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RESEARCH ARTICLE

Combining laser rangefinder and viewshed technologies to improve ground surveys of invasive tree distributions

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Abstract

1. Quantifying the spatial extent, location and habitat associations of invasive tree species is critical to predict their future spread and prioritise areas for management. Species–environment relationship analyses are useful tools for understanding and predicting the potential geographical distribution of these species; however, such tools require rigorous and extensive data about species presence and, crucially, the area surveyed.
2. Here, we describe a method for performing ground-based visual surveys of invasive trees from a set of viewpoints that utilises laser rangefinder and global navigation satellite system (GNSS) technology to detect tree locations. We then highlight the novel use of geographical information system (GIS) viewsheds as a tool to define the area surveyed.
3. Using the invasive conifer, *Pinus radiata*, as our target, we undertook a ground-truthing exercise for 50 trees established in the wild to assess the accuracy of the method and determine the suitable spatial resolution for GIS data that would be used in subsequent species–environment relationship analyses. For these trees, location error was positively related to distance from the tree to the viewpoint. The calculated locations for all trees within 600 m of the observer were within 25 m of the location as determined by the GNSS unit, with a median location error of 4 m. These results indicate that data of a resolution suitable for mapping invasive trees can be efficiently collected over large areas. We also outline suggestions and instructions for computing the viewsheds to determine the surveyed area.
4. This approach allows for efficient collection of accurate data on the occurrence of non-native trees and the land area surveyed. These data can underpin species–environment relationship analyses that then form the basis of risk maps for areas prone to future invasion. Given the speed and accuracy with which data can be obtained using this method, and the use of standard and easily accessible field equipment and GIS software, we recommend this approach to other spatial and invasion ecologists.

KEYWORDS
alien, GPS, invasion, laser rangefinder, LiDAR, spatial ecology, species distribution modelling, viewshed analysis, wilding conifer

1 | INTRODUCTION

Invasive tree species can pose significant threats to biodiversity, ecosystem processes and agricultural productivity. Conifer species such as *Pinus* spp. and *Pseudotsuga menziesii*, widely planted for forestry purposes, are a particular threat throughout the southern hemisphere, predominantly in low-stature plant communities such as grasslands and shrublands where high light levels facilitate their establishment (Nuñez et al., 2017; Richardson & Rejmánek, 2004). Many of the most problematic conifer species are those able to spread long distances via wind dispersal (Wyse & Hulme, 2021), while habitat suitability, grazing pressure and other environmental conditions are fundamental in determining their establishment success (Ledgard, 2001). Species–environment relationship analyses (e.g. habitat suitability, ecological niche models, resource selection functions, species distribution models, etc.) can be used to establish environmental limits for survival of a species to predict its potential distribution (Peterson, 2003), and can be used as the basis of risk assessments that map vulnerable locations to prioritise control efforts (Venette et al., 2010).

Field-based methods to survey for invasive or non-native trees are important to understand the extent of species spread and to collect data that underpin species–environment relationship analyses. However, when choosing a data collection methodology, data accuracy and the potential area that can be surveyed must be balanced against time and labour costs, and landscape accessibility. Current techniques frequently used to study the distribution of non-native trees each have benefits and limitations, and have emerged to best meet the needs of a specific situation or goal. Road-based surveys provide highly efficient data collection, but are inevitably restricted to non-native species in or proximate to roadside habitats (Deus et al., 2016; Maxwell et al., 2017). The use of plots located randomly or along transects attempt to representatively capture the array of habitats in a study area and provide accurate presence and absence data of the non-native or invasive species, but are limited in the area that can feasibly be surveyed (Brummer et al., 2013; Maxwell et al., 2017). Visual surveys along transects that sample all individuals of a target non-native species visible from the transect line (Jordan et al., 2012), potentially within a pre-defined distance (hundreds of metres; Medawatte et al., 2010), can survey a large and representative area, but have been unable to accurately define the area surveyed. Here, we propose a technique that combines aspects of these methodologies to efficiently survey a large and representative proportion of a study site to obtain the locations of individuals of a non-native tree species, while accurately defining the area surveyed.

Any species–environment relationship analysis that compares species occurrences to some form of available or background environmental conditions will be dependent on the definition of those conditions (Anderson & Raza, 2010; VanDerWal et al., 2009). It is therefore critically important to exclude areas not surveyed from the species–environment relationship analysis, and thus survey methods must aim to accurately define the area surveyed. Furthermore, definition of the surveyed area allows bias-checking to ensure the surveyed area is representative of the study site as a whole, assessment of the proportion of the landscape sampled, and estimates of the density of the target species or proportion of the landscape infested. Our approach utilises the widely used laser rangefinder (Wing & Kellogg, 2004; Wing et al., 2004) and global navigation satellite system (GNSS) tools to survey individual trees, similar to the methods of Medawatte et al. (2010). This technique employs visual surveys from a series of ground-based viewpoints located along public walking tracks and roads to detect individual trees over distances <1 km from the observer, allowing efficient surveys over large areas. Crucially, we then combine these surveys with the use of viewshed algorithms (Tomlin, 1990) to accurately define the area surveyed. This technique utilises the efficiency of roads and walking tracks for accessing a landscape, but the use of a survey radius of hundreds of metres ensures habitats captured are not restricted to the immediate proximity of the observer. This is of particular importance for terrain that is difficult or unsafe to access, such as bluffs or cliffs.

The viewshed is a computational approach widely available in geographical information system (GIS) software since its inception (Tomlin, 1990), which uses land surface data to identify the area with an unobstructed line of sight to the observer location. Despite its long history within GIS analysis, there has been little uptake of viewshed analysis within ecology. Recent work has called for the use of the approach within ecological research, demonstrating the utility of the method from the perspective of wildlife ecology (Aben et al., 2018; Lecigne et al., 2020). Here, we extend this call and recommend the use of viewsheds by forest ecologists and invasion biologists. We suggest that the visible area at a location determined by the viewshed algorithm can be used to define the area surveyed for a target tree species in a similar manner to defining the surveyed area for a radiotelemetry study (Etherington & Alexander, 2008), thus providing an accurate representation of the surveyed area for subsequent species–environment relationship analyses.

Here, we describe our methodology developed to survey naturalised *Pinus radiata* on Banks Peninsula, Canterbury, New Zealand; a study area of approximately 880 km^2. The method uses ground-based visual surveys from a series of viewpoints to provide presence data, and viewshed algorithms to determine the area surveyed. When performing any survey, it is necessary to have an understanding of the accuracy of the presence data so analytical methods can be matched to the spatial resolution of the data (Sillero &

Barbosa, 2021). We therefore assess the accuracy of the survey technique, demonstrating that it is of a resolution suitable for use with openly available and commonly used GIS raster data.

2 | MATERIALS AND METHODS

2.1 | Study area and species

Our research was conducted on Banks Peninsula in Canterbury, New Zealand; a once-forested landscape of volcanic origin but which is now dominated by pasture and other grassland (73% of the land area; Manaaki Whenua—Landcare Research, 2020). Early successional plant communities, dominated by non-native species such as *Cytisus scoparius* and *Ulex europaeus*, or native species such as *Kunzea robusta*, *Pseudopanax arboreus* and *Melicytus ramiflorus*, comprise a further 19% of the land area (Manaaki Whenua—Landcare Research, 2020). Banks Peninsula ranges in elevation from sea level to 920 m, and rainfall gradients across the site range from approximately 500 to 2,000 mm annual rainfall (Wilson, 2013a).

Within the study area, *P. radiata* is a widespread naturalised conifer species and the most common *Pinus* species, with other *Pinus* species either rare or barely naturalised (Wilson, 1999). *Pinus radiata* is visually distinct from the other common non-native conifers naturalised in the study area, *Pseudotsuga menziesii* and *Cupressus macrocarpa* (Wilson, 2013b), as well as indigenous conifer species such as *Podocarpus hallii* and *Podocarpus totara*, and native and non-native angiosperm trees. As is typical for *Pinus* species, *P. radiata* is strongly light demanding, and regenerates most readily in grasslands, early successional plant communities, and other high-light environments such as bluffs and slip faces (Sullivan et al., 2006; Williams & Wardle, 2007).

2.2 | Survey technique for determining tree locations

The survey method is based on a set of viewpoints located within the study area. We chose these manually prior to the study, to maximise the visible area and ensure thorough and unbiased geographical representation of the study site, although precise locations were refined in the field to ensure safety of the field team. The number of viewpoints required will depend upon the terrain and vegetation cover, but we were able to sample approximately 12% of our 880 km^2 study area from 124 viewpoints. With the assistance of relevant GIS data about the study area's environmental conditions, effort should be made to ensure the viewpoints are distributed in a manner that is representative of the study area as a whole, not being biased towards certain elevations, land cover types or microclimates. We used the viewshed analysis described subsequently to confirm that our surveyed area was representative of the entire study area, such as with respect to land cover classification; however, such analyses could also be used at the planning stage to guide choice of viewpoint locations.

Coordinates of each viewpoint are obtained using a handheld global positioning system (GPS) unit (we used a Garmin GPSmap 60CSx ensuring good satellite coverage producing stable locations to minimise location error), and converted to a projected coordinate system. At each viewpoint, binoculars are used to identify all naturalised individuals of the study species visible within the survey radius (Figure 1a); we used binoculars with 20× magnification and 50 mm objective lens diameter. Due to the visual distinctiveness of *P. radiata* in our study area, we were able use the binoculars to identify the species with confidence; however, higher magnification scopes could be used to aid identification in situations where the target species is less readily identifiable. A laser rangefinder and sighting compass are then used to determine

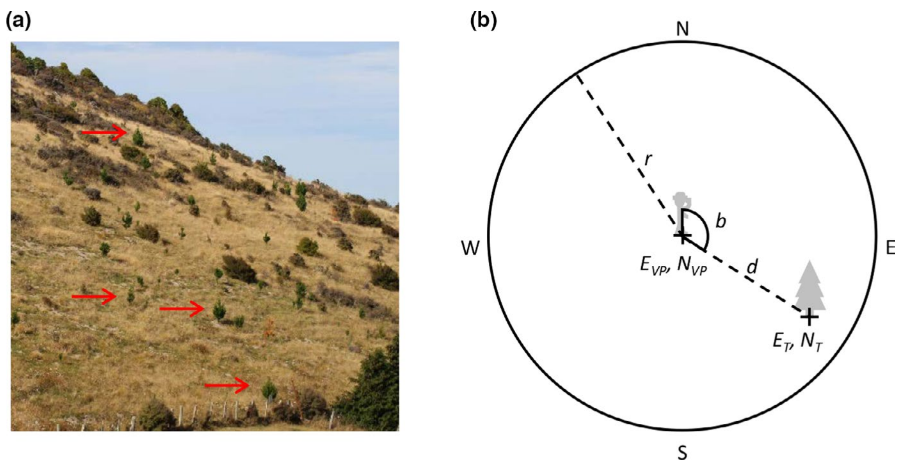

FIGURE 1 Illustration of the field sampling technique for determining the locations of *Pinus radiata* trees observed from a viewpoint. (a) A site in the early stages of *P. radiata* invasion, arrows indicate a selection of the individuals present. (b) All *P. radiata* visible from the viewpoint at coordinates E_{VP}, N_{VP} within radius of distance *r* are recorded. For a given tree at coordinates E_T, N_T, the tree's position relative to the viewpoint is quantified using a laser rangefinder to measure the horizontal distance *d* between the tree and the observer, and a sighting compass to measure the bearing *b*. Using these data and the coordinates E_{VP}, N_{VP} determined by a GPS unit, the coordinates of E_T, N_T can be calculated using trigonometry

the horizontal distance and bearing from the viewpoint to each tree (Figure 1b). We used a Bushnell Prime 1300 laser rangefinder (ranging performance for trees = 731.5 m) and a Suunto KB-14/360R hand-bearing precision sighting compass (accuracy = 1/3°, precision = 0.5°). The survey radius (*r*) will be defined by the performance capability of the laser rangefinder and the level of error in tree locations considered acceptable, as detailed in subsequent sections.

The horizontal distance to each tree can be calculated from the line-of-sight distance and the angle of the sighting from the horizontal, both returned by the laser rangefinder. However, when used in 'bow mode', the Bushnell Prime 1300 laser rangefinder performs internal calculations to return both the line-of-sight and true horizontal distances. Using a projected coordinate system and after accounting for magnetic declination, the locations of each tree (E_T, N_T) can be calculated from the easting and northing of the viewpoint (E_{VP}, N_{VP}), the bearing (*b*) from the viewpoint to the tree, and the horizontal distance (*d*) between the viewpoint and the tree, using trigonometry (Figure 1b; Wyse et al., 2021a). Where many densely growing individuals occur in a single group in an area of homogeneous land cover or topography, and it is impractical to measure the distance and bearing to each individual, the locations of the perimeter individuals can be determined and number of individuals within the group counted. The locations of the perimeter individuals will then form a polygon that outlines the group. The interior individuals can then be incorporated into subsequent analyses by randomly locating points within the polygon totalling the observed number of individuals.

2.3 | Assessment of accuracy of tree locations

To understand and quantify the spatial accuracy of our observed tree locations, we tested the method by ground-truthing the locations of 50 trees ranging from 26.9 to 717.6 m in distance from the observation locations. For each of these trees, we calculated the location error as the Euclidean distance between the location determined using our remote survey technique and the actual location of the trunk of the tree as recorded by our GPS unit. We examined the relationship between the location error (log-transformed) and the distance of the tree from the observer using a linear model, in R version 4.0.2 (R Core Team, 2020). We then separated the error into the distance and bearing components by calculating the differences in the distances and the bearings from the viewpoints to the actual and determined locations of the trees (Wyse et al., 2021a). Additionally, we used linear models to quantify the relationships between the measured distances or bearings, and those values calculated from the GPS coordinates.

The results of these tests can be used to assess the accuracy of the survey tools, to define the most suitable resolution for GIS data that may be used in subsequent analyses, and also contribute to establishing the survey radius. This process will also allow assessment of whether the correct magnetic declination has been applied to the compass bearings, which is essential for accurate determination of tree locations. We recommend undertaking accuracy assessment when commencing a survey campaign, as location error is likely to vary among observers, rangefinder units and particularly among styles of compass.

2.4 | Viewshed technique to determine area of the surveys

To determine the area surveyed at each viewpoint, we calculated viewsheds from a 1 m resolution digital surface model (DSM) derived from LiDAR data (Figure 2a; Land Information New Zealand, 2020), using the *ViewshedGenerate* function (Wang et al., 2000) from the GDAL package (version 3.1.0; GDAL/OGR Contributors, 2021) in Python version 3.5.5 (Pérez et al., 2011). Using a DSM rather than a digital elevation model (DEM) means that objects such as trees and

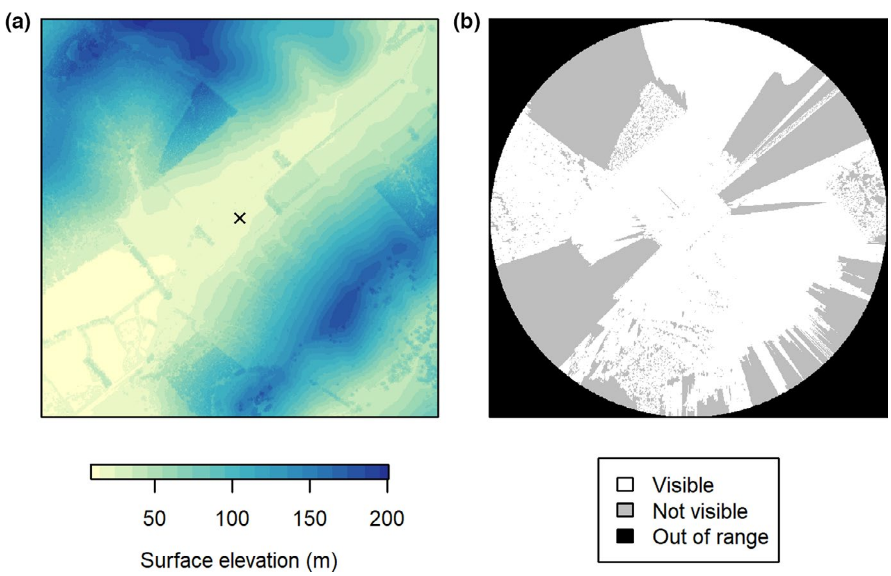

FIGURE 2 Example 1 m resolution digital surface model (a) used to create a viewshed (b). The viewshed in (b) is centred on point '×' shown in (a), and calculated using a maximum range (*r*) of 600 m, an observer height (h_o) of 1.52 m and a target height (h_t) of 4 m

buildings that obscure views, in addition to the landforms, are incorporated into the viewshed calculations. The *ViewshedGenerate* function generates a viewshed describing the geographical area in which trees of target height h_t are visible to an observer with eye height h_o at a given viewpoint and for maximum viewing distance radius *r*. We used values $h_o = 1.52$ m, $h_t = 4$ m, and $r = 600$ m. The resulting viewshed is in the form of a raster with the resolution of the input DSM with pixels valued as either visible, not visible, out of range, or no data (Figure 2b; Wyse et al., 2021a). In addition to providing a background area from which to build species environment models, we used the viewsheds to assess whether the representation of land cover classes, landform and microclimates within the surveyed area matched that of the study area as a whole, to prevent bias. As described previously, we can envisage that such an analysis could be incorporated into the planning of a field campaign to guide the locations of viewpoints, particularly if viewpoint locations were being chosen in an automated manner to aid in the reduction of selection bias.

3 | RESULTS

The distances and bearings calculated from the GPS coordinates were strongly related to the distances measured using the laser rangefinder (Figure 3a; $R^2 = 0.999$, $p < 0.0001$) and the bearings measured with the compass (Figure 3b; $R^2 = 0.999$, $p < 0.0001$). The almost perfect agreement between all three technologies indicates that these methods are all capable of producing highly accurate data suitable for our survey methodology.

Our assessment of the accuracy of the tree locations determined by our remote sampling methodology showed that for our 50 ground-truthed trees, most estimated locations were within 5 m of their actual location as determined by the GPS unit (Figure 3c). However, as would be expected there was a positive relationship between location error and the distance of a tree from the observer, with location error increasing exponentially with distance (Figure 3d; $R^2 = 0.487$, $p < 0.0001$). The desired spatial resolution of GIS data for subsequent analyses will therefore trade off against the viewshed radius and thus the area able to be surveyed per viewpoint. Here, the location error was within 25 m for all trees within 600 m of the observer, with a median location error of 4 m. These results suggest that a survey radius of 600 m would be appropriate for subsequent analyses utilising a 25 m spatial resolution, which is a common resolution for GIS raster data.

When we separated the location error into the distance and bearing components, 76% of the measured distances were within four metres of the distances calculated from the GPS coordinates (Figure 3e), while 94% of the measured bearings were within 5° of the bearings calculated from the GPS coordinates (Figure 3f). The use of a digital compass may improve the accuracy and precision of the sightings, and aid in reducing tree location error from that reported here. The rangefinder distances were biased towards underestimating rather than overestimating the distance to the tree, presumably due to the width of the canopy as the rangefinder would return the distance to the nearest vegetation on the tree in most instances, rather than the trunk. Our bearing errors were centred on 0°, indicating that the appropriate magnetic declination was applied in our calculations.

4 | DISCUSSION

4.1 | Viewshed analysis

Accuracy and precision of land surface data can have significant effects on GIS analyses (Fisher & Tate, 2006), and it is therefore important to recognise that the accuracy of a viewshed will depend upon the data used to create it. We used a high-resolution LiDAR DSM in presenting our methodology, and DSM data that include visibility obstacles such as vegetation and buildings has been shown to be highly effective at producing accurate viewsheds (Klouček et al., 2015). However, we acknowledge that LiDAR data will not always be available, and more conventional DEM data of lower resolution and accuracy can also be utilised to compute viewsheds. In such circumstances, the heights of vegetation and buildings must be estimated and added from other GIS data sources. While the suitability of the viewshed approach will depend upon the specific situation of a given study, users should be aware that the computed viewsheds are unlikely to be free from error, and that this error will be biased towards overestimating the visible area (Fisher, 1991; Lagner et al., 2018). Where land surface data are poor it may be preferable to create fuzzy viewsheds that can give a more nuanced viewshed in which the possibility of seeing different areas is given on a scale from zero to one (Fisher, 1992).

In addition to the underlying data layer from which the viewshed is computed, the specified parameter values are critical to viewshed accuracy. The maximum viewing distance radius (*r*) will be informed by the capabilities of the laser rangefinder, the accuracy of the measurements and the desired spatial resolution as described previously, while the eye-height of the observer (h_o) is straightforward. However, when choosing the value for the target height (h_t) parameter, a balance needs to be struck as lower values reduce the area classified as visible, while higher values increase this area. Values of h_t that are too low could lead to presences being recorded in pixels classified as not visible, while h_t values that are too high would erroneously inflate the area surveyed, increasing the likelihood that cells are incorrectly classified as being absent of individuals of the target species.

4.2 | Utility of the method

We foresee this method as being widely applicable throughout the Southern Hemisphere where non-native conifer invasions are

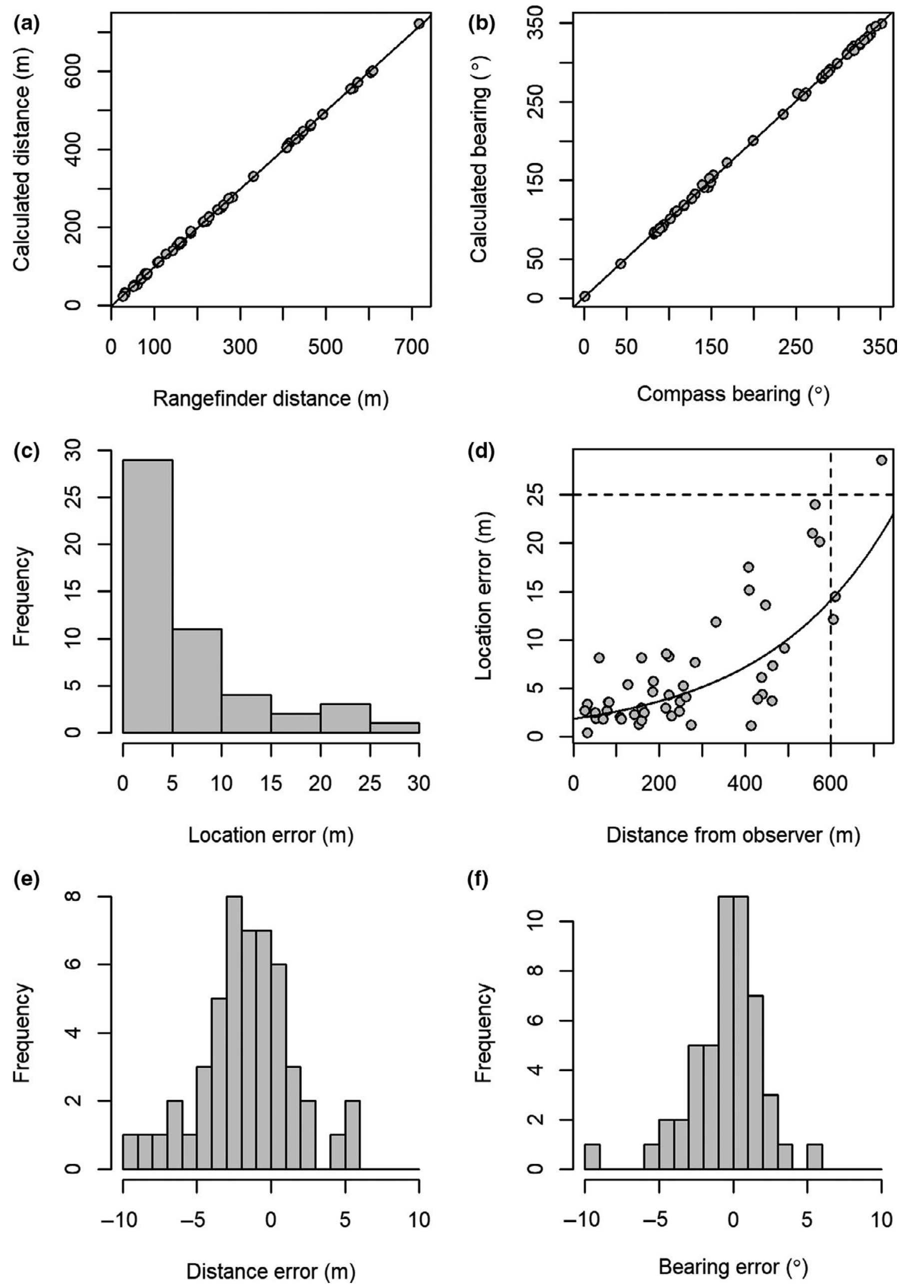

FIGURE 3 The error in the locations of 50 trees determined by our remote sampling technique, relative to their locations determined by a GPS unit during a ground-truthing exercise. (a) the relationship between distance between a tree and the observer measured with the laser rangefinder and the distance calculated from the GPS coordinates; (b) the relationship between the bearing from the observer to a tree measured with the compass and the bearing calculated from the GPS coordinates; (c) histogram of the frequency distribution of the location errors, (d) the relationship between location error and the distance between a tree and the observer, (e, f) histograms of the frequency distributions of the distance (e) and bearing (f) errors. Solid black line in (d) depicts the linear relationship between the log-transformed location error and the distance from the observer ($R^2 = 0.487$, $p < 0.0001$). Dashed lines highlight the spatial resolution (25 m) recommended for subsequent analyses, and the maximum distance radius (600 m) recommended based on these data

a significant concern in grasslands and other plant communities characterised by open vegetation and high light levels (Franzese et al., 2017; Nuñez et al., 2017; Peltzer, 2018; Taylor et al., 2017). These conifer invasions have negative impacts on biodiversity and landscape values, reduce agricultural productivity, and modify fire regimes, hydrology and nutrient cycling. The vegetation communities in which these light-demanding conifers typically establish are similar to our Banks Peninsula landscape for which this method was developed, with low-growing and open plant communities, and thus we recommend the use of the method in this context. However, we can also envisage other circumstances where our method may be of use for deriving efficient and accurate data of a species' distribution over large areas. For example, where a tree species of interest is highly visible against the surrounding forest at certain times of year, such as when flowering or during autumn when leaves of a deciduous species change colour. In a hillside forest, the coniferous *Larix* species are conspicuous against surrounding evergreen vegetation during autumn, while some angiosperm trees or climbing plants are highly obvious when in flower. In New Zealand, such native species could include those in the genera *Metrosideros*, *Sophora* and *Clematis*. The method could therefore be applied outside of a plant invasions context, to understand the distribution of a native plant of interest, particularly for a genus such as *Metrosideros* that is under threat from the recently-arrived pathogen *Puccinia psidii* (myrtle rust; McCarthy et al., 2021). Likewise, rapid surveys of the visually obvious diseased or dead trees resulting from this or other plant pathogens (including *Phytophthora* species) could also be made using this method.

Our method provides other clear advantages over ground-based surveys, in terms of time efficiencies and the ability to survey large landscapes quickly and cost-effectively. However, our study site exhibited considerable topographic variation across a relatively large area ensuring that viewpoints at relatively high elevation could be used to survey surrounding areas at lower elevations. The method also allows habitats such as cliffs and recent landslide scars, which are optimal habitats for a light-demanding tree, to be sampled without physical risk to the field team. An obvious alternative approach is that of remote sensing, which has previously been explored previously for similar species and in similar environments to our experiments (Dash et al., 2017, 2019; Sprague et al., 2019). However, these studies demonstrate that remote sensing is reliant on the availability of suitable imagery that ideally has a resolution in the order of centimetres to ensure smaller trees can be identified. Such data may not be available or may be suboptimal; it is either too old or because aerial photography is usually from summer months, yet optimal visual observation of some species may occur at other times such as during autumn for the deciduous *Larix*. In addition, given the requirement for centimetre resolution imagery, many ecologists or institutions globally may lack the specialist skills or finances to collect, store and process the vast amounts of image data that are required to cover a large area. Thus, while ecologists should continue to consider remote sensing as it may provide a better option in some situations, our approach here provides an alternative viable option that is flexible, low cost, scalable and readily accessible to most ecologists, including the community volunteers who are often engaged in ongoing monitoring of invasions.

5 | CONCLUSIONS

The method described here, integrating GNSS, laser rangefinder and GIS technologies to conduct visual surveys from a set of viewpoints coupled with a viewshed analysis, is effective for obtaining time- and cost-efficient invasive tree occurrences over large and well-defined surveyed areas for use in species–environment analyses to form the basis of invasion risk mapping. For example, using this method, we were able to visually survey approximately 107 km^2 of land from 124 viewpoints during just 15 days of field work. The method is particularly relevant for invasive tree species as they are often visually distinct from the native vegetation, and conifer species in particular typically invade native vegetation communities of low stature such as grasslands (Ledgard, 2001). However, we also foresee the potential for the method to be used to survey visually distinct trees within a forest, such as during flowering or a deciduous species during autumn, or for surveying standing dead or dying trees to gauge the impact of a plant pathogen. The required equipment (hand-held GNSS unit, sighting compass and laser rangefinder) may already be part of standard field equipment held by institutions, while GIS software is a fundamental skill for any ecologist, and viewshed functionality is widely available in many GIS software systems including freely available and open-source software. Therefore, we see few obstacles to other ecologists adopting our approach, and given the accurate data that can be quickly produced we would recommend the approach to other researchers.

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CONFLICT OF INTEREST

The authors have no conflict of interest to declare.

AUTHORS' CONTRIBUTIONS

S.V.W., P.E.H. and T.R.E. conceived the ideas; P.E.H. obtained the funding; S.V.W. and T.R.E. designed and tested the methodology; S.V.W. undertook the analyses. All authors contributed to writing the manuscript.

DATA AVAILABILITY STATEMENT

R and Python code used in the manuscript are archived and made publicly available on FigShare (https://doi.org/10.6084/m9.figshare.17108387; Wyse et al., 2021a). Data associated with this manuscript are also archived and made publicly available on FigShare (https://doi.org/10.6084/m9.figshare.17108321; Wyse et al., 2021b).

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