Optimisation of tower site locations for camera-based wildfire detection systems

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Abstract. Early forest fire detection can effectively be achieved by systems of specialised tower-mounted cameras. With the aim of maximising system visibility of smoke above a prescribed region, the process of selecting multiple tower sites from a large number of potential site locations is a complex combinatorial optimisation problem. Historically, these systems have been planned by foresters and locals with intimate knowledge of the terrain rather than by computational optimisation tools. When entering vast new territories, however, such knowledge and expertise may not be available to system planners. A tower site-selection optimisation framework that may be used in such circumstances is described in this paper. Metaheuristics are used to determine candidate site layouts for an area in the Nelspruit region in South Africa currently monitored by the ForestWatch detection system. Visibility cover superior to that of the existing system in the region is achieved and obtained in several days, whereas traditional approaches normally require months of speculation and planning. Following the results presented here, the optimisation framework is earmarked for use in future ForestWatch system planning.

Additional keywords: facility location, maximal cover, NSGA-II.

Background

Wildfires, when left untreated and under the right conditions, can spread rapidly and go on to cause enormous destruction to rural and urban landscapes. The early detection of their onset is of critical importance – the sooner suppressing action can be taken, the more manageable the size of the fire may be, potentially allowing minimisation of the scale of destruction (Rego and Catry 2006). Camera-based wildfire detection systems (CWDSs) provide early detection in the form of several specialised cameras that monitor the surrounding environment (Martell 2015). The research presented here has been conducted in collaboration with EnviroVision Solutions, which operates the South African-developed ForestWatch CWDS in South Africa, Australia, Spain, Canada and the USA. ForestWatch CWDSs monitor the surrounding environment for smoke using a proprietary pattern-recognition algorithm that is based on South African Antarctic research into the automated detection of aurora (Hough 2007). Once smoke is detected, human operators at dedicated workstations – located at detection centres of local fire protection agencies – are alerted in order to validate fires and send out detection reports. The location of a fire is estimated by triangulation if the smoke is visible from two or more cameras, or from the location of the smoke within an image when only visible from one camera (Matthews *et al.* 2012).

Fig. 1*a* shows a typical camera, while a 32-m tower with a camera mounted on top is displayed in Fig. 1*b*. Terrain features and vegetation growth cause varying degrees of obstruction between the cameras in a CWDS and possible smoke plumes, as seen in Fig. 2. The towers are therefore typically placed at elevated sites that have good visibility of their surroundings, e.g. peaks on mountains and hills. Cost considerations mean that potential sites that offer good visibility will generally far

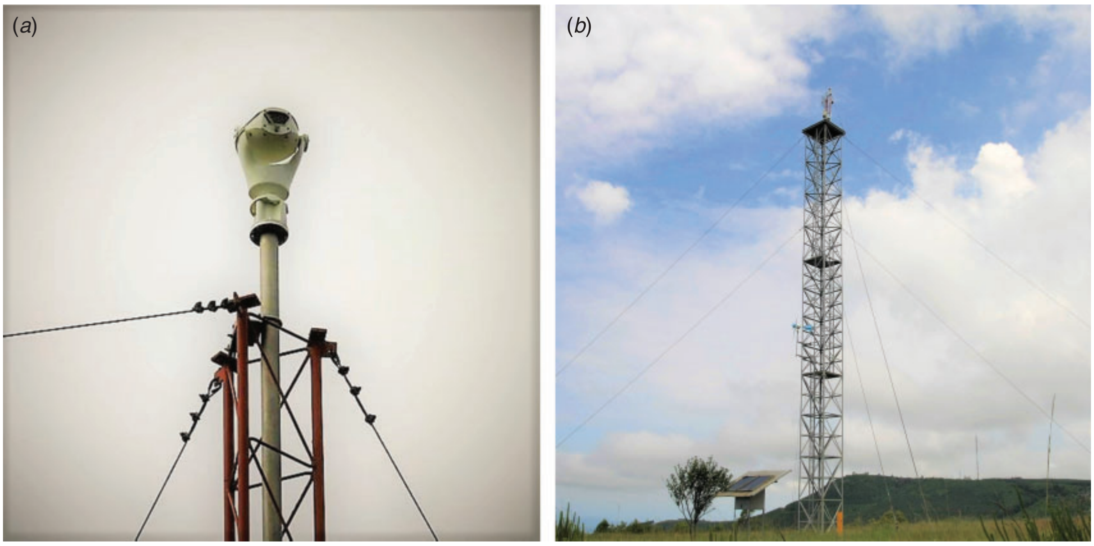

Fig. 1. (*a*) Camera used in ForestWatch fire detection systems; (*b*) a 32-m tower on top of which a camera is placed, with the solar power supply visible near the base of the tower.

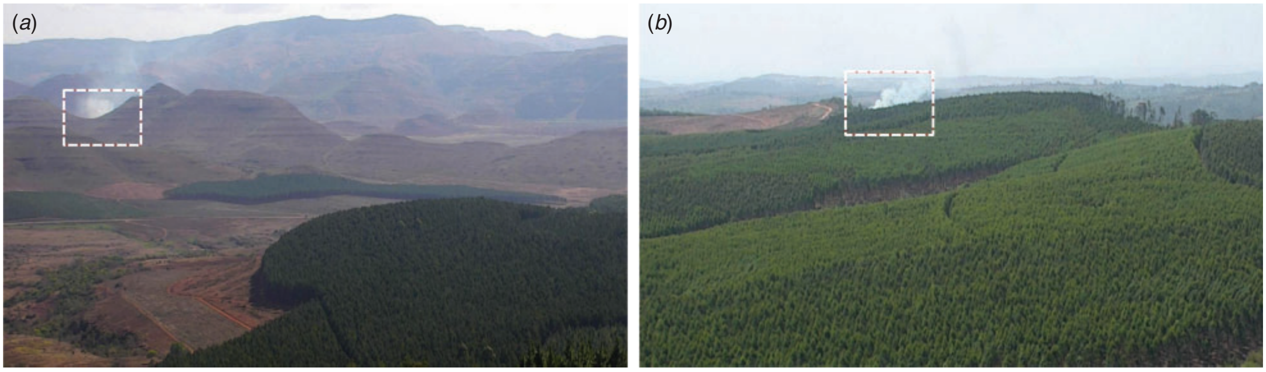

Fig. 2. Fires detected by the ForestWatch camera-based wildfire detection system (CWDS), displaying typical visibility obstruction that may be caused by (*a*) terrain and (*b*) vegetation.

outnumber the camera towers available for placement. The challenge is therefore to identify at which sites to place the towers. This is an intricate process, because the overall system detection potential relies on more than simply identifying several sites according to their individual visibility cover, but rather the identification of a combination of sites that offer the best combined system visibility cover.

Literature on the topic of candidate site identification intended for CWDS purposes is scarce – two recent publications, however, demonstrate typical approaches that may be followed. Bao *et al.* (2015) followed an approach in which 30 candidate sites were manually identified from peaks and ridges on hilltops within a study area of 10 km^2. Candidate layouts were then determined from the 30 sites for CWDSs comprising between 6 and 16 towers, using integer programming (Newman and Weiss 2013) and a genetic algorithm similar to the one employed later in the present paper. The manual site selection approach followed by Bao *et al.* (2015) is not considered desirable here, as it would be impractically laborious and time-consuming for the intended application. The average ForestWatch system covers surface areas of well over 1000 km^2 that contain numerous mountains, hills and ridges that may be considered for tower placement – significantly larger and more complex than the area considered by Bao *et al.* (2015). The manual candidate site identification and evaluation process took over 5 months for the existing ForestWatch system considered below that monitors an area of 1505 km^2. Shortening the duration of such processes to allow wildfire detection systems to become active earlier is a driving factor behind ForestWatch's interest in optimisation methods.

The second candidate site identification approach was proposed by Eugenio *et al.* (2016) using geographical information systems (GIS) software, when they selected sites for manned watchtowers in an area covering 46 000 km^2. GIS processes were used to identify land within feasible geographical and administrative or municipal boundaries, while terrain feature classification analyses were used to identify ridges on mountains and hills. Areas on the terrain that were within suitable distances of roads were also identified. The area that satisfied all three criteria of feasible land, ridge features and suitable road access areas resulted in a final feasible terrain surface that was considered for watchtower placement. The study area was then subdivided into uniform square cells of 15 × 15 km and the feasible site with the highest altitude in each cell was specified as a watchtower site. This method of site identification offers a fairly simple method of identifying multiple sites across a very large surface area. The disadvantage of such an approach is that the sites are identified according to the expected visibility of each individual watchtower based on terrain features and altitude. This may yield good individual tower visibility, but neither considers nor guarantees good overall system cover (Franklin and Clark 1994; Rana 2003; Kim *et al.* 2004).

The standard approach in similar surveillance and detection research is to evaluate a system's detection potential with respect to the terrain surface only (Franklin 2002; Kim *et al.* 2004; Bao *et al.* 2015). However, ForestWatch systems detect smoke patterns *above* the terrain surface (Schroeder 2005; Hough 2007), and as the smoke rises, it typically needs to clear interference from terrain and vegetation to be detectable, as shown in Fig. 2. The closer to the terrain surface a smoke plume may be detected, the sooner an alert may be generated and suppressing action initiated. A CWDS's potential for detecting smoke at multiple levels above the terrain surface therefore plays a role in gauging its effectiveness for near-surface (early) and higher (secondary) smoke detection. CWDSs may also be configured with consideration given to their visibility cover achieved over buffer zones that extend coverage beyond the client boundaries. This is because external fires may well encroach onto the client area, meaning that external fires are also crucial to monitor. Two smoke detection heights and a buffer zone are considered in the evaluation of candidate system layouts here, resulting in a coverage maximisation problem with two objectives. ForestWatch have also expressed their intention to incorporate additional objectives in future work, including the maximisation of backup (overlapping) cover (Hogan and ReVelle 1986; Heyns and van Vuuren 2016), the maximisation of their towers' triangulation accuracy in determining fire locations and cost minimisation. As a result, the process of configuring CWDS layouts becomes a complex multi-objective combinatorial optimisation problem, for which recent novel approaches are necessary (Heyns 2016).

The first steps taken towards a comprehensive CWDS tower-site selection optimisation framework are presented. The main aim was to provide an approach capable of determining multiple, high-quality CWDS layouts within practical computation times. Multiple candidate layouts allow decision makers to evaluate the trade-offs between different layouts when selecting a final solution. An area in the Nelspruit region in South Africa, which is currently covered by an existing ForestWatch CWDS, was used as the study area, and the optimisation framework was used to compute CWDS layouts comprising 20 cameras. A multi-objective evolutionary algorithm (Cheshmehgaz *et al.* 2015) combined with a multi-resolution approach (Heyns and van Vuuren 2016) is proposed for the optimisation of CWDS layouts. This algorithm considers areas that are deemed feasible for tower placement, which are determined by terrain characteristics and proximity to features such as roads. The quality of the generated CWDS layouts is determined by evaluating the coverage of two smoke layer heights over primary and buffer zones. The outputs include multiple candidate CWDS configurations and visibility coverage maps that can be analysed by decision makers before a final layout is selected.

Methods

Study area and existing tower sites

In order to demonstrate the practicality and effectiveness of this research for future tower site-selection problems, a comparative platform had to be established for evaluation purposes. An existing CWDS of 26 cameras was identified by ForestWatch experts for this purpose. This CWDS is located in the vicinity of Nelspruit, in the north-east of South Africa, and monitors forestry plantations. This specific system was selected because of its mountainous and challenging terrain (see Fig. 2) and because the existing CWDS is reliable and regularly detects potential fires on a daily basis. In 2017 alone, the system logged 2786 alerts within the subscribed client area, and many more outside. Although many of these fires are authorised prescribed burns or smoke rising from informal settlements on the edges of the client area, fires that are actual threats are also regularly detected. Wildfires in the region occur primarily between July and October (Strydom and Savage 2016), with the most recent large wildfire occurring in August 2016 destroying over 2500 ha of plantations and natural forests. An additional reason for the selection of this CWDS as a basis for comparison was that experts with extensive experience in the region were available for feedback and discussions.

The client area is non-contiguous and covers a surface area of ~1505 km^2. The cameras have a specified detection range of 8 km and are placed on towers that range in height from 12 to 54 m at the locations shown in Fig. 3. The actual detection range of the cameras is well over 8 km, and fires are often detected at twice this range. The range of 8 km is used for contractual purposes and to mitigate the negative effects of bad weather on practical detection potential. The planning of the existing CWDS layout was a collaborative effort between ForestWatch technicians, GIS managers from the forestry clients and local experts. Numerous potential sites were manually identified over 5 months in 2010, and this was followed by physical inspections to assess the sites according to their distance from power lines, access to roads and site security (vandalism and theft are common in the region). Six of the sites were easier to select than the others and are indicated as 'preferred sites' in Fig. 3. These are the sites of old watchtowers and were selected without need for deliberation because of the existing infrastructure, road access and historically proven visibility cover. The remaining 20 sites required further investigation, analysis and comparison with other sites in terms of the aforementioned criteria and predicted coverage potential.

The base tower structure height that was used by ForestWatch for this system is 12 m. However, extensions to base tower heights are often added because an increase in tower height improves overall smoke detection potential by allowing a camera to see over obstructions. When required, height increases were achieved by adding extensions to the base structure, generally in increments of 3 m. The requirement for

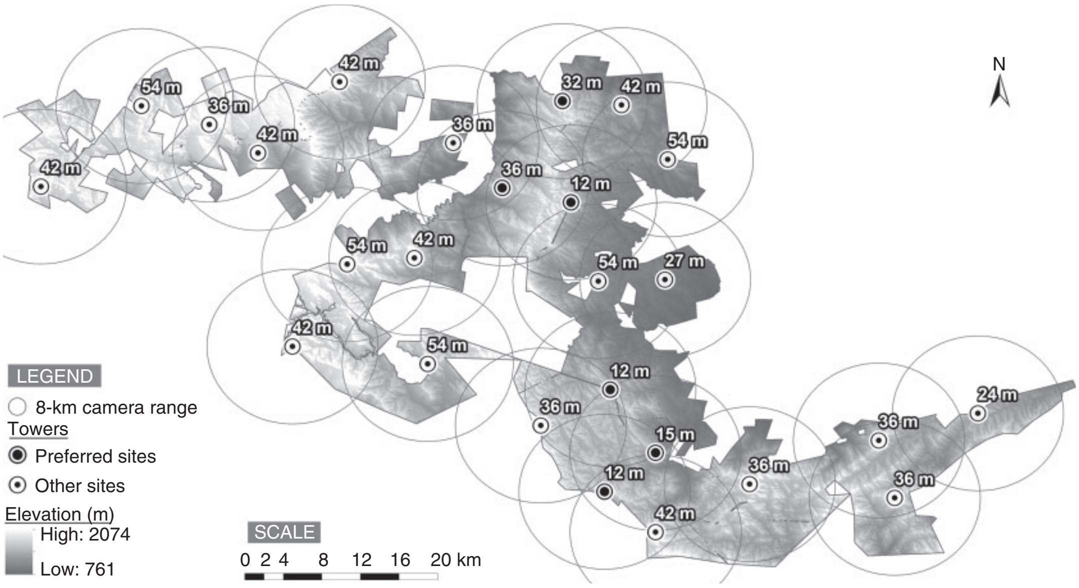

Fig. 3. Top view in relief of the ForestWatch system and client area that was identified to provide a benchmark for the evaluation of the optimisation approach followed in this paper.

an increase in tower height at each site depended on (i) whether surrounding vegetation demanded an increase in tower height so that the camera could rise above the trees' canopy; (ii) the actual need for an increase in tower height, depending on client coverage already achieved from the base tower height; and (iii) whether the terrain could accommodate the demands of an increase in structure size and support (in terms of the tower foundation and stabilisation wires that increase in span as tower height increases). The criterion of proximity to power supplies was eventually dismissed, and solar power supplies were installed at all sites owing to an inconsistent power supply system in the region (a solar power supply can be seen in Fig. 1*b*).

Terrain modelling and viewshed analyses

Raster data represent the Earth's surface and geospatial information as uniformly spaced sample points across the terrain and are used for both the terrain model and candidate site selection in this paper. Raster data are employed extensively for solving facility location problems owing to their simplicity and ease of implementation (Franklin 2002; Kim *et al.* 2004; Tanergüçlü *et al.* 2012; Kwong *et al.* 2014; Heyns and van Vuuren 2015).

An example of a raster data representation of terrain is provided in Fig. 4*a*. The non-contiguous blue area in the figure is an example of terrain that has been identified as suitable for the placement of towers. The green area is an example of an area of interest, which in the present paper is typically land belonging to one or more forestry clients. The terrain surface in this figure is, in fact, generated from sampled (raster) elevation data with the dots being on the terrain surface. The distance between neighbouring sample points is ~30 m at the highest resolution of raster data that is typically available to the public. The sites within the area that may be considered for facility placement (the blue dots) collectively form what is referred to as the Placement Zone.

The CWDS's detection potential is determined with respect to smoke above the terrain surface that falls within the client and buffer boundaries. As mentioned above, this process is performed with respect to multiple smoke heights, and each specified smoke detection height can be depicted as a smoke layer following the contour of the terrain. The smoke layers and their associated boundaries are termed Cover Zones, i.e. areas with respect to which a CWDS's visibility cover is determined. As is the case for the Placement Zones, Cover Zones are represented by raster data and are the rasterised terrain surface that falls within client and buffer boundaries raised to specified heights, as illustrated in Fig. 4*b* for a Cover Zone (the brown surface and markers) above the client area.

The portion of a Cover Zone that is visible from a camera is referred to as a viewshed, and is computed from a collection of line-of-sight queries calculated between the camera and all the demand points within the Cover Zone, limited by terrain interference and the camera's detection range (Nagy 1994; Franklin 2002; Kim *et al.* 2004). A CWDS's viewshed of a Cover Zone is then the merged viewsheds of all the individual cameras in the system with respect to the Cover Zone, i.e. the demand points in the Cover Zone that are visible from at least one camera in the system. Fig. 4*c* provides a top view of the terrain discussed in Fig. 4*a* and *b*, and an example of a CWDS viewshed (the red surface and markers) achieved by an example tower site layout for a system with four cameras (the black markers).

Placement Zone specification

The basic criterion to consider in the process of identifying a feasible Placement Zone is that towers may only be placed at sites within the client area because properties outside this area belong to entities that do not collaborate with ForestWatch. Two additional geospatial criteria were identified by ForestWatch experts as vital in determining site suitability. First, only terrain with a degree of slope under 12° (or 20%) should be considered

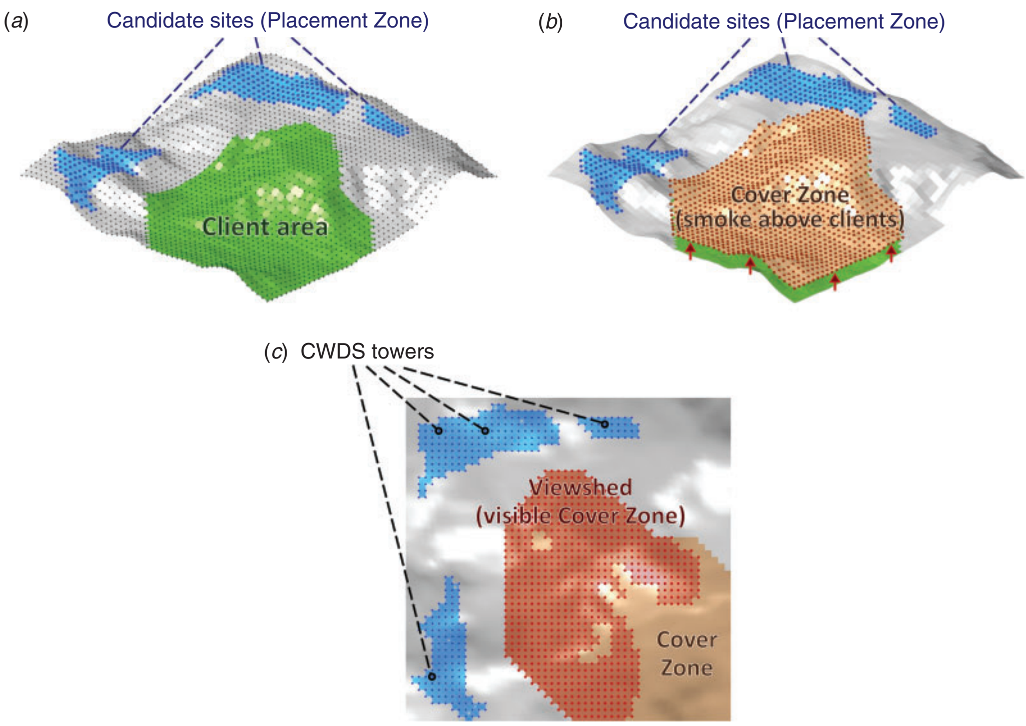

Fig. 4. Raster data represent the Earth's surface as uniformly spaced sample points. (*a*) Raster representation of a terrain surface with a Placement Zone and client area; (*b*) raster representation of a Cover Zone above the client area; (*c*) top view of the terrain, displaying an example camera-based wildfire detection system (CWDS) tower layout (the black markers) and its viewshed achieved with respect to the Cover Zone (the red area and markers).

to ensure that tower installation may be performed without the need for excessive terrain alteration, in addition to ease of access on foot. Second, a distance of 100 m or less to roads is deemed necessary for transportation (e.g. construction and maintenance) and general access purposes. Selecting the candidate sites according to criteria such as altitude and terrain features, as proposed by Eugenio *et al.* (2016), would reduce the number of sites in the Placement Zone. However, there is a risk that high-quality candidate sites may be discarded by this approach, so it was not considered further.

The commercially available *ArcGIS 10.5.1* software (ESRI, www.esri.com) was used to process the data required to determine suitable sites according to slope and road access. Feasible slope sites were determined with 30-m-resolution raster elevation data and the *ArcGIS* slope tool, while road-accessible sites were determined with roads data obtained from the clients in the study area and the *ArcGIS* Euclidean distance analysis tool. The feasible slope and road access areas are displayed in Fig. 5*a* and *b*, respectively, and Fig. 5*c* shows the resulting Placement Zone where both slope and road access are feasible. The number of candidate sites from the raster representation of the Placement Zone totals 741 813. The locations of the 26 towers of the existing system are all placed at sites in the feasible Placement Zone, indicating that the feasibility criteria considered here are indeed realistic.

System evaluation

Two smoke layer heights were agreed on for the evaluation of the benchmark and optimisation systems: 15 and 30 m. The heights chosen here are for the investigative purposes of this research. (Future projects may well include more than two smoke layer heights and different heights to those considered here.) An illustration of the client area viewed in perspective from the south-east, with a 15-m smoke layer that follows the contours of the terrain, is provided in Fig. 6*a*. The smoke layer's actual height above the terrain surface is exaggerated for illustrative purposes. The purpose of the 15-m smoke layer is for near-immediate detection above the client area and is aimed at rapid response.

The 30-m smoke layer is shown in Fig. 6*b* and includes a 2-km buffer zone that extends beyond the client area. The purpose of this smoke layer is for the detection of smoke that may not have been visible 15 m above the client area owing to obstructions, and that has risen further clear of the obstructions to be (potentially) visible at 30 m. Furthermore, the buffer zone added to the smoke layer allows monitoring of the progress of fires outside the client area – fires that need to be monitored by ForestWatch, but that do not necessarily require client response if their properties are not under immediate threat.

It was made clear by ForestWatch experts that the towers placed at the six existing sites (indicated by full markers in Fig. 3) were non-negotiable in the original site-selection process. It was decided to follow a similar approach during the optimisation process, so these six towers were considered as 'existing' and included in all developed CWDSs by default. This approach mimics a scenario that is frequently encountered, where new towers are to be sited around existing towers to expand an existing system's coverage over new clients or blind

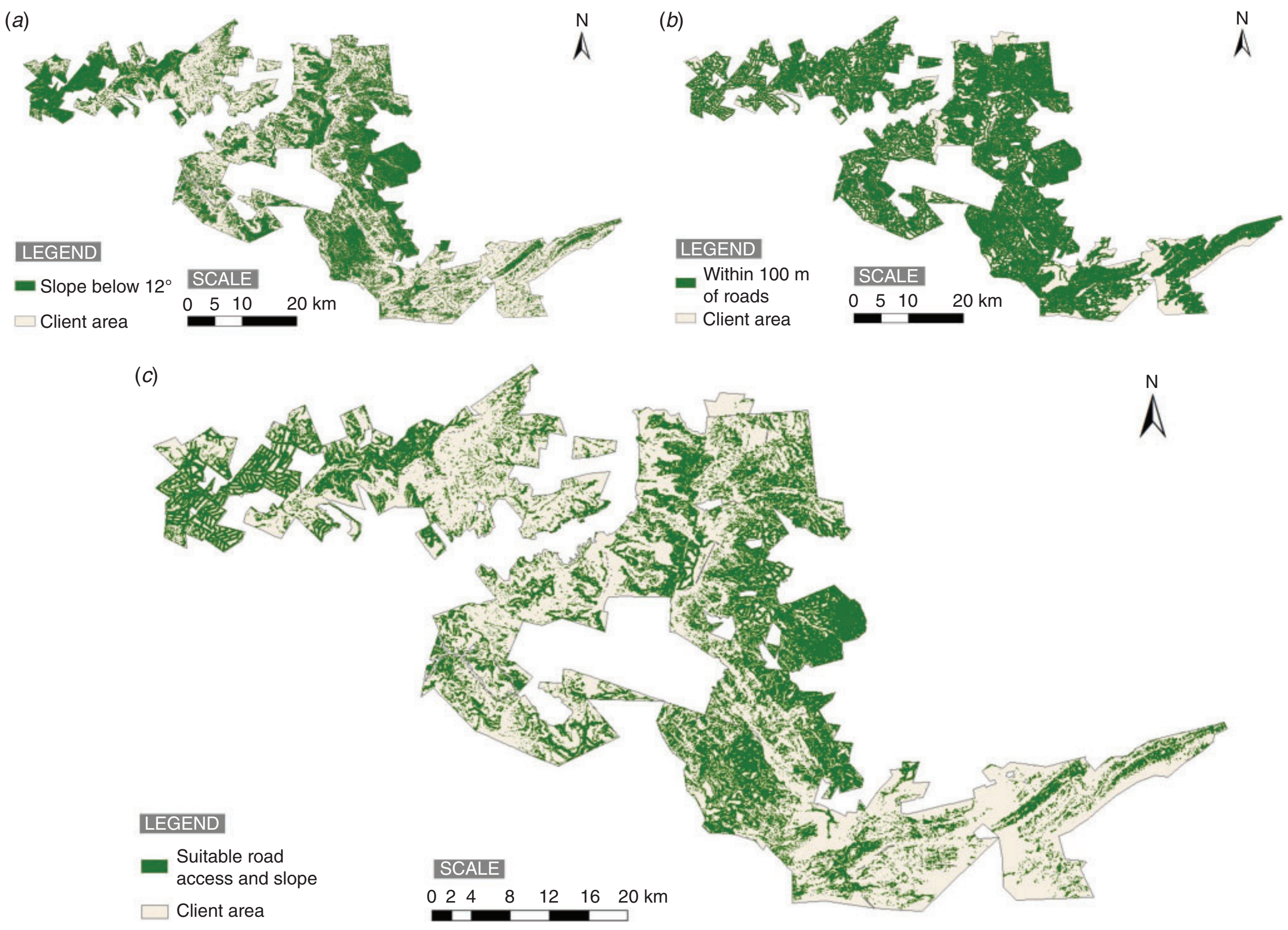

Fig. 5. Determination of the feasible Placement Zone within the client area. (*a*) Terrain degree of slope under 12°; (*b*) within 100 m of roads; (*c*) Placement Zone, where both slope and road access are suitable.

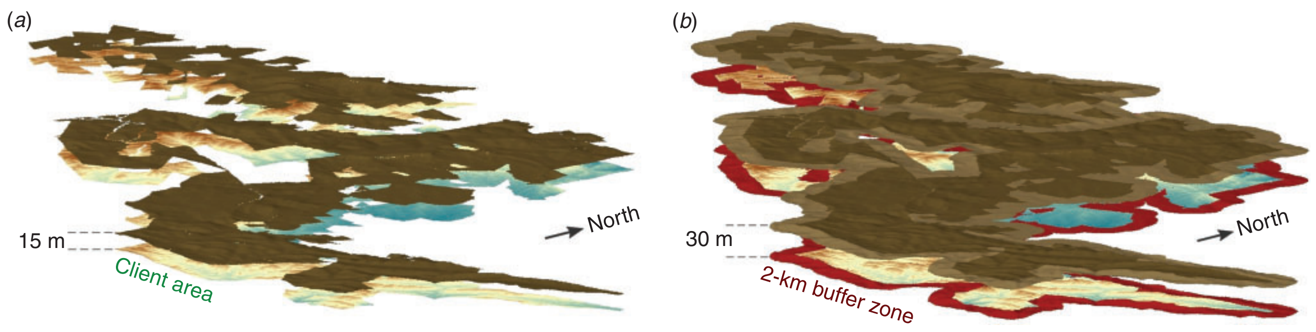

Fig. 6. Client area and smoke layers viewed in perspective from the south-east, showing (*a*) 15-m and (*b*) 30-m smoke layers above the client area with a 2-km buffer zone included in (*b*).

spots, for example. The actual tower site selection process thus focused on selecting the sites for the remaining 20 towers.

The six existing towers and the coverage they achieve with respect to the smoke layers are shown in Fig. 7*a* and *b*. As the indicated areas are already visible to these towers and are thus covered, the placement of additional towers does not require coverage of these areas. The remaining uncovered areas of the smoke layers, shown in Fig. 7*c* and *d*, are then the Cover Zones used to evaluate the coverage of the remaining 20 towers – Cover Zone 1 (15-m smoke height) and Cover Zone 2 (30-m smoke height with a 2-km buffer). The aim of the study was therefore to use an optimisation approach to determine new CWDS layouts and to compare their coverage with that of the tower sites of the existing CWDS.

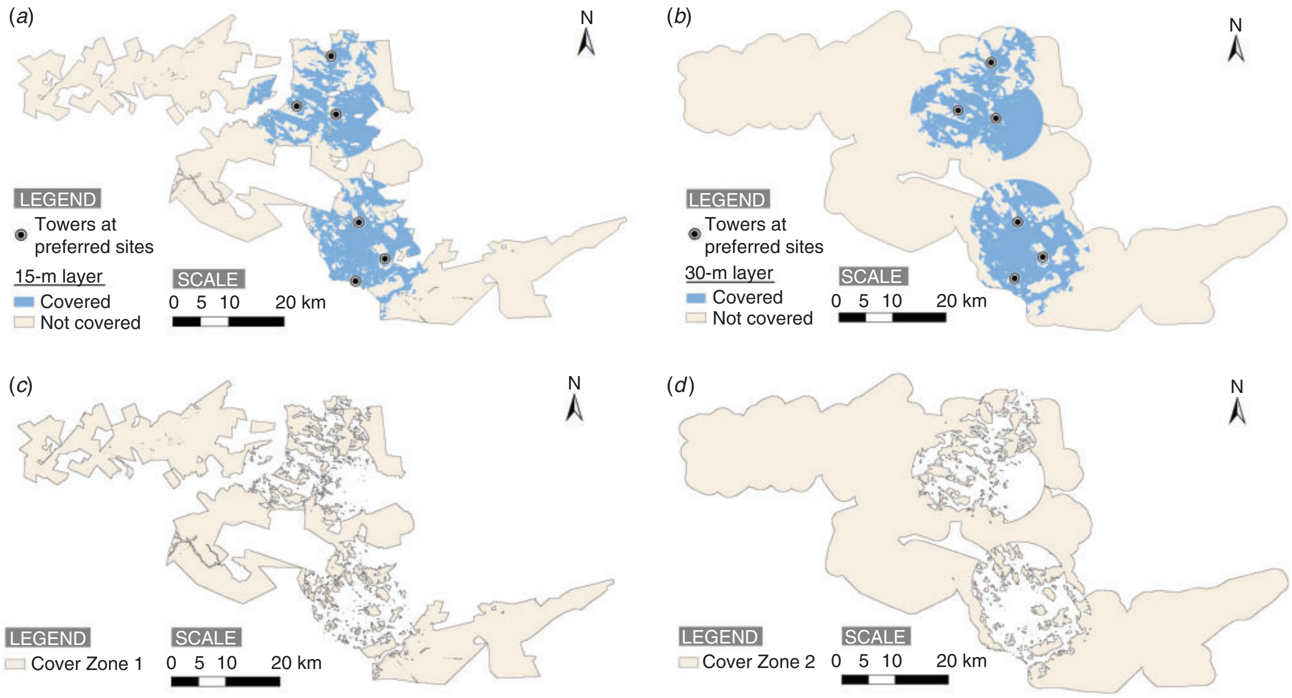

Fig. 7. The process followed to determine the Cover Zones used for system evaluation in this paper. Cover achieved from six existing towers (determined at a detection range of 8 km and their actual heights) that are included in the optimisation approach are shown with respect to (*a*) a 15-m smoke layer, and (*b*) a 30-m smoke layer with a 2-km buffer. This cover is removed from the smoke layers and result in (*c*) Cover Zone 1 and (*d*) Cover Zone 2.

The optimisation process followed here focuses on initial, computational site selection and does not include the physical site inspection process where height added to that of the base tower height is considered. This means that only the base tower height of 12 m is considered during the optimisation process, and viewsheds are therefore determined from this observer height above the terrain surface. In order to provide a fair comparative platform, the benchmark cover achieved by the existing towers is determined at simulated tower heights of 12 m with respect to the Cover Zones. Under this assumption, the existing towers were determined as being able to see 56.0% of the demand points in Cover Zone 1 and 54.6% of those in Cover Zone 2, as shown in Fig. 8 (the demand points in the Cover Zones are spaced at the same raster resolution as that of the Placement Zone, namely 30 m). For reference, the 20 towers at their actual heights (an average of 42 m) achieve 64.5 and 61.1% coverage with respect to Cover Zones 1 and 2 respectively.

Optimisation approach

A candidate CWDS layout is evaluated by objective functions – mathematical functions that calculate the performance of the layout with respect to each of the objectives. Here, the candidate CWDS layouts are evaluated with respect to the percentage of points in each Cover Zone that are visible. The results correspond to a single point in objective function space, as is illustrated in Fig. 9 in which several candidate layouts (candidate solutions) have been evaluated. Fig. 9 considers a problem instance involving two Cover Zones, which correspond to the two objectives on the axes. In multi-objective optimisation, the solutions in Fig. 9 are classified as either non-dominated or dominated.

When comparing the non-dominated solutions in Fig. 9 with each other, moving from one solution to another results in an improvement in at least one objective, but the degradation in at least one other objective. No non-dominated solution is better than another with respect to *all* the objectives. The inferior solutions that are not included in the non-dominated set are said to be dominated by the non-dominated solutions because at least one non-dominated solution that is at least as good with respect to all the objectives and better in at least one exists for each dominated solution. The non-dominated solutions are sought for decision-making purposes because they offer superior objective function values and trade-off alternatives to those of the dominated solutions. The representation of the set of non-dominated solutions is commonly known as the Pareto-optimal front, or simply the Pareto front, as they form a frontier in multi-objective space as seen in Fig. 9 (Zitzler *et al.* 2004; Knowles *et al.* 2006). Decision makers need only consider solutions on the Pareto front owing to the superiority of these solutions.

One approach to obtaining approximate solutions on the Pareto front is the use of commercial software, such as *CPLEX* (www.ibm.com/analytics/cplex-optimizer) and open-source software, such as *Gurobi* (www.gurobi.com). These software packages take integer-linear programming formulations of the objective functions and constraints as input. Solving multi-objective problems with these packages requires transforming the multiple objective functions into a single objective function

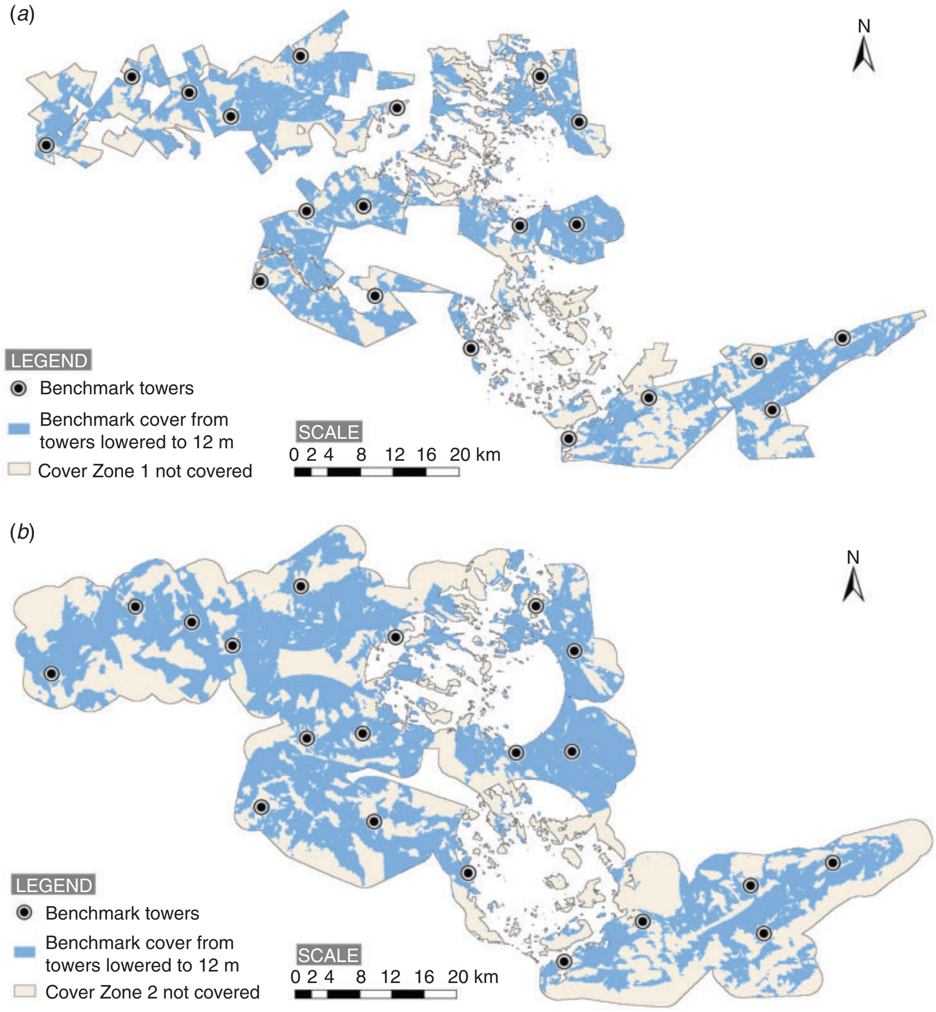

Fig. 8. Cover achieved by the 20 benchmark towers, determined with a detection range of 8 km and a simulated height of 12 m, with respect to (*a*) Cover Zone 1 (56.0%) and (*b*) Cover Zone 2 (54.6%).

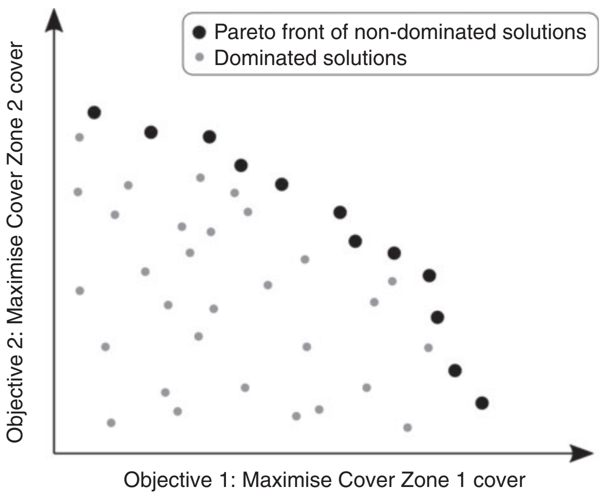

Fig. 9. The notions of solution domination and of a Pareto front in objective function space.

using a weighted sum (Cohon 1978; Murray *et al.* 2007). The weighted-sum objective function O_s is given by

$$O_s = \sum\nolimits_i w_i O_i \tag{1}$$

where the objectives O_i are combined using weights w_i. By varying the objective weights in multiple runs, a Pareto-front approximation may be traced out. However, determining points on the Pareto front in this manner may require a prohibitively large number of weight combinations when many objectives and large solution spaces are considered (ReVelle and Eiselt 2005; Tong *et al.* 2009). The solution space is the set of all possible solutions to a problem, i.e. all the possible candidate CWDS layouts on the terrain. The number of possible solutions, N_p, is

$$N_p = \binom{N_s}{N_t} = \frac{N_s!}{N_t!(N_s - N_t)!} \tag{2}$$

where N_t and N_s denote the number of towers available for placement and the number of feasible sites respectively. Here,

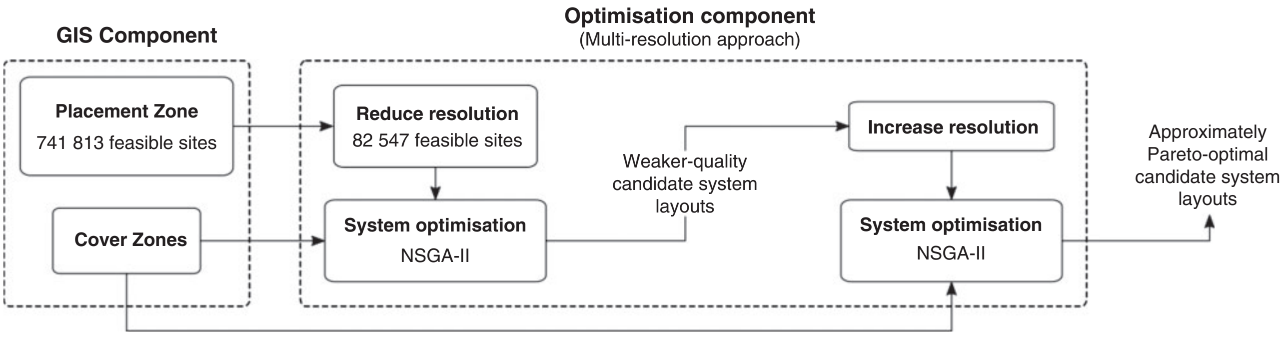

Fig. 10. The camera-based wildfire detection system (CWDS) tower site-selection optimisation framework followed in this paper.

20 tower sites have to be selected from 741 813 sites in the Placement Zone of Fig. 5*c* – a solution space that is sufficiently large to render the use of the weighted-sum approach infeasible.

Instead of the weighted-sum approach, powerful metaheuristic optimisation procedures are often employed in order to approximate the Pareto front within realistic computation times (Zitzler *et al.* 2004; Tong *et al.* 2009). Multi-objective evolutionary algorithms are popular for this purpose and are able to approximate the Pareto front in a single run (Fonseca and Fleming 1993; Purshouse and Fleming 2003). The non-dominated sorting genetic algorithm-II (NSGA-II) is a multi-objective evolutionary algorithm that has been used extensively in the literature for multi-objective optimisation problems (including applications that consider covering problems) (Raisanen and Whitaker 2005; Kim *et al.* 2008; Kwong *et al.* 2014; Heyns and van Vuuren 2016, 2018) and was employed in the current paper. More information on multi-objective evolutionary algorithms and the NSGA-II may be found in the Appendix.

At the highest resolution of terrain data representation (30-m spacing), the number of feasible sites in the Placement Zone of Fig. 5*c* is 741 813. This is significantly more than is generally encountered in facility location problems (Kim *et al.* 2004, 2008; Tanergüçlü *et al.* 2012; Bao *et al.* 2015), mainly because manual intervention to reduce the number of possible sites is impractical for the terrain sizes for which this research is intended. This large number of feasible sites increases the computational complexity of the algorithm by increasing the number of possible CWDS layouts. In instances such as these, the multi-resolution approach of Heyns and van Vuuren (2016) may be employed. The multiresolution approach is an optimisation tool that was specifically developed for geospatial facility location problems with unusually large solution spaces. The approach reduces the number of sites considered during the search for the Pareto front by first solving the problem at a coarse geographic resolution for site selection (exploration), after which a finer resolution is used around promising site locations and the optimisation process repeated (exploitation). This results in reduced computational complexity, fewer viewshed computations and reduced computation time requirements (Heyns and van Vuuren 2016). Implementation of the multi-resolution approach results in little or no reduction in the quality of solution in the Pareto-front approximation, and can even lead to improved quality in some instances (Heyns 2016; Heyns and van Vuuren 2016). Pseudo-code descriptions of the NSGA-II and its multi-resolution approach implementation are available in the literature (Kim *et al.* 2008; Heyns and van Vuuren 2016).

The proposed site-selection optimisation framework is summarised graphically in Fig. 10, and is divided into a GIS component and an optimisation component. The GIS component comprises (i) the identification of suitable candidate sites within the Placement Zone, and (ii) the determination of the Cover Zones, based on smoke layer heights, buffer zones and existing cover. The Placement Zones and Cover Zones are the inputs to the optimisation component, which performs two runs of the NSGA-II – the difference in each run being the candidate site inputs as determined by the multi-resolution approach. Here, the first NSGA-II run takes as input sites that are extracted from the original Placement Zone at a resolution of 90 m between sites (from the original 30-m resolution), resulting in 82 547 candidate sites. The second NSGA-II run takes as input the sites included in the candidate layouts returned by the first NSGA-II run, as well as all the feasible sites at the original, highest 30-m resolution that are within 60 m of these sites.

Owing to the stochastic nature of the Pareto-front approximation process of the NSGA-II (see Appendix A1), the solutions returned by different optimisation runs generally vary in quality, and it is therefore standard practice to repeat the process multiple times (Knowles *et al.* 2006; Kim *et al.* 2008; Tong *et al.* 2009). The results of all the runs are then combined and a final attainment front (the globally best set of the approximately Pareto-optimal solutions from all optimisation runs) is identified. The process in Fig. 10 was repeated 40 times, after which additional optimisation was performed as described below.

Results

Pareto-front approximation

The 40 Pareto-front approximations generated by the framework in Fig. 10 produced a total of 1818 unique solutions, which are shown by the grey squares in objective function space in Fig. 11. It is observed that the benchmark CWDS, evaluated with 12-m towers and indicated by the black cross marker, is outperformed in at least one objective by most of the optimisation-determined solutions while being outperformed in both objectives (i.e. dominated) by a large number of these solutions.

On closer inspection, it was revealed that the solutions returned by the 40 optimisation runs are, in fact, unique

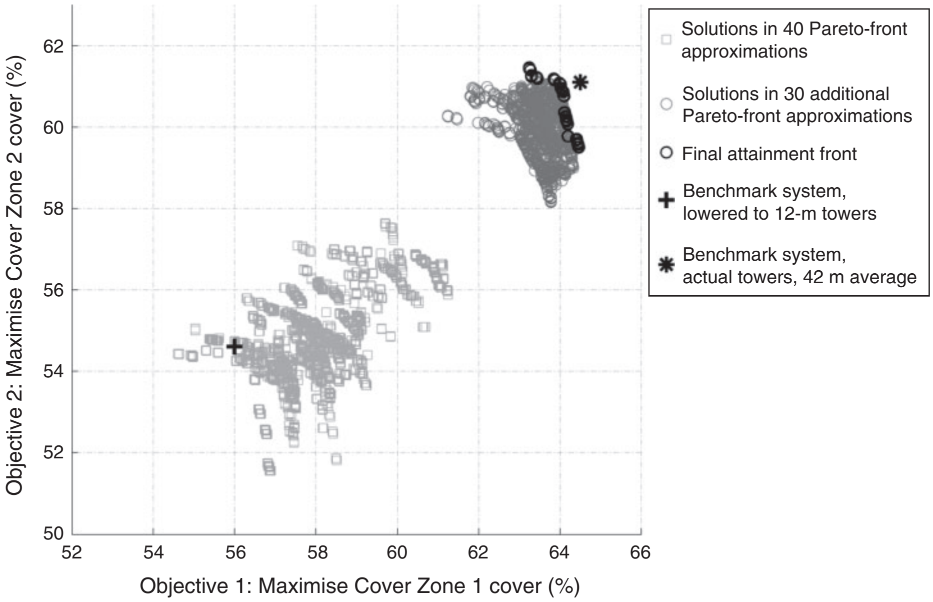

Fig. 11. Results in objective function space of multiple runs of the optimisation framework in Fig. 10, in which the objective was to place 20 towers at sites within the Placement Zone in Fig. 5*c*, so that visibility cover with respect to the Cover Zones in Fig. 7*c* and *d* is maximised.

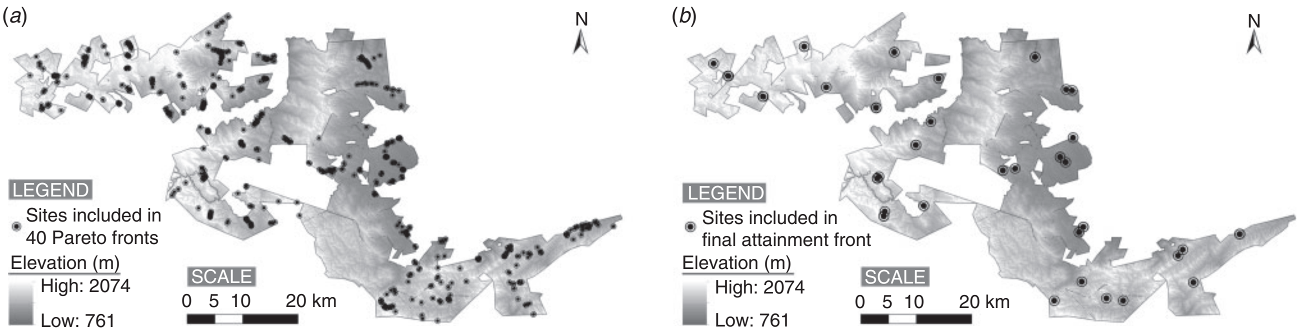

Fig. 12. Sites included in (*a*) the solutions in 40 Pareto-front approximations obtained by the framework in Fig. 10, and (*b*) the solutions in the final attainment front in Fig. 11 obtained by additional optimisation runs.

combinations of 917 sites (which generally neighbour each other), which are shown in Fig. 12*a*. As these sites are included in multiple Pareto-optimal solution approximations, it may be assumed with confidence that they are higher-quality candidate sites than the other sites in the entire original Placement Zone of 741 813 sites. It was therefore decided to investigate the use of these 917 sites as a new Placement Zone for 30 additional optimisation runs – thereby excluding a large number of weaker sites that were considered in the 40 initial optimisation runs, and as a result, limiting the search to better sites only. These sites were considered as a single level by the NSGA-II and without multi-resolution optimisation. The 1219 solutions that were contained in the resulting Pareto-front approximations are shown by the grey circles in Fig. 11 – achieving a marked improvement over the solutions returned by the first 40 Pareto-front approximations (the grey squares).

The final attainment front contained 72 solutions, which are indicated by black circle markers in Fig. 11. When compared with the benchmark system with 12-m towers, the solutions contained within the final attainment front exhibit an increase in cover of up to 8.5% with respect to Cover Zone 1, while an increase of up to 6.9% is observed with respect to Cover Zone 2. Most impressive is that these solutions achieve objective-function values that are similar to those achieved by the benchmark towers when evaluated with their actual heights that average 42 m (the asterisk marker), and some solutions even outperform these towers with respect to the second objective. The 72 solutions comprise different combinations of 61 sites that are shown on the client area in Fig. 12*b* – a significant decrease from the 917 sites in Fig. 12*a*.

The results were obtained within 1 week, which included data collection, processing, preliminary analysis and optimisation.

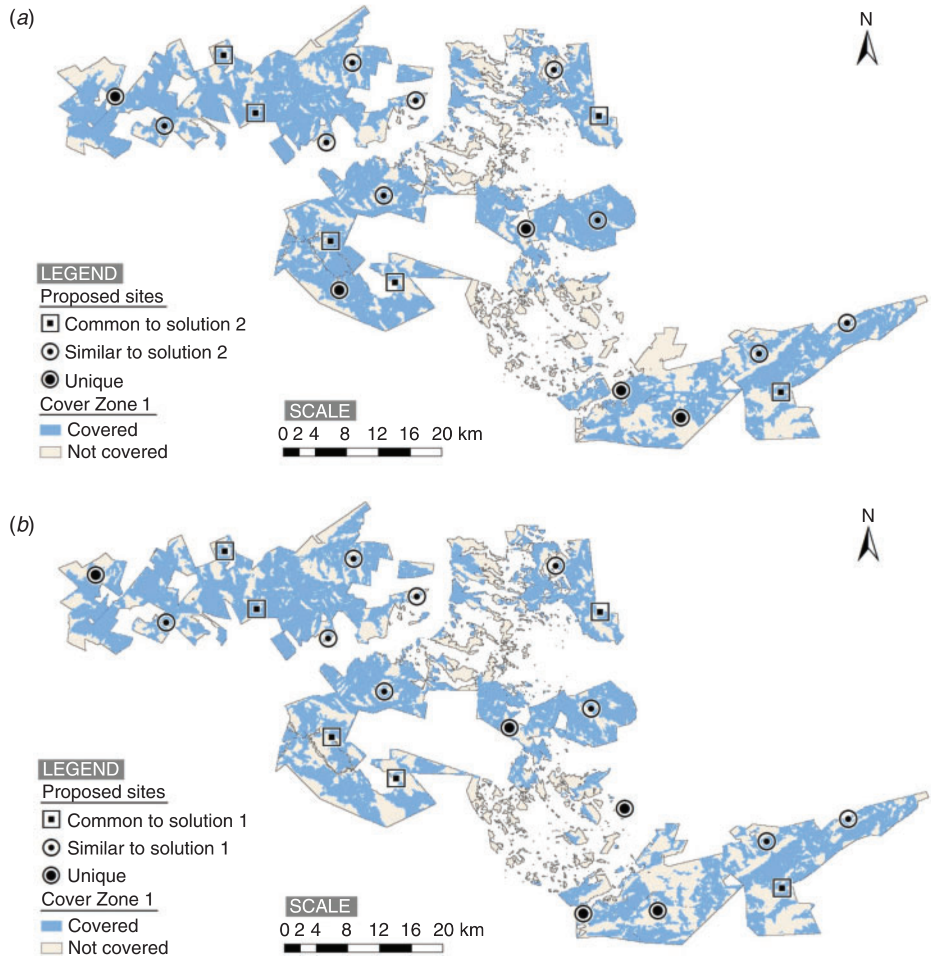

Fig. 13. Physical site locations and cover achieved with respect to Cover Zone 1 for two solutions from the final attainment front in Fig. 11. Solution 1 in (*a*) achieves the best cover with respect to Cover Zone 1, whereas Solution 2 in (*b*) achieves the best cover with respect to Cover Zone 2.

Candidate layouts

The site locations and coverage achieved by two solutions on the final attainment front in Fig. 11 are shown with respect to Cover Zone 1 in Fig. 13 and Cover Zone 2 in Fig. 14. Solution 1 is the solution on the attainment front that achieves the best coverage with respect to Cover Zone 1, and its site locations are shown along with its coverage of Cover Zone 1 and Cover Zone 2 in Figs 13*a* and 14*a* respectively. Solution 2 is the solution on the attainment front that achieves the best coverage with respect to Cover Zone 2, and Figs 13*b* and 14*b* show its site locations and resulting coverage of the two Cover Zones.

Several similarities may be observed when analysing the proposed sites of these two candidate layouts. Six sites are, in fact, common to both layouts. When comparing the remainder of the sites, nine are similarly located in the two layouts and the slight differences in location of between 25 and 70 m are indistinguishable in Figs 13 and 14. The remaining five sites in each layout differ more significantly and are at least 2 km from the nearest site in the other layout. What may be noticed when analysing these five sites is how their locations in each layout are a result of the objective with respect to which their layout achieves the best result – an indication of how the multi-objective optimisation process simultaneously pursues site combinations for different objectives. In Figs 13*a* and 14*a* for Solution 1, these five sites tend to be located more inward from the boundaries, with the result that their coverage contributes more to that achieved with respect to the client area in Cover Zone 1, and less with respect to the buffer zone in Cover Zone 2. In Figs 13*b* and 14*b* for Solution 2, these sites are mostly located closer to the boundaries, which means that their coverage contributes more to that achieved with respect to the buffer zone in Cover Zone 2 while reducing cover of the client area in Cover Zone 1.

Expert feedback

A selection of optimised system layouts was presented to a group of experts at the Nelspruit Fire Protection Agency in the form of Figs 11, 13 and 14. The experts included foresters each with over 20 years of experience in forest and fire management in the region, GIS specialists from forestry clients and ForestWatch

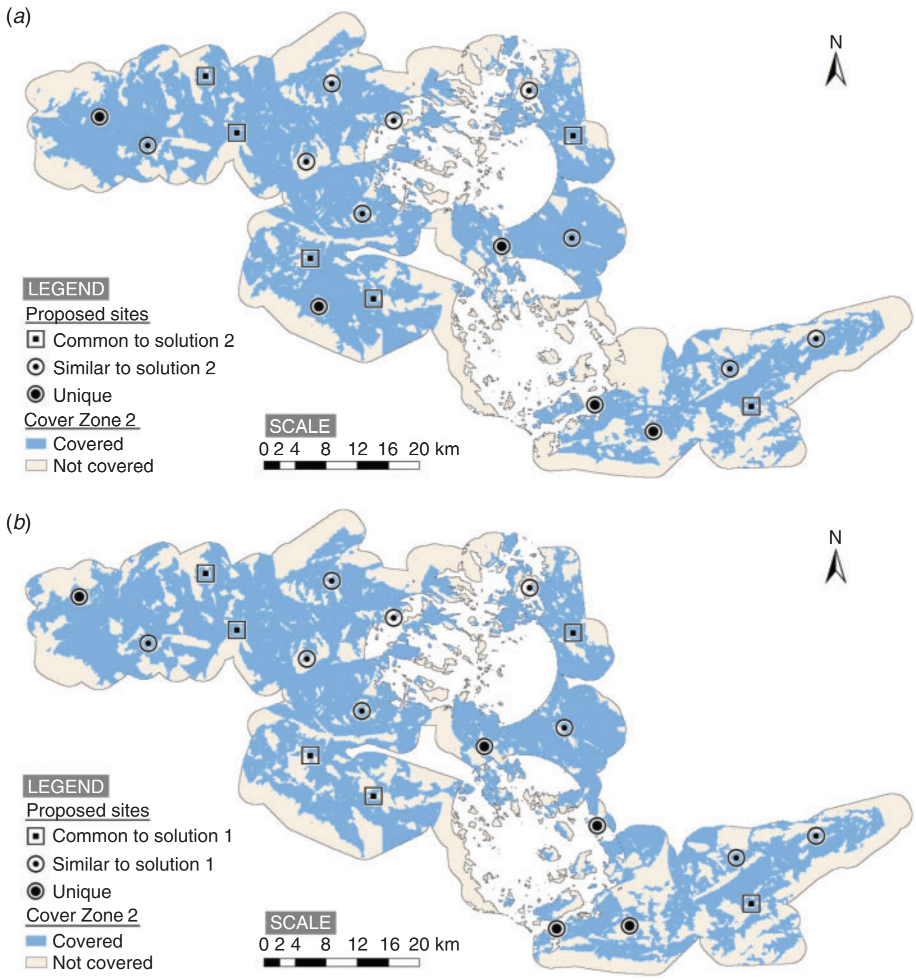

Fig. 14. Physical site locations and cover achieved with respect to Cover Zone 2 for the same layouts presented in Fig. 13. Solution 1 in (*a*) achieves the best Cover Zone 1 cover, whereas solution 2 in (*b*) achieves the best cover with respect to Cover Zone 2.

decision makers and detection centre operators (some of whom were involved in the planning of the existing CWDS). Physical site locations of candidate layouts were also presented in *Google Earth Pro*, allowing proposed sites to be viewed on top of a satellite image representation of the terrain. This visualisation provided an effective means of estimating practical site suitability without having to physically visit any of the sites.

The experts agreed that the sites comprising the optimised layouts presented were suitable from a practical, real-world perspective, demonstrating the effectiveness of the Placement Zone determination process outlined above. A few of the sites in each of the candidate system layouts were located precisely at or immediately adjacent to actual sites, whereas others were within 500 m of actual sites. Sites that were considered for tower placement during the original site-selection process, but that were not used, were also present in many of the candidate solutions; this renewed discussions between the experts about these sites' suitability compared with the actual sites. The remaining sites were judged by all those present to be good proposals as well.

Discussion

The first steps taken towards a comprehensive CWDS tower-site selection optimisation framework have been described. The GIS component of this framework comprises the determination of feasible candidate sites (the Placement Zone) in addition to determining discrete demand points within areas with respect to which visibility cover from the cameras is determined (the Cover Zones). Metaheuristics are applied in the optimisation approach to determine candidate CWDS layouts that aim to achieve optimal results with respect to specific objectives. The multi-resolution approach was used in conjunction with the popular NSGA-II algorithm in the metaheuristic approach, and the objectives were to maximise visibility cover with respect to two different smoke layer levels above the terrain surface. An area in the Nelspruit region in South Africa, which is currently covered by an existing ForestWatch CWDS, was used as the study area, and the optimisation framework was used to compute high-quality trade-off solutions for CWDSs comprising 20 cameras.

The framework can provide multiple candidate CWDS layouts in under 1 week (including data collection, data processing, preliminary analysis and optimisation), compared with the actual site-identification process that spanned more than 5 months. The solutions obtained by the optimisation framework were found to significantly outperform the actual configuration with respect to both covering objectives when considering identical tower heights of 12 m. Furthermore, the optimisation-determined solutions achieved similar coverage to the existing system with its actual tower heights – despite the optimisation solutions being limited to 12-m tower heights although the existing system has an average tower height of 42 m. The fact that a 12-m tower costs more than three times less to install than a 42-m tower (determined from tower installation costs provided by ForestWatch technicians) is an indication of the potential cost savings that may be achieved by the optimisation approach. The optimised solutions were able to reliably identify the most important sites, thereby further reducing the time required to implement a full CWDS by allowing site visits to focus on sites that are most likely to form part of the final system.

The results were presented to experts from ForestWatch and forestry organisations from the Nelspruit region and the feedback was positive. The presented candidate CWDS layouts were considered practically implementable in a real-world scenario, and it was concluded that the optimisation framework is a tool that should be used in future CWDS planning and decision-making processes. Elements of the CWDS site-selection optimisation framework described above have already been used for the planning of new tower sites.

In a real-world CWDS site-selection problem, the decision makers would compare results such as those presented in Figs 11, 13 and 14 in terms of objective-function values and tower site locations in order to make a final decision. A set of solutions that is diverse with respect to objective-function values and tower site locations is desirable in order to provide a good set of alternatives that may be considered, and this goal has been achieved as shown in Figs 11 and 12. It is possible, however, that attainment fronts consisting of an undesirably large number of solutions may be returned, e.g. the 72 solutions in the attainment front in Fig. 11. Many of these solutions offer negligible trade-offs in terms objective function values and tower-site locations, rendering decision making a long and tiresome process (Heyns 2016). In future work, techniques to filter the Pareto front to generate a smaller number of solutions should be investigated. Possible techniques include those that are performed in objective-function space, such as the epsilon-grid method (Mavrotas 2009), and those performed in physical solution space, such as site proximity-dependent declustering investigated by Heyns (2016).

Two smoke layers and a buffer zone were used for the Cover Zones with respect to which a CWDS's smoke detection potential was evaluated. In future work, additional Cover Zones may include certain priority areas within the larger area to be covered. Examples may include areas around key infrastructure points such as power plants and chemical storage facilities. In such instances, a priority Cover Zone is simply added as an additional covering objective and the problem solved as usual by the multi-objective optimisation framework. If desired, decision makers may then turn their focus towards solutions that perform well with respect to the priority areas in determining a suitable layout.

Conflict of interest

The authors declare no conflicts of interest.

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Appendix A1. Multi-objective evolutionary algorithms

A popular alternative to the weighted-sum approach is multi-objective evolutionary algorithms, which are able to approximate a diverse set of trade-off solutions on the Pareto front in a single run (Fonseca and Fleming 1993; Purshouse and Fleming 2003) and are also known to achieve good results fast (Alp *et al.* 2003). Multi-objective evolutionary algorithms iteratively evolve a population of candidate solutions to an optimisation problem based on natural principles (Cheshmehgaz *et al.* 2015). An initial, randomly generated population of candidate solutions undergoes carefully controlled evolution over multiple generations, finally arriving at a set of solutions that approximate the Pareto front (Deb *et al.* 2002; Cheshmehgaz *et al.* 2015). It has been shown how a multi-objective evolution algorithm may find more non-dominated solutions than are found by a weighted-sum approach, and as a result, may achieve a superior Pareto-front approximation to a weighted-sum approach (Kim *et al.* 2008). Examples of the application of multi-objective evolutionary algorithms to placement problems include the placement of transmitters (Meunier *et al.* 2000; Raisanen and Whitaker 2005), wind turbines (Kwong *et al.* 2014; Yamani Douzi Sorkhabi *et al.* 2016) and observation equipment (Kim *et al.* 2004; Tong *et al.* 2009; Bao *et al.* 2015; Heyns and van Vuuren 2015, 2018).

The NSGA-II is a multi-objective evolutionary algorithm that is classified as a genetic algorithm, in which a candidate CWDS layout is represented as a chromosome string of N_t feasible tower site numbers (Deb *et al.* 2002; Heyns and van Vuuren 2016). Site numbers are predetermined by an indexing scheme for all the sites within the Placement Zone's raster representation and are typically derived with respect to row and column indices (Heyns and van Vuuren 2016). For example, a chromosome (33, 125, 8333, 12 045) represents a candidate CWDS with four towers located at sites 33, 125, 8333 and 12 045.

The NSGA-II iteratively performs evolution-inspired selection processes and modification operators on a randomly generated population of such candidate CWDS chromosomes until a termination criterion is met (Deb *et al.* 2002). A typical termination criterion is when the algorithm has reached a point where successive populations fail to significantly improve on the solution quality of previous generations (Heyns 2016). Two mechanisms are utilised in order to adequately explore the solution space. Crossovers performed between substrings of parent chromosomes create new offspring solutions that consist of new site combinations, without altering the constituent sites that are inherited from the parent solutions (Deb *et al.* 2002; Heyns and van Vuuren 2016). Parents are randomly selected for crossover, although solutions that perform well with respect to the objective functions are favoured – meaning that the offspring solutions typically exhibit some of the strong properties of their parents. After crossover, mutation promotes site diversity by stochastically introducing new, unexplored site locations into the chromosomes, as opposed to merely exchanging already explored sites by means of crossover (Deb *et al.* 2002; Heyns and van Vuuren 2016).