alongside fuel management zones to maximize effectiveness. The integration of these methods significantly enhances wildfire resilience in fire-prone landscapes like Curacaví.

Under this scenario, the largest fire recorded is only 1,231 Ha, confirming that the combined strategy is the most effective mitigation measure. This is a major decrease from previous scenarios, especially the one without Eco-DRR strategies, demonstrating the strong ability of firebreaks, thinning vegetations and fuel management to disrupt fire growth.

The fire perimeters in this scenario ranged from 19,681 and 21,832 meters for wildfires over 1,000 Ha. In contrast, under the worst-case scenario without eco-DRR strategies, perimeters extended beyond 130,000 meters, confirming that the combined strategies effectively restricted fire movement, and are highly effective, due to this it is the only worst-case scenario in which no fire exceeded 1,231 Ha, and the complete absence of megafires in this scenario confirms that this combination is the most effective mitigation strategy for reducing fire spread under extreme weather conditions.

6. Discussion

6.1 Interpretation of Findings

This study identifies critical factors influencing megafire probability in Curacaví, confirming that low RH is the dominant driver of fire spread, followed by wind speed, wind direction, and temperature. The probability maps revealed that megafire-prone areas are concentrated in the northern and central regions of the study area, where steep slopes, high fuel loads, and favourable wind corridors converge.

The key finding of this research is RH as the dominant driver. Low RH significantly increases fire ignition and spread potential by drying fuels, making them more flammable. This aligns with previous studies (e.g. Jain, 2022), which found that decreasing RH was responsible for over three-quarter of global increases in wildfire index.

Followed by topography and fuel load influence fire risk, with HBP areas corresponding to ridgelines, steep slopes, and dense vegetation, confirming that elevated terrain accelerates fire spread due to preheating effects and convective heat transfer (Finney, 2005).

Furthermore, while temperature increases evaporation and fuel drying, wind direction and speed determine fire propagation corridors. However, temperatures alone were found to be a secondary driver unless combined with other factors.

Finally, repeated fires in historically burned areas suggest that fire-prone regions remain at HBP over time, emphasizing the need for targeted mitigation efforts.

The worst-case scenario confirmed that when multiple meteorological factors align, fire spread intensifies dramatically, underscoring the necessity of integrated fire management strategies to mitigate megafires. Likewise, the results align with global trends where a small fraction of fires causes most of the burned area and destruction

(Lorimer, 1989). This supports the argument that fire management should focus on preventing extreme events rather than controlling small fires.

6.2 Comparison with previous studies

The dominant role of low relative humidity in driving fire behaviour aligns with previous studies in Mediterranean and semi-arid ecosystems. Research in California and Australia has demonstrated that fuel moisture content, largely dictated by relative humidity, is the most critical factor in wildfire propagation (Bradstock et al., 2012; Abatzoglou et al., 2017). The present research corroborates these findings, showing that relative humidity alone increased BP up to 18%, while wind speed alone only reached 9%.

Unlike studies that emphasize wind-driven fires (Garcia et al., 2019), this research suggests that wind speed alone does not significantly increase megafire BP unless combined with dry fuel conditions. This discrepancy may be due to differences in fuel load, topography, or regional wind patterns in Curacaví compared to other fire-prone regions.

Regarding Eco-DRR strategies, the study supports findings by Syphard (2011), who concluded that fuel treatments are more effective than firebreaks in reducing fire spread. The combined approach in this study reduced burn probability to 3.5%, the lowest across all scenarios, reinforcing the argument that integrating fuel reduction with strategically placed firebreaks maximizes fire mitigation potential.

6.3 Implications for fire management in Curacaví

6.3.1 Eco-DRR as a key strategy for megafire prevention

The effectiveness of thinning vegetation and fuel management suggests that land-use policies should prioritise these methods in high-risk areas. The reduction of fuel continuity proved to be the most effective strategy, indicating that fire mitigation efforts should include selective thinning of dense mesomorphic shrubs to limit fire intensity; conversion of non-evergreen renewals into low-density native trees, which act as natural fire barriers; and integrated firebreaks in high-risk corridors to enhance containment.

6.3.2 Prioritizing HBP areas for fire prevention

Given that megafires are not randomly distributed but concentrated in northern and central Curacaví, targeted fire prevention efforts should focus on these areas, including fuel load reduction in northern ridgelines and steep slopes, where fire propagation is widespread; enhanced fire monitoring in historically burned areas, as past fire scars indicate recurring fire-prone zones; and community preparedness in WUI, where BP is moderate but human exposure is high.

6.3.3 Firebreaks: complementary, not standalone measures

This studio revealed that firebreaks alone reduced megafire occurrence by 57%, but their effectiveness was limited compared to fuel management strategies. Firebreak should not be the primary mitigation tool but rather integrated into a broader landscape management plan. Their role should focus on preventing fire spread near urban areas; segmenting HBP zones to limit large fire expansions; and acting as emergency containment lines during extreme fire events.

Thinning vegetation and fuel management are more effective than firebreaks alone. Unlike firebreaks, which only interrupt fire spread, fuel reduction actively lowers fire intensity and ignition potential. Therefore, firebreaks are useful but need to be complemented with fuel management.

On the other hand, combined Eco-DRR strategies are the most effective solution. The significant reduction in burn probability (3.5%) and fire size (maximum 1,231 Ha) proves that Eco-DRR strategies can fully prevent megafires under extreme known weather. This suggests that these Eco-DRR strategies combined not only reduce fire size but also prevent excessive fire spread, making suppression easier. Finally, these results reinforce that proactive land management is more effective than reactive fire suppression.

6.4 Limitations of the Study

Throughout this research, some limitations were acknowledged. For instance, the study did not incorporate firefighting strategies, which could alter fire spread patterns.

Furthermore, the use of historical ignition points may not fully represent future ignition dynamics under changing climate conditions.

Likewise, fuel loads were assumed constant, whereas real-word vegetation changes over time due to regrowth, drought, and human activity.

Finally, regarding firebreak limitations, remaining HBP zones indicate that firebreaks do not eliminate fire spread, especially under extreme conditions. Besides, wind-driven embers can cross firebreaks, meaning that they should be complemented with additional fuel reduction strategies.

These limitations suggest that future research should incorporate dynamic fire suppression models, climate projections, and long-term vegetation changes to obtain more accurate results.

6.5 Future Research Directions

Given the insights from this study, the following research directions are recommended:

Future studies should **incorporate climate change projections** modelling temperature and humidity shifts under climate change scenarios to assess long-term fire BP. Besides, simulations should include firefighting interventions to **evaluate the impact of fire suppression efforts**, exploring how response times and suppression resources influence megafire containment. **Social and economic impacts of fire mitigation** should be explored in future work, integrating economic cost-benefit analyses of Eco-DRR strategies. Finally, further research could refine firebreak placement using machine learning, leveraging **spatial optimization models to enhance firebreak efficiency** by identifying the most effective locations.

7. Conclusions and recommendations

This study has demonstrated the significant role of environmental variables in determining megafire probabilities in Curacaví, Chile, with low relative humidity emerging as the dominant driver of fire spread. Through predictive fire simulations, it was observed that areas with steep slopes, high fuel loads, and favourable wind corridors exhibit the highest burn probability, confirming that fire behaviour is not solely dependent on meteorological conditions but also landscape and vegetation characteristics.

The worst-case scenario analysis reinforced the compounding effect on extreme weather variables, showing that when low humidity, high temperatures, and strong winds align, megafires become nearly uncontrollable. However, the implementation of Eco-DRR (Ecosystem-based Disaster Risk Reduction) strategies significantly reduced fire probability and spread. Among the tested interventions, thinning vegetation and fuel management proved to be the most effective, reducing fire risk more substantially than firebreaks alone.

The combined approach of firebreaks, thinning and vegetation management was the most successful, reducing burn probability from 22.5% (worst-case scenario without Eco-DRR) to just 3.5%. The result highlights that proactive landscape management is more effective than reactive fire suppression. Additionally, these strategies prevented megafire occurrences, as no fires in the final Eco-DRR scenario exceeded 1,231 hectares, a drastic improvement from the baseline.

These finding align with the global research on fire-prone regions, confirming that integrated fire management strategies are essential for mitigating megafire risk in Mediterranean landscapes. The results suggest that prioritizing fuel reduction and targeted mitigation efforts in high burn probability areas is critical for preventing large-scale wildfires in Curacaví.

Based on the findings, the following recommendations are proposed to enhance wildfire prevention and mitigation in Curacaví.

First, **Eco-DRR strategies in large-scale** should be implemented, being thinning vegetation and fuel management expanded within high burn probability areas, particularly in northern and central Curacaví, especially considering current vegetation conditions. For example, conversion of non-evergreen renewals into low-density native trees could be prioritised to create natural fire-resistant landscapes or firebreaks could be strategically positioned alongside fuel reduction areas to maximise containment.

Second, high burn probability areas for **fire prevention** should be prioritised. These efforts should be focused not only on northern ridgelines and steep slopes, where fire spreads faster but also on enhancing fire education and community preparedness in WUI areas, promoting human-caused ignition reduction.

Third, **firebreak design and effectiveness** should be strengthened and expanded in high burn probability zones and regularly maintained to prevent vegetation regrowth. Furthermore, integration with fuel management strategies is necessary to optimise fire containment.

Finally, **long-term studies on climate change** impacts on fire risk in Curacaví should be conducted, since further research on fire suppression modelling and effectiveness of Eco-DRR strategies is needed, being this research just an approximation to this topic in the study area. Furthermore, social and economic analysis should be integrated into fire risk models to assess a more holistic approach.

By implementing these recommendations, fire management authorities, policymakers, and communities can significantly reduce the likelihood and impact of megafires, protecting both ecosystems and human settlements in Curacaví.

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