Territorial Resilience Through Visibility Analysis for Immediate Detection of Wildfires Integrating Fire Susceptibility, Geographical Features, and Optimization Methods

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Abstract Climate change effects tend to reinforce the frequency and severity of wildfires worldwide, and early detection of wildfire events is considered of crucial importance. The primary aim of this study was the spatial optimization of fire resources (that is, watchtowers) considering the interplay of geographical features (that is, simulated burn probability to delimit fire vulnerability; topography effects; and accessibility to candidate watchtower locations) and geo-optimization techniques (exact programming methods) to find both an effective and financially feasible solution in terms of visibility coverage in Chalkidiki Prefecture of northern Greece. The integration of all geographical features through the Analytical Hierarchy Process indicated the most appropriate territory for the installment of watchtowers. Terrain analysis guaranteed the independence and proximity of location options (applying spatial systematic sampling to avoid first order redundancy) across the ridges. The conjunction of the above processes yielded 654 candidate watchtower positions in 151,890 ha of forests. The algorithm was designed to maximize the joint visible area and simultaneously minimize the number of candidate locations and overlapping effects (avoiding second order redundancy). The results indicate four differentiated location options in the study area: (1) 75 locations can cover 90% of the forests (maximum visible area); (2) 47 locations can cover 85% of the forests; (3) 31 locations can cover 80.2% of the forests; and (4) 16 locations can cover 70.6% of the forests. The last option is an efficient solution because it covers about 71% of the forests with just half the number of watchtowers that would be required for the third option with only about 10% additional forest coverage. However, the final choice of any location scheme is subject to agency priorities and their respective financial flexibility.

Keywords Burn probability · Greece · Spatial optimization · Topography effects · Viewshed coverage · Watchtowers · Wildfire detection

1 Introduction

Climate change tends to create a warmer environment increasing the number and intensity of wildfires around the world (Wotton et al. 2017; Ruffault et al. 2018; Di Virgilio et al. 2019; Dowdy et al. 2019). Because of this, early detection of wildfire events is of crucial importance. Sophisticated geospatial technologies have emerged to deal with this critical issue, incorporating GIS, remote sensing, and artificial intelligence (Xu and Zhong 2017; Zhao et al. 2018; Sousa et al. 2020). Visibility analysis constitutes a popular and effective technique for immediate detection of wildfires (Alkhatib 2014; Kucuk et al. 2017; Sakellariou et al. 2017). However, for this type of analysis the integration of multiple interrelated factors is required in order to achieve an optimal result in environmental and financial terms. Generally, viewshed analysis focuses either on computational capabilities (optimization methods based on specific algorithms) (Shi and Xue 2016; Zhang et al. 2019) or geographical criteria (for example, elevation and slope) to find the optimal solution (Eugenio et al. 2016; Sakellariou et al. 2017).
The primary computational objective in visibility analysis is the maximization of visible area under certain potential restrictions (for example, budget limitations, minimum number of watchtowers) (Bao et al. 2015; Shi and Xue 2016; Zhang et al. 2019). Magalhaes et al. (2010) adopted heuristics algorithms to minimize the number of viewshed positions for certain percentages of visibility coverage. Shi and Xue (2016) designed a model with which they initially extracted the candidate viewpoints from ridges, instead of taking each grid (image) point as a candidate position (Ferreira et al. 2014). Next, they adopted sweep algorithms to minimize the visibility analysis processing time. This type of algorithms was previously proposed by van Kreveld (1996). Finally, they calculated the minimum number of locations for maximum visibility while meeting two criteria: the limitation of overlapping effects between given points and the establishment of the distance threshold between them in case of equal (joint) visible area (Shi and Xue 2016). The latter criterion was already supported by Franklin (2002) and Franklin and Vogt (2006) who highlighted the importance of the geographical dispersion of candidate locations in determining the optimal solution. In the same context, Kim et al. (2004) proceeded to a comparative analysis of optimization algorithms (swap, genetic, and spatial simulated annealing algorithms) using as candidate positions the places with specific topographic features, such as points on ridges or peaks within valleys, concluding that the points on ridges are generally more efficient in terms of visibility. The visibility effectiveness on locally high topographic features has been supported by other studies as well (Bao et al. 2015; Zhang et al. 2019), though rough topography may heavily affect the viewshed coverage, allowing locations with lower elevation to have greater visibility potential (Sakellariou et al. 2017).

Another interesting approach is the combination of viewshed analysis with location-allocation models. Bao et al. (2015) developed such an optimization model suggesting differentiated location schemes of watchtowers based on three main assumptions: (1) cost minimization (by minimizing the number of viewshed locations) with full coverage of the study area; (2) cov-

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More recently, additional geographical criteria tend to be integrated into these types of problems. Eugenio et al. (2016) computed the maximum visibility, as estimated by a certain number of locations, based on different geographical criteria. The candidate locations were derived from the intersection of specific geographical zones, such as points on ridges that are located within suitable land covers and in close proximity to road networks. Sakellariou et al. (2017) estimated the minimum number of viewshed positions based on the combination of maximum visible area and the type of land cover. Other authors integrated fire hazard as a key factor in visibility analysis, paying special attention to the most vulnerable regions (Sivrikaya et al. 2014; Zhang et al. 2020).

To the authors’ knowledge, the current study constitutes a first approach to visibility analysis that combines simulation modeling outputs (that is, burn probability estimation to delimit fire vulnerability), specific topographic features (that is, focusing not only on the highest positions but on the most efficient ones: locations on ridelines with a certain distance between them to reduce overlapping), and geographical features (increased accessibility to watchtowers, minimizing disturbance to the natural ecosystems), with optimization methods (development of dynamic algorithms that maximize the visible areas and simultaneously minimize the number of candidate locations and overlapping effects). The primary aim of this study was the spatial optimization of fire resources (that is, watchtowers) considering the synergistic effect of geographical-topographic features and fire susceptibility, to find an effective and financially feasible solution in terms of visibility coverage. This process would significantly contribute to the territorial resilience of the study area to wildfires.

2 Materials and Methods

This section consists of (1) a description of the primary characteristics of the study area (that is, topography, primary land covers, weather); (2) the types of data used; and (3) the required methodological steps to fulfill the visibility analysis objective.

2.1 Study Area

The study area is the Prefecture of Chalkidiki, which is situated in the northern part of Greece. Figure 1a depicts the relief across the study area, and the upper map inset shows the geographical location of the study area in Greece.

The geographic coordinates of the study area are 40°20′N and 23°30′E. The terrain is rough—more than 50% of the study area is occupied by semi-mountainous terrain and almost 25% is occupied by mountainous terrain. Rough topography plays a key role in viewshed analysis for wildfire prevention. The highest altitude is 1,161 m (NCMA 2012).

The dominant land cover in the prefecture is broad-leaved forests (19%), followed by sclerophyllous vegetation (17%), non-irrigated arable land (17%), olive groves (10%), and complex cultivation patterns (5%), while coniferous forests, mixed forests, and shrubs occupy 4% each (CLMS 2018). Figure 1b shows the land covers that were included in the visibility analysis. We included only forested areas (including grasslands), since 92% of the burned area in 2000–2017 consisted of forests and grasslands, whereas the remaining 8% consisted of agricultural land (HFB 2018).
The Mediterranean climatic conditions are favorable for wildfire ignition in the summer when high temperatures prevail. In the summer months from June to August (1997–2017), the monthly mean temperatures ranged from 25.6 to 28.1 °C; the monthly mean relative humidity ranged from 49.4 to 52.2%; the monthly mean precipitation ranged from 16.2 to 25.1 mm; and the monthly mean wind speeds ranged from 10.8 to 11.9 km/h (HNMS 2018).

2.2 Materials

The primary data used for the visibility analysis consisted of: (1) digital elevation model (DEM)—we used the DEM to estimate the elevations, slopes, and ridgelines; (2) road network—we used road network data to determine the accessibility zones; (3) land cover data—we selected the suitable land covers to be considered in the visibility analysis; (4) systematic sampling data—we used these data to ensure a relative distance between candidate locations to avoid a first order redundancy; and (5) viewed surfaces (raster surfaces visible to observers)—we developed several algorithms to compute individual and maximum joint visibility with the least number of locations. Table 1 summarizes the essential characteristics of each data type.

2.3 Methodology

Generally, the methodology of visibility analysis includes the initial selection of the most appropriate land covers, where the installation of watchtowers is feasible. Next, the determination of fire susceptibility through burn probability (BP), the effect of various geographical criteria (that is, altitude and topography), and technical restrictions (that is, slope and accessibility) was thoroughly considered in an interactive framework, so we could focus on the most suitable areas for the installation of candidate watchtowers. Finally, the development of robust geo-optimization algorithms would provide the essential location schemes of optimal positions in order to maximize the visible area with the least possible number of watchtowers, while simultaneously meeting a certain threshold for overlapping effect. Figure 2 summarizes all the processes involved in the visibility analysis.
2.3.1 Selection of the Most Appropriate Land Covers

First, we restricted our analysis to forested areas given that other land covers (agricultural fields) yield fires of low intensity due to limited biomass load (van Leeuwen et al. 2014). Additionally, many socioeconomic activities normally take place in the cropland areas (for example, agricultural and livestock breeding activities; tourist activities), and fires are readily visible from the nearby residential areas and roads (Sakellariou et al. 2017). Hence, we delimited the study area of the entire prefecture to five land covers: (1) Broad-leaved forests; (2) Coniferous forests; (3) Mixed forests; (4) Natural grasslands—natural grasslands were included in the visibility analysis because they are repeatedly burned by breeders in Greece for the rejuvenation and supply of grazing resources for their livestock (Christopoulou 2011), and these fires can easily spread to the neighboring forests; and (5) Sclerophyllous vegetation and shrubs (see Fig. 1b).
2.3.2 Fire Susceptibility—Geographical Features Contributing to the Visibility Analysis

(1) Determination of burn probability (BP) through wildfire simulation modeling

A key factor is the identification of the most vulnerable areas in terms of BP, so that a certain number of watchtowers for the immediate detection of fire hotspots can be established in these regions. The mapping of fire susceptibility has been conducted by many authors in terms of fire hazard/risk or BP for prevention planning (Mota et al. 2019; Sakellariou, Cabral, et al. 2020; Sakellariou, Parisien, et al. 2020; Tian et al. 2020). We estimated the BP across the entire study area through the Burn P3 model, a spatial wildfire simulation model that estimates the BP, fire intensity, and other critical factors of forest fire propagation (for example, fire spread) (Parisien et al. 2005). The deterministic fire growth model Prometheus that simulates fire evolution has been integrated into Burn P3 (Tymstra et al. 2010), a model that requires a lot of inputs to produce representative and reliable fire products. To this end, it demands fire ignitions data (that is, fire history, spatial distribution of previous fires); burning conditions data (that is, Fire Weather Index System Indices) (van Wagner 1987); estimation of the number of most destructive days; estimation of spatially varying wind fields for wildland fires (through WindNinja simulator—USDA 2018); and fire growth data (estimation of burning hours under maximum conditions, effect of grass features (grass load and moisture), fire propagation). The reliability of the simulation was assessed through the calibration process that tries to produce (simulated) fire products similar to actual ones (in terms of burned area frequency). The conjunction of probabilistic and deterministic capabilities of Burn P3 produces reliable and representative fire products. The entire process of simulation for the study area was conducted by Sakellariou et al. (2022). The higher the BP of each geographical area, the higher the demand for constant surveillance.

(2) Elevation

Elevation is an important factor in visibility analysis. Generally, higher altitudes can yield larger visible areas (Bao et al. 2015; Zhang et al. 2019). However, this is not always the case, as the topography of the study area plays an important role. Consequently, we can find locations with lower elevation but higher visibility. In addition, regions of low altitude are primarily visible from the dense road network, passing vehicles, and the neighboring villages/towns (Sakellariou et al. 2017).

(3) Slope

Intense ground slope is a limiting factor for the construction of watchtowers for technical reasons. Terrains with very steep slopes make it difficult and/or economically infeasible to install watchtowers, whereas the flatter the slope the fewer difficulties we face in the construction of candidate observatories. This factor should not be confused with the slope effect in forest fires. The latter has already been considered in the simulation modeling. Finally, steeper slopes face higher erosion rates (Wu et al. 2018) that increase the viability uncertainty of investments in the construction of watchtowers.

(4) Accessibility

Another significant factor in visibility analysis is the accessibility of watchtowers (Eugenio et al. 2016). Accessibility, beyond the obvious reasons for direct approach by volunteers, technicians, or other staff, must be limited to the extent that it does not disrupt compact forests. Thus, we defined accessibility zones (that is, desirable regions for the construction of watchtowers) every 100 m from the current road network up to 500 m. Beyond this threshold, it is considered that the installation of watchtowers may disturb rare animals and reduce the aesthetic value of these vulnerable regions.

2.3.3 Weighting Process of Key Factors through the Analytical Hierarchy Process and Experts’ System

In order to find the most appropriate surfaces that will serve as the candidate locations for the installment of watchtowers, we need to proceed to a ranking of the contribution of each factor to the visibility analysis. Based on the above analysis, we initially provided an individual ranking of each factor to determine the desired territories. We ranked the above factors, highlighting the regions with the highest BP, elevation, road network proximity, and the least slope. We then applied the Analytical Hierarchy Process (AHP) (Saaty 1990), where we conducted a pairwise evaluation of all the involved factors. These ratings and rankings were applied by academic experts and professional foresters.1 Table 2 shows the final weight for every factor, representing the significance of each dimension for the visibility analysis.

The BP of the most vulnerable regions received the highest weight (50%), since these areas will need greater protection. Elevation is the second most important factor (26%), as in general, higher altitudes tend to offer greater visibility potential. Proximity to the road network takes the third place (15%) to ensure direct access to watchtowers and disturbance minimization to solid forest ecosystems. Ground slope takes the least weight, since the advancement of construction technology minimizes the effect of this factor. The combination of all these factors will provide the final rating of the most suitable regions in terms of fire susceptibility, geographical appropriateness, and technical feasibility. This territory will serve as the background for the selection of candidate watchtower locations.

After the classification of the final score into four groups, the surfaces that belong to the two upper categories (that is, 1 The experts’ system consists of Greek university professors with knowledge of local conditions and professional foresters working in three forest agencies in the prefecture of Chalkidiki. Personal communications with these experts aimed to assess each of the factors contributing to a visibility analysis.
more than half of the final score) will be selected. This occurs so that we can have a clear representation of areas that significantly meet the above criteria, setting aside only regions that are not considered particularly attractive for the installation of watchtowers (that is, low BP, low altitude, significant distance from existing road networks, steep slopes). Areas with very low elevation, accessibility, and BP are deemed inappropriate for the installation of candidate observatories.

### 2.3.4 Extraction of Ridge Points to Serve as Candidate Watchtower Locations

Many authors have pointed out that certain topographic features (peaks and ridges) tend to exhibit greater visibility potential (as they are associated with higher altitudes) compared to other locations (Shi and Xue 2016; Zhang et al. 2019), though additional factors (for example, topography) may also play a distinct role (Franklin and Ray 1994; Lee 1994; Rana 2003; Kim et al. 2004). In addition, as supported by Kim et al. (2004), neighboring locations are very likely to show positive spatial autocorrelation in terms of visibility, that is, neighboring positions usually tend to present similar visibility potential covering similar surfaces. But this is not always the case due to topographical effects (for example, due to the locational difference between a topographical or actual crest and a military crest\(^2\)). Therefore, to achieve the best possible result, the independence of location choices must be ensured, as well as a relatively “safe” distance between them. The current study considers both these critical factors.

First, we extracted the ridgelines of all surfaces of the study area with the aid of hydrology tools (Spatial Analyst Toolbox inside ArcGIS). Initially, we filled the DEM to eliminate any inaccuracies and errors in the original elevation data. Next, we reversed the DEM to identify the areas where water would flow (these areas will become the ridgelines, as they are now processed in inverted form). Then we calculated the flow and accumulation of water in the reference area. Finally, the main waterways were created with their respective branches, where they become the ridgelines (when inverted) of the study area (Esri 2019).

To guarantee the independence and continuity of the possible candidate points along the ridgelines, we extracted all the points that have a certain distance from each other (selection of one ridge point every 10% of the total distance of each ridgeline). This process yielded 308,839 points. In addition to the independence of location options, we must also guarantee a relatively “safe” distance, so that neighboring locations will not be selected to avoid the overlapping effect. However, this distance should not be significant, so as not to lose potential positions that cover areas that are not visible from other neighboring positions. To this end, we applied spatial systematic sampling to divide the study area into 1 km\(^2\) (1000 m × 1000 m) pixels, so that only one candidate location will be selected for each pixel. Thus, we simultaneously ensured the criteria of proximity and avoidance of the (first order) overlapping effect. This systematic sampling yielded 1502 points located in the center of each 1 km\(^2\) pixel. The final step constitutes the “transfer” of all these locations (as derived from the systematic sampling) to the nearest ridge points (as previously calculated) to serve as candidate locations.

### 2.3.5 Selection of Final Candidate Watchtower Locations

The overlay of the most appropriate surfaces (in terms of BP, geographical criteria, and technical restrictions) with the candidate locations along ridgelines within 1 km\(^2\) provided the final geodatabase of candidate locations for the installation of watchtowers. This geodatabase includes 654 candidate positions.

### 2.3.6 Individual Visibility Analysis

Before proceeding with the optimization process, we must calculate the individual visibility of the 654 candidate positions. The visible area for each location was calculated through ArcGIS (Viewshed tool inside Spatial Analyst Toolbox) (Esri 2020) considering three settings: (1) the earth curvature coefficient equals 0.13; (2) the watchtower altitude equals 15 m; and (3) each location has received the respective elevation through the DEM.

### 2.3.7 Visibility Optimization—Maximization of Visible Area with the Least Possible Number of Watchtowers

The ultimate goal of visibility optimization focuses on finding the minimum number of locations that maximize the cumulative visibility coverage. Exact programming methods were adopted through the Python programming language (Numeric Python—NumPy) (Python 2020). We initially wrote a Python script to apply viewshed analysis to each candidate location, integrating the Python code with ArcGIS (ArcPy) (Esri 2020).

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\(^2\) With the term “military crest,” we mean “an area on the forward or reverse slope of a hill or ridge just below the topographical crest from which maximum observation covering the slope down to the base of the hill or ridge can be obtained” (Preparedness Advice 2022).
After calculating the visible surfaces for all candidate positions, we proceeded to the development of optimization algorithms. The primary goal of the following iterative, greedy algorithm is to determine the optimum subset of viewpoints that offers the largest coverage based on specific parameters of the algorithm. These parameters constitute two different ways of determining the size of the subset. The first parameter is related to the desired visibility coverage that the optimum subset should offer—the larger the visibility coverage, the more viewpoints will be included in the subset. The second parameter is an optional percentage threshold. That is, for every additional viewpoint to be added to the subset, the viewpoint must increase the joint viewshed of the subset at least by the specified percentage (for example, by 1% of the previous joint visibility coverage or 1% of the entire study area).

The algorithm initially selects the viewpoint offering the greatest visibility coverage and creates a subset consisting of that viewpoint. Then, it iteratively chooses the viewpoint that, when added to the subset, increases the joint viewshed of the subset the most. The NumPy Python module for scientific computing was used to calculate joint viewsheds of viewpoints. The algorithm terminates when at least one of two conditions is met: (1) the joint viewshed of the subset reaches the desired coverage (1st parameter); and (2) there is no viewpoint that, when added to the subset, increases its joint viewshed by a percentage larger than or equal to the one specified as the second parameter of the algorithm.

Aiming at performance enhancement and reduction of computation time, the calculations for each iteration of the algorithm were run in parallel by dividing all the viewpoints into groups. In each iteration the optimum viewpoint of each group is determined in parallel, and then the viewpoint that offers the most visibility among the optimal viewpoints of each group is included in the subset. To achieve this, the multiprocessing module of Python was used.

The following pseudo-code describes the process of selecting the optimum subset of viewpoints. The parameters of the algorithm are the desired total coverage ($TC$) and the determination of the percentage threshold ($PC$), below which the added visibility of a viewshed is insignificant. The $PC$ is defined as 0.01 (1%) of the previous optimum joint viewshed coverage, so that we can control the entire process, performing a sensitivity analysis at the same time. The final output is the minimum subset $S$ of the viewpoints that achieve the desired total coverage, or the highest possible coverage while satisfying the constraint of the percentage threshold:

1: Initialize empty set $S$
2: WHILE $CVRG(S) < TC$
3:   FOR EACH $G_i$:
4:     $B_i <\gets G_i[0]$
5:   FOR EACH point $P$ IN $G_i$:
6:     $C <\gets CVRG(UNION(S, P))$
7:     IF $C - CVRG(S) < PC * CVRG(S)$
8:       remove $P$ from $G_i$
9:     ELSE IF $C > CVRG(UNION(S, B_i))$
10:        $B_i <\gets P$
11:   ENDIF
12: ENDFOR
13: SELECT $B$ from all $B_i$ such that $CVRG(UNION(S, B))$ is maximized
14: Add $B$ to $S$
15: IF every $G_i$ is empty:
16: RETURN $S$, $CVRG(S)$
17: ENDIF
18: ENDWHILE
19: RETURN $S$, $CVRG(S)$
Line 1 initializes the subset of optimal viewpoints to an empty set. In Line 2, the algorithm will run until the joint viewshed of $S$ reaches the desired total coverage $TC$ (it is controlled and determined by the user). Lines 3–13 iterate through each group $G_i$ and find the viewpoint that offers the greatest visibility in each group. This is achieved by calculating the joint viewshed of $S$ that each viewpoint in the group offers, and by selecting the viewpoint that maximizes it (line 14). In lines 7–8, any viewpoint that does not increase the visibility of $S$ by at least $PC$ is removed from the respective groups. Lines 4–13 can be executed in parallel for every group if the number of groups reflects the number of processor cores on the machine that executes the algorithm. Lines 14–15 select the overall optimal viewpoint among the previously selected viewpoints and add it to $S$. Since the algorithm has possibly removed viewpoints from their groups, there is a chance that all groups will become empty before the desired total coverage $TC$ is reached. Lines 16–17 terminate the execution of the algorithm if that is the case. In line 20, the subset $S$ and its total coverage is returned.

3 Results

Figure 3a depicts the BP of the entire study area after a simulation of more than 30,000 fires. A high BP score indicates a high degree of fire susceptibility. The more vulnerable regions are located in the middle extension of the Chalkidiki peninsula, where compact forests and highly burnable material (coniferous forests, shrubs) exist. A few more regions with high BP can be found in the western part of the prefecture. Therefore, we need watchtowers inside the most vulnerable regions to cover this territory. Figure 3b presents several elevation zones. The candidate locations’ “attractiveness” increases as we move to higher altitudes, since these locations may cover larger areas. The highest locations can be found in the interior of the study area and the center of the middle extension of peninsula. Figure 3c shows the spatial arrangement of ground slopes, separated by five degrees. The location “attractiveness” decreases as we move to ground with steep slopes. There are very few places with extreme slopes throughout the study area. Figure 3d depicts the road network proximity every 100 m. The
location “attractiveness” decreases as we move away from the existing road network. There is a highly dense network throughout the study area except in places with compact forests.

The integration of all these factors through the AHP created Fig. 4, which delimits the regions with the highest score, describing areas with increased efficiency in terms of visibility (increased BP and locally high topographic features) as well as minimum technical constraints and natural environment disturbance (proximity to existing road network and gentle slopes).

At the scale from 0.8 (minimum value) to 9 (maximum value), all areas with a score above 4.5 (half of the maximum value) will be selected. That is, we delimit the most appropriate locations for the regions that concentrate the highest visibility attractiveness.

Figure 5 shows the transitional process to the final selection of appropriate locations for watchtowers. Figure 5a divides the study area into pixels of 1 km², so that we can avoid redundancy in visibility potential between very close positions. The total number of locations amounts to 1,502. This process guarantees the existence of 1 potential location every 1 km². After we ensured a relatively “safe” distance between the positions, we optimized the process by transferring the previous locations to the nearest point of a ridgeline. This second procedure tries to eliminate the topography effect (that is, the military crest issue) (Fig. 5b).

Figures 4 and 5b were combined, so that we select only those points that are located within surfaces with the highest scores in terms of visibility efficiency and technical feasibility. The result of this process generated 654 candidate locations to be considered in the optimization (Fig. 5c).

After we estimated the final number and locations of candidate viewpoints based on a series of geospatial criteria, we proceeded to the optimization module. It is important to emphasize the significant effect of topography on visibility analysis. The optimization results demonstrate that we would
need 341 watchtowers to cover almost all the forested territories, that is 98.8% of the total possible visible area, which can be achieved by 654 locations (hereafter maximum visible area). This fact indicates that topography heavily affects the cumulative visibility and the corresponding number of proposed watchtowers. The very last location (that is, the 654th position) can only cover an additional area of 13 ha.

The maximum visible area seen from the 654 locations equals to 86.5% of the total forested areas (including shrubs and natural grasslands). Thus, 13.5% of the total forested areas are not visible from any position. But the analysis indicates that these are categories of relatively low fire risk (BP) and/or low altitude. Therefore, the cumulative weight is low, and these areas were excluded from the possible installation of potential watchtowers. In quantitative terms, we need: (1) 75 locations to cover 90% of the maximum visible area; (2) 47 locations to cover 85% of the maximum visible area; (3) 31 locations to cover 80.2% of the maximum visible area; (4) 16 locations to cover 70.6% of the maximum visible area, and so on.

The analysis indicates that after adding the 18th best location, the added visible area tends to be marginal (< 1% of the total maximum visible area). However, examining the dynamic nature of the algorithm, there is one more index that explores the added visible area compared to the previously maximum visible area. With this index, the added visible area tends to be marginal after the insertion of the 21st location (< 1%).

Figure 6 contrasts the achieved maximum joint visibility each time a new location is added, with the newly added visibility that this last location offers (without overlapping). The first points have a dominant position in the visibility classification. This happens for mainly two reasons: (1) the great individual visibility potential of first locations is due to the fact that the algorithm searches the locations with the greatest visibility among all 654 candidate positions; and (2) the overlapping effect—in order to maximize the joint
visibility with the least overlapping, we need antidiametrical positions that offer the least degree of overlapping. However, beyond a given threshold, a high degree of overlapping is inevitable (Zhang et al. 2020). Therefore, we should terminate the analysis when a highly satisfactory joint visibility potential is achieved with the least possible number of watchtowers. To reach 80% coverage of the maximum visible area, we need 31 locations.

Figure 7a depicts the visibility coverage for the first six best locations. These six positions cover about 53% of the maximum visible area of forests. The locations are almost antidiametrical, reducing the overlapping effect and maximizing the added visible area.

Aiming to increase the visibility of the study area, we can cover 60.5% of the maximum visible area by adding just three new locations (Fig. 7b). Figure 7b shows the coverage of nine locations. Among the three new locations, two of them are located in the eastern part of the prefecture and one in the northwestern area. The two candidate positions in the east are located close to each other, indicating that they cover different territories. A relative distance between them has already been established from the initial stages of analysis for the selection of candidate positions.

To increase the visibility by 10%, additional seven locations will be required. Thus, 16 proposed positions will be able to cover 70.6% of the reference area. The seven new locations focus on areas where the previous positions achieved much less visibility. Therefore, these locations can be found in the west, central, east, but also in the southern part of the middle extension of the Chalkidiki peninsula. Figure 7c presents the visibility coverage achieved by 16 locations (70.6% of the total maximum visible area).

Finally, the target of 80% of visible coverage of forests requires another 15 positions. It is obvious that the added value of extra locations is significantly reduced. Although the installation of 31 watchtowers for such a large area with this topography is a viable option, the addition of new watchtowers could be considered a financially unprofitable option. The added value of each new location (after the selection of the 31st point) would be marginal. The added visible area for the last (after the best 31 locations) positions is close to 500 ha (0.4% of the total maximum visible area) with a declining trend. For this reason, we consider the possible installation of 31 observatories with 80% coverage as the best choice from an environmental and financial point of view. However, in the absence of financial resources, the fire agency may choose differentiated spatial patterns with fewer watchtowers, but inevitably with less visible coverage. Figure 7d depicts the spatial arrangement of the proposed 31 locations and their respective visibility throughout the reference area.
4 Discussion

Viewshed or visibility analysis for wildfire detection constitutes a complicated and multifaceted task. Most difficulties usually occur with respect to the interaction of geographical features (that is, elevation, slope) and the computation limitations (processing time of a large number of viewshed calculations). Several authors developed notable algorithms for the optimization of certain locations (that is, peaks) (Kim et al. 2004; Bao et al. 2015; Shi and Xue 2016), while others used filtering algorithms to reduce the computation time and requirements for finding the most efficient viewpoints in terms of visibility (Wang and Dou 2020). Even though the highest positions tend to present the greatest visibility potential (Kim et al. 2004; Göltäş et al. 2017; Zhang et al. 2019), the topography effect can drastically alter this potential allowing lower locations to manifest greater visibility (Franklin and Ray 1994; Sakellariou et al. 2017).

The current study confirmed that elevation is a key factor in viewshed analysis but not the most decisive one. While several points with a relatively high altitude (over 700 m) were selected, there are also points with very low altitude that offer large visibility potential. For instance, two positions located at 321 m and 187 m offer 7% additional visibility, making them the 3rd and 4th best points in terms of added visible area.

However, beyond topographic peculiarities, additional factors can play a critical role in visibility analysis. Fire risk/hazard (Sakellariou et al. 2019; Çolak and Sunar 2020) and BP estimation (Sakellariou, Parisien, et al. 2020; Milanović et al. 2021) constitute two primary methods for the delimitation of the most susceptible regions in terms of fire ignition and propagation (for example, existence of highly flammable material that facilitates fire transmission). This vital factor should definitely be integrated into a viewshed analysis. However, very few studies (Kucuk et al. 2017; Zhang et al. 2020) have begun to incorporate this dimension to this type of analysis. In the same context, many authors apply AHP to objectively assess the contribution of each key factor (for example, topographic and climatic conditions; proximity to human structures) to fire risk (Busico et al. 2019; Hysa 2021).
To the authors’ knowledge, this is the first time that the AHP framework has been used for determining the most appropriate territories for visibility efficiency. The process considers the most contributing factors such as BP, elevation, proximity to the road network, and slope. Burn probability based on simulation modeling and slope are of two factors that are integrated in viewshed analysis for the first time. Similarly, Zhang et al. (2020) effectively combined the determination of fire risk with visibility analysis. The slope factor has never been considered as a technical requirement. Even though slope may heavily affect fire propagation (it has already been modeled in BP estimation), there might be many places with large visibility potential on steep slopes. Such places may be at high risk due to other geomorphological factors, such as erosion. Consequently, this dimension should be part of viewshed analysis despite the rapid technical and technological advancements. The last fact justified the lowest ranking of slope in the AHP.

Another innovative approach of the study is the selection of candidate locations based on terrain features. We simultaneously guaranteed the independence and proximity of location options applying spatial systematic sampling. The resulting points were moved to the nearest ridge points limiting the topography effect. This process was then combined with the most attractive territories in terms of visibility, as estimated by the AHP framework. Thus, the integration of geographical features led us to the selection of a certain number of candidate viewpoints, drastically minimizing the computation time and requirements. In this context, the use of the multiprocessing module in Python reduced the computation time even more.

Moreover, the development of a greedy algorithm with specific parameters allowed us to simultaneously select the optimal locations with the greatest visibility potential and the least degree of overlapping (second degree of redundancy). The overlapping effect constitutes a critical dimension from a financial perspective because the minimization of overlapping would lead us to the minimization of the number of watchtowers. Inevitably, after we determined the (first) best locations in terms of viewshe coverage, the addition of extra positions yielded a declining added visible area, satisfying the criterion of overlapping effect that is expressed through the maximization of the joint visible area (Zhang et al. 2019). Some authors put greater emphasis on this perspective (Shi and Xue 2016), while others paid greater attention to geographical features (Eugenio et al. 2016). We tried to integrate all these factors (geographical features including fire susceptibility and optimization methods) to produce the best outcome in environmental and financial terms.

Nevertheless, the current study points to some new perspectives and limitations. Beyond the visibility coverage of forests in general, it would be beneficial to explore the inter-relation of visible area and BP. Thus, we would be certain that the most vulnerable regions (with the highest BP) are adequately covered by the suggested location schemes. Even though we managed to cover more than 80% of all forests, there might be some places that are exposed to high risk. To deal with this gap, we could propose the coverage of the remaining area with supplementary means, such as the adoption of unmanned aerial vehicles (UAVs) or the establishment of optimal location plans for mobile firefighting forces for initial attack (Sakellariou, Samara, et al. 2020).

Another limitation is the uncertainty of the slope factor as a technical requirement. This dimension has never been considered in this type of analysis, but it is very important to know the geological stability of the areas where we propose the installment of any type of watchtower.

One more limitation is related to the inherent uncertainty in BP modeling. Beyond the general knowledge of uncertainty in these types of phenomena, one critical aspect is associated with the adequacy and validity of input data (Cruz and Alexander 2013; Parisien et al. 2013) as well as with the different data resolution categories involved in simulation modeling (Sakellariou, Cabral, et al. 2020). Especially forest fuel data of low spatial resolution may feed the fire modeling with less accurate information, since fuel moisture variability cannot be fully represented at such a spatial level (Parisien et al. 2013). The integration of higher resolution geospatial data (for example, aerial photographs) could lead to even more precise BP estimates.

Finally, the development of artificial intelligence algorithms with even more capabilities may provide accurate outcomes on large viewpoint datasets, simultaneously incorporating financial details (for example, budget requirements) in a more integrated framework (multi-objective optimization).

5 Conclusion

The immediate detection of wildfires at certain locations is a complex process, since it should take into account multiple criteria simultaneously, such as fire vulnerability, geographical appropriateness (in terms of topography and technical feasibility with respect to watchtower locations), and financial requirements. The maximization of viewshed coverage was achieved by the least number of viewpoints and the least degree of overlapping through differentiated location schemes of watchtowers. Hence, a fire agency will choose the optimal combination of environmental protection and financial balance. The construction of 31 watchtowers should not be considered a high number of viewing sites for such a large territory as the study area, especially given the rough relief. This location scheme would cover 80.2% of the forests in the study area. However, there is
the option of another efficient solution that covers 70.6% of the forests with just half (16) the number of watchtowers. Even if we adopted the (financially) worst-case scenario, only six watchtowers could cover more than half (53%) of all the forests in the Chalkidiki Prefecture study area. The final choice is subject to the respective agency priorities and the respective financial flexibility.

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