The solution reveals an emphasis on the "Do-nothing" approach, covering the largest area (16,122 ha) and the highest number of stands (2,004). This suggests a predominant strategy of passive forest management or limited human intervention. One notable change is the significant increase in the area designated for Clearcutting, which has expanded from 877 ha to 3,348 ha across 336 stands (Table 19). This suggests a more aggressive harvesting approach. Other management action such as Fruit picking & Shrub-cleaning, remain largely unchanged, maintaining their roles in fire risk mitigation and selective maintenance. Thinning & Shrub-cleaning has increased in both area (160 ha) and number of stands (25), indicating a growing emphasis on selective thinning as a forest management tool factors.

Table 19 Summary of Optimized silvicultural treatments when maximizing wood removal (excluding adjacency and clearcut constraints).

Actions	Total area (ha)	Number of stands
Clearcut	3348.7	336
Do-nothing	16122.6	2004
Fruit picking and Shrub-cleaning	1656.9	207
Non-burnable	7653.2	633
Thinning and Shrub-cleaning	160.4	25

- With adjacency and harvest constraints

In this model, we incorporated the clearcut and adjacency constraints established by Portuguese law, which restrict the harvesting of more than 50 hectares of adjacent stands of the same species. Under these constraints, the objective function Volt was maximized, resulting in a total harvested volume of 220,046 m^3. Additionally, the corresponding RAit value obtained in this scenario was 0.99080, reflecting the wildfire resistance index under regulated harvesting conditions.

The latest run continues to show a strong preference for the "Do-nothing" approach, which has slightly increased to 17,014 hectares across 2,071 stands (Table 20). While "Do-nothing" remains dominant, its expansion suggests that more forest stands are being left to evolve naturally, potentially indicating a shift away from active management in certain areas.

On the other hand, Clearcutting has decreased compared to the previous run, dropping from 3,348 hectares to 2,457 hectares across 269 stands (Table 20). This reduction suggests a more restrained approach to large-scale timber harvesting, due to the 50-ha harvesting constraint. Other management actions, such as Fruit picking & Shrub-cleaning and Thinning & Shrub-cleaning, remain unchanged, indicating consistency in their roles within forest management. Overall, the data suggests a continued reliance on passive management, with some adjustments in clearcutting practices, possibly reflecting a balance between economic activities and environmental sustainability (Figure 224).

Table 20 Summary of Optimized silvicultural treatments when maximizing wood removal (excluding adjacency and clearcut constraints).

Actions	Total area (ha)	Number of stands

Clearcut	2457.3	269
Do-nothing	17014.1	2071
Fruit picking and Shrub-cleaning	1656.9	207
Non-burnable	7653.2	633
Thinning and Shrub-cleaning	160.4	25

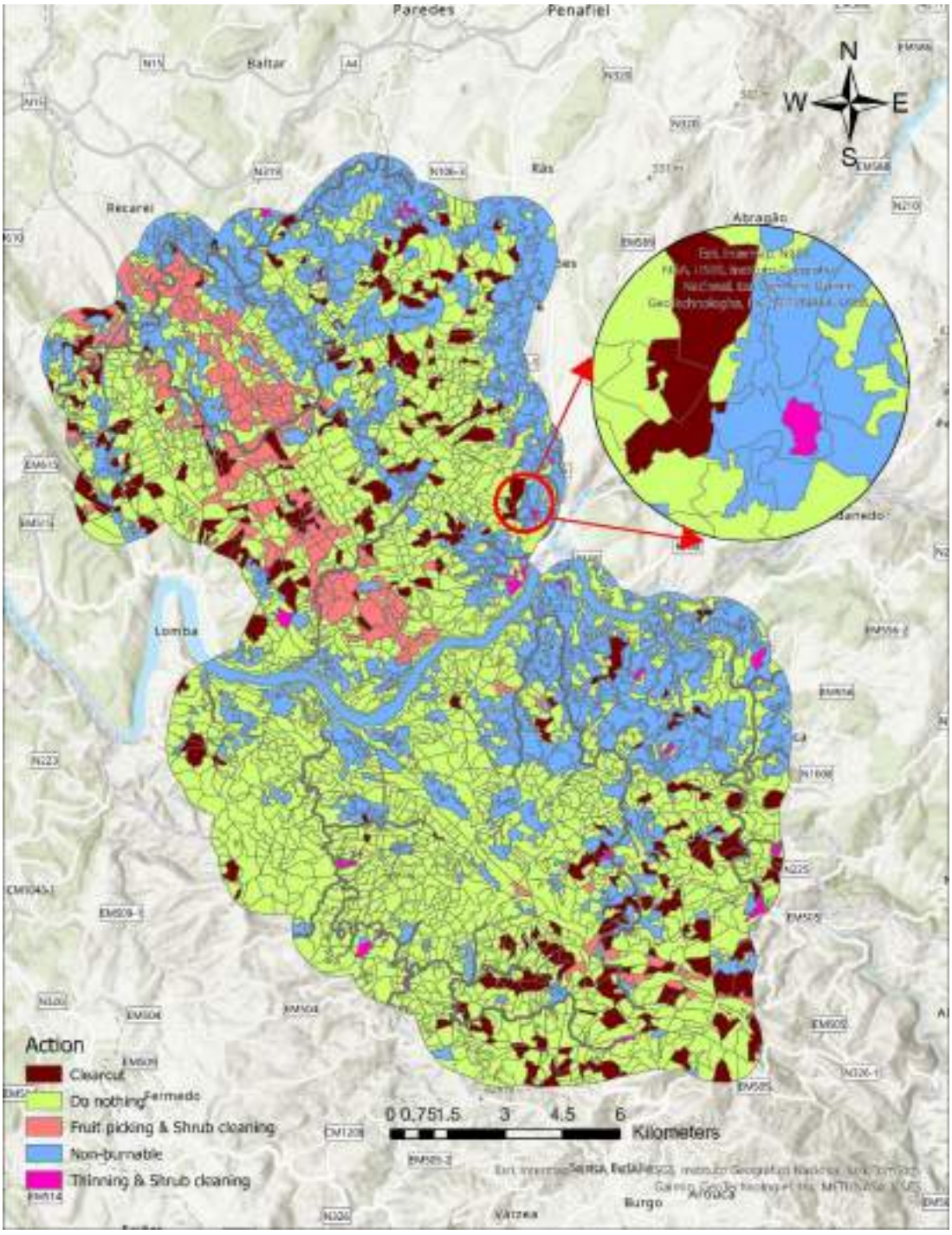


Figure 224 Silvicultural options to maximize wood removal (including adjacency and clearcut constraints) for the year 2025 in Vale do Sousa, Portugal.

This approach evaluates the trade-offs between maximizing wildfire resistance (RAit) and maximizing the volume of wood removed (Volt) using a MIP model. The findings demonstrate how variation in different objective can influence optimal actions to be taken over the landscape.

This study considers the simulated dataset for the year 2025 basing the inventory of 2022 and aims to make a tactical decision to be taken before the wildfire season of 2026 starts. For both objectives the model was run twice; one with harvesting constraints and other excluding the harvesting constraints. The RAit (Wildfire Resistance Index, that take in to account the fire spread between neighbour stands), maximization scenario in both runs resulted in an adjusted wildfire resistance index of ~0.9977, indicating a High resistance class. By contrast, the wood removal maximization was modelled considering Portuguese law not to exceed harvest area for same species adjacent to each other more than 50 ha. This scenario yielded maximum Volume removal as 220,046 m^3 and RAit as 0.9908. However, in the model, setting no limitation on harvesting and RAit, the volume of wood removal was maximized with the value of 271,075 m^3 revealing all the stands at harvesting age being harvested and is nearly 19% more than wood removal maximization complying Portuguese harvesting law. RAit value was found to be 0.990461, which is the lowest of all and falls under the Low resistance class. This gradual increase in harvested volume led to decrease in wildfire resistance reducing live fuel moisture. The omission of shrub cleaning in this scenario, as seen in Table 19 and Table 20, contributed in increasing the fuel load and thus increasing flammability and fire spread of a stand.

The two management approaches differ based on several factors. Wood Removal Maximization model randomly selected all the fuel treatment scenario to be 0 which mean no fuel treatment. The exclusion of shrub cleaning increases the fuel load in the forest stands thereby increasing the probability of fire spread as well as the creation of vertical continuity. Additionally, the model prioritized the selection of high yield stands for harvesting thus leading to a greater number of clearcut areas. In contrast, both scenarios in RAit maximization promoted a more balanced distribution of management prescriptions selecting actions to shrink flammability across stands rather than maximizing economic returns.

While Ferreira et al. (2023) employed a Mixed Integer Programming (MIP) model for a 90-year strategic planning horizon, our study adopts a one-year tactical planning approach. Their model ensures long-term sustainability by incorporating adjacency constraints on not harvesting the stands more than 50ha, if it is occupied with the same forest species. However, our LP model focuses on does not consider any constraints in harvesting and emphasize only on immediate intervention; planning for 2025. Despite these methodological differences, both studies emphasize the importance of integrating wildfire resistance into forest management. Nevertheless, the LP model used in this research offers an efficient and effective decision-support system for instant fire risk mitigation, especially in the aftermath of fire seasons with high-risk potential. This research also supports evidence of Gonzalez et al. (2005) and Thompson et al. (2016) that emphasizes the significance of high-frequency fuel treatment in maintaining the resilience of wildfires.

The implication of these can also be extended beyond immediate fire prevention. Differences in RAit and volume maximization highlights the importance of tactical planning in balancing economic and ecological objectives. Maximizing wood removal may yield short-term economic benefits, however, increases long-term vulnerability to wildfires. Conversely, prioritizing fire resistance ensures greater landscape resilience but limits immediate timber revenues. This trade-off can help policy makers and managers to design an adaptive methodology considering increase wildfire risk.

9.2 Living Lab Greece (Lesvos Island)

9.2.1 Land Classification

The Agiasos forest is the largest, comprised of 66 pure stands of *P. brutia*, covering an area of 3178 hectares. The largest stand is 173 ha, the smallest 8 ha, and the average stand area is 48 ha. The Vasilika forest has 29 stands, most dominated by *P. brutia*, covering an area of 2132 ha. The largest stand is 137 ha, the smallest 25 ha, and the average stand area is 73 ha. Last, the Ampeliko forest, which is the smallest, is comprised of 12 *P. brutia* dominated stands, covering an area of 808 ha. The largest stand is 83 ha, the smallest 42 ha, and the average stand area is 67 ha. Overall, the stands in all three forests are uneven-aged and the age of trees ranges from seedlings up to 85-110 years old. Each of the forests has a designated Forest Management Plan (FMP), where all stands need to receive some type of silvicultural measures, mainly selective thinning at defined intervals varying by forest and stand (thinning intensity varies from 5% to 30%, usually). In the region, the dominant wind direction is the northeast (17%), followed by the NNE (12%).

9.2.2 Resource capability models

Forest Growth

The Table 21 presents forest-related metrics for three locations—Agiasos, Ampeliko, and Vasilika—focusing on forest area, standing volume (tree biomass), thinning volume, canopy cover, and canopy height. All forests show an increase in standing volume, indicating positive growth in biomass. Agiasos exhibits the highest increase (+67.96 m^3), followed by Vasilika (+38.16 m^3) and Ampeliko (+24.61 m^3). Thinning is proportionally conducted across the forests, typically 10% of the 2025 standing volume. Agiasos has the highest thinning volume (40.9 m^3), aligning with its larger area and higher growth. Canopy cover is relatively uniform (57.5%–59.2%), indicating consistent forest density. Canopy height varies slightly (16.9 m–17.9 m), suggesting similar tree growth patterns across locations. Ampeliko has the highest canopy height (17.9 m), possibly due to species composition or site conditions.

Table 21 Forest growth projection in Agiasos, Ampeliko and Vasilika forests

Forests	Area (ha)	Standing Volume (m^3) 2000	Standing Volume (m^3) 2025	Thinning Volume (m^3)	Canopy cover (%)	Canopy height (m)
Agiasos	3,182	341.1	409.1	40.9	58.2	16.9
Ampeliko	824	68.4	92.9	9.3	57. 5	17.9

Vasilika	2,142	154.5	192.7	19.3	59.2	17.0
	6,148	563.9	694.7	69.5	58.4	17.1

Table 22 presents slope (Slp) and road distance (Rd_d) data for different directional sectors across three forests: Agiasos, Ampeliko, and Vasilika. Ampeliko has the steepest slopes, especially in SE (19.8°), S (21.5°), and SW (20.7°). Agiasos has moderate slopes, ranging mostly from 10.6° to 15.5°, indicating a varied terrain. Vasilika shows the lowest slope values, particularly in SE (7.3°) and SW (8.8°), making it the least steep area. Total average slopes are highest in the South (17.2°) and lowest in SW (12.1°), suggesting terrain variability across regions.

Ampeliko has extreme variations, with a very high road distance in SE (736.3 m), suggesting large roadless areas, which can be problematic for accessibility and fire response. Agiasos has relatively even road distances, with shortest access in the South (55.0 m) and longest in SE (209.5 m). Vasilika has the longest distances in the West (331.8 m) and SE (302.2 m), indicating remote areas requiring better access.

Steeper slopes (Ampeliko) may increase soil erosion and fire spread potential due to rapid downhill movement. Long road distances (Ampeliko SE & Vasilika W) suggest difficult access, making fire management and logging more challenging. Agiasos has a balanced terrain with better road access, making it the most manageable for forestry operations.

Table 22 Forest stand general characteristics

Orientation	E		N		NE		NW	
Forests	Slp	Rd_d	Slp	Rd_d	Slp	Rd_d	Slp	Rd_d
Agiasos	12.9	165.9	12.4	95.7	14.5	171.5	15.5	161.8
Ampeliko	-	-	-	-	-	-	19.8	736.3
Vasilika	13.3	163.6	-	-	8.9	214.8	12.5	227.3
Total	12.9	165.7	12.4	95.7	13.5	179.8	14.2	212.5
Orientation	**S**		**SE**		**SW**		**W**	
Forests	**Slp**	**Rd_d**	**Slp**	**Rd_d**	**Slp**	**Rd_d**	**Slp**	**Rd_d**
Agiasos	14.7	55.0	11.7	209.5	11.7	166.5	10.6	115.2
Ampeliko	21.5	162.8	20.7	234.1	18.8	37.0	17.5	377.6
Vasilika	11.4	175.0	7.3	302.2	8.8	93.8	13.0	331.8
Total	17.2	118.4	12.7	235.6	12.1	144.0	13.5	260.4

The Table 23 shows the fire metrics in Agiasos, Ampeliko and Vasilika forests. Agiasos has the highest ignition probability (12.48), indicating a greater likelihood of fire initiation compared to Ampeliko (2.27) and Vasilika (4.23). The variation in ignition probability may be influenced by climatic conditions, human activities, fuel load, and topography.

Ampeliko has the lowest ignition probability, suggesting it may have lower fuel accumulation or less human activity triggering fires.

Agiasos (0.486) has the highest stand flammability, indicating more fire-prone vegetation. Ampeliko (0.083) and Vasilika (0.156) have significantly lower flammability, suggesting differences in tree species, moisture levels, or fuel characteristics. Agiasos combination of high ignition probability and high flammability makes it the most fire-vulnerable forest.

Agiasos again has the highest fire spread probability (6.94), aligning with its high ignition risk and flammability. Vasilika (2.85) and Ampeliko (1.33) have lower fire spread probabilities, but still non-negligible risks. Fire spread probability depends on wind conditions, forest connectivity, and fuel continuity—Agiasos likely has conditions that promote fire propagation.

Agiasos is the most fire-prone forest, with high ignition potential, flammability, and spread risk. Ampeliko is the least at risk, having the lowest values across all fire-related parameters. Vasilika falls in between, with moderate fire risk but still significantly lower than Agiasos.

Table 23 Fire metrics in Agiasos, Ampeliko and Vasilika forests

Forests	Ignition Probability	Stand Flammability	Fire Spread Probability
Agiasos	12.48	0.49	6.94
Ampeliko	2.28	0.08	1.33
Vasilika	4.23	0.16	2.85
	0.18	0.01	0.10

Fire spread between stands probabilities

The spatial relation between the 107 forest stands were analysed (Table 24) and we can observe that each stand usually shares the border limits with several other stands having the grand total average length across all stands is 539 meters. The grand total fire spread probability averages 0.0464. In some locations, such as Ampeliko_99 and Vasilika_87, have significantly higher length values exceeding 900, while Vasilika_87 also exhibits a high fire spread probability 0.1152). Agiasos_46 (0.2172) and Agiasos_42 (0.1321) have among the highest probabilities of fire spread, suggesting potentially high-risk areas. There is noticeable variation in fire spread probability among locations, with some below 0.01 while others exceed 0.1, indicating uneven fire risk distribution.

Table 24 Fire spread probability in forest stands in Lesvos Island

Forests	N. neighbor relations	Average shared border (m)	Average Fire spread prob
Agiasos	410	477	0.0445
Ampeliko	51	751	0.069

Vasilika	161	632	0.043
Total	622	539	0.046

To put it simple, the ignition 255 that originated in Stand 1 of the Agiasos forest burned in total 10 ha, 5 ha of which in Stand 2 of the Agiasos forest, 3 ha burned in Stand 13 of Vasilika forest, and 2 ha burned in the Stand 12 of Vasilika forest. This process is repeated for every ignition that originates from each stand. Then for all ignitions that originate from that stand and burn the same neighbouring stand, we sum the total burned area. With that process, conducted with XFire given that all necessary inputs are provided, we were able to estimate the total burned area originating from one stand and burning on a neighbouring one. The raw burned area value, by using all stands, was converted into a fire spread probability value, with the highest value from all stand couples (sending and receiving) be closer to 1 and the lowest value closer to zero (Table 25).

Table 25 Adjacency and fire spread probability example between all forest stands used for Lesvos Island

ID	Sending	Receiving	Length	Fire spread probability
4	Agiasos_1	Ampeliko_102	667.56	0.0218
5	Agiasos_1	Ampeliko_103	535.78	0.0128
6	Agiasos_1	Ampeliko_105	347.35	0.0327

9.2.3 Results from the MILP

9.2.3.1 Minimizing fire risk

The optimization results effectively highlight the selection of forest plots for thinning in 2025 using the Mixed-Integer Linear Programming (MILP) approach. Two distinct methods were employed to select plots based on fire risk reduction: one focusing on a 10% area constraint (Approach 1.1) and the other selecting 11 plots with thinning year prioritization constraints (Approach 1.2). The analysis for 2026 demonstrated that the average fire risk of the plots selected under the 10% area constraint was 0.3105, while the average fire risk for the 11 selected plots was 0.3087. Although these values exist outside the normalized 0-1 scale, where the maximum fire risk is approximately 2.2, they still effectively represent the relative fire risk within the selected plots.

Under the 10% area thinning constraint, a total of 19 plots were identified for intervention. These selections were made based on factors such as historical thinning records and potential fire risk reduction. The selected plots exhibit variability in size, with some undergoing complete thinning while others have only a portion designated for treatment. The spatial distribution of thinning activities, illustrated in the corresponding map, suggests a well-strategized allocation across different forest regions, optimizing resilience to wildfires. Notably, several plots had their last thinning intervention over two decades ago, reinforcing the urgency of intervention to sustain forest health and mitigate

fire risk. The selection process aligns with predefined constraints, ensuring an efficient and balanced forest management approach.

For the 11 selected plots under Approach 1.2, prioritization was based on the earlier thinning year. These plots were strategically chosen to enhance forest resilience and optimize the reduction of fire risk. The results indicate that prioritizing plots based on past thinning years provides slightly improved fire risk reduction compared to the area-based constraint approach.

The Table 26 presents the forest plots selected for thinning in 2025 based on the optimization model. It includes details such as the unique plot ID, total shape area, thinning area, and the last thinning year, while

Table 27 shows the same information but for the 11 plots of the MILP.

Table 26 Selected Forest Plots for Thinning in 2025 (MILP- 10% Area)

SN	Plot Unique Id	Shape Area (ha)	Thinning Area (ha)	Last Thin Year
1	Agiasos_2	37.39	0.37	2001
2	Agiasos_6	44.92	0.45	2000
3	Agiasos_28	93.63	93.63	2009
4	Agiasos_29	28.079	28.079	2009
5	Agiasos_33	74.078	74.078	2008
6	Agiasos_37	59.44	59.44	2003
7	Agiasos_38	28.62	0.29	2003
8	Agiasos_42	88.51	88.51	2004
9	Agiasos_45	25.89	25.89	2004
10	Agiasos_51	140.65	140.65	2002
11	Agiasos_52	94.09	52.39	2004
12	Agiasos_64	25.74	25.74	2002
13	Agiasos_66	19.82	19.82	2008
14	Vasilika_69	13.77	1.38	1999
15	Vasilika_74	75.70	0.76	2007
16	Vasilika_83	65.26	0.65	2002
17	Vasilika_93	98.01	0.98	2005
18	Ampeliko_99	83.91	0.84	2006
19	Ampeliko_101	83.26	0.83	2008

Table 27 Selected Forest Plots for Thinning in 2025 (MILP- 11 Plots)

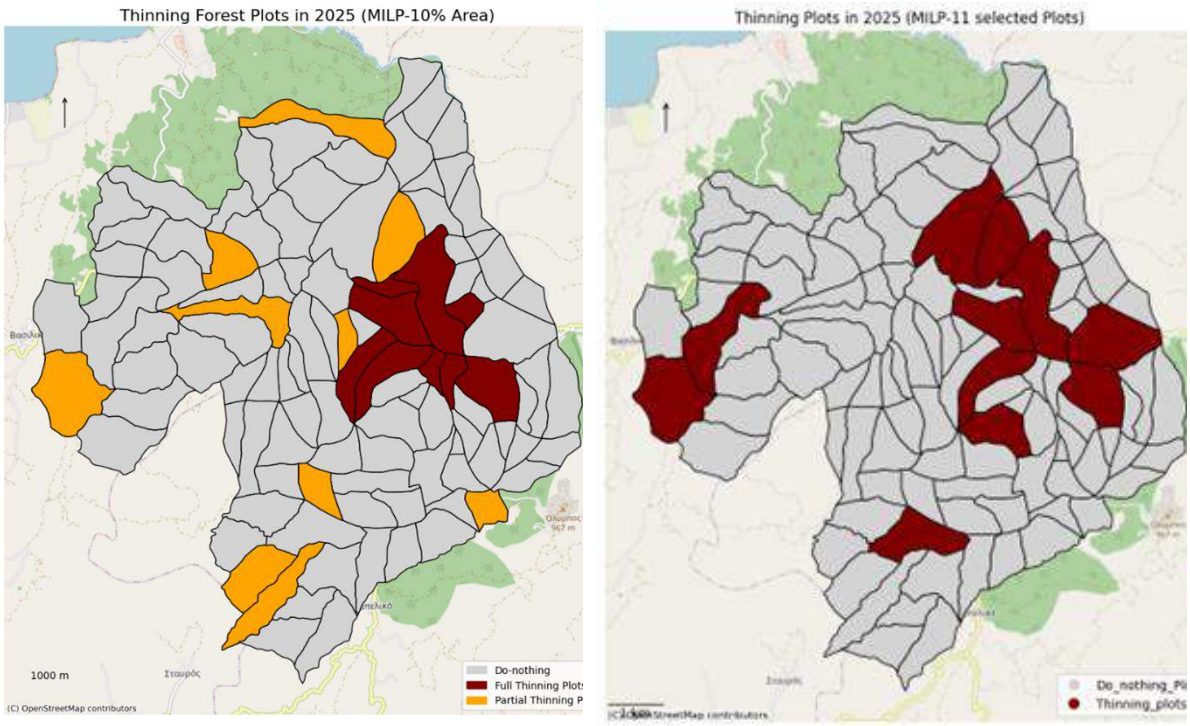
SN	Plot Unique Id	Shape Area (ha)	Thinning Area (ha)	Last Thin Year
1	Agiasos_21	71.52	71.52	2008
2	Agiasos_28	93.64	93.64	2009
3	Agiasos_33	74.08	74.08	2008
4	Agiasos_42	88.51	88.51	2004
5	Agiasos_46	132.05	132.05	2002
6	Agiasos_51	140.65	140.65	2002
7	Agiasos_52	94.09	94.09	2004
8	Agiasos_56	163.78	163.78	2004

9	Vasilika_69	137.76	137.76	1999
10	Vasilika_76	114.92	114.92	2007
11	Ampeliko_105	89.99	89.99	2008

The maps in Figure 225 illustrates the forest plots selected for thinning in 2025 based on the MILP optimization model. The red-coloured plots represent the areas where thinning will be conducted, while the grey areas indicate non-selected plots or do-nothing option. The 10% area constraint method is more closely aligned with the "Thinning Year" constraint, allowing for partial thinning of plots, thus enabling a more flexible selection of areas to thin, even including fractional portions of plots. This flexibility is a consequence of the continuous nature of the decision variables in this formulation.

In contrast, the 11-plot selection method employs binary variables, where each plot is either fully selected or not. This binary formulation tends to prioritize risk minimization by selecting contiguous plots that cover a larger area than the 10% constraint, resulting in a lower overall fire risk for the selected plots. Moreover, selecting entire plots, rather than partial fractions, is more economically viable, as it reduces logistical complexities associated with partial thinning, particularly in plots that may be geographically dispersed. The 11 selected plots, as observed, are spatially closer to one another, optimizing operational efficiency and minimizing transportation and resource costs.

Notably, there is overlap in the plots selected by both methods, particularly in the case of plots that receive full thinning. These plots, selected under the 10% area constraint, are the same as those selected under the 11-plot method, highlighting that the most critical high-risk plots are consistently prioritized across both methods. This consistency ensures that both approaches effectively target high-risk areas, albeit with slight variations in coverage and logistical considerations.



a. b.

Figure 225 a. Thinning Forest Plots in 2025 (MILP Model- 10 % Area); b. Thinning Forest Plots in 2025 (MILP Model- 11 plots (10 % Plots).

The fire risk maps for 2025 and 2026 (Figure 226) illustrate the spatial distribution of fire risk across the study area, categorized into low (green), medium (yellow), and high (red) risk zones. The observed minimal difference between the two years can be attributed to the conservative assumptions applied in the risk reduction model, where thinning was assumed to decrease fire risk by only 5%, while areas left untreated experienced a 1% risk increment. Additionally, the spatial extent available for thinning was constrained, limiting the overall impact of risk reduction interventions. The risk classification was based on absolute values rather than a normalized scale, with the minimum risk set at 0.02 and the maximum at 2.2. Plots were categorized as low risk (≤ 0.2), medium risk (≤ 1), and high risk (> 1) to prioritize high-risk areas for thinning. A more precise categorization could be achieved with empirical data on the actual risk reduction effects of thinning and the rate of risk increase in untreated areas. Future improvements in risk assessment could incorporate such data to refine the classification and optimize intervention strategies. The primary objective remains the identification of high-risk plots for targeted thinning under the given constraints.

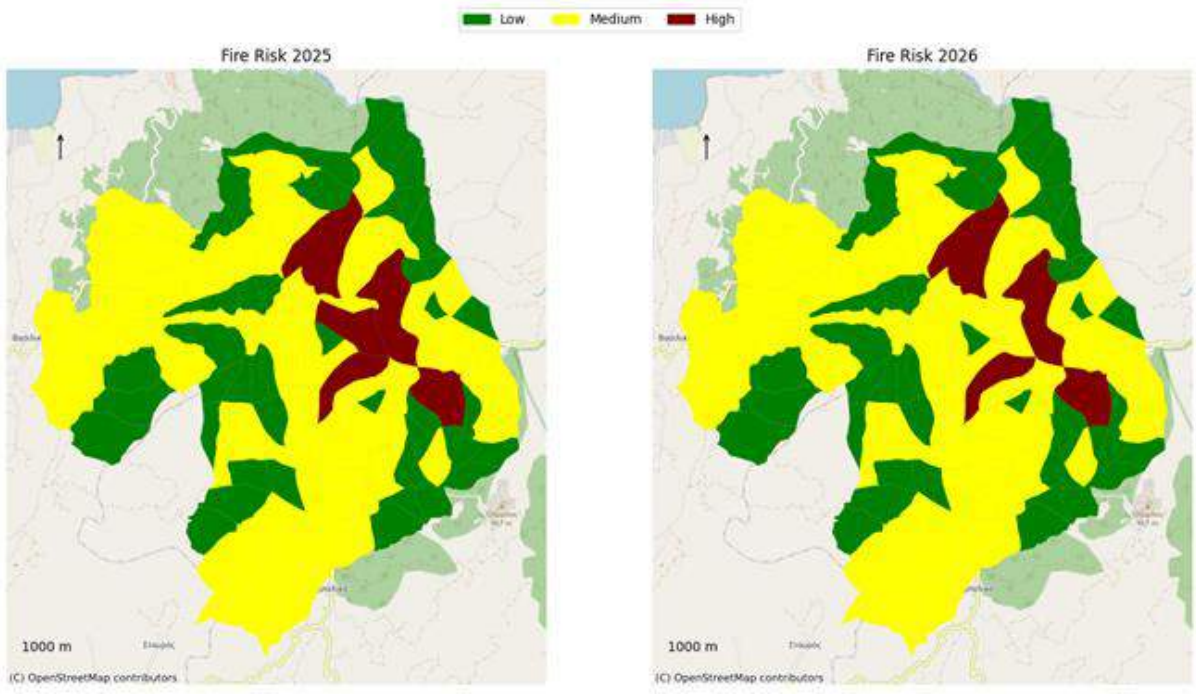


Figure 226 The fire risk maps for 2025 and 2026.

10 Discussion, Conclusions and Suggestions

10.1 Reflections and Suggestions from the application of Scenario Planning to the five Living Labs

This work provides measurable outcomes on how focusing on one forest management priority results in trade-offs in the others, and it identifies fuel treatment projects to achieve multiple fire management outcomes (Ager et al., 2017; Pohjanmies et al., 2019; Schroder et al., 2016; Triviño et al., 2017). Recent studies in the United States showed that treating less than 30% of landscapes (ideally between 10-20%) can have substantial effects on wildfire spread and intensity; in other words, not every stand needs to be treated (Ager et al., 2021; Finney et al., 2007). A homogeneous fuel landscape generally favours fire spread (Baker, 1994), while a fragmented landscape with heterogeneous fuel patches reduces fire spread (Turner et al., 1989). Fire spread is influenced by the spatial arrangement of land cover and land use types (LULC) and their characteristics. However, fire spread under extreme conditions, such as those found at EWE (fire spread rate is ≥ 50 m/min (Tedim et al., 2018)), appears to be insensitive to landscape structure and is primarily determined by weather conditions (Moreira et al., 2020; Moritz et al., 2010; Turner & Romme, 1994). However, targeting the reduction of the amount and connectivity of fuels would reduce fire growth rate, increase the potential for fire suppression, and mitigate fire damage (Moreira et al., 2020). Percolation theory studies suggest that reducing fuel connectivity is an effective approach to mitigating fire spread across the landscape, but the thresholds for percolation (i.e., the threshold at which functional landscapes transition from unconnected to connected) reported in different studies vary. Using generic landscapes, Bevers et al. (2004) determined a percolation threshold of 59% of landscapes resistant to fire spread, and Loehle (2004) determined a lower value of about 18%. Additionally, fire modelling techniques can be applied to analyze the potential for landscape-level fire spread in response to the timing and location of fuel treatments. For example, Alcasena et al. (2018) showed that treating approximately 15% of the landscape with prescribed burns, strategically distributed is effective in interrupting large wildfires. This value is similar to that of Fernandes (2015) who shows that 5-10% of the landscape in strategic locations should be treated with prescribed fire annually to reduce wildfire size. For more information for the above, please refer to the FIRE-RES deliverable D1.11 “Ecological factors driving resistant and resilient landscapes to high intensity and extreme wildfire events”.

Recent studies emphasized the need to incorporate wildfire uncertainty into effective fuel reduction plans, prompting discussions on whether future wildfires burn the project areas prioritized for fuel treatments prior to their scheduled implementation, and whether this would be executed at a fast pace (Ager et al., 2021). For example, despite the widespread implementation of fuel treatments in the United States, their benefits are diminished over time on large landscapes due to the low probability that treated areas will be burned by a sub-sequent fire within a treatment’s lifespan (temporal mismatch) (Barnett et al., 2016). Our prioritization process results indicate how much area should be treated and where, but to achieve the estimated levels of attainment, forest management should be effectively applied with vegetation and fuel treatment methods

aligned with international experience and practice, while considering the abovementioned temporal mismatch (Graham et al., 2010; Jain et al., 2012). In brief, fuel treatment strategies should employ a combination of surface fuel loading, depth, and continuity reduction treatments (e.g., prescribed burns and mastication), silvicultural practices to change tree crown structure (e.g., thinning and low pruning), and the creation of infra-structure and safety areas to facilitate fire suppression activities (e.g., road networks and water points). Mechanical treatments such as thinning (either commercial or non-commercial depending on stand conditions), mastication, or entire tree harvesting are required in high fuel load conditions or dense forest ecosystems with ladder fuels to reduce canopy bulk density and to mitigate hazard prior to using fire to reduce fuels. Most recent studies agree that thin and burn treatments had positive effects in terms of reducing fire severity, tree mortality, and crown scorch, but burning or thinning alone had either less of an effect or none, compared to untreated sites (Kalies & Yocom Kent, 2016). In the work of Vilà-Vilardell et al. (2023) it is highlighted that the reduction of fire intensity, severity and spread rates can be better achieved when combining overstory and understory treatments, with the resistance ability more influenced by understory treatment than thinning intensity, while mechanical treatments followed by burning more beneficial than mechanical only. They also found that prescribed burning after light or heavy thinning led to resistant forests. In another study by Davis et al. (2024), it was found that forest treatments that reduce surface fuels decrease subsequent wildfire severity, thinning with prescribed burning was the most effective and persistent treatment in several cases across the Western US, and treatment efficacy for reducing wildfire severity declined for older treatments. They also highlighted that prior low or moderate severity wildfire can reduce subsequent wildfire severity (Davis et al., 2024).

The temporal mismatch and the appropriate fuel treatment prescriptions for each area should be considered when fire management agencies want to apply fire risk reduction fuel treatments. Significant administrative and application constraints need to be addressed to implement the simulated scenarios and increase the chances for reducing fire behaviour. In our previous research (Palaiologou et al., 2018; Palaiologou, Kalabokidis, Troumbis, et al., 2021), we highlighted that prescribed burning is illegal in Greece and that a policy reform is required to allow for its application. As a result, the investment cost to achieve the expected outcomes is significantly higher compared to a similar application in other countries with a well-established fire use culture. Moreover, the major logistical constraint is how downed logs are moved to the closest timber mill and what infrastructure is required (e.g., opening of new roads). Another consideration is the management of logging residuals to avoid increasing fire risk in cases where no pile burning or mastication follows.

Once the projects and the stands for fuel management are selected on the larger scale that this analysis was conducted, a smaller scale approach is then required to allocate and arrange treatments on the landscape to maximize their efficiency. For the case of stands with high attainment for the suppression difficulty priority, our results can be used to design fuel breaks in the form of a network with sufficiently modified fuels that can decrease the potential fire intensity and the rate of spread to a level where suppression resources succeed in containing the fire (Moriarti et al., 2015; Oliveira et al., 2016).

We identified some limitations in our assumptions and modelling. The ForSys model is data driven, and the inputs used for both fire simulation modelling and scenario planning were a snapshot of the most recent forest and fuel conditions, confined by data availability for each Living Lab. Results should be interpreted and applied within a short-term timeframe (1 to 10 years maximum). Moreover, management activities were simulated without the effect of potential disturbances that can occur within the application timeframe. As a result, forest growth was not considered in our estimations, and results are applicable until substantial forest growth occurs or until the effect of a disturbance substantially changes stand structure or fuel conditions.

The major assumptions we made in scenario planning modelling included the following: (1) the stands selected for forest management would receive an appropriate suite of treatments, including mechanical thinning, fuels mastication, and pile burning of logging residuals; and (2) the posttreatment conditions of the stand would meet priority goals for the various objectives, i.e., reduce transmission of wildfires to developed areas or timber retrieval goals. In addition, our approach for assessing the levels of attainment from applying forest management in the selected project areas are relative rather than absolute values. In terms of forest production, since recent estimates of merchantable timber volume were not available, we used aboveground biomass minus foliage which was the only good available analog to merchantable timber volume. Some of the selected stands within projects might not be accessible due to lack of roads, which implies the cost of treatments there would be increased.

Finally, since increasing fuel loads and continuity represent the main factor responsible for the recent catastrophic fire events in the Mediterranean region, we anticipate that our results can inform fire risk management agencies on the optimization of forest management to improve fire suppression efficiency and reduce fire spread to the wildland–urban interface and protected areas. Managing forest fuels has been internationally demonstrated to be an efficient strategy to fragment fuels and reduce fire spread rates and severity.

10.2 Reflections and Suggestions from the application of Optimization approach for the two Living Labs

Forest management is a complex and multifaceted task that involves balancing ecological, economic, and social factors. It includes decisions regarding logging schedules, conservation efforts, species protection, forest regeneration, and ecosystem services. Given the dynamic and unpredictable nature of forests, coupled with the growing pressure from climate change and increasing human activity, efficient management of forest resources has never been more critical. One effective way to address these challenges is through the application of mathematical programming.

Mathematical programming, particularly optimization techniques, provides a robust framework for tackling forest management problems by enabling decision-makers to consider multiple objectives simultaneously. Forest managers must often make decisions that balance maximizing timber production, minimizing environmental degradation, ensuring biodiversity conservation, and meeting community and economic needs. Mathematical programming models can incorporate these diverse objectives and constraints, offering decision support in a way that is both quantitative and transparent.

One of the key advantages of using mathematical programming is its ability to handle the complexity of forest systems. Forests are inherently dynamic, with growth, harvesting, and regeneration processes that are subject to numerous variables such as species interactions, environmental factors, and market conditions. By utilizing optimization models, forest managers can simulate different management strategies, predict long-term outcomes. For instance, a linear programming model or a Mixed integer programming model can be used to determine the optimal schedule for silvicultural treatments in the landscape that minimizes losses while meeting sustainability goals of wood of fire resistance.

The adaptability of mathematical programming also makes it invaluable in addressing the evolving challenges of forest management in the face of climate change. By considering variables such as changing precipitation patterns, temperature increases, and altered growth rates, forest managers can develop strategies that account for future uncertainties. This proactive approach allows for more resilient forest management practices that adapt to changing environmental conditions and help mitigate the effects of climate change.

The approach proposed by Ferreira et al. (2023) to estimate fire resistance offers valuable insights into landscape planning and fire risk mitigation, but it also comes with several limitations that should be considered when interpreting its results. While the approach incorporates some environmental factors, the approach may not fully account for the increasing variability and intensity of climate conditions (e.g., extreme droughts, heatwaves) that directly influence fire resistance and behaviour. The estimation of fire resistance may rely on generalized landscape features and fuel models, which can obscure fine-scale heterogeneity (e.g., microtopography, small fuel breaks) that significantly influence fire spread and intensity.

Ferreira et al. (2023) focus on fire resistance (the ability to avoid ignition or initial spread), but this does not fully reflect resilience, which includes post-fire recovery and adaptive capacity. A landscape that resists fire may still be ecologically vulnerable after a severe event. This approach also excludes socioeconomic and Land Use Feedbacks, tending to emphasize biophysical attributes of the landscape and may underrepresent how human decisions—such as land abandonment, afforestation, or agricultural expansion—interact with fire risk and resistance over time.

In addition to its technical advantages, it promotes collaboration and communication among stakeholders. Forest management often involves diverse groups, such as government agencies, private landowners, conservationists, and local communities, each with different interests and objectives. By applying optimization models, stakeholders can better understand the consequences of different management scenarios and work towards consensus-driven decisions that are supported by data and analysis.

In conclusion, the relevance of solving forest management problems using mathematical programming lies in its ability to address the complexities of sustainable forest management through optimization. By incorporating ecological, economic, and social factors into a comprehensive model, mathematical programming enables more informed, efficient, and adaptable decision-making. As the challenges facing global forests continue to grow, the role of mathematical programming in forest management will be increasingly essential in ensuring the health, productivity, and sustainability of these vital ecosystems.

11 Appendices

11.1 Python code for ranking

```
import arcpy
import os

# Set the workspace to your geodatabase
arcpy.env.workspace = r"C:\DATA\Research\Ongoing\Fire-
Res\WP2\WebGIS\wetransfer_for_web_greece_tradeoffs-rar_2024-11-
27_1115\wetransfer_for_web_ch_tradeoffs-rar_2024-11-
27_1143\For_WEB_CH_TRADEOFFS\CH_RUN10.gdb"

# List all feature classes in the workspace
feature_classes = arcpy.ListFeatureClasses()

# Iterate through each feature class
for fc in feature_classes:
    # Get the feature class name
    fc_name = os.path.basename(fc)

    # Split the name by underscores
    parts = fc_name.split("_")

    # Check if the name has at least 6 underscores to process
    if len(parts) >= 6:
        # Extract the part between the 4th and 6th underscores
        # Add a new field named 'W1' (if it doesn't already exist)
        field_name = "W1"
        field_list = [f.name for f in arcpy.ListFields(fc)]
        if field_name not in field_list:
            arcpy.management.AddField(fc, field_name, "SHORT", field_length=2)
            print(f"Field '{field_name}' added to {fc_name}")

        # Update the field values for all records
        with arcpy.da.UpdateCursor(fc, [field_name]) as cursor:
            for row in cursor:
                row[0] = parts[4]  # Assign part[4] to the field
                cursor.updateRow(row)

        # Add a new field named 'W2' (if it doesn't already exist)
        field_name = "W2"
        field_list = [f.name for f in arcpy.ListFields(fc)]
        if field_name not in field_list:
            arcpy.management.AddField(fc, field_name, "SHORT", field_length=2)
            print(f"Field '{field_name}' added to {fc_name}")

        # Update the field values for all records
        with arcpy.da.UpdateCursor(fc, [field_name]) as cursor:
            for row in cursor:
                row[0] = parts[5]  # Assign part[4] to the field
                cursor.updateRow(row)

       # Add a new field named 'W2' (if it doesn't already exist)
        field_name = "R1"
        field_list = [f.name for f in arcpy.ListFields(fc)]
        if field_name not in field_list:
            arcpy.management.AddField(fc, field_name, "SHORT", field_length=2)
            print(f"Field '{field_name}' added to {fc_name}")

        # Rank records based on descending 'aaa' values
        with arcpy.da.SearchCursor(fc, ["SUM_FIRIN_PCP", "OID@"]) as search_cursor:
            records = [(row[0], row[1]) for row in search_cursor]

        # Sort records by 'aaa' in descending order
        records.sort(key=lambda x: x[0], reverse=True)

        # Create a dictionary for rankings
        rankings = {record[1]: rank + 1 for rank, record in enumerate(records)}

        # Update the R1 field with rankings
        with arcpy.da.UpdateCursor(fc, ["OID@", field_name]) as cursor:
            for row in cursor:
                row[1] = rankings[row[0]]  # Assign rank based on OID
                cursor.updateRow(row)
        print(f"Updated field '{field_name}' in {fc_name} with rankings based on
'SUM_PRTSO_PCP'")

     # Add a new field named 'W2' (if it doesn't already exist)
        field_name = "R2"
        field_list = [f.name for f in arcpy.ListFields(fc)]
        if field_name not in field_list:
            arcpy.management.AddField(fc, field_name, "SHORT", field_length=2)
```

```
            print(f"Field '{field_name}' added to {fc_name}")

        # Rank records based on descending values
        with arcpy.da.SearchCursor(fc, ["SUM_IGNPR_PCP", "OID@"]) as search_cursor:
            records = [(row[0], row[1]) for row in search_cursor]

        # Sort records by '' in descending order
        records.sort(key=lambda x: x[0], reverse=True)

        # Create a dictionary for rankings
        rankings = {record[1]: rank + 1 for rank, record in enumerate(records)}

        # Update the R1 field with rankings
        with arcpy.da.UpdateCursor(fc, ["OID@", field_name]) as cursor:
            for row in cursor:
                row[1] = rankings[row[0]]  # Assign rank based on OID
                cursor.updateRow(row)
        print(f"Updated field '{field_name}' in {fc_name} with rankings based on
'SUM_PRTSI_PCP'")

    #new_name = "_".join(parts[4:6])

    else:
        print(f"Skipped {fc_name} (less than 6 parts)")

print("Processing completed!")
```

11.2 Python code for merging feature classes

```
import arcpy
import os


# Set the workspace to your geodatabase
arcpy.env.workspace = r"C:\DATA\Research\Ongoing\Fire-
Res\WP2\WebGIS\wetransfer_for_web_greece_tradeoffs-rar_2024-11-
27_1115\wetransfer_for_web_ch_tradeoffs-rar_2024-11-
27_1143\For_WEB_CH_TRADEOFFS\CH_RUN10.gdb"

# Output feature class name and path
output_fc = os.path.join(arcpy.env.workspace, "Run10_CH")  # Replace "Merged_FeatureClass"
with your desired output name

# List all feature classes in the geodatabase
feature_classes = arcpy.ListFeatureClasses()

# Check if there are feature classes to merge
if feature_classes:
    # Perform the merge
    arcpy.management.Merge(feature_classes, output_fc)
    print(f"Successfully merged {len(feature_classes)} feature classes into {output_fc}")
else:
    print("No feature classes found in the geodatabase.")

print("Processing completed!")
```

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