Table 7 Changes in basic wildfire behaviour metrics between untreated areas (all landscapes) and areas returned from ForSys as candidates for receiving fuel treatments where we tested two scenarios (thinning & clearcut). MTT: Minimum Travel Time algorithm.

SETTLEMENT	MTT Rate of Spread			MTT Fireline Intensity		
	All Landscapes	Thinning	Clearcut	All Landscapes	Thinning	Clearcut
PATRA	3.77	1.24	5.45	1490	103	96
KALAMATA	6.45	1.37	7.42	2084	113	130
KORINTHOS	5.21	2.22	6.94	1327	184	122
TRIPOLI	9.66	2.38	4.82	4172	197.97	84.95
PYRGOS	13.81	1.96	11.19	9761	162	197
ARGOS	10.16	1.78	9.19	4947	147	162
AIGIO	4.18	0.72	6.74	212	59.86	118.84
SPARTI	2.39	0.47	6.19	269	39	109
KIATO	3.71	0.96	7.15	2289	79	126
K AXAIA	3.57	1.52	4.12	1279	126	73
OMBRYA	4.90	1.08	5.49	2391	90	97
MEGALOPOLI	3.38	0.81	7.23	474	67	127
KYPARISSIA	6.08	1.46	7.74	2371	120	136
FILIATRA	5.36	1.34	6.71	1523	111	118
KRANIDI	3.03	1.52	2.87	707	126	51
NEMEA	6.44	2.15	6.58	2478	178	116
KAVOMALIAS	7.76	1.93	10.31	3547	160	181
LAGKADIA	5.73	1.41	5.72	1930	117	101
KATO VLASIA	3.37	1.78	4.86	746	148	86
KALENTZI	1.84	0.35	6.36	441	29	112
KALAVRYTA	3.46	1.43	5.28	1063	118	93
LEVIDI	8.57	1.84	6.85	2325	153	121
ANDRITSAINA	5.55	1.45	7.41	1970	121	131
SKALA	7.31	2.28	8.03	2284	189	141
GERAKI	9.62	3.04	8.41	3557	253	148
AMALIADA	1.58	0.79	7.11	869	66	125
LAPPAS	5.59	1.18	6.32	2532	98	111

There are some characteristic examples that shows that the proposed fuel treatments are effective in altering the fire behaviour from potential fires that can reach communities. In the absence of fuel management, settlements such as Pyrgos, Geraki, Argos, Tripoli, Levidi and Kavomalias are severely affected by fast-moving and high-intensity fires (Figure 196). For all thirty Peloponnese's settlements, comparing the "all landscapes" fuel treatment scenario to other scenarios, the thinning scenario shows an almost 71% lower ROS and a 91% lower FI; the clearcut scenario exhibits an almost 45% increase ROS and 89% decrease in FI (Figure 197). When comparing thinning and clearcutting as fuel treatment methods, the clearcut scenario shows a 76% higher ROS and about a 12% lower FI compared to the thinning scenario (Figure 198). Inside thinned stands, wind tends to have higher speed since it blows with less obstructions from the forest canopy and it can penetrate the stands, instead of getting diverted upwards in dense forest stands. This has the result to allow fires to expand with higher spread rates. On the other hand, the reduced fuel inside the stands allows for the reduction of fireline intensity (less fuel results in less energy released from the combustion process).

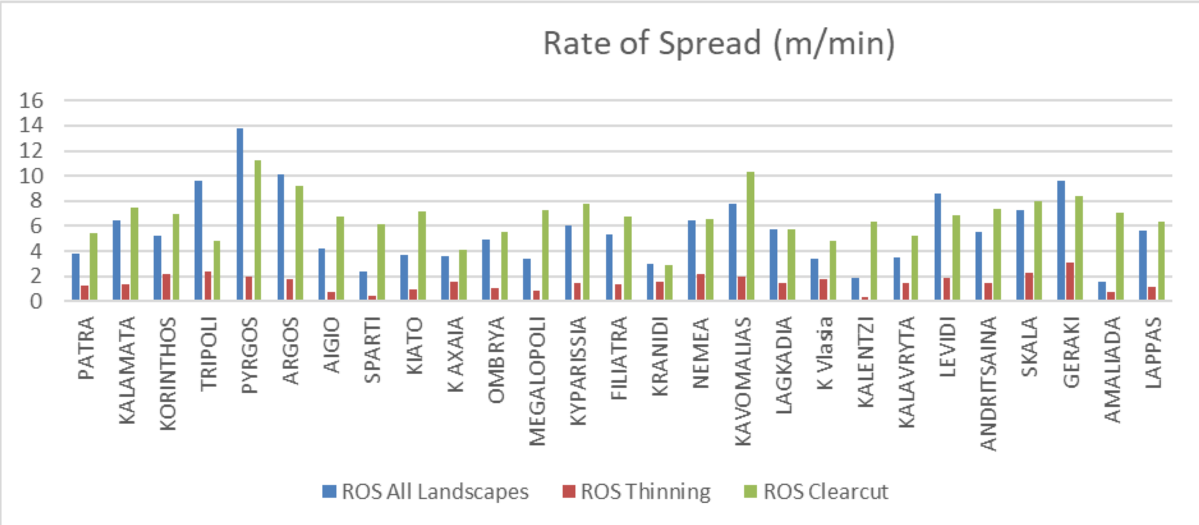


Figure 196 Changes in rate of spread among the three simulation scenarios that tested the effectiveness of potential fuel treatments around communities, as returned by ForSys.

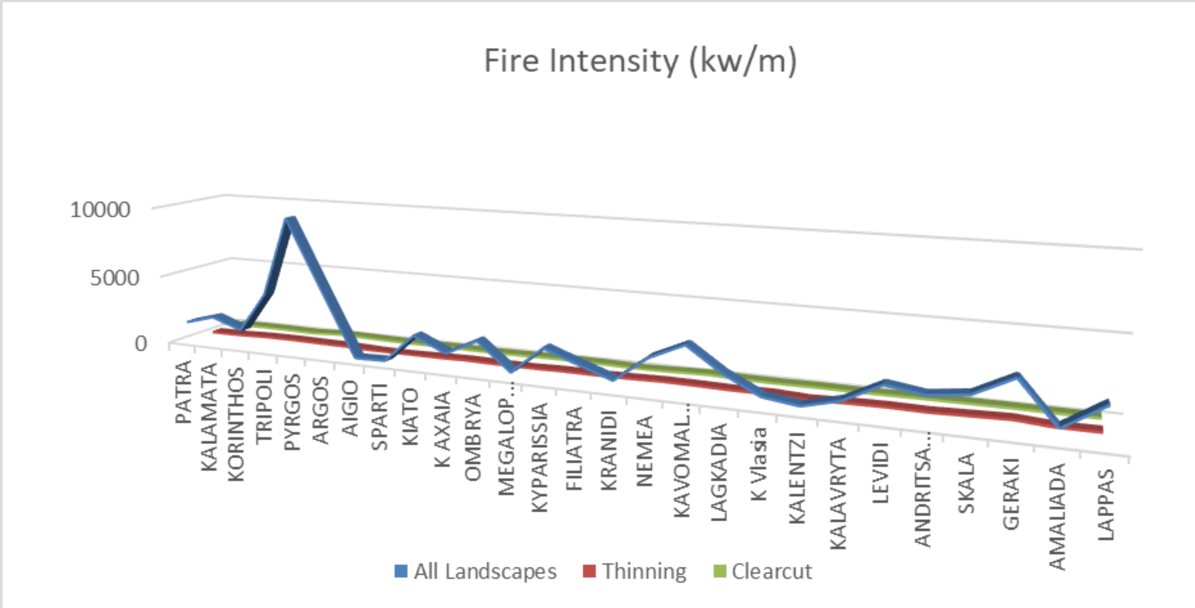


Figure 197 Changes in fire intensity among the three simulation scenarios that tested the effectiveness of potential fuel treatments around communities, as returned by ForSys.

The impact of fuel treatments like thinning and clearcutting can vary based on specific conditions at each settlement. This variability happens because factors like topography, vegetation type, wind speed, and weather conditions can affect how fire behaves and how effective a given treatment will be in reducing fire intensity or rate of spread.

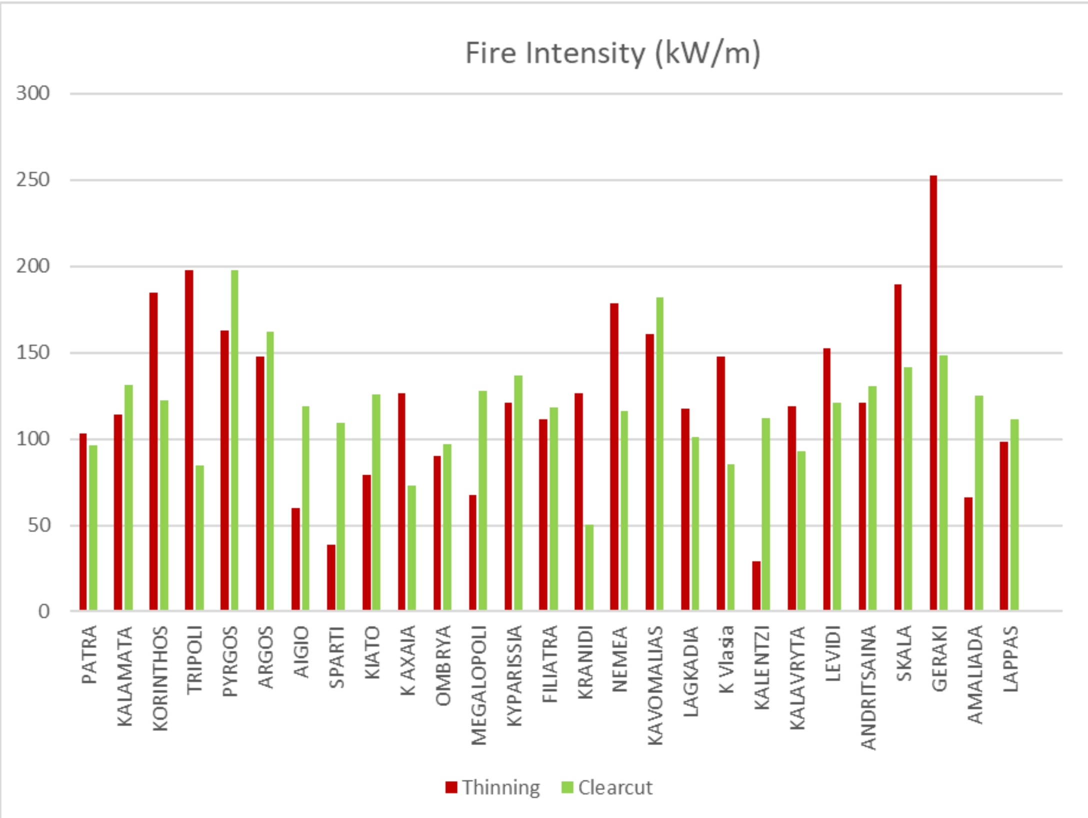


Figure 198 Changes in fire intensity among thinning and clearcut simulation scenarios that tested the effectiveness of potential fuel treatments around communities, as returned by ForSys.

In settlements Pyrgos and Geraki, the fire behaviour is so severe that it affects them in any fuel treatment scenarios. The all-landscape fuel treatment scenario seems to be the more alarming. In Geraki settlement, the ROS reaches the 13.8 m/min and the FI reaches 9,761 kW/m under the all-landscape fuel treatment scenario. ROS of Pyrgos dropped nearly by 85.8% in the thinning scenario and by almost 19% in the clearcut scenario, while FI decreased by 98.3% in the thinning scenario and by 98% in the clearcut scenario compared to no fuel management. Comparing clearcutting and thinning treatment scenarios, there is an 82.5% reduction of ROS and 17.5% of FI (Figure 199; a1, b1). Furthermore, in Geraki settlement, the ROS reaches the 9.62 m/min and the FI reaches 3,557 kW/m under the all-landscape fuel treatment scenario. Compared to this scenario, ROS and FI are decreased by 68.4% and 93%, respectively in the thinning scenario, while ROS and FI are decreased by 12.5% and 95.8% respectively in the clearcut scenario. Taking into consideration the clearcutting treatment scenarios, the ROS decreased by 63.8% while the FI increased by 70.3% in relation to the thinning fuel treatment scenario (Figure 199; a2, b2).

The fire behaviour near Tripoli and Argos seems comparable to that observed in the Pyrgos and Geraki. Compared to all-landscape fuel management, ROS and FI in Tripoli are decreased by 75.3% and 95.2%, respectively, in the thinning fuel treatment scenario, while ROS and FI are decreased by 50% and nearly 98% respectively, in the clearcut scenario. The thinning scenario in the Argos settlement results in a loss of 82.5% and 97% in ROS and FI, respectively, while the clearcut scenario results in a decrease of 9.6% and 96.7% compared to all-landscape fuel management.

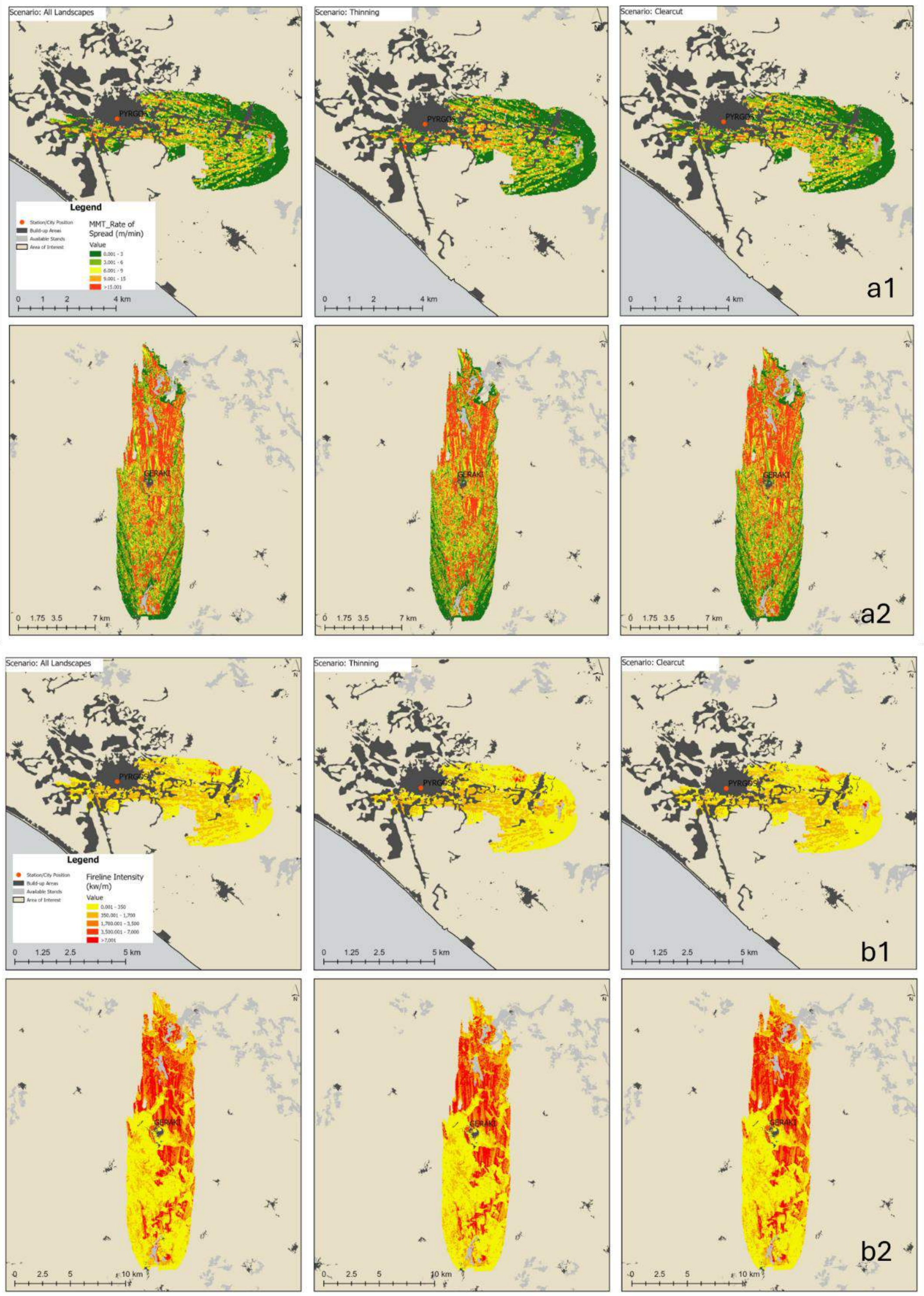


Figure 199 FlamMap results for MTT Rate of Spread (a) and Fire Intensity (b) from forest fire simulations under different fuel treatment scenarios (by ForSys) for Pyrgos and Geraki.

For settlements, such as Andritsaina, Aigio, Kalamata, Kalabryta, Kavomalias, Korinthos, Kyparissia Megalopoli, Nemea, Lagkada, Lappas, Lenidi, Filatra, Ombrya, Patra, K.Vlassia, and Skala, the thinning scenario leads to a significant decrease in ROS and FI, while the clearcutting scenario results in increased ROS and decreased FI compared to all-landscape fuel treatment (Figure 200).

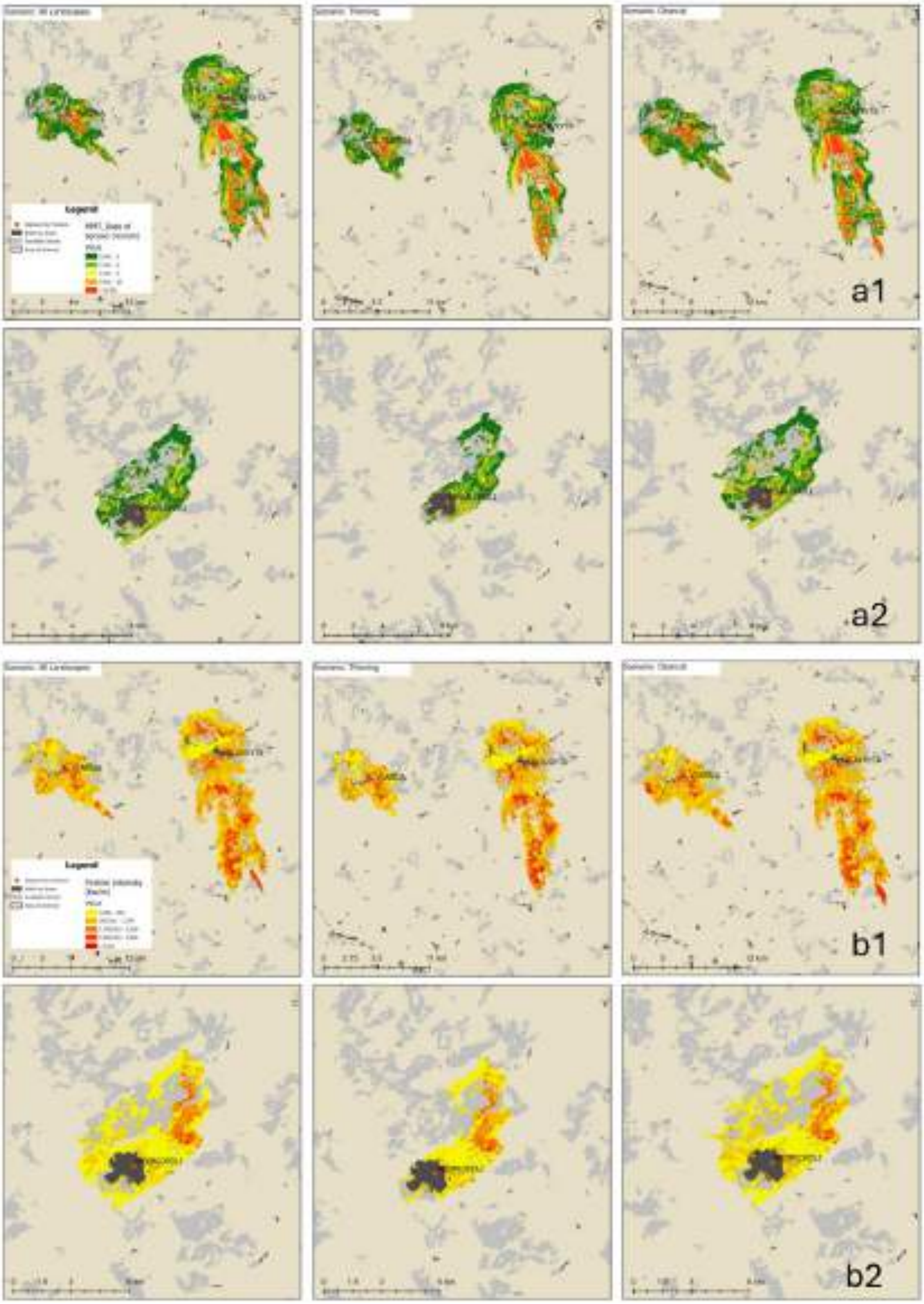


Figure 200 FlamMap results for MTT Rate of Spread (a) and Fire Intensity (b) from forest fire simulations under different fuel treatment scenarios (by ForSys) for Vasia, Kalavryta and Megalopoli.

For Instance, compared to all-landscape fuel treatment scenarios:

- In Kalamata, the ROS decreased by 78.7% in the thinning scenario and increased by 15.2% in the clearcut scenario and FI decreased by 94.5% in the thinning scenario and 93.7% in the clearcut scenario.
- In Patra, the ROS decreased by 67% in the thinning scenario and increased by 44.6% in the clearcut scenario and FI decreased by 93% in the thinning scenario and 93.5% in the clearcut scenario.
- In Kyparyssia, the ROS decreased by 76% in the thinning scenario and increased by 27.3% in the clearcut scenario and FI decreased by nearly 95% in the thinning scenario and 94.2% in the clearcut scenario.
- In Megalopoli, the ROS decreased by 76% in the thinning scenario and increased by 114 % in the clearcut scenario and FI decreased by nearly 85.8% in the thinning scenario and 73.1% in the clearcut scenario.
- In K.Axaia the ROS decreased by 57% in the thinning scenario and increased by 15.4% in the clearcut scenario and FI decreased by nearly 90.1% in the thinning scenario and 94.3% in the clearcut scenario.
- In Filiatra, the ROS decreased by 75% in the thinning scenario and increased by 25% in the clearcut scenario and FI decreased by 92.6% in the thinning scenario and 92.2% in the clearcut scenario.
- In Kiato, ROS decreased by 74.2% in the thinning scenario and increased by 92.6% in the clearcut scenario and FI decreased by 96.5% in the thinning scenario and 94.5% in the clearcut scenario.

The settlements of Sparti, Kalentzi as well as Amaliada provide evidence of how three fuel treatment scenarios influence forest fire behaviour. Specifically, clearcutting results in an increased ROS and a decreased FI. In Sparti, the clearcut scenario shows an almost 158% increase in ROS and a 59.6% decrease in FI, while the thinning scenario shows an almost 80.5% lower ROS and an 85.6% lower FI when compared to the all-landscape fuel treatment option. The clearcut scenario exhibits a 92.4% greater ROS and around a 64.4% lower FI than the thinning scenario when comparing the two fuel treatment techniques (Figure 201; a1, b1). In Kalentzi settlement, thinning fuel treatment results in an approximately 81% reduction in the ROS and 93.4% in the FI, while the clearcut fuel treatment scenario results in an almost 246% increase in ROS and a 74.6% increase in FI compared both to the all-landscape treatment (Figure 201; a2, b2). Also, in Amaliada clearcutting treatment scenario results in an increased ROS by 348% and a decreased by 85.5% FI, while thinning treatment scenario ROS and FI are decreased by almost 45% and 92.4%, respectively, compared to the all-landscape treatment.

Forest fuel treatments are crucial tactics to manage forest ecosystems and reduce the risk of wildfires. Particularly in Peloponnese landscape that is prone to fire, the thinning fuel treatment scenario seems to have more effective results as aid in controlling fuel loading, reducing fire intensity, and eventually changing fire behaviour.

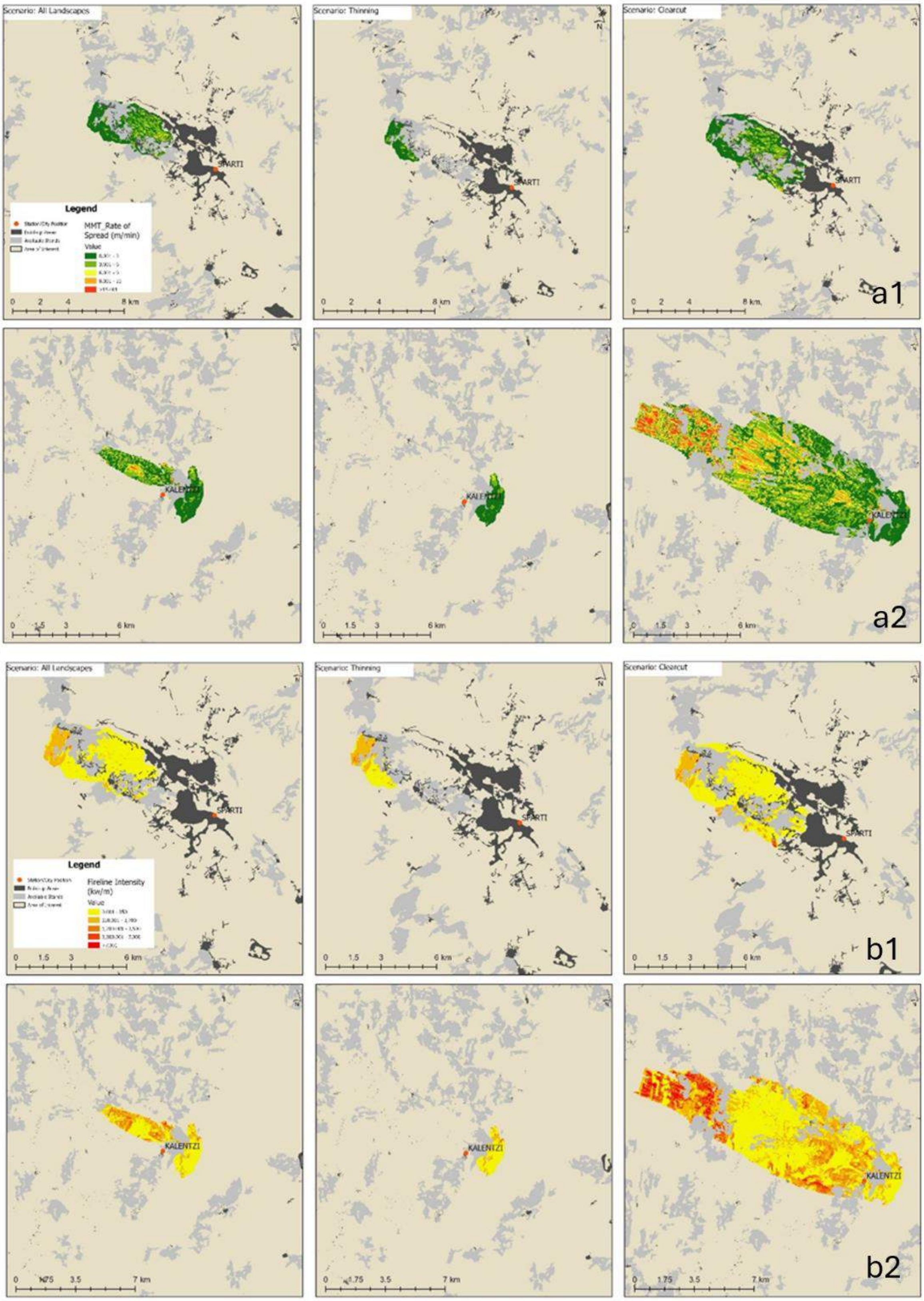


Figure 201 FlamMap results for MTT Rate of Spread (a) and Fire Intensity (b) from forest fire simulations under different fuel treatment scenarios (by ForSys) for the settlements of Sparti and Kalentzi.

7 Enhancing Silvicultural Practices: A Strategic Approach to Minimize Fire Risk and Losses

7.1 Data Acquisition and Landscape Classification

7.1.1 Data Acquisition

Data acquisition in forestry is a critical process that involves the systematic collection of information related to forest resources, ecosystems, and environmental conditions. Accurate data collection is essential for forest management, conservation, and sustainable use of forest resources. Advances in technology have significantly improved the efficiency, precision, and scope of data acquisition methods, allowing researchers, policymakers, and forest managers to make well-informed decisions.

Historically, forestry data collection relied on manual techniques, including field surveys and direct measurements. Field data collection is crucial for accurate forest management, providing ground-truth validation for remote sensing and GIS-based assessments. Various methods and tools are used to acquire forestry data through fieldwork, focusing on different aspects of the forest ecosystem.

One essential category of data collected in the field involves tree and vegetation measurements. Tree height is measured using clinometers, laser rangefinders, or smartphone apps, while diameter at breast height (DBH) is assessed with a diameter tape or calipers. The basal area, which helps estimate stand density, is derived from DBH measurements. Tree age is determined using increment borers that extract core samples, and species identification is conducted either visually or with AI-based mobile applications.

Environmental and ecological data collection is another critical component of forestry fieldwork. Soil conditions, including pH, moisture content, and nutrient levels, are analysed using soil probes. Microclimate data such as temperature, humidity, and wind speed are recorded with portable weather stations. Biodiversity assessments involve documenting the presence and abundance of flora and fauna species, while water quality is monitored by checking pH, turbidity, and nutrient levels in nearby water bodies.

Fieldwork also plays a key role in assessing forest health and disturbances. Pest and disease monitoring involves identifying symptoms of infections or insect infestations, while fire risk assessment is conducted by measuring fuel load and dryness levels. Additionally, deforestation and land use changes are evaluated through direct observation to determine human impact on the forest.

Several field data collection methods are employed to ensure comprehensive data acquisition. Plot sampling and transect surveys are commonly used techniques. Fixed-area plots, which are circular, square, or rectangular, allow for systematic measurement of trees and other vegetation. Variable radius plots, also known as point sampling, utilize a prism or angle gauge to estimate tree density without measuring each tree individually.

Line transects involve collecting data at regular intervals along a straight line to assess biodiversity and vegetation patterns.

Manual data collection methods include traditional paper forms and field notebooks, though they are prone to errors. Instrument-assisted methods further enhance data accuracy. Dendrometers are used to measure tree growth over time, soil probes and augers assist in soil property analysis, portable spectrometers assess leaf pigments and plant health, and acoustic sensors detect wood-boring insects and tree decay.

The advent of remote sensing technology has revolutionized forestry data acquisition. Satellites, drones, and LiDAR (Light Detection and Ranging) provide high-resolution imagery and three-dimensional mapping of forest landscapes (Ciobotari et al., 2024).

- Satellite imagery allows large-scale forest monitoring, detecting deforestation, land-use changes, and vegetation health. Sensors such as Landsat, Sentinel, and MODIS capture multispectral and hyperspectral data, providing valuable insights into forest conditions.
- Unmanned Aerial Vehicles (UAVs) or drones equipped with high-resolution cameras and multispectral sensors collect real-time data on canopy structure, species identification, and forest gaps. They provide cost-effective and flexible solutions for precision forestry.
- LiDAR technology generates detailed 3D models of forest stands, enabling precise measurements of tree height, biomass estimation, and carbon stock assessment. LiDAR data improve forest inventories and habitat modelling.

The integration of big data analytics and artificial intelligence (AI) further enhances forestry data acquisition. Machine learning algorithms (Bot & Borges, 2022; Peng et al., 2018) process vast amounts of satellite and sensor data to identify patterns, predict forest growth, and assess risks such as pest outbreaks or wildfires. AI-driven models improve decision-making in forest conservation and resource management.

Modern data acquisition methods in forestry have transformed the way forests are monitored, managed, and protected. The combination of traditional techniques with advanced remote sensing, IoT, and AI-driven analytics enables more efficient, accurate, and sustainable forestry practices. As technology continues to evolve, the future of forestry data acquisition will be characterized by greater automation, precision, and integration of real-time monitoring systems, ensuring the long-term health and productivity of forest ecosystems.

7.1.2 Land Classification: Importance, Methods, and Applications

Land classification is the systematic process of categorizing land based on its physical, chemical, and biological characteristics, as well as its suitability for various uses. It serves as a crucial tool for land use planning, sustainable resource management, and environmental conservation (Nedd et al., 2021). By classifying land, governments, planners, and landowners can make informed decisions regarding agriculture, urban development, forestry, conservation, and infrastructure projects.

The main goals of land classification include: a) Optimizing land use by identifying the most suitable activities for different areas, b) Preventing land degradation through sustainable management practices, c) Supporting economic development by promoting efficient land allocation, d) Enhancing conservation efforts by protecting ecologically sensitive areas, e) Improving policy-making by providing scientific data for land use regulations.

Several methods exist that are used globally, each focusing on different land characteristics and uses but essentially depending on the purpose and criteria applied

1. Land Use Classification: Land can be classified based on its current or intended use:

- Agricultural land – Used for farming, livestock, and crop production.
- Forest land – Covered by natural or managed forests, supporting timber and biodiversity.
- Urban land – Areas designated for residential, commercial, and industrial activities.
- Wetlands and water bodies – Includes lakes, rivers, and marshes critical for ecosystem services.

2. Soil-Based Classification: This method categorizes land based on soil properties such as texture, fertility, drainage, and erosion susceptibility.

3. Ecological and Environmental Classification: This classification considers factors such as climate, topography, vegetation, and biodiversity. It is used for conservation planning, habitat protection, and climate adaptation strategies.

4. Remote Sensing and GIS-Based Classification: Modern land classification integrates satellite imagery, drones, and Geographic Information Systems (GIS) to map land cover, detect land use changes, and assess environmental conditions. This technology enables real-time monitoring and better decision-making for sustainable land management.

The classification of forested landscapes into homogeneous spatial units is a crucial process in forestry, ecology, and land management (Başkent & Jordan, 1995; Borgesa & Hoganson, 2000). This classification enables researchers and managers to understand forest dynamics, assess biodiversity, and implement sustainable management strategies. Homogeneous spatial units are delineated based on similar ecological, biological, or structural characteristics, which allow for more effective conservation and resource management.

Classifying forested landscapes into homogeneous spatial units has several benefits: a) Enhanced Forest Management since enables targeted conservation, afforestation, and sustainable harvesting practices, b) Improved Biodiversity Conservation once it Helps identify ecologically sensitive areas and prioritize conservation efforts, c) Climate Change Mitigation by supporting carbon stock assessment and climate adaptation planning, d) Disaster Risk Reduction, assisting predicting and managing risks such as wildfires, landslides, and floods and e) Scientific Research and Monitoring, providing a structured approach for long-term ecological studies and policy development.

The classification of forested landscapes into homogeneous spatial units is a fundamental process in environmental science and land-use planning. By integrating ecological, remote sensing, physiographic, vegetation, and functional criteria, forest managers can make informed decisions that balance conservation and sustainable development. As technology and methodologies advance, this classification process will continue to improve, facilitating more effective forest management strategies globally. The output of a classification map may look like in Figure 202.

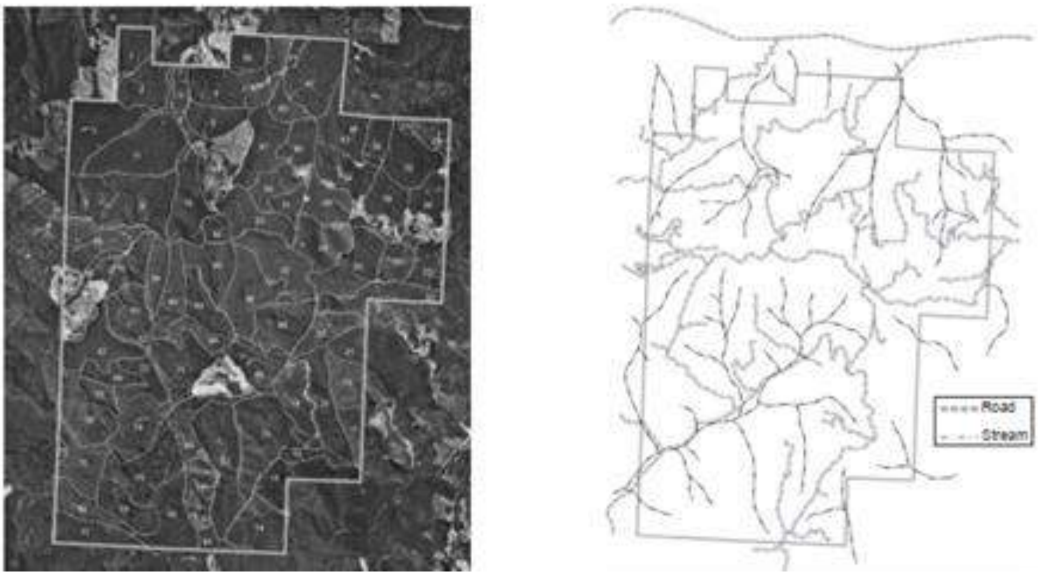


Figure 202 Forested landscape homogeneous spatial units.

With advancements in remote sensing, artificial intelligence, and data analytics, land classification is becoming more precise and adaptive to changing environmental conditions. Proper classification and management ensure the long-term productivity and health of land resources, benefiting both present and future generations.

7.2 Designing Resource Capability models integrating wildfire spread

Growth and yield models are essential tools for forecasting forest development, helping land managers, ecologists, and policymakers make informed decisions about forest management, timber production, carbon sequestration, and wildfire risk assessment. These models use historical and empirical data, biological principles, and mathematical algorithms to estimate how forests will grow over time under different conditions (Peng, 2000). Growth and yield models describe forest dynamics (i.e., the growth, mortality, reproduction, and associated changes in the stand) over time and hence have been widely used in forest management because of their ability to update inventories, predict future yield, and to explore management alternatives and silvicultural options, thus providing information for decision-making (Burkhart, 1990; Vanclay, 1994). Consequently, predicting future forest growth and yield under different management scenarios is a key element of sustainable forest management (Kimmins, 1990, 1997).

Growth models predict the development of individual trees or entire stands by estimating changes in height, diameter, and volume over time. These models account for factors like species, site conditions, competition, and climate, providing valuable insights for forest management and conservation. By simulating growth patterns, they help determine optimal thinning schedules, carbon sequestration potential, and long-term forest productivity.

Yield models, on the other hand, estimate the total biomass, merchantable timber volume, or other ecological outputs at a given future time. They are essential for planning sustainable harvesting, assessing economic returns, and evaluating forest health. Yield projections support decision-making in timber production, wildlife habitat conservation, and carbon offset programs. Together, growth and yield models provide a comprehensive framework for understanding forest dynamics, aiding in resource allocation, and promoting ecological sustainability in a changing climate.

These models are classified in 4 types (Bosela et al., 2023), essentially:

- Empirical Models that are based on historical data and statistical relationships between forest variables commonly used for predicting tree growth, volume, and yield without considering underlying biological processes.
- Process-Based Models are used to Simulate physiological processes such as photosynthesis, respiration, and nutrient uptake and provide insights into how environmental factors influence forest growth.
- Hybrid Models Combines empirical and process-based approaches to improve prediction accuracy. They are useful for integrating long-term trends with site-specific conditions.
- Distance-Dependent vs. Distance-Independent Models; Consider spatial relationships between individual trees and the other Focus on average stand-level growth without spatial interactions, respectively.

They are essential components of forest growth simulators, which help predict the future conditions of forest stands under various management scenarios. These models estimate the development of forests over time based on factors such as species composition, site conditions, climate, and silvicultural treatments.

In Portugal, empirical growth and yield models are widely used in forest management, where forests are diverse and subjected to varying environmental conditions, empirical models help land managers make informed decisions on sustainable forest management, timber harvesting, and conservation. While empirical models have been successful in many aspects of forest management in Portugal, there are some challenges, specially, Data Availability: Although the national forest inventories are extensive, some regions may lack enough high-quality data, particularly in remote or less-studied areas.

This can limit the accuracy of some models, especially for species that are less commercially significant or have complex growth patterns. Another important limitation on the use of this type of models is that they often rely on historical data, which may not fully account for the impacts of climate change. Shifting rainfall patterns, rising temperatures, and altered disturbance regimes (such as more frequent wildfires or pest outbreaks) can affect forest growth in ways that are difficult to predict with traditional empirical models. Models developed for specific regions or species may not be easily applicable to other areas with different environmental conditions. Therefore, more localized calibration and validation are necessary to improve the accuracy of predictions for different forest types.

These models can also be classified based on the level of detail and the specific unit of the forest system they focus on. Two common types of growth models are stand-level growth models and tree-level growth models. Both play significant roles in forest management, but they differ in terms of the scope of analysis and the level of detail they provide (Yue et al., 2008).

Stand-level growth models are designed to predict the growth of a forest stand—a group of trees of similar species and age growing in a specific area. These models work at the aggregate level, focusing on the overall structure and dynamics of a stand, rather than individual trees. Key Features of Stand-Level Growth Models may be listed based on the Focus on Forest Composition and Structure: Stand-level models look at the collective characteristics of the forest, such as the average tree size, tree density, and species composition. These models may aggregate variables such as the average diameter at breast height (DBH), tree height, and tree density to predict the growth and yield of the entire stand.

In contrast to stand-level models, tree-level growth models focus on individual trees, predicting their growth over time based on specific tree attributes and environmental conditions. These models provide detailed information about the development of individual trees within a stand and can be particularly useful for forest management decisions that involve selective harvesting, thinning, and assessing the health and quality of individual trees (Vanclay, 1991). These models focus on Individual Tree Growth: Tree-level models consider the specific characteristics of individual trees, such as diameter, height, and crown size, and use these to predict future growth. These models often look at how a single tree's growth responds to competition, environmental conditions, and management practices. While both types of models are valuable for forest management, they differ in terms of their scope, complexity, and applications (Table 8).

Table 8 Tree level vs. stand level models

Aspect	Stand-Level Models	Tree-Level Models
Unit of Analysis	Entire forest stand	Individual trees
Focus	Forest composition, structure, and yield	Growth of individual trees
Data Inputs	Stand age, density, species composition, site conditions	DBH, tree height, species, competition, environmental factors
Output	Stand volume, biomass, and yield	Tree diameter, height, and value estimation
Primary Use	Timber harvest planning, thinning, carbon sequestration	Selective harvesting, tree health, individual tree value
Complexity	Simpler and more aggregated	More detailed and specific

In practice, both stand-level and tree-level models are often used together to provide a comprehensive approach to forest management. Stand-level models can help assess overall productivity and plan for large-scale harvests, while tree-level models can guide the management of specific trees, ensuring selective harvesting that maximizes both ecological and economic outcomes.

The use of wildfire simulators has provided a better understanding of forest fire dynamics and paved the way for the development of spatially-explicit forest management problem formulations that recognize the risk of fire (Ferreira et al., 2015). In these formulations, the probability that a forest stand will burn depends on stand-level characteristics and biophysical factors (Botequim et al., 2015; Gonzalez-Olabarria et al., 2011). This probability also acknowledges neighbourhood relations and the potential of wildfire spread between sets of neighbours (Marques et al., 2017). Yet it does not consider the potential of a stand to burn because of ignitions in distant stands. This Innovative Action (IA) will address this technological gap.

For that purpose, IA will build from four key types of parameters: 1) the probability of an ignition occurring in a stand, 2) the flammability of a stand, 3) the tendency for a fire to spread to a given stand from each of the stands that are adjacent to it, and 4) the value at risk in each stand. Each of these parameters are a function of the characteristics of the stand, the characteristics of the surrounding stands and the local climate and terrain.

7.3 Exploring the criteria and decision spaces with management planning techniques

Optimization models play a vital role in forest management planning by providing decision-makers with quantitative tools to maximize or minimize specific objectives while considering constraints. These models help in balancing ecological, economic, and social goals, ensuring sustainable forest use and conservation (Baskent et al., 2024). By utilizing mathematical modelling and computational techniques, optimization models enhance decision-making in areas such as timber harvesting, wildlife conservation, carbon sequestration, and disaster prevention.

Optimization models in forest management can be broadly classified into several categories based on their approach and objectives:

- Linear Programming (LP) mostly used for optimizing timber harvest scheduling, resource allocation, and sustainable yield. The objective functions may include maximizing economic returns while ensuring sustainability and constraints include forest growth rates, biodiversity protection, and land-use regulations.
- Mixed-Integer Programming (MIP) that incorporates both continuous and discrete decision variables, being useful for problems such as road network design, spatial allocation of management units, and harvest scheduling.
- Dynamic Programming (DP). breaks the decision-making process into stages and solves problems recursively. This approach is used for multi-period forest planning, adaptive management strategies, and regeneration planning.
- Goal Programming (GP), Extends linear programming by handling multiple conflicting objectives, very useful for balancing timber production, carbon sequestration, and biodiversity conservation, fire protection.
- Heuristic and Metaheuristic Approaches includes genetic algorithms, simulated annealing, and tabu search. They are applied to complex, large-scale forest management problems where exact solutions are computationally challenging. Helps in finding near-optimal solutions in reasonable computational time.
- Multi-Criteria Decision Analysis (MCDA) combines optimization techniques with stakeholder preferences and expert judgment. Frequently used for integrating ecological, economic, and social aspects of forest management.

Optimization models offer several advantages in forest and fire management, including: a) Enhanced Decision-Making: Provides data-driven insights for long-term planning, b) Sustainability: Balances ecological conservation with economic profitability, c) Efficiency: Reduces waste and optimizes resource use, d) Adaptability: Can incorporate changing conditions such as climate change and policy shifts, e) Cost Reduction: Helps in minimizing expenses related to operations and logistics and f) Policy Support: Assists governments and organizations in designing better forest management policies.

Optimization models are indispensable tools in modern forest management planning. By integrating mathematical models with ecological and economic considerations, these approaches support sustainable forest management, ensuring the efficient and responsible use of forest resources. The continuous evolution of computational methods, combined with AI and big data technologies, will further enhance optimization-based forest management strategies. These advancements will enable more effective conservation, economic sustainability, and climate resilience in forested ecosystems worldwide.

The design of resilient landscapes building from the knowledge of the fire parameters, requires the use of effective, but simple, problem formulations in which the practitioners can fully understand the driving mechanisms of the models and algorithms involved. The model of the system needs to be accurate and yet flexible and capable of providing feasible solutions for real and complex problems within a limited amount of computational time. The implementation of exact methods such as mixed integer programming (Tóth & McDill, 2008) can be constrained by problem size in the context of modern forest planning, and heuristics approaches are often preferred in the optimization arena to solve complex combinatorial problems, even though these approaches cannot guarantee global optimality (Borges et al., 2002). However, the tuning process can be optimized (Jin et al., 2017) and nearly optimal outcomes for very complex formulations can be achieved at acceptable computational cost (Bettinger et al., 2016). Recent work also reports the potential of machine learning to solve this problem.

Based on a proposed methodological framework on a forest matrix scenario that reflects alternative spatial distributions of forest biophysical attributes, the specific objectives of this component of the IA are: i) to obtain an optimized spatial landscape configuration in order to increase resilience and address concerns with EWE ii) to minimize potential losses caused by EWE by the optimal allocation of management options over the landscape.

8 Optimizing Landscape Configuration for Minimizing Fire Risk and Reducing Losses

8.1 Vale do Sousa, Portugal

8.1.1 Data Acquisition and Landscape Classification

8.1.1.1 Field Inventory

The fieldwork was conducted by the forest technician of the Vale do Sousa Forestry Association. The first survey carried out between August and September 2019 was limited to areas within the ZIF borders. A total of 158 plots were inventoried, with 17 parcels considered non-forested or inaccessible. Due to clear-cutting, fires, and other circumstances, 45 plots lacked information on forestland. Of the 158 plots, only 69 contained tree and plot information, while 89 were classified as regenerative.

The second and third survey took place between July and September 2022 and in the summer of 2023. Fieldwork was suspended in August due to the high risk of forest fires to ensure the safety of the forest technicians. A total of 113 plots were inventoried (Figure 203 & Figure 204) with 11 classified as built areas and 47 as regenerative. The plots were established using a stratified random sampling strategy based on land cover classes and their proportion in the study site. Land cover classification was conducted using multispectral satellite images and forest inventory sampling plots.

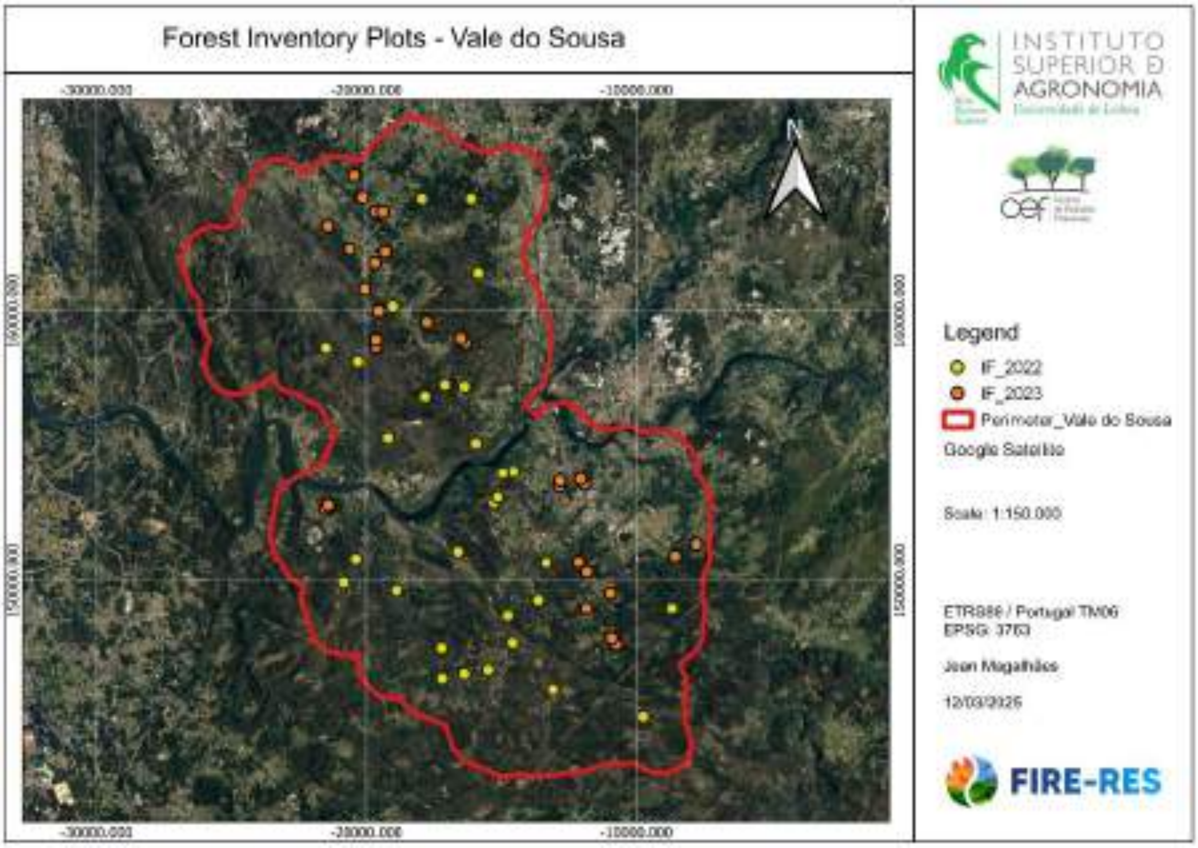
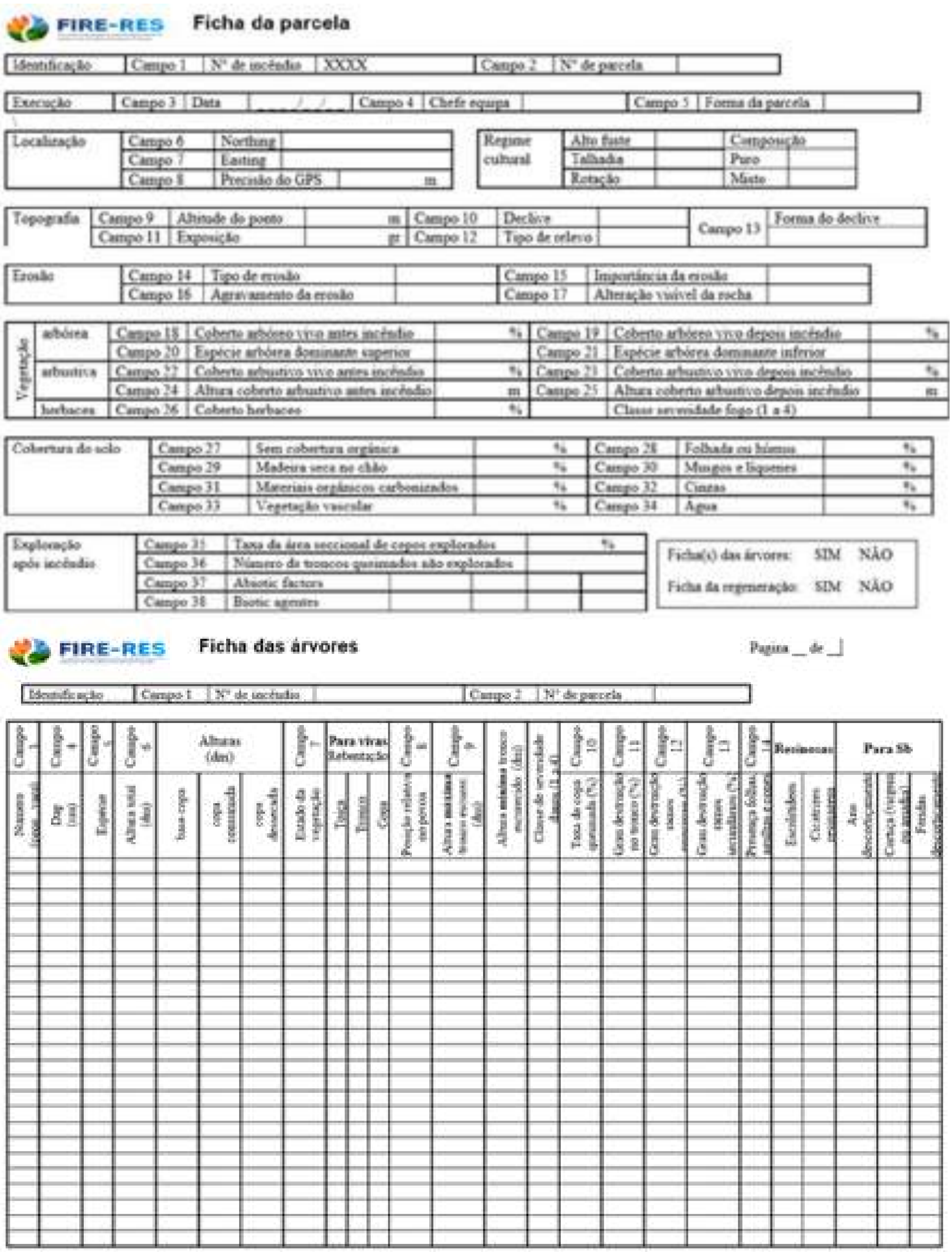


Figure 203 Forest inventoried plots in 2022 and 2023.



FIRE-RES **Ficha da parcela**

Identificação	Campo 1	Nº de incêndio	XXXX	Campo 2	Nº de parcela	

Execução	Campo 3	Data	__/__/__	Campo 4	Chefe equipa		Campo 5	Forma da parcela

Localização	Campo 6	Northing	
	Campo 7	Easting	
	Campo 8	Precisão do GPS	m

Regime cultural	Alto fuste		Composição	
	Talhadia		Puro	
	Rotação		Misto	

Topografia	Campo 9	Altitude do ponto	m	Campo 10	Declive		Campo 13	Forma do declive
	Campo 11	Exposição	gr	Campo 12	Tipo de relevo			

Erosão	Campo 14	Tipo de erosão		Campo 15	Importância da erosão	
	Campo 16	Agravamento da erosão		Campo 17	Alteração visível da rocha	

Vegetação	arbórea	Campo 18	Coberto arbóreo vivo antes incêndio	%	Campo 19	Coberto arbóreo vivo depois incêndio	%
		Campo 20	Espécie arbórea dominante superior		Campo 21	Espécie arbórea dominante inferior	
	arbustiva	Campo 22	Coberto arbustivo vivo antes incêndio	%	Campo 23	Coberto arbustivo vivo depois incêndio	%
		Campo 24	Altura coberto arbustivo antes incêndio	m	Campo 25	Altura coberto arbustivo depois incêndio	m
	herbacea	Campo 26	Coberto herbaceo	%		Classe severidade fogo (1 a 4)	

Cobertura do solo	Campo 27	Sem cobertura orgânica	%	Campo 28	Folhada ou húmus	%
	Campo 29	Madeira seca no chão	%	Campo 30	Musgos e líquenes	%
	Campo 31	Materiais orgânicos carbonizados	%	Campo 32	Cinzas	%
	Campo 33	Vegetação vascular	%	Campo 34	Água	%

Exploração após incêndio	Campo 35	Taxa da área seccional de cepos explorados	%
	Campo 36	Número de troncos queimados não explorados	
	Campo 37	Abiotic factors	
	Campo 38	Biotic agentes	

Ficha(s) das árvores: SIM NÃO

Ficha da regeneração: SIM NÃO

FIRE-RES **Ficha das árvores** Pagina __ de __

Identificação	Campo 1	Nº de incêndio		Campo 2	Nº de parcela	

Campo 1	Campo 4	Campo 5	Campo 6	Alturas (dm)			Campo 7	Para vivas Rebentação			Campo 8	Campo 9			Campo 10	Campo 11	Campo 12	Campo 13	Campo 14	Resinosas		Para Sb		
Número	Dap (cm)	Espécie	Altura total (dm)	base copa	copa queimada	copa dessecada	Estado da vegetação	Toiça	Tronco	Copa	Posição relativa	Altura máxima	Altura mínima	Classe de severidade	Taxa de copa queimada (%)									

Figure 204 Field work sheets

To characterize the WUI, 11 plots were also sampled and inventoried. The field sheets in Figure 205 were used.