Combining Species Distribution Models and Value of Information Analysis for spatial allocation of conservation resources

by
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ABSTRACT

1. Managers often have incomplete information needed to make decisions about threatened species management, and do not have the time or funding needed to obtain complete information. Value of Information (VOI) theory has the potential to assist managers in making the decision to monitor or manage, but it has not been applied to assessing spatial allocation of monitoring resources to multiple units across a landscape.

2. I use data from species distribution models (SDMs) to apply VOI analysis across a landscape to assess the utility of single and multiple objective decisions. I determine in which situations one should monitor before purchasing land for conservation, and when one should act based on current information. Further, I prioritize units based on cost effectiveness and identify target properties for conservation.

3. When managing for a single species, the optimal decision for target management units was to act based on current information when survey accuracy was low. When detectability was high, it was most effective to monitor the majority of units. When managing for multiple species, monitoring was only optimal in 50% of cases. Using VOI to determine when monitoring is warranted, and when one should act on current information led to an increase in the expected number of occurrences protected when an optimization algorithm was used to simulate the selection of management units given a budget of $100,000 CAD.

4. *Synthesis and applications*. Using SDMs in combination with VOI allows for large scale analysis, and can assist managers in most efficiently distributing limited resources. My results suggest that if managers can utilize VOI to more efficiently monitor, it can lead to a greater number of protected occurrences of threatened species.

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AUTHOR CONTRIBTUIONS

All research was conducted by C. Raymond, with the exception of the construction of the species distribution models described in Chapter Two - Section 2.4. These models were constructed by J. McCune (see McCune, J.L. (2016). Species distribution models predict rare species occurrences despite significant effects of landscape context. Journal of Applied Ecology, 53, 1871-1879), but are described in detail here for the ease of the reader. The entirety of the manuscript was written by C. Raymond.

CHAPTER ONE – INTRODUCTION

The number of species being lost to extinction or listed as endangered is increasing at an alarming rate (Barnosky et al., 2011; Pimm et al., 2014). This is a result of multiple factors such as habitat loss and modification, invasive species, pathogens, over-exploitation of economically valuable species and climate change (Barnosky et al., 2011; Pimm et al., 2014; Maxwell et al., 2016). Maintaining biodiversity is important, not just for the intrinsic value provided but for maintaining the ecosystem services provided by rich ecosystems (Balmford et al., 2011).

Preventing the extinction of endangered species is a complex task, not only because there are so many variables at play but also due to limited time (Martin et al., 2012), and limited funding (Naidoo et al., 2006; Naidoo & Adamowicz 2006; McCarthy et al., 2012) available to carry out actions. Funding available for conservation projects is severely inadequate compared to what would be required to achieve all goals; thus, there is a need to prioritize both species and actions (Margules & Pressey, 2000). In the past, extensive work has been done on optimal selection algorithms, and they have most often been used to solve place prioritization (i.e. reserve selection) problems (Vane-wright, Humphries & Williams, 1991; Sarkar et al., 2004). Deterministic integer programs are a common approach to this problem, which aims to optimize a solution based on a given constraint (Sarkar at al., 2006). The two most common types of these problems are the minimum set, and maximal coverage problems. In minimum set coverage problems, the goal is to select the lowest number of sites or total area needed to meet a given constraint such as species richness or habitat representation (Pressey, Possingham & Day 1997; Ando et al., 1998; Wilson et al., 2007). Maximal coverage problems are similar but aim to maximize the amount of species richness or habitat representation, constrained by a given budget (Ando et al., 1998; Church et al., 1996; Wilson, 2007).

Many techniques have also been applied to these optimization problems, such as stochastic dynamic programing (SDP) (Wilson, 2006; Marescot et al., 2013) and heuristic methods (Pressey et al., 1997; McDonnell et al., 2002; Sarkar et al., 2004). In the conservation literature, SDP often refers to problems which utilize a Markov decision process (MPD) (Marescot et al., 2013). Markov decision processes are comprised of a Markov chain, which models the future state of the system, according to the initial state, and a specified decision model, which prioritizes actions at each state to maximize a given objective. Thus, Markov decision processes are a type of optimization problem solved using stochastic dynamic programing (Marescot et al., 2013). Heuristic algorithms on the other hand, consist of a rule which is applied after each step in the selection process, using updated measures at each successive iteration (Sarkar et al., 2006). For example, in greedy algorithms, after each selection, values of the remaining selections are recalculated and selected to obtain the largest decrease (or increase) in the objective function (McDonnel et al., 2002; Joseph et al., 2009). Their simplicity and decreased processing time have made them a popular alternative to more traditional methods such as deterministic integer problems. Heuristic methods can also be modified to account for additional objectives such as irreplaceability, or vulnerability of species within sites (Pressey et al., 1997; Aropnen et al., 2005). Yet another approach is simulated annealing, which introduces elements of randomness, sometimes allowing the algorithm to pick a temporary worsening solution, to avoid getting 'stuck' in a local optimum (McDonnell et al., 2002). The acceptance probability of the suboptimal option is specified in the algorithm and helps to prevent the solution from reaching a local maximum early on in the iterations, forcing the solution more towards the optimal solution (McDonnell et al., 2002; Joseph et al., 2009).

All of these prioritization techniques share common goals of efficiency, and economy. However, many approaches lack integration with real world socio-political factors (Naidoo et al., 2006). Economic influences are a huge portion of conservation planning that is often overlooked (Naidoo et al., 2006). A disconnect between research and implementation of findings is also an issue (Knight et al., 2008). Many protocols or studies on species conservation published in scientific literature are not applied at all (Bowman et al., 2016). A study by Cook et al. (2010), revealed that most decisions made by practitioners of two Australian based conservation agencies were based on experience, rather than experimental evidence. This low rate of implementation may be due to a number of factors. First, published scientific studies are often not realistic, and would be out of the scope of what is possible to complete with the resources of most conservation authorities (Knight et al., 2008). They also tend to lack a goal of implementation, with a majority of assessments performed with the objective of improving research techniques, making it hard for managers to translate the results of the study into action (Pullin & Knight, 2005; Knight et al., 2008). Even if studies are realistic, with the goal of implementation, it is difficult for managers to access them (Knight et al., 2008; Cook et al., 2010; Bowman et al., 2016). The amount of time and money going into determining which methods are most effective for conservation is hard to justify if managers are not actually applying the techniques discovered.

Managers on the ground are faced with many decisions and need a way to assess potential outcomes quickly (Pullin & Knight, 2005). Little research has focused primarily on this subject, and it merits further exploration. It is often difficult to determine which action to take, especially when dealing with endangered species, as stakes are high and there are usually large

amounts of uncertainty in the data (Cook et al., 2010). Managers are then plagued with the task of deciding whether to gather more information or to act on the current information.

On one hand, poor quality or limited data can lead to poor decision making, and suboptimal conservation outcomes which ultimately waste already limited funds available for conservation (Hermoso et al., 2014). This phenomenon is illustrated by the case of the endangered Humel deer (*Hippocamelus bisulus)* (Flueck & Smith-Flueck, 2006; Corti et al., 2010; Wittmer et al., 2013), where a decision was made in an attempt to facilitate recovery, but actually led to a further decline. Sheep were removed from the park, in attempt to decrease competition with the deer for food. However, this led to an increase in the amount of deer being predated by pumas. This situation may have been avoided if more accurate information about the cause of decline was available (Flueck & Smith-Flueck, 2006; Corti et al., 2010; Wittmer et al., 2013).

However, the choice to gather more information also has risks (McDonald-Madden et al., 2010; Maxwell et al., 2015). Data collection takes time and money, both of which can be in short supply when dealing with endangered species. Taking the time to collect additional data means that one could miss a window of opportunity to perform a beneficial action, which might result in the further decline of the species at risk. There are cases, such as the Christmas Island pipistrelle (*Pipistrellus murrayi)*(Lunney et al., 2011) where species have been monitored to extinction (Martin et al., 2012; Lindenmayer, Piggott & Wintle 2013; Martin et al., 2017). The choice to continue monitoring the Christmas Island pipistrelle, rather than act quickly to initiate captive breeding, resulted in the extinction of a species which may have been prevented if action had been taken earlier (Martin et al., 2012). It is often believed that more data will lead to a better quality decision, however, this has been found to not always be the case (McDonald-

Madden et al., 2010; Carwardine et al., 2012). In fact, it has been shown that there is often a diminishing return on investment as more data are collected (Williams and Araujo, 2002; Chadès et al., 2008; Grantham et al., 2008; McDonald-Madden et al., 2010, 2011; Hermoso et al., 2014). Collecting more information can be very valuable (Balmford & Gaston, 1999), but only when the new information will affect the management strategy taken and provide a superior conservation outcome.

Value of information analysis (VOI) is a field of decision theory which has long been applied in other disciplines as a way to assess the potential outcomes of management decisions (Raiffa & Schlaifer, 1961; Dakins, 1999). VOI theory is based on the concept that each possible set of actions has an expected outcome, surrounded by a degree of uncertainty. Each action has a theoretical perfect outcome, which would be achieved if all uncertainty was eliminated. The 'value' is represented by the difference in outcome based on current versus perfect information and represents the maximum amount that one should expend on obtaining that information. The value of sample information can also be assessed and used to determine if gathering more data will result in a valuable increase in the decision.

VOI has been applied in many different fields such as environmental health risk (Yokota & Thompson, 2004), disease control (Shea et al., 2004), environmental remediation (Dakins et al., 1994; Dakins et al., 1996; Dakins et al., 1999), and resource management (Williams et al., 2011; Williams & Johnson, 2015). However, its application to conservation has been limited, only being applied at small scales or when using simulated data (Costello et al., 2010; Runge, Converse & Lyons 2011; Moore & Runge, 2012; Runting et al., 2013; Canessa et al., 2015; Maxwell et al., 2015; Williams & Johnson, 2015; Bennett et al., 2018; Nicol, Ward, Stratford,

Joehnk & Chadès 2018). Currently there is no methodology to spatially allocate monitoring resources over multiple sites using VOI.

This scenario portrays more accurately the decisions that would actually be faced by managers, as agencies are often responsible for managing large geographical areas. Further application of VOI to address spatially allocating VOI decision scenarios would be beneficial to conservation biology as it would provide a defensible, quantitative basis for decisions on when, and where to monitor or act.

In my research I will apply VOI theory to a complex system involving multiple woodland patches and threatened plant species in Southern Ontario (McCune, 2016). The system presents a real situation in which many species are at risk of extinction or extirpation, but we have varying levels of confidence in their true abundance and distribution on the landscape. I will use VOI analysis to assess the value of monitoring versus acting, taking into account the estimated costs for surveying a patch to determine the presence of a rare plant species and the costs of management to determine the optimal course of action for a given budget. This approach to monitoring versus acting decisions is much more flexible and realistic than previous methods considering only single decisions. Calculations will also account for the potential of false negative survey results by using a measure of survey accuracy. This measure will be based on the life history traits of a given species, as some may be more difficult to identify in the field and have a higher chance of being missed in a survey (Chen et al., 2009; Chen et al., 2013). Accounting for survey accuracy will provide a more accurate prediction of when monitoring is the most efficient choice. Species distribution models (SDMs) have already been built for several woodland species in this region (McCune, 2016), which I will use to determine the probability of occurrence for each species in the various woodland patches. Depending on the accuracy of the

SDM, the habitat requirements of the target species, and the cost of acquiring land, the optimal action may be different for each species. If managers can adopt a method utilizing VOI theory to optimize decision making, they can increase the efficiency of monitoring and protection methods and hopefully save more species from extinction.

CHAPTER TWO – COMBINING SPECIES DISTRIBUTION MODELS AND VALUE OF INFORMATION ANALYSIS FOR SPATIAL ALLOCATION OF CONSERVATION RESOURCES

1 | INTRODUCTION

Funding available for conserving threatened species is often limited (Naidoo et al., 2006; Naidoo & Adamowicz, 2006); thus there is a need to prioritize, both which species to protect, as well as the management actions taken to protect them (Margules & Pressey, 2000; Bottrill et al. 2008). However, the data needed to make these decisions are often unavailable or of insufficient quality (Cook, Hockings, & Carter, 2010). Managers are faced with the decision to gather more information or take action based on the information currently available. Both choices have associated risks. On one hand, poor quality or incomplete data may lead to poor decision making and suboptimal conservation outcomes, wasting valuable time and money. Actions may even have a negative effect on the target species, leading to a further decline (Flueck & Smith-Flueck, 2006; Corti, Wittmetr, & Festa-Bianchet 2010; Wittmer, Elbroch & Marshall 2013). Conversely, time and money spent monitoring species takes away from time and money available to perform management actions. In the time needed to collect additional data one may miss out on a window of opportunity to perform an action or see a target species disappear altogether (Martin et al., 2012, 2017; Lindenmayer, Piggott & Wintle 2013). It is generally thought that collecting more data will result in a better decision outcome. However, this is not always the case and studies have reported diminishing returns on additional monitoring investment (Chadès et al., 2008; Grantham et al., 2008; McDonald-Madden et al., 2010, 2011). Although additional information can be useful, it is only valuable for conservation management when it will result in a superior conservation outcome.

One way to address the issue of when to monitor and when to act is through the use of Value of Information (VOI) analysis. VOI is a field of decision theory that is based on the idea that each possible set of actions has an expected outcome, surrounded by a degree of uncertainty (Raiffa & Schlaifer, 1961). Each action has a theoretical true outcome which could be obtained if all uncertainty in the system was resolved. The 'value' of perfect information (EVPI), is represented by the difference in outcome achieved based on current versus perfect information, and when calculated in financial terms, it denotes the maximum amount that should be allocated to collecting additional information, or the maximum theoretical expected value given an available suite of actions, assuming risk neutrality.

In most cases in ecology, perfect information about a system is unattainable. Even if additional information cannot completely eliminate uncertainty, it may partially reduce the level of uncertainty in possible actions and lead to a decision closer to the optimal outcome. How much this new information is expected to improve a decision, is known as the expected value of sample information (EVSI) and can be used to evaluate different information gathering scenarios (Raiffa & Schlaifer, 1961). VOI theory has been explored in many disciplines such as environmental health risk (Yokota & Thompson, 2004), disease control (Shea, Tildesley, Runge, Fonnesbeck, & Ferrari 2004), environmental remediation (Dakins, Toll, & Small 1994; Dakins, Toll, Small & Brand 1996; Dakins, 1999), and resource management (Williams, Eaton & Breininger 2011; Williams & Johnson, 2015; Morris, Runge & Vesk 2017). However, application of VOI to conservation has been limited, and has yet to be applied at realistic scales using true associated costs (e.g. Costello et al., 2010; Runge, Converse & Lyons 2011; Runting, Wilson & Rhodes 2013; Canessa et al., 2015; Bennett et al., 2018; Nicol, Ward, Stratford, Joehnk & Chadès 2018).

Sequential decisions involving the allocation of conservation resources over time have been assessed previously using stochastic dynamic programing (SDP) to solve Completely (MDP) or Partially (POMDP) Observable Markov Decision Process (Marescot et al., 2013) for situations involving fewer than three populations (Chadès et al., 2008, McDonald-Madden et al., 2011). However, these problems are computationally challenging because they account for the dynamics of species populations, making them difficult for managers to utilize. They are limited in the number of states and species to which they can be applied by 'the curse of dimensionality' (Chadès et al., 2008; McDonald-Madden et al., 2011; Marescot et al., 2013), meaning that as the number of state variables increases, the size of the state space also increases exponentially, requiring an intractable number of iterations at each step in the problem. At present, there is no methodology to assess the spatial allocation of monitoring resources across multiple patches using VOI. Application of VOI using this approach could provide a quantitative basis for decision-making and would be more representative of real decisions being faced by managers, who are often responsible for distributing resources across large geographical areas. If management agencies can utilize VOI theory to improve decision making, they can optimize the allocation of limited monitoring resources.

Here we use VOI to assess spatial allocation of management resources for a threatened woodland plant, false rue-anemone (*Enemion biternatum*), across multiple patches in Southern Ontario, Canada, using realistic cost variables to determine in which situations one should survey to collect additional information, and in which situations action should be taken based on current information for a single time step. Additionally, we examine the utility of VOI in decisions involving multiple threatened plant species at the same time by also including purple twayblade (*Liparis lilifolia*) and the cucumber tree (*Magnolia acuminata*), to maximize the number of

protected occurrences of any of the three threatened plants. As agencies are often managing for more than one species, considering actions which will benefit multiple species simultaneously is an aspect which has been overlooked in previous applications of VOI. To further demonstrate the applicability of VOI, we also simulate the selection of management units across the landscape given a budget of 100,000 CAD, prioritizing based on the cost effectiveness of each decision, and further use this to identify potential target properties composed of multiple management units. Our results illustrate how conservation can be made more efficient by using VOI to accurately assess potential management options, and spatially allocate available resources.

2 | MATERIALS AND METHODS

2.1 | BACKGROUND

Ontario is the most populated province in Canada, and the majority of its population resides in a relatively small area in the south. Southern Ontario is currently both densely populated and dominated by intense agriculture, but historically the region was dominated by rich deciduous forests (Larson et al., 1999). The forest region farthest to the south and west is known as the Carolinian zone, within the Lake Erie-Lake Ontario Ecoregion (Crins et al., 2009). The Carolinian zone is a hotspot for threatened plants. Approximately 40% of Ontario's threatened plant species are restricted to this habitat (Allen, Eagles & Price 1990). However, for many species the number of extant populations is uncertain, making it an ideal location for applying VOI to plant conservation.

2.2 | CASE STUDY ONE: SINGLE-OBJECTIVE DECISION

Our first case study considers management of a single species, false rue-anemone (*Enemion biternatum*). False rue-anemone is a small, spring-flowering perennial herb, which occurs in moderate climates, preferentially in open wooded slopes and river floodplains (COSEWIC, 2005). It occurs in Canada as well as the United States, and although common in its core range,

is considered rare at the Northern and Western edges of its range (COSEWIC, 2005). Typically, the plant grows to 10-40 cm tall and flowers in early June producing white flowers, with five petal-like sepals (COSEWIC, 2005). In Canada, false rue-anemone is listed as threatened both nationally and in Ontario (SARA, 2018; SARO, 2018). In the United States the plant is extirpated from New York and South Dakota, legally endangered in Florida, and considered a conservation concern in South Carolina, although not listed federally (COSEWIC, 2005). Primary threats are habitat loss and disturbance due to development and recreational activities (COSEWIC, 2005). Currently there are fewer than 10 known extant populations in Canada, all of which occur in Southern Ontario (COSEWIC, 2005). False rue-anemone was historically known to occur within Norfolk County, and thus we chose this county for the location of our study because we know that suitable habitat likely exists there, and there is a real possibility of discovering new populations. Picking a scale of one county also maintains consistency of management costs as property values can vary from county to county.

2.3 | Case study two: Multiple-objective decision

Agencies are often concerned with monitoring and decisions to benefit more than one species. Therefore, we consider a second case study managing for multiple threatened plant species. Purple twayblade (*Liparis liliifolia*), and cucumber tree (*Magnolia acuminata*) are both known to occur in Norfolk County. Purple twayblade is a small purple-flowered orchid that can be found in a variety of habitats and is listed as threatened in Ontario as well as across Canada (SARA, 2018; SARO, 2018). Cucumber tree is a medium-sized tree, reaching up to 30 m tall, and is the only magnolia species native to Canada. It is endangered in Ontario and throughout Canada (SARA, 2018; SARO, 2018). See Table A1 for more information. We consider these species, along with false rue-anemone, in multi-species VOI described below.

2.4 | Value of Information Analysis

We used VOI to calculate the cost effectiveness of monitoring, contrasting this with cost effectiveness of purchasing land for conservation based on current knowledge, assuming that the more cost-effective option represents the better use of limited conservation resources. We outline the information required, and the steps to calculate the cost effectiveness of each approach using two case studies.

To complete our VOI analysis, five pieces of information are required:

1. *Prior probabilities:* In this case, prior probabilities represent the best available estimate of whether or not the target species is present, and could be based on previous surveys, expert opinion on habitat affinity or more quantitative modeling.
2. *Survey accuracy:* Survey accuracy is a measure of detection, representing the likelihood of a plant being detected in a survey given that it is present. For example, some showy species may have high probability of detection, whereas smaller, cryptic, or less-showy species have lower probability of detection.
3. *Cost of gathering additional information:* The cost of gathering information includes the money required for the personnel, equipment, and other costs of performing more surveys.
4. *Cost of performing an action:* The cost of performing an action is represented in this case by the costs associated with purchasing land.
5. *Expected value of management actions*: This is the benefit of the protecting land, given the plant is present, and represents an occurrence being protected.

Prior Probabilities: Species Distribution Model Data

We used species distribution models (SDMs) followed by detailed plant surveys to estimate the probability of presence of false rue-anemone, purple twayblade, and cucumber tree across Norfolk County. First, we obtained SDMs built by McCune 2016 for each species across southern Ontario using the program MaxEnt (Phillips et al. 2006). We obtained spatially accurate presence records for each species from the Ontario Natural Heritage Information Centre (NHIC). Using these, we built 8 SDMs for each species, varying the predictor variables and MaxEnt settings used for each model. We then tested these SDMs by conducting detailed plant surveys at 156 one-hectare sites throughout Southern Ontario that were each predicted to have suitable habitat for one or more of the modeled plant species (see McCune 2016 for details). We compiled a dataset of independent presences and absences for each species based on these 156 sites in addition to independent presence records held by the Ontario NHIC that were not used to build the SDMs. We set the threshold for predicting a species to be present as the MaxEnt cumulative output value resulting in omission errors for no more than 10% of the presence records used to build the model, or 0% if there were fewer than 15 presence records available. We then chose the best SDM version based on the model's ability to correctly predict the highest number of independent presences based on this threshold. If two SDM versions predicted independent presences equally well, we chose the best model among them based on the highest AUC value (Area Under the Receiver Operating Curve; Fielding & Bell 1997). All SDM versions for all three species had high overall performance based on the independent data, with all AUC values >0.80 (considered "excellent" discrimination; Hosmer & Lemeshow 1989). We then used generalized linear models (GLMs) with a binomial link function to convert the predicted habitat suitability of the best SDM to an estimated probability of presence value for each species in each one-hectare (100m x 100m) grid cell (hereafter referred to as a

‘management unit’, Fig. A1) across Southern Ontario (Rosner-Katz et al. in prep.). From these GLMs we obtained the probability of presence of false rue-anemone, purple twayblade, and cucumber tree in each management unit within Norfolk County. Deriving prior probabilities for VOI using SDMs has not been explored previously, and potentially provides a technique to obtain probabilities for threatened species over large areas, where data are often lacking.

Survey Accuracy

Imperfect detection is common in plant surveys (Chen et al., 2009; Moore et al., 2011; Chen et al., 2013). We include an estimate of survey accuracy to account for possible false negatives in survey data. This is a measure of detectability and represents the estimated probability that a surveyor will detect the plant if it is present, based on the life history characteristics of each species (Table A1). Estimates for plants range from 0.05 (extremely cryptic) to 1.0 (detectable 100% of the time; Chen et al., 2013). For the single species analysis, we demonstrate the effect of detectability on decisions by modeling the entire range of realistic accuracies from 0.05 to 0.95 probability of detection.

For the multi species analysis, we assign a smaller range of values for each plant. These ranges (Table A1) reflect our best guesses of the detectability of each species, though we note that they are not based on detectability tests in the field. We use the mean of the assigned range for each species in the VOI calculations.

Cost of Gathering Information: Monitoring

Based on a survey of 10 local environmental consultants, we estimate the cost of survey as $750 Canadian dollars (CAD) per one-hectare management unit (Bennett, *unpublished data*). In our study area, all sites are reasonably accessible, so we do not need to consider any additional costs to access remote plots.

Cost of Action

Here we consider whether or not to purchase a given management unit (i.e. one-hectare cell). Other actions could be taken to protect the target plant species (e.g. invasive species removal, or assisted dispersal). However, one of the greatest threats to threatened plants in Canada is destruction due to residential and commercial development (McCune et al. 2013). Therefore, we focus on protection from development via land purchase. We used the GeoWarehouse software (Teranet, 2018) to obtain a stratified random sample of properties (parcels of land as defined by the Ontario Land Registry Office) in or directly adjacent to Norfolk County. We overlaid a grid on the sample area using ArcMap 10.4.1(Esri, 2017), taking the GPS coordinates of the points of intersection. We then located the closest property to that point using GeoWarehouse (Appendix C). We only included properties that were woodlots (no existing structures on the property) and larger than one-hectare. We calculated a cost per hectare estimate, based on the Municipal Property Assessment Corporation (MPAC) values for 2018 (Appendix C). Although conservation agencies may purchase properties with existing structures, excluding them from our analysis provides a more accurate cost estimate of forest land because the values are not inflated by the cost of the buildings. We found a strong negative correlation between the size of the property and the cost per hectare (Fig. A2). To extrapolate values to all potential management units, we created a linear model of this relationship and used the size of the property in which the management unit was contained to predict the per hectare cost (Fig. A2; Fig. A1). All costs are in CAD.

Expected value of management actions

In our case studies the expected value, or the benefit, of management actions is represented by the protection of a species occurrence. We calculate value based on the probability that a target species is present, and consider success to be the protection of a management unit where the

target species is present - that is, we only benefit from an action if a presence is protected (Table 1, cf. Bennett et al. 2018).

TABLE 1: Potential benefits for actions (protect, don't protect) given the true state of the unit (species is present or absent). We only benefit if we protect a unit where the species is present.

	Protect	**Don't Protect**
Present	1	0
Absent	0	0

2.5 | Expected value Calculations

Our expected value calculation process is outlined in Fig. 1. We first calculate the value of action before and after monitoring. We then determine the cost of acting with current information, and after monitoring. From this, we obtain a measure of cost effectiveness for both options. The decision to act on current information, or monitor first is determined by taking which ever action is found to be more cost effective for an individual management unit. The units are then ranked from most to least cost effective, and selected up to a given budget, for each accuracy level (Fig. 1).

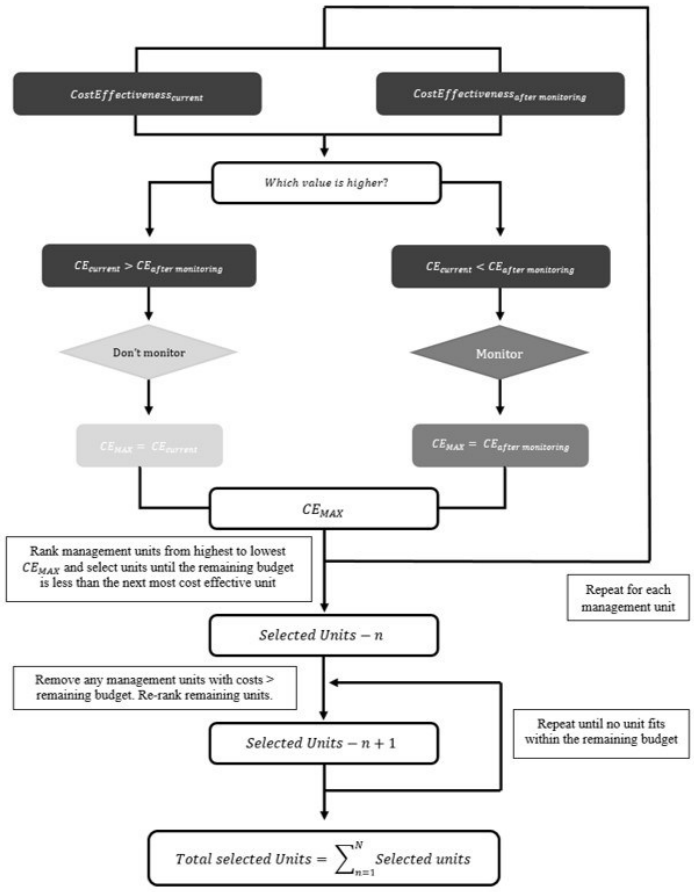

FIGURE 1: Flowchart depicting the decision process for making monitoring/acting decisions for individual one-hectare management unit, and the iterative management unit selection process. If monitoring is not recommended, expected cost is $Cost_{purchase}$. If monitoring is most cost effective, expected cost is based on equation 5 (single objective) or 12 (multiple objective).

I. SINGLE-OBJECTIVE

Ia. Current information (i.e., do not monitor)

We calculate the value of purchasing (protecting) each one-hectare management unit in Norfolk county based on the probability of occurrence of a species (in our case, false rue-anemone).

For a single management unit, we calculate the expected value of action a_i among the suite of available actions A as follows (Canessa et al. 2015; Bennett et al. 2018):

$$\mathbb{E}[V(a_i, s)] = \sum_{s \in S} \{V(a_i, s) \cdot P_s\} \quad (1)$$

where a_i is the action (purchase), s is the uncertain state of the management unit, among the set S of all possible states (present, absent) and P_s = probability that the state s is true (see Table 2 for terms of equations).

TABLE 2: TERMS OF EQUATIONS

Symbol	Term
$\mathbb{E}$	Expected value of a management action
s	State of an individual management unit
S	All possible states of a management unit
A	Set of all possible management actions for a given state
a_i	Individual management action for a management unit
x_i	Binary decision variable identifying whether an action is taken
P_s	Prior probability of a state s
$V(a_i, s)$	Value of a management action for a state, s for an individual management unit
y	Monitoring result
Y	All possible monitoring results
K	Number of species being considered
k	Individual species
P_k	Probability of a species being present

We then calculate the expected value of implementing a management action given current information by taking the maximum value over the available actions from Equation 1. In our case, if only one unit is considered the best action will always be to purchase - since we only benefit if an occurrence is protected (Table 1).

$$EV_{current\ info} = \max_{a_i \in A} \mathbb{E}_s[V(a_i, s)] \quad (2)$$

As per Bennett et al. (2018), Equation 2 can be formulated as a decision problem:

$$EV_{current\ info} = \max_{x_i} \sum_{i=1}^{|A|} x_i \mathbb{E}_s[V(a_i, s)] \quad (2b)$$

where x_i is a binary decision variable denoting whether action a_i is implemented. As mentioned above, in our case study under current information the best action for an individual unit, without

considering limited budgets and opportunities in other units, will always be to purchase, since not purchasing returns no benefit (Table 1). Therefore, the cost of the best action for only one unit is simply the cost of purchasing a management unit ($Cost_{purchase}$).

Cost effectiveness of our best decision using current information represents the expected value obtained per dollar and is calculated as follows:

$$CE_{current} = \frac{EV_{current\ info}}{Cost_{purchase}} \quad (3)$$

We complete these calculations for all management units individually (Fig. A1) within Norfolk County, based on the prior probabilities of false rue-anemone occurrence in each unit and the estimated purchase cost of each management unit. We excluded management units with probabilities <0.05, assuming that such cells would not be chosen as candidate sites for protection in our case studies.

Ib. Monitoring information

For each unit, we calculate the expected value of the best decision after monitoring by taking the maximum value achieved by the suite of possible actions, given the survey result *y*:

$$EV_{after\ monitoring} = \mathbb{E}\{max_{a_i \in A} \mathbb{E}_{|y}[V(a_i, s)]\} \quad (4a)$$

Although a survey does not provide us with perfect information due to imperfect detection, it does alter the probabilities of states, these probabilities are updated using Bayes Theorem, that is, *probability(state s | result y) = probability(result y | state s) × prior probability (state s) / probability(result y)* (Raiffa & Schlaifer 1968). In our case, monitoring results either raise the probability of presence to 1.0 (if the plant is detected) or lower the probability of presence, if the plant is not detected.

Equation 4a can be formulated as a decision problem, as follows:

$$EV_{after\ monitoring} = \max_{x_i^y} \sum_{y \in Y} p(y) \sum_{i=1}^{|A|} x_i^y \sum_{s \in S} V(a_i, s) p(s|y) \quad (4b)$$

where *p(y)* is the probability of monitoring result *y* for this unit, x_i^y is a binary decision variable identifying the action a_i implemented for each possible monitoring result *y*, and *p(s|y)* is the probability of state *s* given monitoring result *y*.

Given that we only receive benefit for protecting, we will again always have a higher expected value when choosing to protect if we only consider one unit and do not consider monitoring costs. However, it is crucial to consider monitoring costs, purchasing costs, and expected values among units. Here, we calculate an expected cost after monitoring, assuming that one would only purchase if the target was found. This is an important difference from the expected cost of purchasing with current information. Given the relatively high number of available units in our study, managers can choose to either move on to another unit if a survey does not reveal a species, or perhaps re-survey in the future if there is still a sufficiently high posterior probability of occurrence. The expected cost of the decision after monitoring for a single time step in a given unit is therefore calculated considering the purchase cost, weighted by the probability that an occurrence is found, plus the cost of monitoring, because we are assuming we only purchase if an occurrence is found:

$$Expected\ cost_{after\ monitoring} = \left(P_{s=present|y} \cdot Cost_{purchase}\right) + Cost_{monitor} \quad (5)$$

Cost effectiveness after monitoring is calculated in the same manner as Equation 3, but uses the expected value and expected cost data after monitoring:

$$CE_{after\ monitoring} = \frac{EV_{after\ monitoring}}{Expected\ cost_{after\ monitoring}} \quad (6)$$

Ic. To monitor or not to monitor?

The decision to monitor or not monitor is made by comparing the cost effectiveness between the two calculations (current information versus monitoring) for each management unit (Fig. 1). If the cost effectiveness is greater using current information, monitoring is not recommended for a management unit. However, if the cost effectiveness is greater using monitoring information, monitoring is recommended (Fig. 1).

Id. Selecting management units given a limited budget

To determine the order in which units would be protected or monitored (then protected if occurrences found) and obtain an estimate of the number of occurrences we would protect, we simulate the selection of management units across the landscape given a budget of 100,000 CAD, prioritizing based on the cost effectiveness of each decision. First, we rank all of the management units by their maximum cost effectiveness value (i.e. cost effectiveness without versus with monitoring). We then use a selection algorithm to select units in sequential order, until the next-ranked unit is more expensive than the remaining budget. The next most cost-effective unit that fits into the budget is sequentially selected, until there are no management units remaining that would fit within the (expected) remaining budget. It is important to note that this process provides us with risk neutral recommendations of the order of decisions among units, as well as the expected costs of management and monitoring and the expected number of protected occurrences. The actual number of units that are monitored and/or protected will vary based on the actual number of times the species is found when completing surveys, and the actual cost of managing units. We complete this selection process, at each probability of detection level. We then simulate the selection of units using a strict always monitor approach, completing the same selection process using only the values obtained from monitoring calculations.

II. MULTIPLE-OBJECTIVE CALCULATIONS

IIa. Current information (i.e., do not monitor)

To incorporate all three species into a multi-objective calculation, we first do the calculations (Equations 2 and 3) for each species individually.

We then calculate the total expected value of each management unit as the sum of the expected value of the best single action, a_i, for considering all k species, of the K potential focal species in a management unit. Again, x_i is a binary decision variable denoting whether action a_i is taken:

$$EV\ Multi_{current\ info} = \max_{x_i} \sum_{k=1}^{|K|} \sum_{i=1}^{|A|} x_i \mathbb{E}_s[V(a_i, s)] \quad (7)$$

As with single objective decisions, the expected cost under current information when considering only one unit is simply the cost of purchasing the unit ($Cost_{purchase}$).Cost effectiveness of the decision to manage a management unit is calculated using the cumulative expected value of all target species, and the expected cost of purchasing a unit:

$$CE_{current} = \frac{EV\ Multi_{current\ info}}{Cost_{purchase}} \quad (8)$$

IIb. Monitoring information

We calculate the expected value after monitoring for all 3 focal species by summing the expected value of each k species individually, for all management units given the state of the unit s, and the potential survey result y (found, not found) for each species:

$$EV_{monitoring} = \max \sum_{k=1}^{|K|} \sum_{y \in Y} p(y) \sum_{i=1}^{|A|} x_i \sum_{s \in S} V(a_i, s) p(s|y) \quad (9)$$

Note that in this case, we assume that the binary decision variable x_i must take only one value for all species (the unit is either protected or not).

To calculate the expected cost for multiple objectives, we assume again that the unit will not be protected if no occurrences are found. We therefore calculate the expected cost using the

probability of finding at least one of the target species. This is done by first calculating the probability of finding none of the targets:

$$P_{none\ found} = \prod_{k=1}^{|K|} (1 - P_k) \quad (10)$$

$$P_{at\ least\ one\ found} = 1 - P_{none} \quad (11)$$

Where K is the total number of possible species k that can be present in an individual unit, and P_k represents the probability of an individual species being present. Expected cost can then be calculated as follows:

$$Expected\ cost\ multi_{monitor} = P_{at\ least\ one\ found} \cdot Cost_{protect} + Cost_{monitor} \quad (12)$$

where $P_{at\ least\ one\ found}$ is the probability of one or more species of interest being found in a patch (Equation 11). The $Cost_{monitor}$ remains $750 CAD, as we assume the monitoring cost is shared, and we can survey for the species simultaneously. We calculate expected cost in this way because we assume that a patch will not be purchased if no species of interest is found. However, we note that this calculation could be modified if the agency prefers to purchase only if all, or multiple species are present.

To calculate the expected value for multiple objectives after monitoring, we add the expected value after monitoring for each species:

$$EV\ Multi_{after\ monitoring} = \sum_{k=1}^{|K|} EV_{monitoring} \quad (13)$$

where expected values of monitoring for each k individual species out of the group of possible K focal species (in our case, $K = 3$).

We calculate cost effectiveness after monitoring using the cumulative expected value for all species expected to occur in the patch, and dividing by the expected cost of protecting the patch after monitoring:

$$CE_{after\ monitoring} = \frac{EV\ Multi_{after\ monitoring}}{Expected\ cost\ multi_{monitor}} \quad (14)$$

All calculations were performed at each accuracy level for single objective calculations, and for the specified range of accuracies for multi-objective calculations.

IIc. To monitor or not to monitor?

After calculating the cost effectiveness before and after monitoring for each management unit, we decide which action to take by taking the maximum of the two values as in single objective decisions (Fig. 1).

IId. Selecting management units given a limited budget

Management units are selected using the same methodology described above for single objective decisions, with the exception that they are performed only using the mean of the assigned range of monitoring accuracy for each species (Table A1).

2.6 | Identifying Target Properties

Managers typically have limited resources and must also choose where to monitor and where to act. To demonstrate this, we determine which properties (Fig. A1) within Norfolk County would be most cost-effective to monitor and/or purchase, by calculating the average cost effectiveness across all management units within a given property. This gives an indication of the properties that would likely be a good conservation target (more likely to purchase an entire property as opposed to a single hectare, i.e. management unit), as properties with the highest average cost effectiveness value represent properties with the largest amount of cost effective suitable habitat.

3 | RESULTS

CASE STUDY ONE: SINGLE-OBJECTIVE

Monitoring decisions were largely driven by the expected value of the management unit (Fig. A3), although the proportion of all management units where monitoring was recommended for individual decisions varied across the range of simulated probability of detection levels (Fig. 2). At 0.05 probability of detection, it was most cost effective to forgo monitoring for almost all management units. When survey accuracy increased to 0.10 probability of detection, this proportion sharply decreased. When probability of detection reached ~0.30, monitoring was recommended for nearly all management units (Fig. 2) (Table A2).

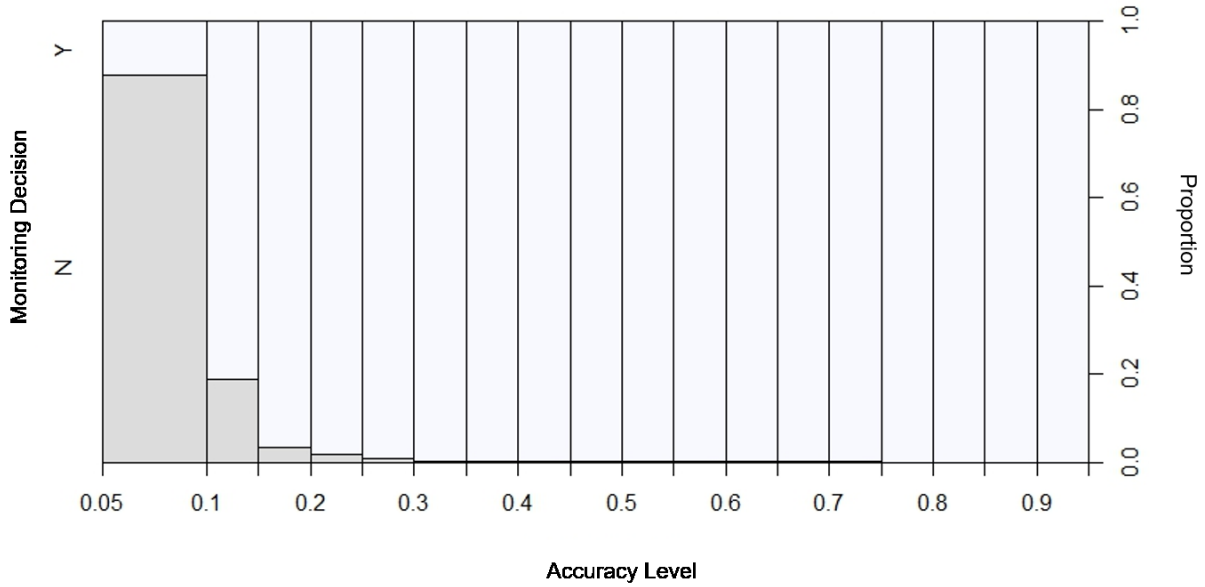

FIGURE 2: Variation in the proportion of monitoring decisions for all possible management units (n = 238,247) among simulated probability of detection levels for the single species, false rue-anemone.

When considering the units selected by our selection algorithm using a limited budget of $100,000 CAD and the single-species case of false rue-anemone, it was most cost effective to forgo additional monitoring for almost all units until probabilities of detection levels were above 0.60 (Fig. 3). This suggests that in this situation, unless there is a relatively high certainty in

monitoring results, it is not cost-effective to monitor prior to purchase. At lower detection probabilities, the additional monitoring information would not justify the cost of monitoring.

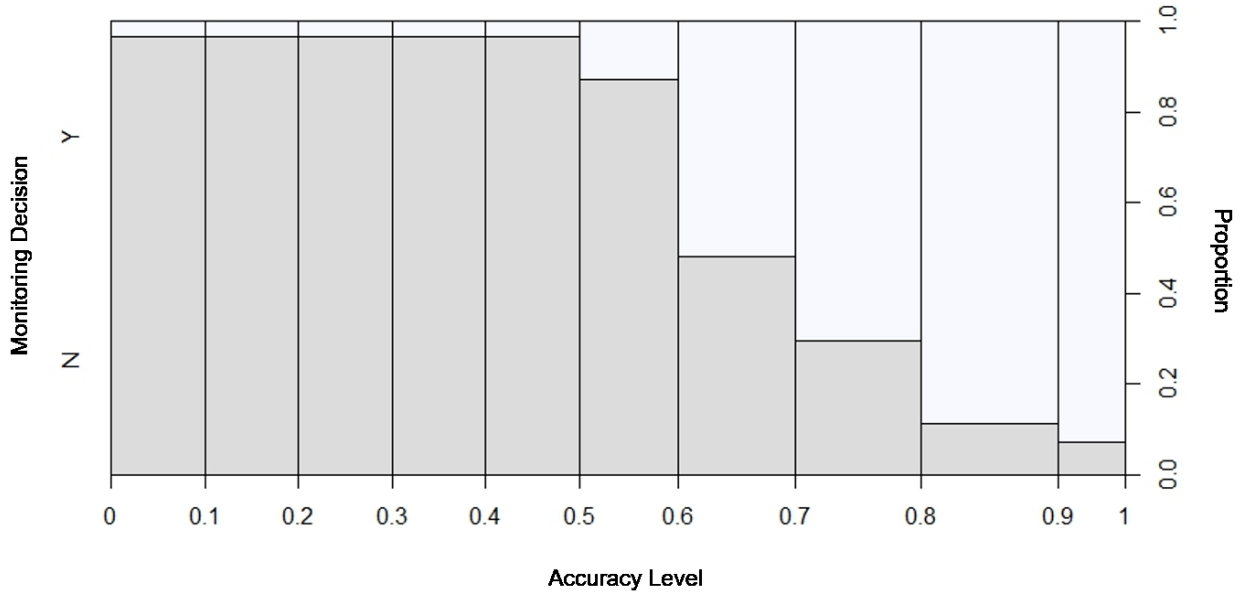

FIGURE 3: Proportion of monitoring decisions for selected management units by probability of detection level for the single species, false rue-anemone with a limited budget of $100,000 CAD (N = 30-44; Table A3).

When approximating the decision process given our limited budget scenario, we found that expected value was higher at all probability of detection levels using our mixed approach of monitoring/acting, compared to a situation in which all management units were monitored (Fig. 4).

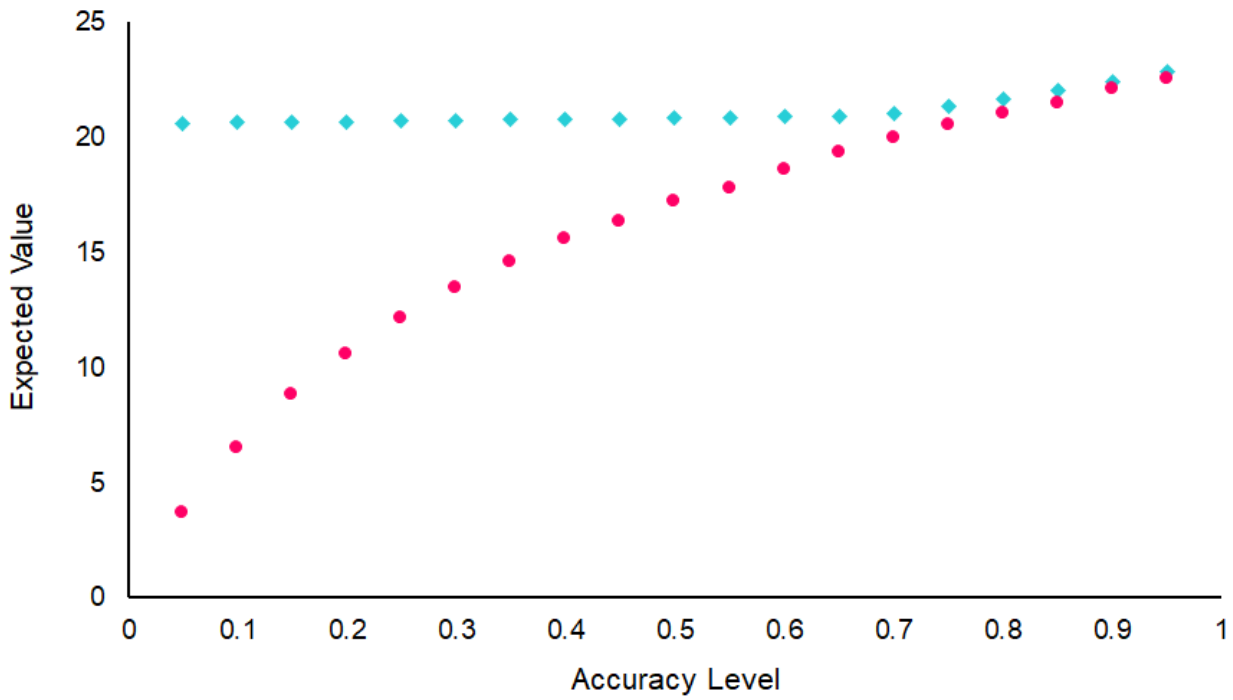

FIGURE 4: Additive expected value of management units selected based on maximum cost effectiveness per unit (blue diamonds) compared to the additive expected value of management units selected if all (red circles) management units were monitored for the single species false rue-anemone, across all probabilities of detection levels given a limited budget of $100,0000 CAD.

CASE STUDY TWO: MULTIPLE-OBJECTIVE

When managing for multiple species (purple twayblade, false rue-anemone and cucumber tree, at detection probabilities of 0.60, 0.70 and 0.90 respectively), amongst units which had at least >0.05 predicted probability for each of the three species (n = 2926) monitoring was recommended for all units except 29 (about 1%) (Fig. A4). However, when considering the proportion of monitoring decisions for the management units selected by our selection algorithm, it was most cost effective to forgo monitoring about 52% of the time (Fig. A5), indicating that many of the 29 units where monitoring is not recommended were selected. As in case study one, when selecting units using our limited budget scenario, expected value was higher using a mixed approach, compared to a monitoring only strategy (Table A4).

IDENTIFYING TARGET PROPERTIES

Single-objective:

Average cost effectiveness values ranged from 0 to 1.4×10^{-4}. The most cost-effective properties were located in close proximity to one another (Fig. 5).

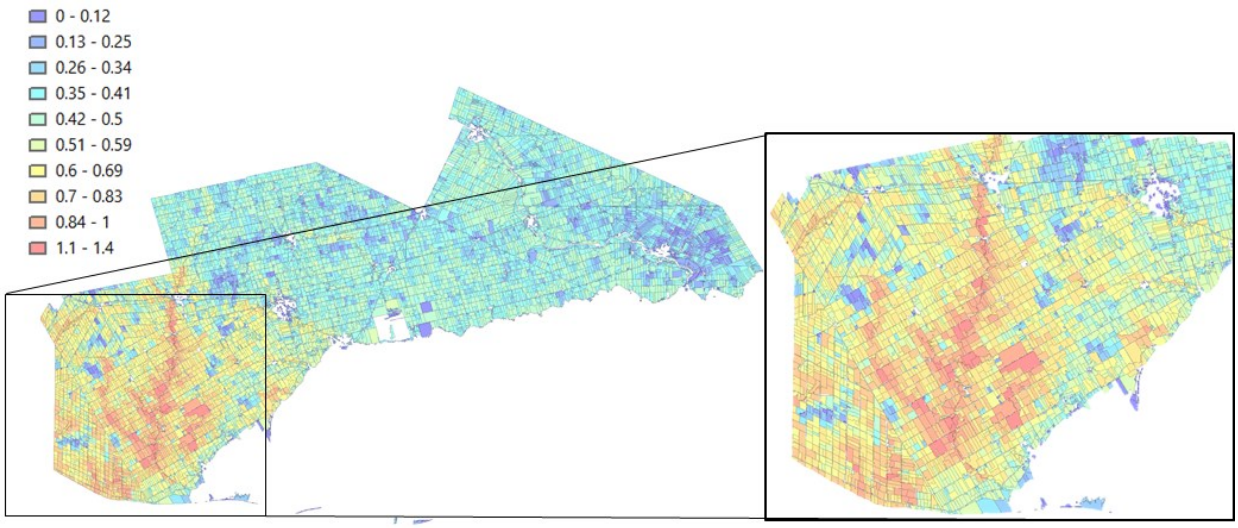

FIGURE 5: Target properties for management of false rue-anemone, at 0.70 probability of detection, considering cells that had >0.05 probability of occurrence. Colours denote average cost effectiveness per property ($\times 10^{-4}$)

Multiple-objectives:

We observed a large change in the properties targeted in comparison to the single objectives priority properties (Fig. 5, Fig. 6). Cost effectiveness values ranged from 0.005 to 1.3×10^{-4}, which is lower than the maximum seen in single-objective calculations.

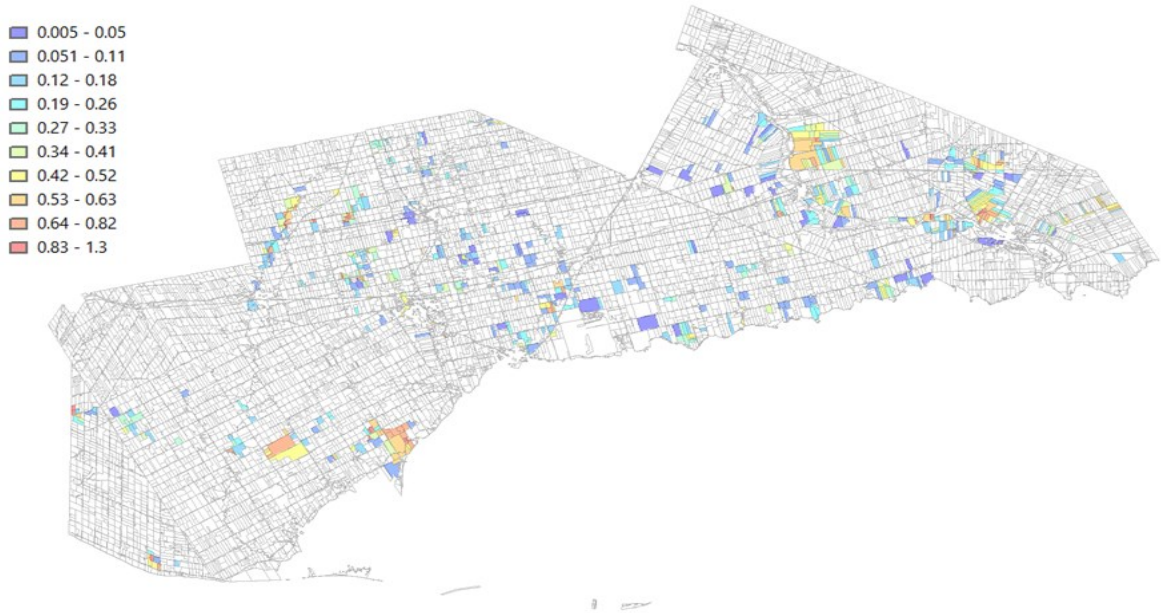

FIGURE 6: Target properties for multiple-objective management as indicated by average cost effectiveness per property ($\times 10^{-4}$), considering cells that had >0.05 probability of occurrence for each target species.

4 | DISCUSSION

Application of value of information analysis in conservation has previously been limited to spatially uniform (e.g. Costello et al., 2010; Runge et al., 2011; Runting et al., 2013; Canessa et al., 2015; Williams & Johnson, 2015) or non-sequential decisions. Here, we demonstrate how VOI can be used to assess multiple decisions to spatially allocate monitoring resources across a landscape, while explicitly considering realistic cost values. Calculating the expected cost of an action given multiple units across a landscape provides a more realistic representation of the situation faced by decision makers, because if monitoring is recommended, the action taken will be influenced by the result of the monitoring survey. We considered whether or not to purchase a unit, which for the study system assessed, is often the most effective conservation action (McCune et al., 2013). However, many other conservation actions could be considered. While of course our method cannot predict the outcomes of decisions, it can estimate the expected values (e.g. number of protected occurrences) one can achieve given limited budgets. We find that in

many realistic scenarios, a mixed approach where some units are monitored, and some are not is optimal.

CASE STUDY ONE: SINGLE-OBJECTIVE

When considering a single objective, we found monitoring decisions were largely driven by the expected value of the management unit (Fig. A3). Units with very high expected values were not cost-effective to monitor, because in this small number of cases the prior probability was high enough to justify purchase. We also found that units where monitoring was recommended were slightly more expensive to purchase per hectare (Fig. A3) than those for which monitoring was not recommended, although monitoring was recommended for most units overall (Fig. 2). Keeping in mind that we assessed all possible units across a landscape, it is logical that the majority will not be highly suitable for the target species, resulting in a low expected value and the recommendation to monitor if purchasing is being considered. In reality, many of these units would not be targets for conservation.

In the scenario to protect false rue-anemone with a limited budget of $100,000, many of the management units which were highly cost effective either i) have a very high expected value and thus do not warrant monitoring (because we are fairly certain the plant will be there), or ii) are very inexpensive, making monitoring not worth the additional cost. This results in a larger proportion of 'no monitoring' units in the selected subset for this scenario, in comparison to the total across the landscape. This may be different depending on the cost of actions being considered, and the range of prior probability values. We also recognize that $100,000 is an arbitrary budget, and that the percentage of units in which management is recommended would change based on the budget. However, our aim is to provide a more realistic demonstration application of this by managers, rather than make specific recommendations.

When compared to a situation where every patch was monitored, we found a higher cumulative expected value in the management unit selection algorithm using a mixed approach at every probability of detection level (Fig. 4). This suggests that by using our technique, one would expect to protect more occurrences than if using a strict always monitor strategy. The difference between the two values is most extreme when probability of detection is low and suggests that in our case VOI analysis may provide the most benefit in situations where monitoring would be the default decision, and probability of detection is below 0.60 (Fig. 4). The importance of 0.60 probability of detection is dependent on the other parameters used in the study, and thus should not be extrapolated. Low detectability may often be the case for plant species. For example, many plants are cryptic or only appear during favorable conditions (Chen et al., 2009; Chen et al., 2013). The same can also be noted for many rare or threatened species, which are often difficult to detect in a survey (MacKenzie et al., 2002; McDonald-Madden et al., 2011; Nicol et al., 2018).

CASE STUDY TWO: MULTIPLE OBJECTIVES

We found it was more cost effective to forgo monitoring about 1% of the time when managing for multiple species, which is five times more often than in case study one, when assuming the same probability of detection of 0.70 for false rue-anemone (Table A2). Although monitoring for three species costs the same as monitoring for one, we found the expected value has a greater impact on monitoring decisions, and thus the additive approach (with higher expected values compared to case study one) resulted in a higher percentage of units where monitoring was not recommended.

As including additional species increases the expected value we believe that adding additional species as targets would lead to an increase in the proportion of “don’t monitor” decisions, provided the cumulative expected value is sufficiently high (Appendix B).

Again, we see that when looking at the units selected using our algorithm, there is a much higher proportion of units where monitoring was not recommended compared to all one-hectare units across the landscape. As in case study one, these units on average had a higher expected value, and slightly lower cost compared to units where monitoring was recommended (Fig. A3). Here our objective was to maximize the number of rare plant occurrences, regardless of the species, however we note that other objectives such as complementarity among units and decisions are possible to assess.

Identifying Target Properties

The suites of properties identified as priorities between case study one and two were different, highlighting the importance of identifying priorities when planning. In the single species case study our algorithm often identified large properties with relatively low cost per hectare. As false-rue anemone prefers to grow in wooded shady slopes and river floodplains (COSEWIC, 2005), selected areas were often in close proximity to river beds (Fig. 5).

In the multiple-objective study, a more diverse suite of properties was identified, representing a range of different sizes (and therefore prices) and locations (Fig. 6). Although all three species are known to occur in the study area, each has specific habitat requirements. Selecting for multiple objectives identified areas which provide suitable habitat for all three species and resulted in selected properties being more widespread across the landscape.

In the multiple objective analysis, we set a minimum probability of presence of 0.05 for each species, guaranteeing that each unit was at least slightly suitable for all three species. However, if this limitation were not included, our method might prioritize areas which are suitable for only one or two species. Depending on the goal of the project, minimum acceptable probabilities for any species can be adjusted to identify areas with the greatest number of expected presences,

regardless of species, or areas which have a high probability of containing multiple threatened plants.

Our results are dependent on the assumption of risk neutrality, and may be different if a risk tolerant, or risk adverse strategy were adopted. Our methodology makes some key assumptions. First, we assume that parameters such as detectability and prior probabilities of presence can be reasonably estimated. However, we note that our method is adaptable to exploring ranges in these parameters, as we demonstrated by simulating various monitoring accuracies for false rue-anemone. Second, we assume that management should be conducted at the one-hectare scale. Typically, the amount of habitat required for an individual of a given species, depends on the characteristic scale of response of that species to habitat amount (Jackson & Fahrig, 2014). For plants, this relationship is largely unknown. However, small patches have been shown to be extremely important for rare plants, especially in highly fragmented landscapes such as Southern Ontario (Eckert et al., 2009; Bennett & Arcese, 2013; Tulloch et al., 2016), suggesting one-hectare is a reasonable scale for our analysis.

Our calculations also assume only a single monitoring step (i.e., plant survey). Ideally, monitoring in both time and space could be assessed simultaneously. However, this greatly increases the computational complexity of the VOI problem, and at present there is no methodology to assess both on such a large scale (Chadès et al., 2008; McDonald-Madden et al., 2011; Marescot et al., 2013). As such, we have applied our method to a single time step, assuming no risk of extinction once the habitat is protected. Although this may be unrealistic for other threatened species, when considering threatened plants, it may often be reasonable to assume populations will persist once protected (Cowling, Pressey, Rouget & Lombard 2003; Eckert et al., 2009; Bennett & Arcese, 2013). Our methodology gives preference to properties

that have high proportion of cost effective units. As large properties are less likely to be entirely covered by cost effective units, this may put these properties at a relative disadvantage. We argue that under budget constraints, prioritizing based on amount of cost effective land is a reasonable assumption, as agencies ideally want to get the most for their dollar.

CONCLUSION

Our method for applying VOI to multiple decisions to spatially allocate monitoring and management resources across a landscape, addresses many of the previous limitations of using VOI in conservation management. We also demonstrate how VOI can be used to consider the value of multiple objectives at once. Our methods can be customized for use in a diverse suite of applications, including multiple potential actions, uncertainty in the data, and can be used in combination with additional prioritization methods, potentially providing extremely useful management tools.

Managers on the ground need to act quickly, often with little or poor-quality data. VOI can be a tool which helps make decisions efficiently, providing a quantitative basis for decisions, and eliminating bias. Gathering additional data does not always improve decision outcomes (Grantham et al., 2008). Our protocol provides a way to determine in which situations it is more cost effective to act and in which it is more cost effective to gather additional data. Our results indicate that making monitoring/acting decisions at the individual management unit level, can lead to a large increase in expected value over universally applied decisions (e.g. to monitor all management units), saving valuable time and money, and leading to higher expected values.

CHAPTER THREE – CONCLUSION

Conservation managers often have to make tough decisions, which are constrained by limited time frames and budgets (Naidoo et al., 2006a; Naidoo & Adamowicz 2006). The stakes of these decisions are high, as each has the potential to either facilitate or hinder species recovery. However, the information required to make these decisions is often unavailable, or largely uncertain (Cook, Hockings, & Carter, 2010). Thus, methods are needed to assist managers in making conservation decisions quickly and efficiently. One of the most common decisions faced by managers is the decision to continue monitoring, or act using current information. Previous studies have attempted to answer this question, but none provide a representation of realistic scales and associated costs (e.g. Costello et al., 2010; Runge et al., 2011; Runting et al., 2013; Canessa et al., 2015; Bennett et al., 2018). Here, I addressed many of these limitations by applying value of information analysis using real cost and probability of occurrence data to spatially allocate monitoring resources across multiple patches in a landscape.

I found that VOI can be useful in making decisions about spatial allocation of resources across a landscape, and that decisions to forgo monitoring were largely driven by the expected value of the management unit (Fig. A3). On average, management units where monitoring was not recommended had higher expected values than those where monitoring was recommended. These units also had a slightly lower purchase cost in both the single and multiple species analysis.

When using a prioritization algorithm to identify management units with the highest cost effectiveness, and selecting units up to a limited budget of $100,000 CAD, I found a higher proportion of units where monitoring was not recommended, compared to the total proportion across the landscape for single (Fig.2, Fig.3) and multiple species analysis (Fig. A4, Fig A5).

This is reflective of the fact that the majority of areas in the landscape will not be suitable for conservation.

Overall, given a set budget, we expect to protect more occurrences using a combined approach of monitoring and acting compared to a strict approach of monitoring before acting at all levels of detection (Fig. 4). For probability of detection less than 0.60, monitoring was generally not cost effective. That is not to say monitoring is unimportant; indeed, monitoring can be valuable in many situations (Lindenmayer & Likens 2010). However, if we can eliminate unnecessary monitoring (e.g. situations where we have enough certainty in the data to make the decision, or where the cost of the action is so low that is more cost effective to accept the uncertainty and save the monitoring costs), we can make more efficient use of resources and likely protect more occurrences.

Although VOI analysis can provide a good starting point, it cannot totally replace human decisions. This method is intended as a tool to assist managers in making decisions, providing them with a quantitative basis for decision making. Given the complexity of these decisions, it is not feasible at this time to model every possible variable, and additional factors may need to be considered. For example, once provided with a list of target properties, it is likely that many will not be available to purchase, and thus the results will differ from the optimal solution provided here. There may also be additional management considerations, such as metapopulation dynamics or risk of management failure, that are difficult to encapsulate in a VOI framework.

I aimed to make the case studies as realistic as possible. However, I assessed only a single management option, to monitor or not to monitor. As many plant species are thought to persist in areas for long periods of time, it is reasonable to assume the probability of presence is relatively stable if land is protected (Cowling et al., 2003; Eckert et al., 2009; Bennett & Arcese,

2013). Although this may be the case for the species assessed here, many species require continued management to ensure persistence (McDonald-Madden et al., 2011; Carwardine et al., 2012). In reality, there are often multiple possible actions to be considered, as agencies must determine the amount of resources to spend on managing current land versus acquiring new habitat. Although I did not consider multiple actions, it would be beneficial to do so in the future.

We applied VOI analysis using a novel approach to analyze decision making across space. However, both space and time are important variables to consider. Conservation programs are often longstanding and may make investments over many years as opposed to all at once. It would be beneficial to add the dimension of time to the calculations, assessing both space and time simultaneously. This would also allow for one to consider the possible positive influences of waiting, such as increased capital (Iacona, Possingham & Bode, 2017).

A key assumption made here was that conservation decisions could be made at the one-hectare scale. Realistically, it is unlikely that land could be purchased in exactly one-hectare parcels which would require the additional step of severing the parcel of land from whichever property it belonged. Additionally, the amount of habitat that should to be conserved for an individual of a given species, depends on the characteristic scale of response of that species to habitat amount (Jackson and Fahrig, 2014). Although for plants this relationship is not well studied, we do know that plants may be able to persist in small patches. If applying the methodology to mobile organisms, it would be important to assess the relationship between persistence and habitat. To make the analysis more applicable, it would be beneficial to analyze whole properties, and consider population dynamics at scales greater than or equal to the characteristic scale of response for the target species.

I freely provide the R code needed to complete the VOI calculations, as well as results for single patch decisions across a range of accuracies (Appendix C; Appendix D). However, as calculations are fairly complex, it would also be beneficial to provide this information in the form of additional decision-making tools, such as user friendly interfaces to help managers carry out VOI calculations.

My research successfully demonstrates the applicability, and utility of VOI in spatially allocating managing resources. If managers adopt a mixed managing and monitoring approach, we expect that they will be able to protect more occurrences when compared to a monitoring only or managing only strategy. As the number of threatened species continues to increase, it is imperative that decisions are made efficiently, and effectively. Although the application to conservation has been limited, decision theory is an extensive field, and the application of VOI analysis demonstrated here only scratches the surface of the potential applications to conservation, providing many exciting opportunities for future advancement.

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APPENDIX A – ADDITIONAL TABLES AND FIGURES

Table A1: Life history characteristics of the focal species, cucumber tree (*Magnolia acuminata)*, false rue-anemone (*Enemion biternatum)* and purple twayblade (*Liparis liliifolia)*, used in analysis with their associated survey accuracy value (in this case, represented by detectability). Characteristics thought to contribute to detectability are highlighted in green.

Species	Average Size	Flowers	Fruits	Leaves	Phenology	Most Detectable?	Distinctiveness	Detectability
Cucumber tree *Magnolia acuminata*	Up to 30 M (in Canada)	Greenish – Yellow Solitary 6-9 cm across	Matures in late summer Red Fleshy pods, each contain one true seed	Oval shaped Simple Smooth Without teeth	Flowers early summer, fruit matures late summer Bark is recognizable all year	June – August, but detectable all year	Only magnolia species native to Canada No similar species	85-95%
False rue-anemone *Enemion biternatum*	10 to 40cm	Single flowers 1.5-2 cm wide Five white petal-like sepals	Early June Smooth seeds	Alternate Usually biternate leaflets Leaflets are 4-18mm with 2-3 deep lobes	Flowers April-June Fruits end of June –August	Late April – Early June	Often confused with rue-anemone	65-75%
Purple twayblade *Liparis liliifolia*	10 to 30cm	Raceme of 5-30 pale purple flowers Purple lips are 10-14mm with a smaller bract Lateral petals are linear and greenish purple in color	Erect ellipsoid capsule ~15mm long	Two basal elliptical globous leaves 4-18 cm long Leaves persist all year	Usually flowers June – late July, but can flower anywhere from May – August Fruits after	May – August	Similar appearance to Fen twayblade May lay dormant when conditions are unfavourable	55-65%

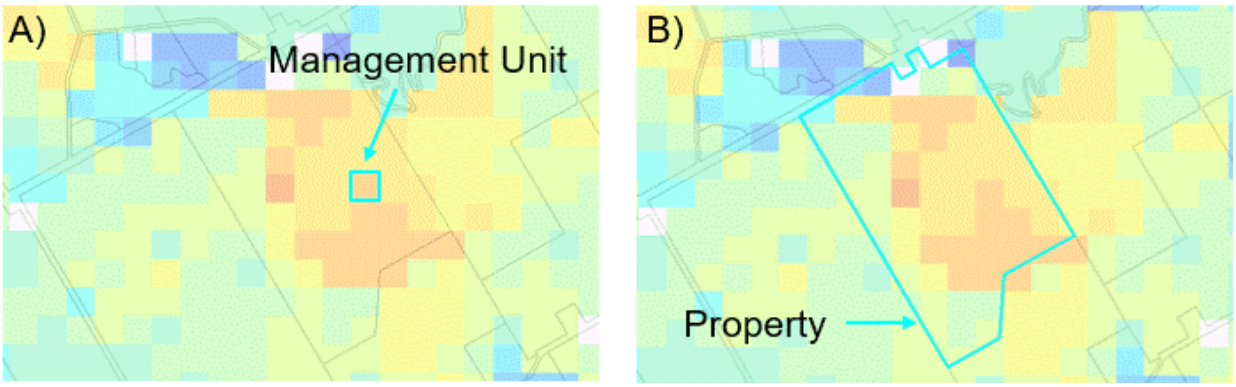

FIGURE A1: A) A single one-hectare (100m x 100m) management unit B) A property within Norfolk County (light blue outline), composed of multiple management Units.

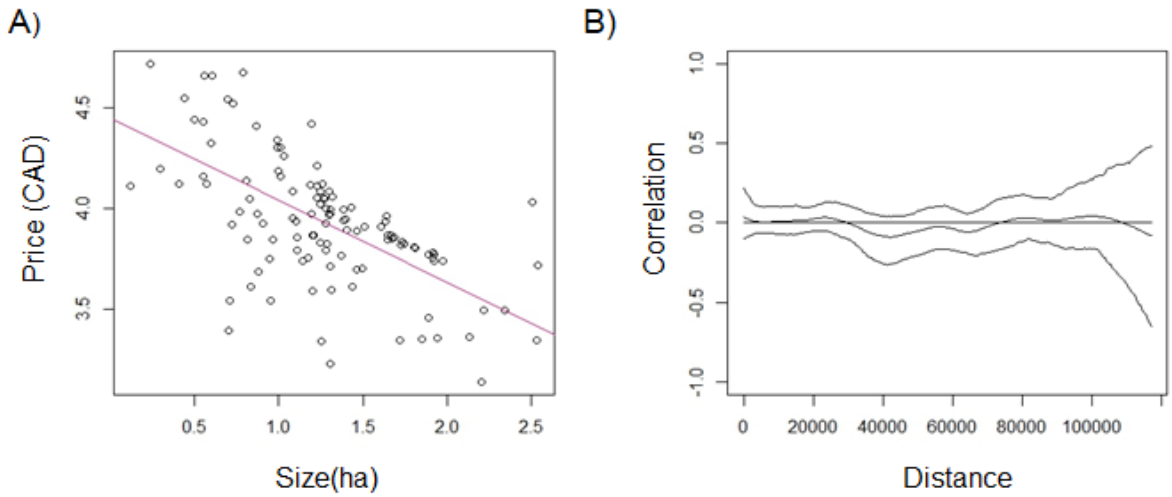

FIGURE A2: A) Log price per hectare versus log size of property (ha), Trend line represents linear model with the equation y = -0.41002x + 4.455 (R-squared = 0.3794, p = 5.4×10^{-14}) B) Spline correlogram showing no significant spatial autocorrelation in the residuals of the model.

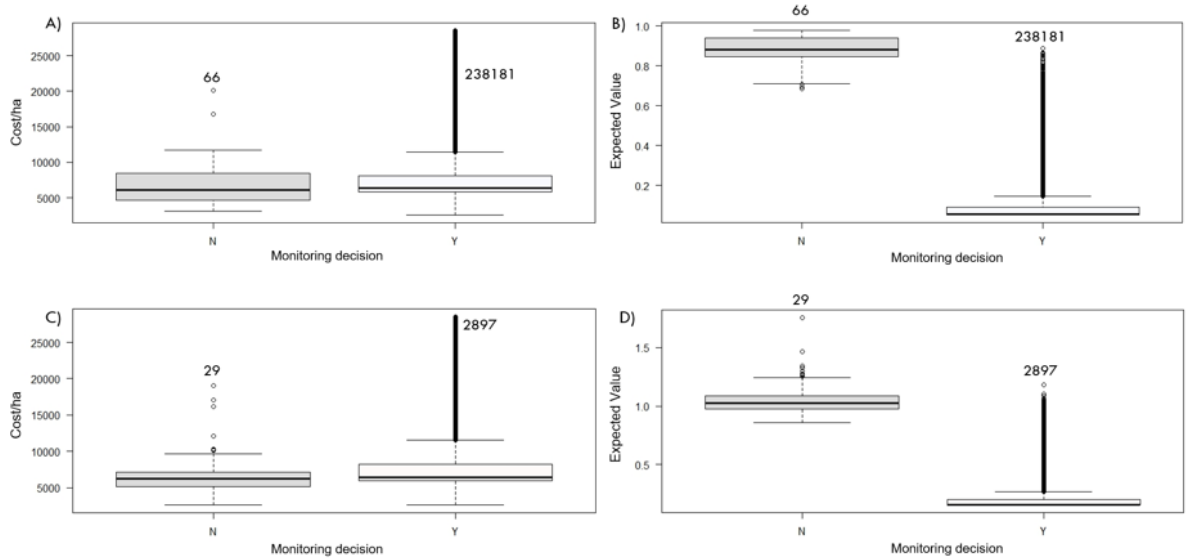

FIGURE A3: A) Cost per hectare by monitoring decision for the single-species analysis. Maximum cost for N = 19029; B) Expected value by monitoring decision for the single-species analysis. Minimum value for N = 0.6842; C) Cost per hectare by monitoring decision for the multiple-species analysis. Maximum cost for N = 19029; D) Monitoring decision by expected value for multi-objective analysis. Minimum value for N = 0.8566.

Table A2: Number of decisions for individual management units at each probability of detection level for single species analysis

Probability of detection	Number of decisions not to monitor	Number of decisions to monitor
0.05	233638	4609
0.10	184952	53295
0.15	44787	193460
0.20	8286	229961
0.25	3923	234324
0.30	1795	236452
0.35	555	237692
0.40	302	237945
0.45	242	238005
0.50	168	238079
0.55	127	238120
0.60	103	238144
0.65	78	238169
0.70	66	238181
0.75	61	238186
0.80	54	238193
0.85	45	238202
0.90	39	238208
0.95	35	238212

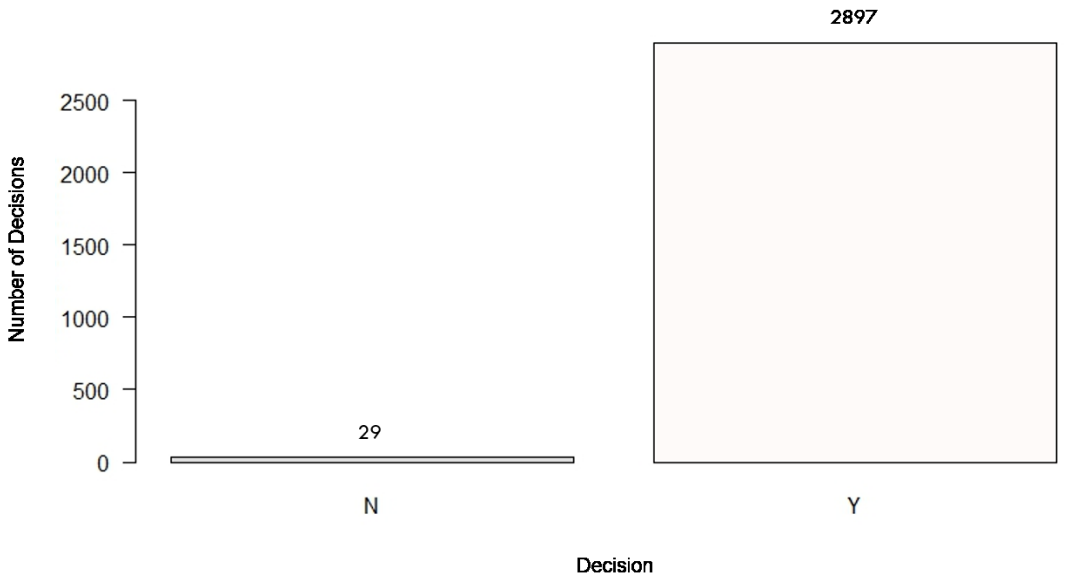

FIGURE A4: Number of monitoring decisions for all possible management units (n = 2926) in multiple-objective analysis.

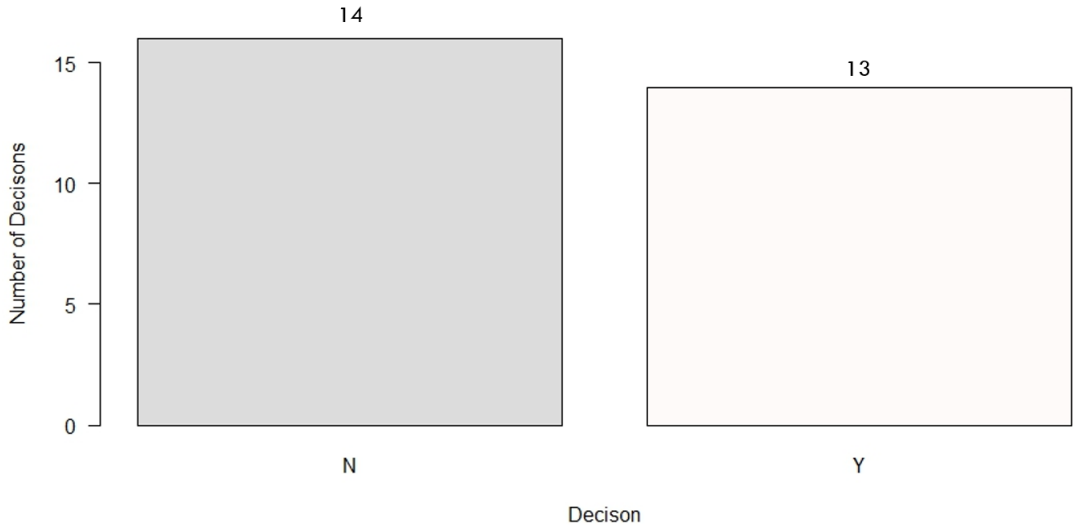

FIGURE A5: Number of monitoring decisions for selected management units in multiple-objective analysis, given a limited budget of $100,000 CAD.

Table A3: Total expected value (i.e., number of occurrences protected) and cost of management units selected using a $100,000 CAD budget for the single species false rue-anemone

Probability of detection	Total expected Value	Additive Cost ($)
0.05	20.61	99645.55
0.1	20.64	99682.62
0.15	20.67	99836.06
0.2	20.69	99731.19
0.25	20.72	99799.21
0.3	20.74	99731.48
0.35	20.76	99753.07
0.4	20.77	99649.80
0.45	20.82	99821.96
0.5	20.85	99823.24
0.55	20.85	99678.46
0.6	20.92	99988.30
0.65	20.93	99990.08
0.7	21.07	99418.57
0.75	21.34	99296.61
0.8	21.68	99998.73
0.85	22.04	99999.30
0.9	22.43	99996.88
0.95	22.85	99999.10

Table A4: Total expected value and cost of management units selected using a $100,000 CAD budget for the multiple species using a monitor, don't monitor and strict monitor only strategy.

	Total expected Value	Additive Cost ($)
Combined	21.94	99307.13
Monitor only	4.72	99628.69

APPENDIX B – SINGLE UNIT RESULTS

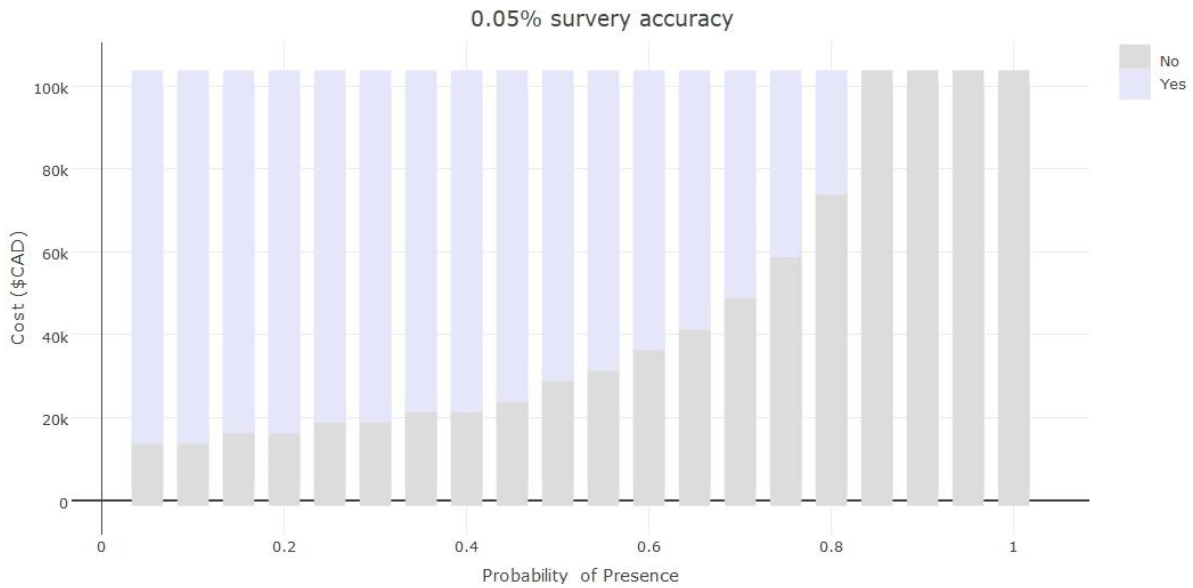

FIGURE B1: Monitoring decision for a single management unit, considering probability of presence values ranging from 0-1, and cost of action values ranging from 0-100,000 dollars ($CAD), assuming monitoring costs of $750 at 0.05 survey accuracy.

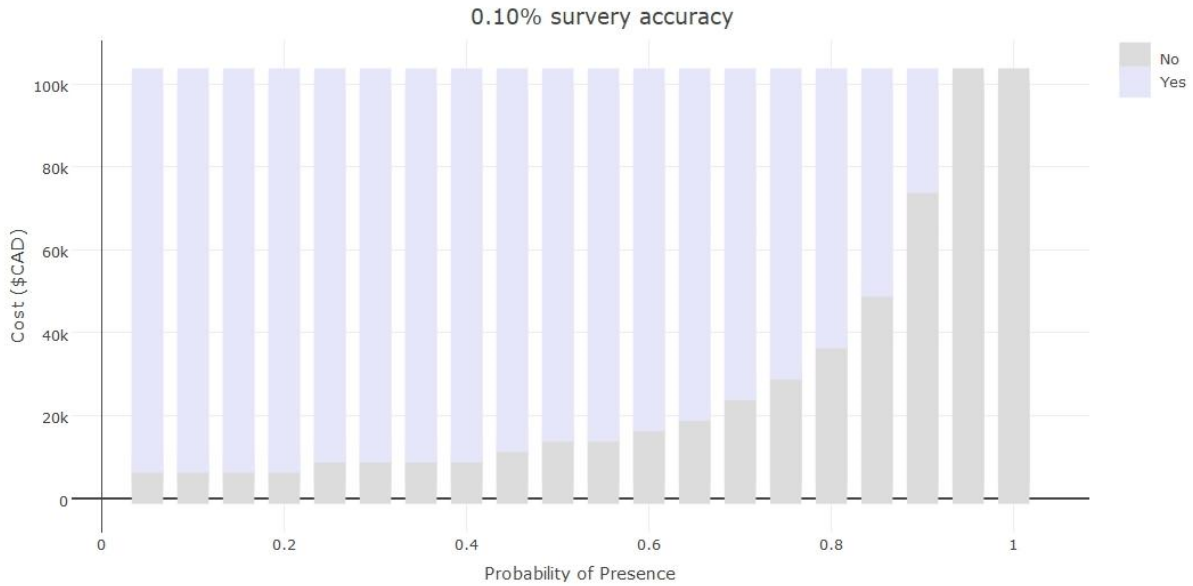

FIGURE B2: Monitoring decision for a single management unit, considering probability of presence values ranging from 0-1, and cost of action values ranging from 0-100,000 dollars ($CAD), assuming monitoring costs of $750 at 0.10 survey accuracy.

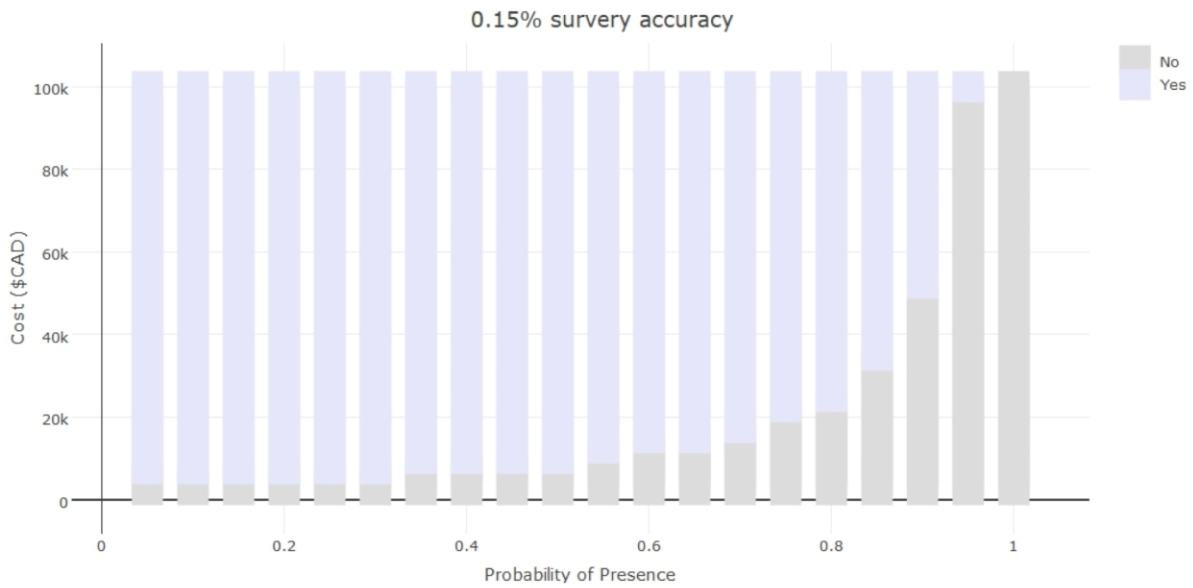

FIGURE B3: Monitoring decision for a single management unit, considering probability of presence values ranging from 0-1, and cost of action values ranging from 0-100,000 dollars ($CAD), assuming monitoring costs of $750 at 0.15 survey accuracy.

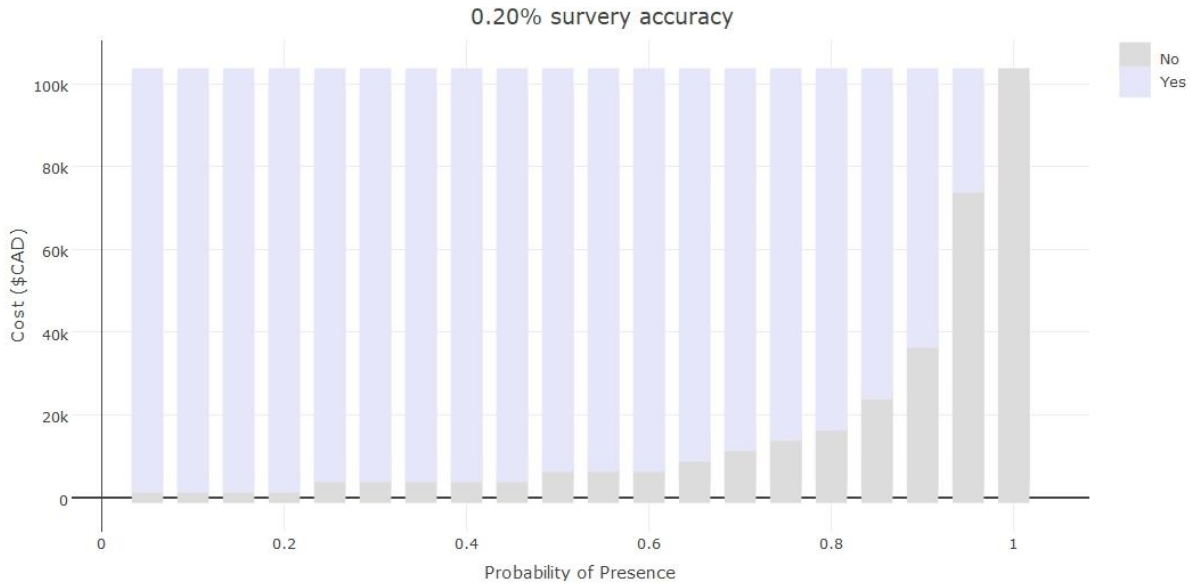

FIGURE B4: Monitoring decision for a single management unit, considering probability of presence values ranging from 0-1, and cost of action values ranging from 0-100,000 dollars ($CAD), assuming monitoring costs of $750 at 0.20 survey accuracy.

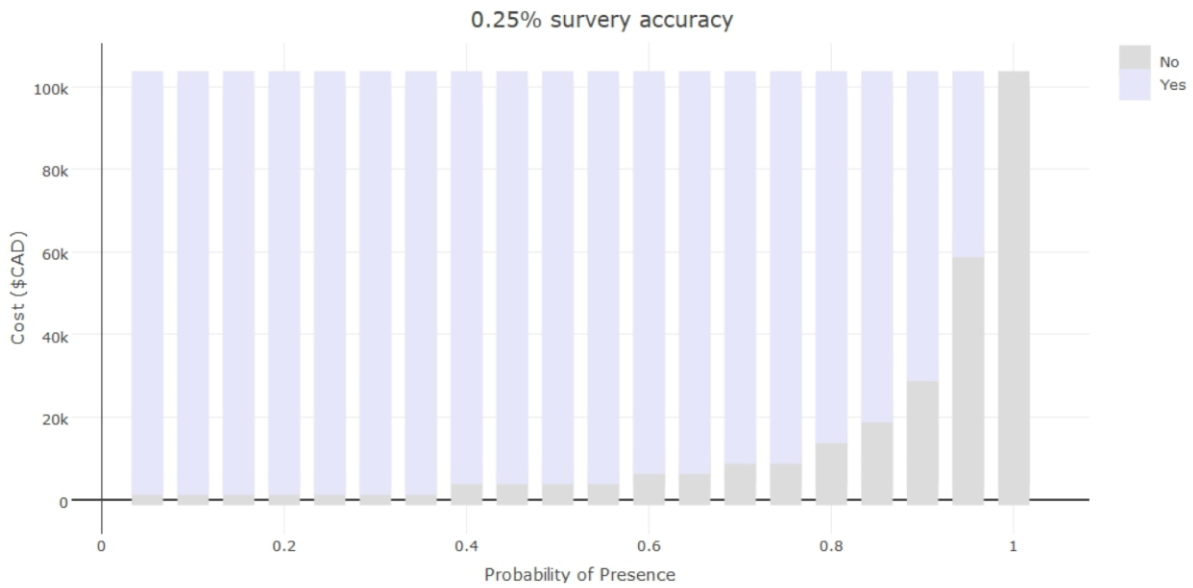

FIGURE B5: Monitoring decision for a single management unit, considering probability of presence values ranging from 0-1, and cost of action values ranging from 0-100,000 dollars ($CAD) assuming monitoring costs of $750 at 0.25 survey accuracy.

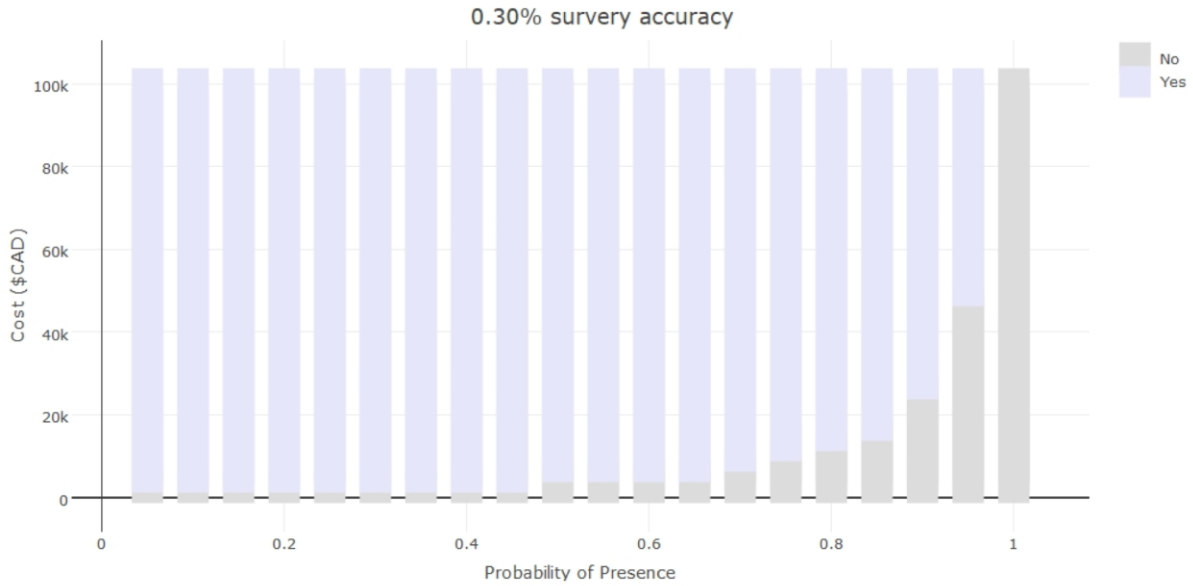

FIGURE B6: Monitoring decision for a single management unit, considering probability of presence values ranging from 0-1, and cost of action values ranging from 0-100,000 dollars ($CAD), assuming monitoring costs of $750 at 0.30 survey accuracy.

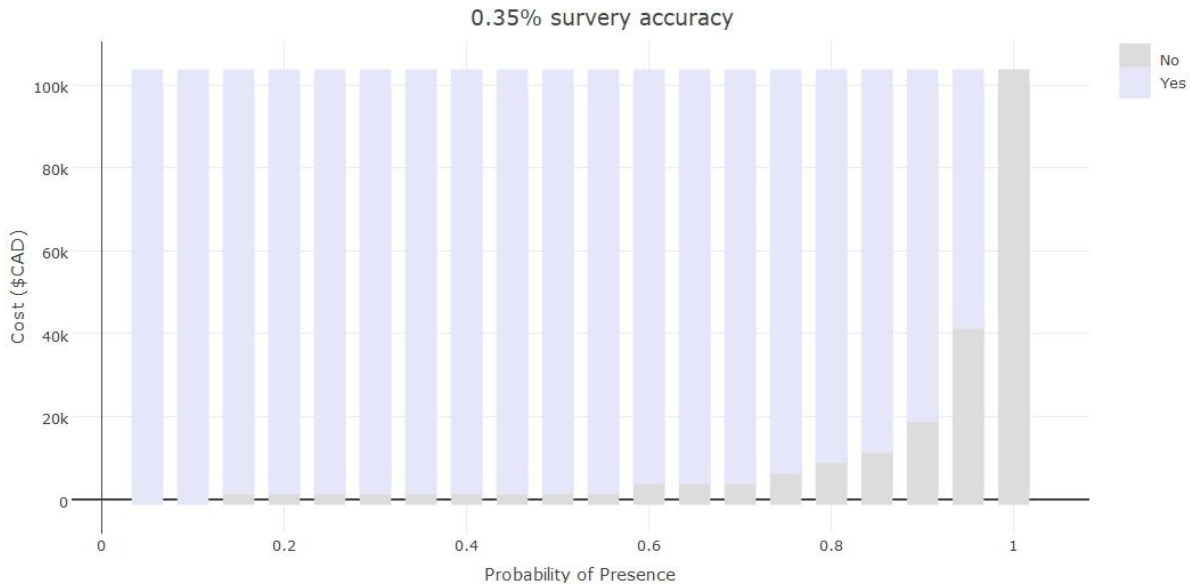

FIGURE B7: Monitoring decision for a single management unit, considering probability of presence values ranging from 0-1, and cost of action values ranging from 0-100,000 dollars ($CAD), assuming monitoring costs of $750 at 0.35 survey accuracy.

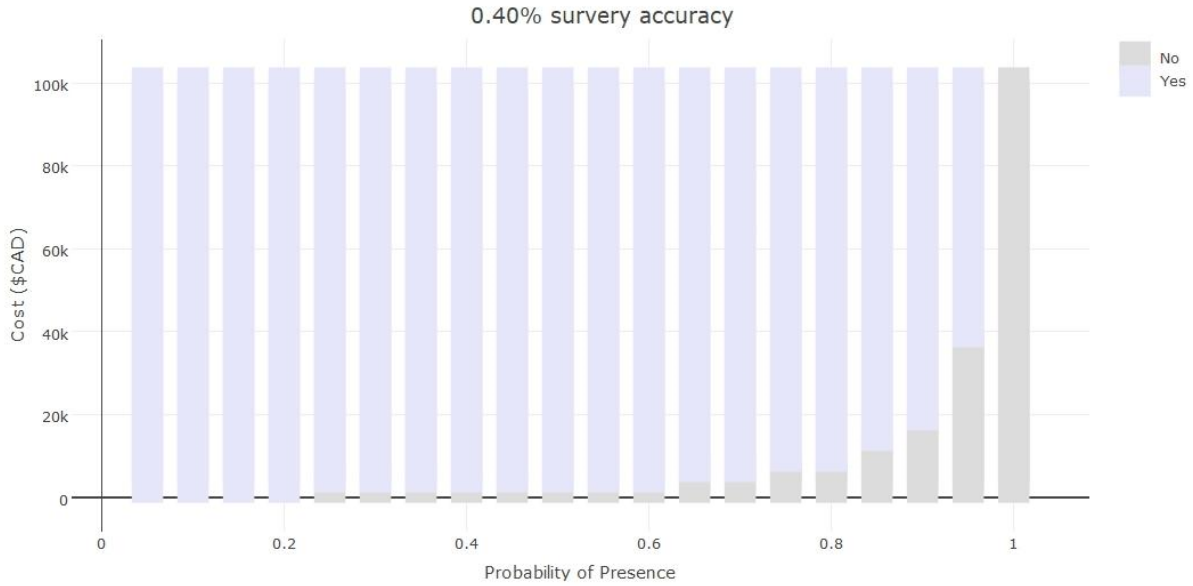

FIGURE B8: Monitoring decision for a single management unit, considering probability of presence values ranging from 0-1, and cost of action values ranging from 0-100,000 dollars ($CAD), assuming monitoring costs of $750 at 0.40 survey accuracy.

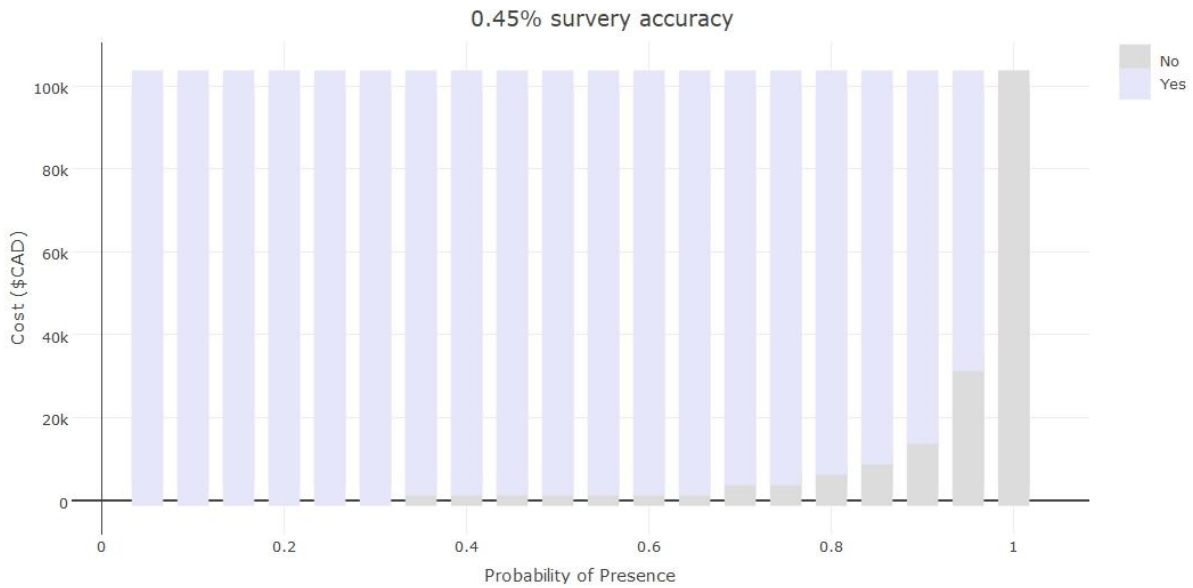

FIGURE B9: Monitoring decision for a single management unit, considering probability of presence values ranging from 0-1, and cost of action values ranging from 0-100,000 dollars ($CAD), assuming monitoring costs of $750 at 0.45 survey accuracy.

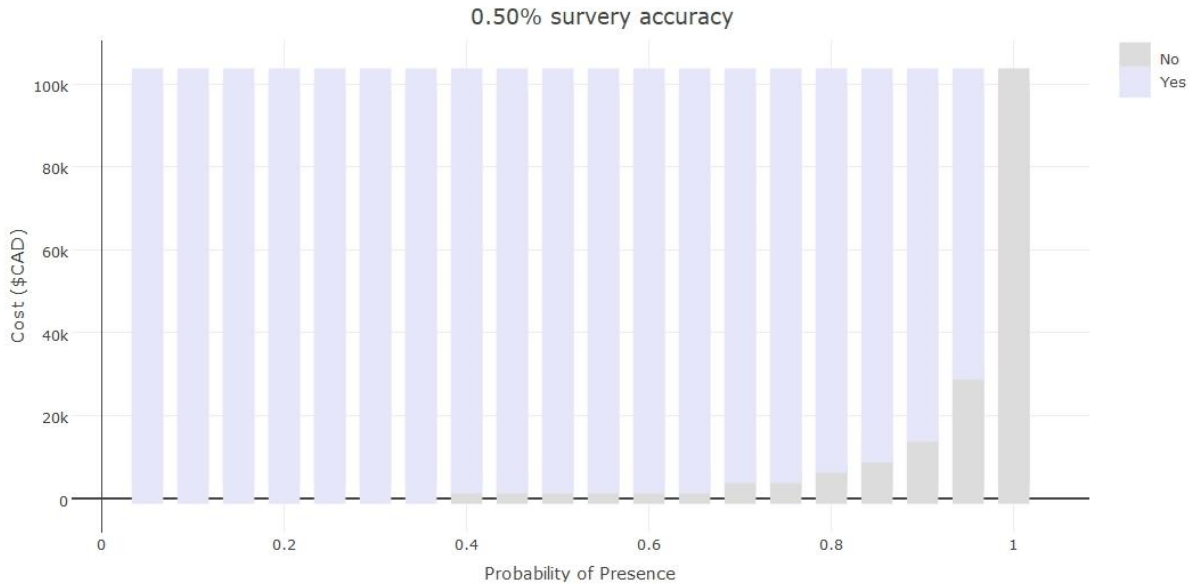

FIGURE B10: Monitoring decision for a single management unit, considering probability of presence values ranging from 0-1, and cost of action values ranging from 0-100,000 dollars ($CAD), assuming monitoring costs of $750 at 0.50 survey accuracy.

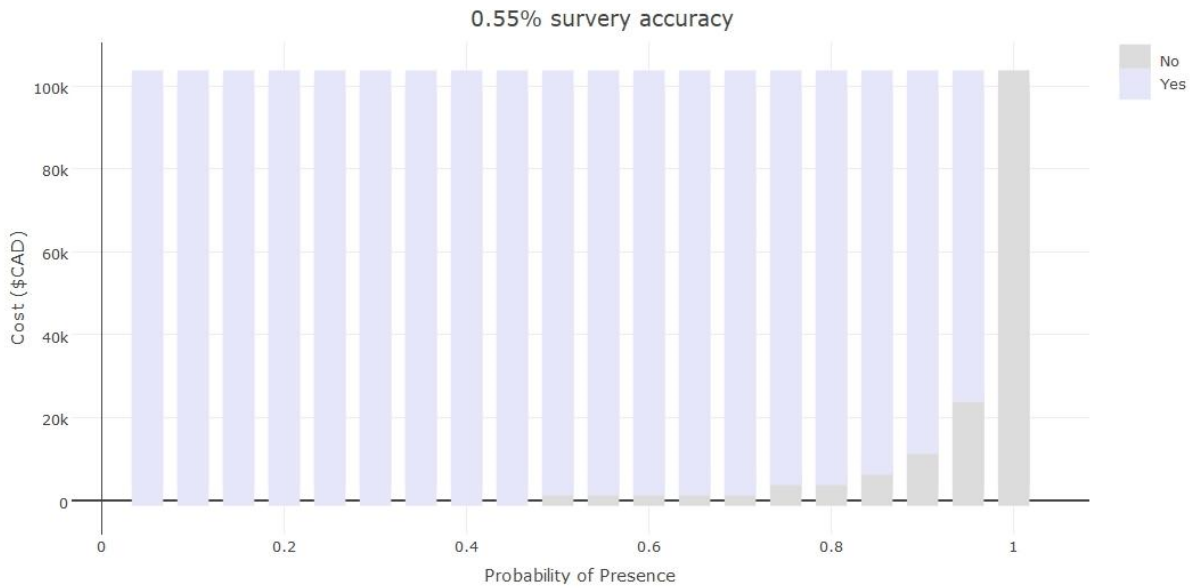

FIGURE B11: Monitoring decision for a single management unit, considering probability of presence values ranging from 0-1, and cost of action values ranging from 0-100,000 dollars ($CAD), assuming monitoring costs of $750 at 0.55 survey accuracy.

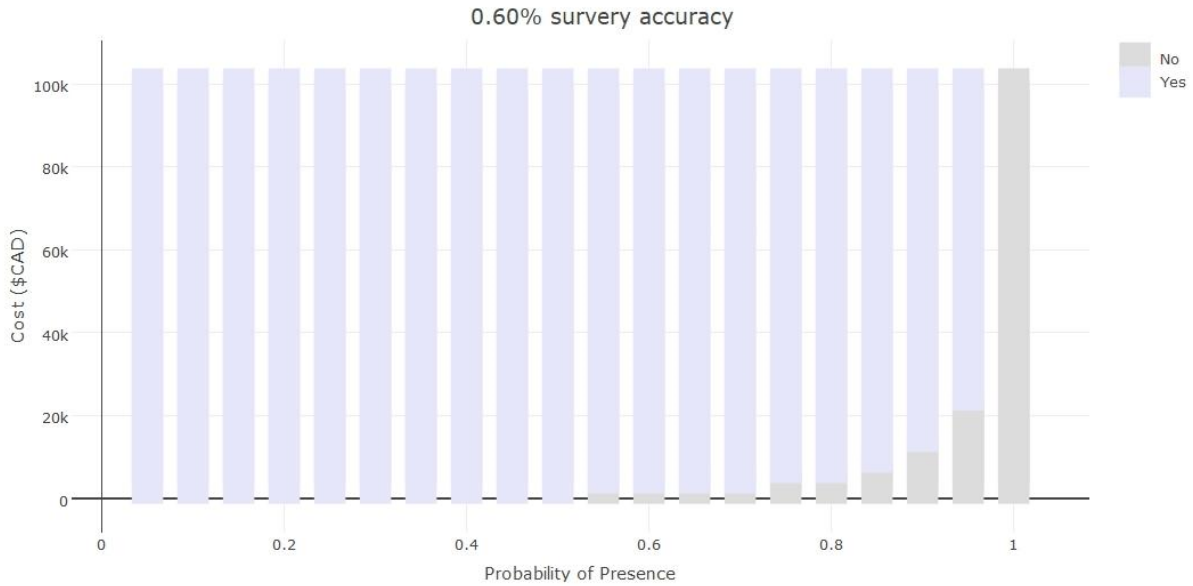

FIGURE B12: Monitoring decision for a single management unit, considering probability of presence values ranging from 0-1, and cost of action values ranging from 0-100,000 dollars ($CAD), assuming monitoring costs of $750 at 0.60 survey accuracy.

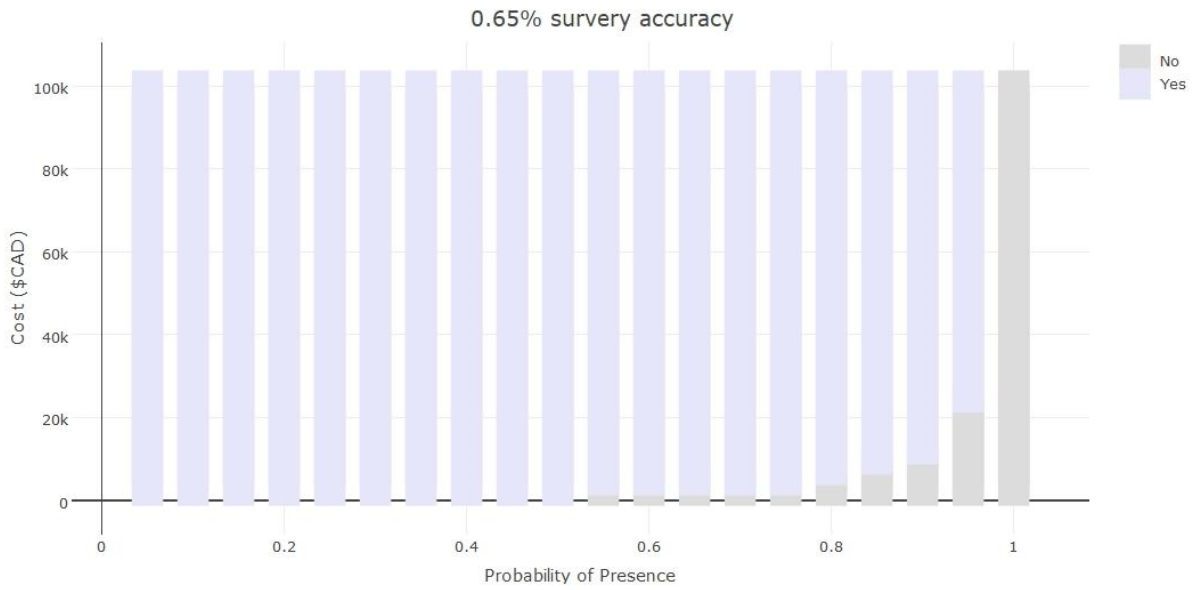

FIGURE B13: Monitoring decision for a single management unit, considering probability of presence values ranging from 0-1, and cost of action values ranging from 0-100,000 dollars ($CAD), assuming monitoring costs of $750 at 0.65 survey accuracy.

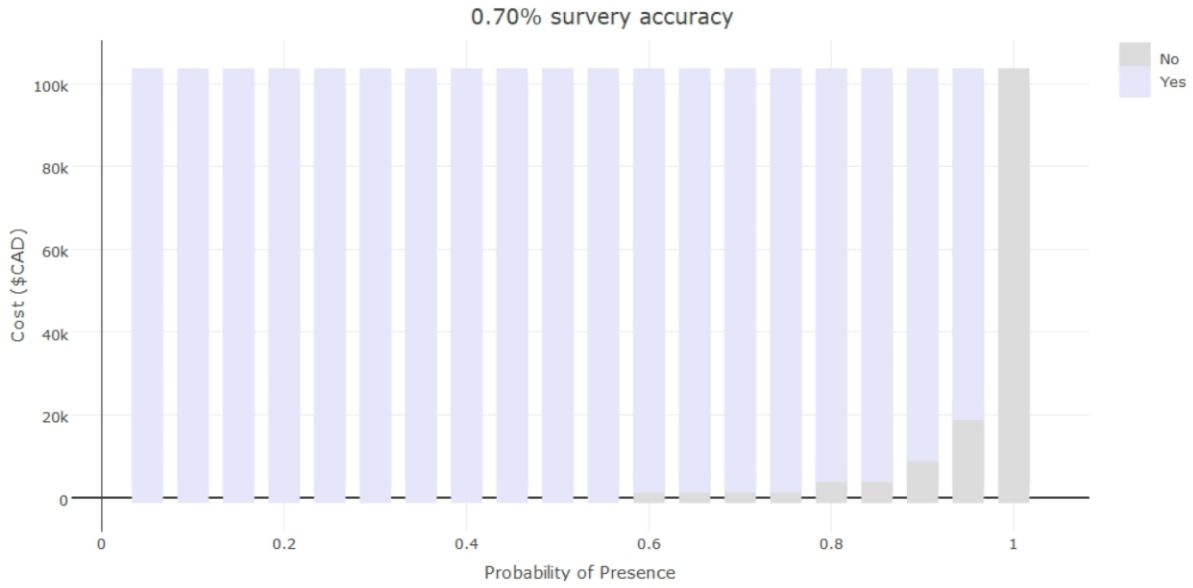

FIGURE B14: Monitoring decision for a single management unit, considering probability of presence values ranging from 0-1, and cost of action values ranging from 0-100,000 dollars ($CAD), assuming monitoring costs of $750 at 0.70 survey accuracy.

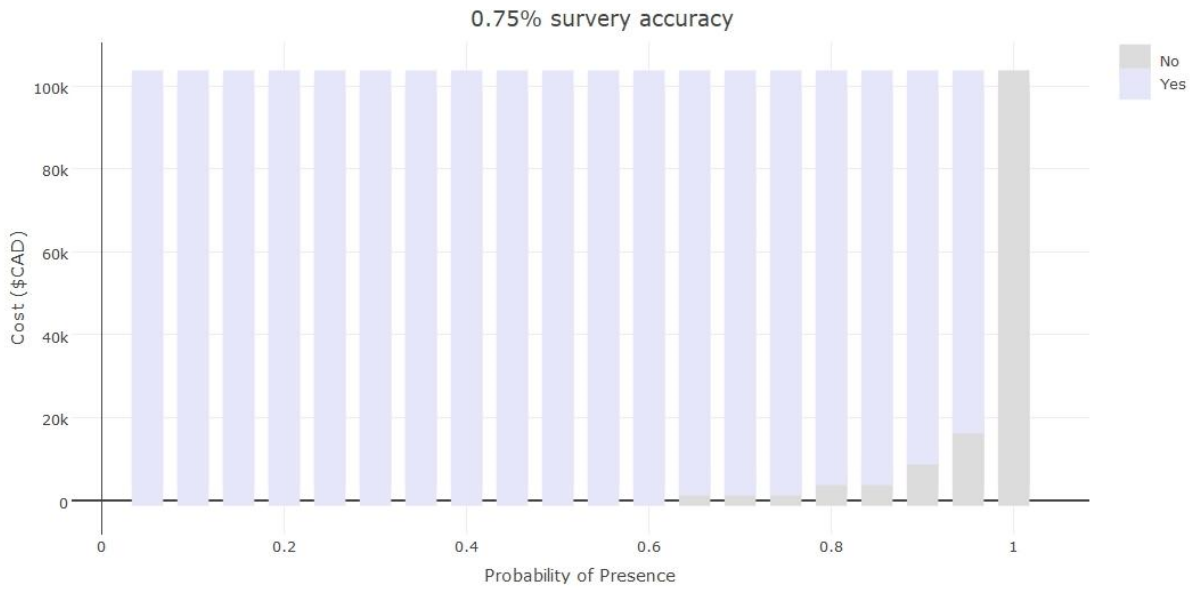

FIGURE B15: Monitoring decision for a single management unit, considering probability of presence values ranging from 0-1, and cost of action values ranging from 0-100,000 dollars ($CAD), assuming monitoring costs of $750 at 0.75 survey accuracy.

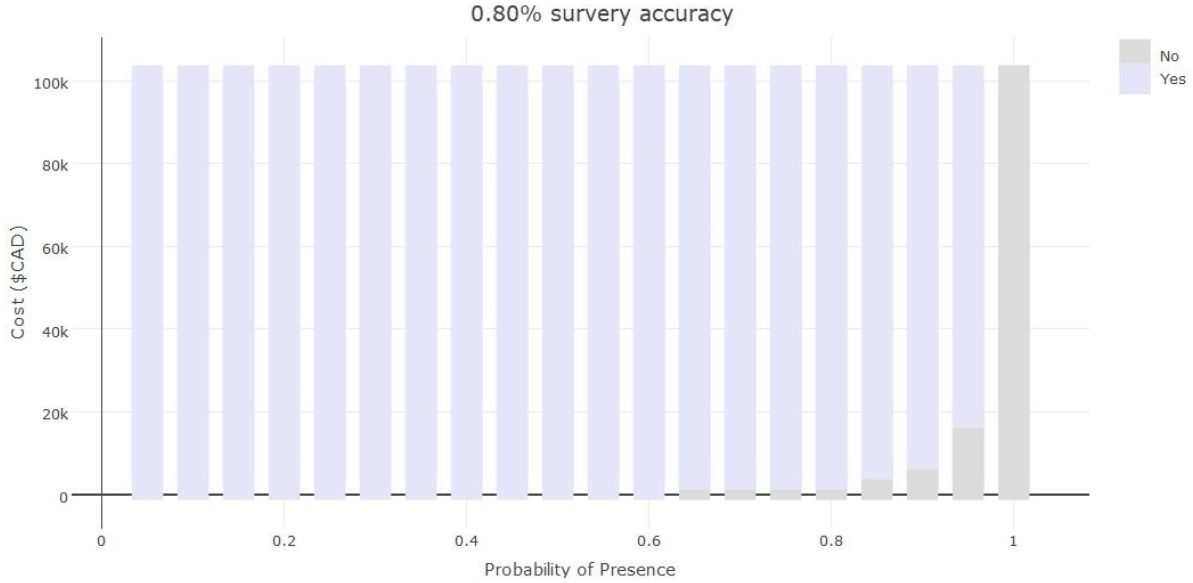

FIGURE B16: Monitoring decision for a single management unit, considering probability of presence values ranging from 0-1, and cost of action values ranging from 0-100,000 dollars ($CAD), assuming monitoring costs of $750 at 0.80 survey accuracy.

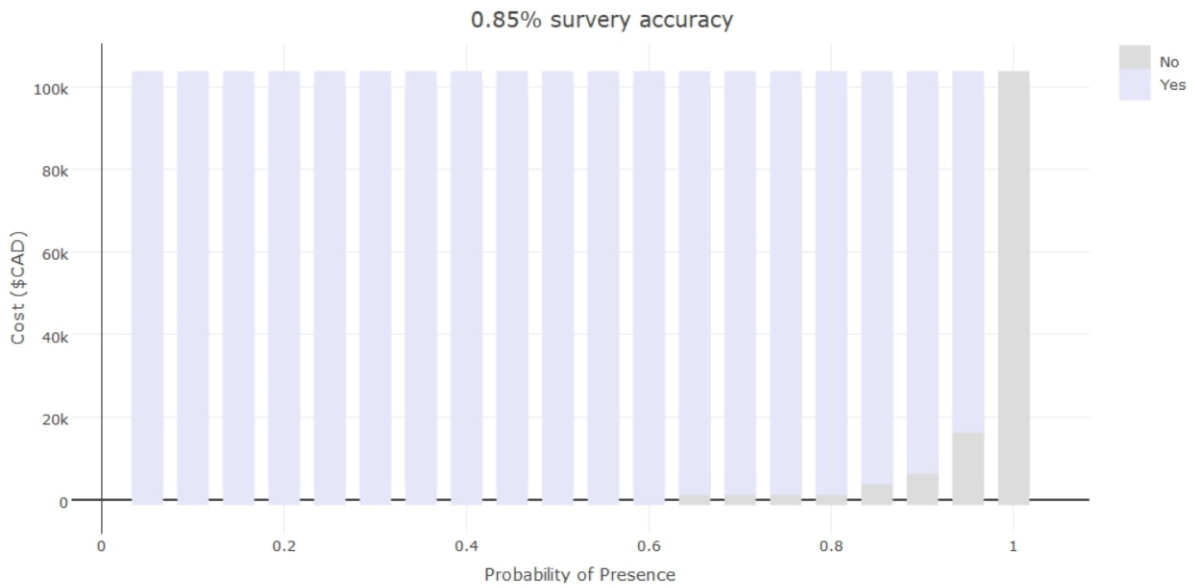

FIGURE B17: Monitoring decision for a single management unit, considering probability of presence values ranging from 0-1, and cost of action values ranging from 0-100,000 dollars ($CAD), assuming monitoring costs of $750 at 0.85 survey accuracy.

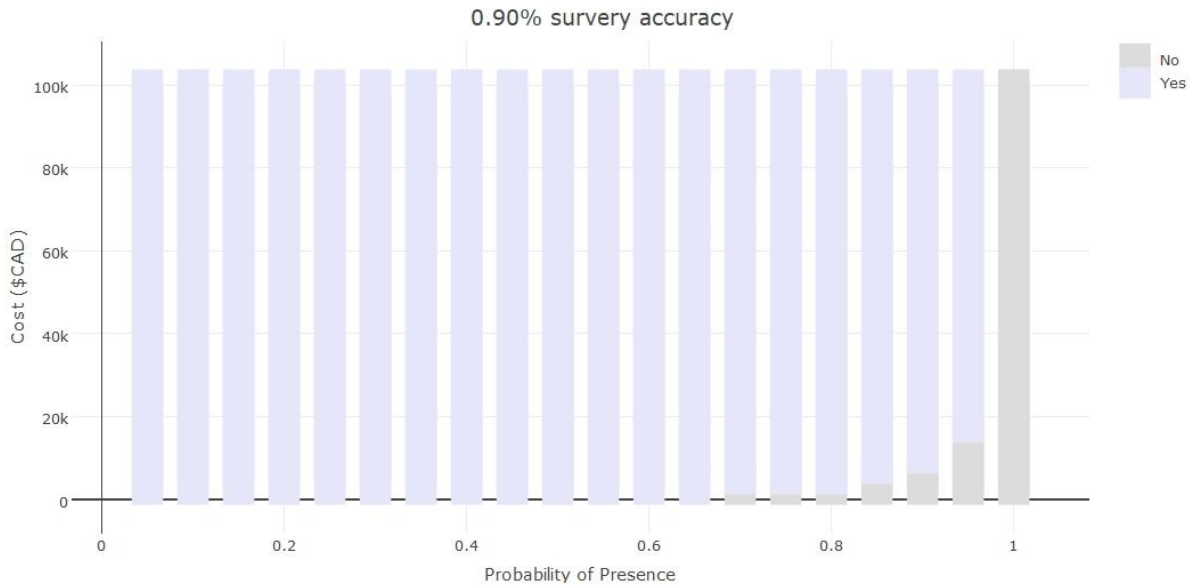

FIGURE B18: Monitoring decision for a single management unit, considering probability of presence values ranging from 0-1, and cost of action values ranging from 0-100,000 dollars ($CAD), assuming monitoring costs of $750 at 0.90 survey accuracy.

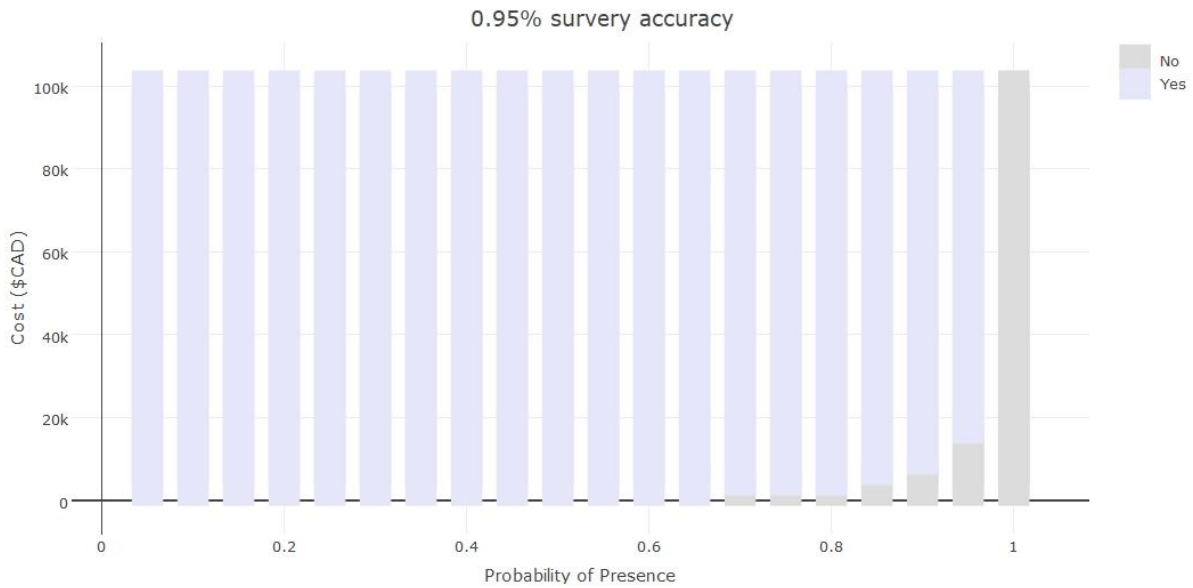

FIGURE B19: Monitoring decision for a single management unit, considering probability of presence values ranging from 0-1, and cost of action values ranging from 0-100,000 dollars ($CAD), assuming a cost of action of $750 at 0.95 survey accuracy.

APPENDIX C – COST DATA

TABLE C1: Cost data acquired from GeoWarehouse used to generate average cost of purchase across Norfolk County.

ID	Latitude Point	Longitude Point	Address - Point	Address - Wood lot	Latitude Woodlot	Longitude Woodlot	Assessed (2016)	Phased in (2018)	Size (ac)	Size (ha)	$/ha	Last Sale Price	Year of Sale
1	42.61558	-80.69128	90 1st Concession Road, Langton	901 5th Concession Road	42.650353	-80.633784	$162,000.00	$128,000.00	47.27	19.13	8469.32	$2.00	1963
2	42.61524	-80.58283	560 Norfolk County 23 Road., Norfolk County	147 3Road Concession Road	42.615075	-80.564324	$210,000.00	$153,000.00	45.70	18.49	11355.70	$224,000.00	2000
3	42.61479	-80.47439	943 Concession A, Walsingham	910 2nd Concession Road	42.629923	-80.49594	$81,000.00	$64,000.00	32.05	12.97	6244.51	$30,000.00	1991
4	42.66515	-80.69103	800 1st Concession Road, Norfolk County	914 1st Concession Road, Houghton	42.676469	-80.691551	$200,000.00	$154,500.00	62.75	25.39	7875.74	$0.00	2001
5	42.66481	-80.5825	395 North-south Townline, Walsingham	1630 Regional Road 45	42.692488	-80.580041	$119,000.00	$92,014.00	39.60	16.03	7425.45	$0.00	2001
6	42.66436	-80.47397	920 4th Concession Road, Walsingham	920 4th Concession Road	42.66682	-80.486334	$44,000.00	$32,250.00	13.07	5.29	8320.68	$2.00	1982
7	42.66381	-80.36545	82 Clubhouse Road, Norfolk County	1454 Front Road	42.680615	-80.367608	$181,000.00	$166,500.00	13.37	5.41	33462.57	$47,500.00	1988
8	42.71472	-80.69079	1440 North Road, Langton	1235 North Road	42.702299	-80.705946	$85,000.00	$65,500.00	9.89	4.00	21241.87	$1.00	2004
9	42.71438	-80.58217	1684 Hazen Road, Langton	1902 West Quarter Line Road	42.703047	-80.588168	$119,000.00	$94,000.00	39.71	16.07	7404.89	$112,500.00	2012
10	42.71393	-80.47356	1575 Nwals-swals Tline, Walsingham	1605 Nwals-swals Town line	42.713518	-80.475337	$191,000.00	$139,000.00	18.26	7.39	25852.94	$6,000.00	1992
11	42.71338	-80.36494	764 Char'ville Road 2, Charlotteville	737 Charlotteville 2 Road	42.719952	-80.37254	$211,000.00	$167,000.00	59.62	24.13	8745.55	$149,500.00	2013
12	42.76429	-80.69054	320 C Line, Orangeville	1790 North Road	42.744745	-80.704104	$244,000.00	$173,500.00	49.18	19.90	12259.31	$3,000.00	1958
13	42.76394	-80.58184	993 Norfolk County 21 Road., Norfolk County	3651 Highway 59	42.757429	-80.59426	$197,000.00	$142,000.00	24.19	9.79	20121.42	$500.00	1938
14	42.7635	-80.47314	118 First Ave, Delhi	3 First St	42.78087	-80.490027	$93,000.00	$74,000.00	31.84	12.88	7218.27	$45,000.00	1995
15	42.76294	-80.36444	1227 Char'ville Road 5, Charlotteville	1079 Highway 24	42.736208	-80.350787	$165,000.00	$154,000.00	8.93	3.62	45642.44	$140,000.00	2011
16	42.76229	-80.25574	306 Port Ryerse Road., Simcoe,	1908 Hwy 24 E	42.764747	-80.284557	$57,000.00	$52,000.00	14.52	5.87	9702.42	$2.00	1972
17	42.81386	-80.69029	115 Watson Mill Road, Norfolk County	249 County Road 30	42.793833	-80.70102	$273,000.00	$200,332.00	66.55	26.93	10136.40	$125,000.00	2005
18	42.81351	-80.5815	894 Second Concession Road Str, Rr3, Delhi	4598 Hwy 59, Courtland	42.811963	-80.619191	$242,000.00	$173,000.00	60.45	24.46	9892.72	$150,000.00	2015
19	42.81306	-80.47272	2118 Highway 3, Delhi	615 Lynedoch Road	42.818097	-80.470893	$148,000.00	$115,000.00	38.84	15.72	9416.93	$2.00	2017
20	42.81251	-80.36393	12 Bill's Cnr Road, Charlotteville	1558 Mcdowell Road E	42.81559	-80.360741	$191,000.00	$162,462.00	49.90	20.19	9458.72	$0.00	2001
21	42.81185	-80.25515	312 Lynn Valley Road, Simcoe	358 Radical Road	42.77614	-80.244192	$108,000.00	$108,000.00	29.81	12.06	8951.59	$100,000.00	2017
22	42.8111	-80.14637	765 Conc 1 Woodhouse, Port Dover	144 The Old Lakeshore Road	42.789709	-80.110413	$414,000.00	$396,500.00	38.79	15.70	26373.88	$0.00	2008
23	42.81023	-80.0376	192 South Coast Drive, Haldimand	133 Brooklin Road	42.807568	-79.991806	$129,000.00	$114,075.00	47.61	19.27	6695.78	$110,000.00	2016

24	42.86308	-80.58117	2060 1st Concession Road Ntr, Delhi	1310 Mall Road, Tillsonburg	42.869812	-80.588785	$207,000.00	$148,500.00	25.45	10.30	20096.18	$2.00	2008
25	42.86263	-80.47229	89 Regional Road 4, Delhi	421 Windham Road 12	42.865003	-80.438058	$187,000.00	$147,000.00	43.92	17.78	10520.39	$1,365.00	1962
26	42.86208	-80.36342	1325 Windham Road 13, Windham	827 Windham 12 Road	42.870321	-80.397541	$52,000.00	$48,250.00	8.82	3.57	14575.18	$2.00	2006
27	42.86142	-80.25456	670 Concession 14, Townsend	59 Decou Road, Norfolk County	42.824741	-80.293073	$75,000.00	$75,000.00	16.62	6.72	11152.98	$112,000.00	2013
28	42.86066	-80.14569	1480 St. John's Road East, R.r.#1, Port Dover	380 East Quarter Line	42.811818	-80.151882	$220,000.00	$173,000.00	61.56	24.91	8831.36	$1,025.00	1965
29	42.85979	-80.03683	790 Sandusk Road, Jarvis	4 Field Road	42.830918	-80.112219	$71,000.00	$71,000.00	18.58	7.52	9443.69	$0.00	2000
30	42.85883	-79.92798	138 Concession Road 4, Haldimand	294 Concession 5 Road	42.873563	-79.923502	$77,000.00	$61,500.00	34.55	13.98	5506.65	$42,500.00	2001
31	42.85776	-79.81913	5235 Rainham Road, Selkrik	1170 Concession 3 Road	42.864995	-79.829671	$62,000.00	$48,750.00	39.37	15.93	3891.82	$0.00	2014
32	42.8553	-79.60145	96 Lighthouse Dr, Haldimand County	44 Dover St	42.859264	-79.580809	$96,000.00	$96,000.00	8.81	3.56	26941.64	$93,000.00	2017
33	42.85392	-79.49262	71 Farr Road, Dunnville	315 Farr Road, Dunnville	42.867603	-79.491048	$88,000.00	$87,000.00	7.82	3.17	27793.04	$10,000.00	1987
34	42.9122	-80.47187	3173 Windham West Quarter, La Salette	578 Windham 7 Road	42.918574	-80.465475	$89,000.00	$81,500.00	15.93	6.45	13802.17	$150,000.00	2007
35	42.91164	-80.36291	1613 Windam road 9, Windam Center	1546 Regional Road 9	42.922167	-80.36818	$69,000.00	$65,511.00	20.08	8.13	8489.90	$200,000.00	2017
36	42.91098	-80.25396	904 Thompson Road E, Norfolk County	705 Concession 6	42.964986	-80.281631	$173,000.00	$160,000.00	12.28	4.97	34820.58	$125,000.00	2007
37	42.91022	-80.14501	65 Concession 9 Walpole, Jarvis	1826 Concession 6 Woodhouse	42.855859	-80.140135	$139,000.00	$111,000.00	58.60	23.72	5861.17	$36,000.00	1988
38	42.90936	-80.03606	665 Concession 8, Jarvis	398 Concession 8 Walpole	42.903599	-80.062813	$98,000.00	$95,500.00	6.80	2.75	35591.31	$1.00	1986
39	42.90839	-79.92712	357 Concession 7 Rd, Haldimnand County	389 Irish Line,	42.929469	-79.894112	$188,000.00	$152,000.00	49.61	20.08	9364.77	$0.00	1994
40	42.90731	-79.81818	513 Wilson Road, Cayuga	1539 River Road	42.913362	-79.828122	$17,200.00	$13,550.00	3.28	1.33	12977.75	NA	NA
41	42.90614	-79.70925	3888 County Road 20, South Cayuga	8095 Highway 3	42.926185	-79.652906	$39,500.00	$37,500.00	44.34	17.94	2201.57	$50,000.00	2012
42	42.90486	-79.60033	202 Bolton Tract Road, Dunnville	173 Concession St East	42.913724	-79.607738	$91,000.00	$84,868.00	4.27	1.73	52637.15	$179,646.00	2018
43	42.90347	-79.49142	764 Hutchinson Road, Haldimand County	249 Townline Road	42.867642	-79.491097	$88,000.00	$87,000.00	7.82	3.17	27793.04	$10,000.00	1987
44	42.96176	-80.47145	730 County Road 19 West, Vanessa	909 Windham 7 Road	42.924864	-80.435106	$196,000.00	$177,000.00	26.61	10.77	18198.19	$1,000,000.00	2007
45	42.96121	-80.3624	1527 Windham Road 5, Windham	1446 Concession road 7	42.932769	-80.380004	$202,000.00	$156,500.00	50.26	20.34	9931.22	$2.00	1987
46	42.96055	-80.25336	2536 Cockshutt Road, Norfolk County	705 Concession 6, WaterfoRoad	42.964541	-80.282025	$173,000.00	$160,000.00	12.28	4.97	34820.58	$125,000.00	2007
47	42.95978	-80.14432	262 Concession 13 Walpole, Haldimand County	14 Concession 5 Townsend Point Road	42.970849	-80.253089	$218,000.00	$192,000.00	41.58	16.83	12954.57	$55,000.00	1987
48	42.95892	-80.03529	29 Regional Road 20, Hagersville	343 2nd Line, Haldimand County	42.986116	-80.001699	$85,000.00	$67,250.00	36.90	14.93	5692.13	$1.00	1989
49	42.95794	-79.92626	233 Grant Road, Hagersville,	581 Townline Road W	42.951183	-79.936241	$12,600.00	$12,350.00	12.55	5.08	2480.50	$0.00	2007
50	42.95687	-79.81724	1820 Hwy #3, Cayuga	20 Concession North	42.971218	-79.808241	$50,000.00	$38,750.00	21.75	8.80	5680.58	$1.00	2012
51	42.95569	-79.70822	383 Ortt Road, Haldimand County	25 Junction Road	42.9929038	-79.71616	$50,000.00	$39,500.00	9.24	3.74	13367.16	$255,000.00	2017

52	42.95441	-79.59921	860 Robinson Road, Dunnville	237 Hines Road, Dunnville	42.9358776	-79.5756	$46,000.00	$35,000.00	16.13	6.53	7048.33	NA	NA
53	43.01077	-80.36189	4704 ON-24, Scotland	Adjacent to 1446 Windham 7 Road	42.933659	-80.383529	$202,000.00	$156,500.00	50.26	20.34	9931.22	$2.00	1987
54	43.01011	-80.25276	1241 Concession 3 Townsend, Wilsonville	705 Concession 6,	42.9634931	-80.284662	$173,000.00	$160,000.00	12.28	4.97	34820.58	$125,000.00	2007
55	43.00848	-80.03451	2 3Road Line, Hagersville	357 Concession 8 Walpole	42.90382	-80.06466	$98,000.00	$95,000.00	6.80	2.75	35591.31	$1.00	1986
56	43.0075	-79.9254	1461 Haldimand Road 9	1803 Haldimand Road 9	43.026959	-79.909865	$65,000.00	$52,000.00	22.91	9.27	7010.85	$300,000.00	2017
57	43.00643	-79.81628	391 Singer Road	392 Singer Road	43.011205	-79.842493	$158,000.00	$127,500.00	77.50	31.36	5037.89	$1.00	1969
58	43.00525	-79.70718	1948 Hald-Dunn Townline	LT 14 Concession 1	43.00283	-79.66634	$145,000.00	$132,500.00	72.03	29.15	4974.49	$22,500.00	2016
59	43.05706	-79.92453	4234 River Road, Haldimand County	581 Townline Road W	42.950986	-79.936242	$12,600.00	$12,350.00	13.00	5.08	2480.50	$1.00	1967
60	43.05598	-79.81533	202 Concession 4 Ln, Haldimand County	879 Townline Road E	42.980351	-79.811382	$241,000.00	$241,000.00	51.60	20.88	11541.61	$40,000.00	2002
61	43.10662	-79.92366	770 Highway 6, Caledonia	148 Harrison Road	43.092901	-79.9859825	$261,000.00	$212,500.00	47.00	18.90	11244.09	$90,000.00	2005
62	42.76499	-80.79926	9385 Stewart Road, Eden	8429 Beattie Road	42.744381	-80.832603	$123,000.00	$110,000.00	31.25	12.65	8697.83	$288,900.00	2016
63	42.715	-80.80003	55652 Calton Line, Vienna,	7173 Bogus Road	42.706879	-80.801226	$280,000.00	$192,000.00	47.00	19.02	10095.59	$33,900.00	1993
64	42.8146	-80.80003	56070 Talbot Line, Aylmer	57108 Carson Line	42.816022	-80.761817	$287,000.00	$215,000.00	24.31	9.84	21854.24	$2.00	1996
65	42.66557	-80.80075	4899 Plank Road, Port Burwell	5056 Plank Road Road	42.662527	-80.788788	$145,000.00	$111,500.00	67.27	27.22	4096.08	$143,000.00	2006
66	42.86356	-80.69077	144682 Potters Road, Tillsonburg	16496 New Road	42.882857	-80.670636	$146,000.00	$105,000.00	49.82	20.16	5207.86	$2,000.00	1972
67	42.91277	-80.58057	OxfoRoad 59, Otterville	2320 Concession Road North	42.863599	-80.550577	$207,000.00	$148,500.00	25.35	10.26	14476.55	$65,000.00	1991
68	42.85816	-80.79858	312253 Dereham Line, Tillsonburg	243655 Airport Road, South-west	42.906712	-80.823494	$36,500.00	$31,750.00	22.29	9.02	3520.26	$18,000.00	1979
69	42.96107	-80.58025	265829 Maple Dell Road, Norwich	79 Windham 4 Road	42.954805	-80.513922	$259,000.00	$225,000.00	71.68	29.01	7756.84	$1,400.00	1944
70	43.01208	-80.47003	326 Norwich Road, Scotland	110 Hatchley Road, Brant	43.031763	-80.797384	$519,000.00	$373,500.00	106.21	42.98	8689.59	$2,250.00	1987
71	43.0607	-80.36122	75 Maple Grove Road, Scotland,	75 Maple Grove Road	43.062612	-80.370037	$42,000.00	$34,750.00	50.24	20.33	1709.11	$1.00	2015
72	43.0606	-80.25126	200 Burtch Road, BrantfoRoad	1083 Concession 6 Townsend	42.971034	-80.252705	$218,000.00	$192,000.00	41.58	16.83	11409.53	$55,000.00	1987
73	43.107	-80.03296	483 Big Creek Road, Caledonia	301 Big Creek Road	43.115113	-80.059097	$389,000.00	$331,793.00	100.46	40.65	8161.24	$2.00	1994
74	43.10552	-79.81447	3120 Kirk Road, Binbrook	4204 Ferris Road	43.122915	-79.911121	$219,000.00	$203,000.00	38.12	15.43	13160.11	$4,000.00	1997
75	43.05118	-79.70714	9531 N Chippawa Road, Caistor Centre	9574 David St, West	43.044559	-79.717228	$263,000.00	$263,000.00	79.94	32.35	8129.69	$215,000.00	2007
76	43.00356	-79.59673	7605 S Chippawa Road, Wellandport	7998 Chippawa Road South	43.00783	-79.627287	$128,000.00	$119,500.00	47.19	19.10	6257.49	$30,500.00	2007
77	42.95132	-79.49128	54251 Shafley Road, Wellandport	294 Gore A Road	42.971307	-79.523566	$38,500.00	$28,100.00	16.95	6.86	4095.83	$1.00	1996
78	42.89895	-79.38289	12199 Side Road 22, Wainfleet	12448 Lakeshore Road	42.876405	-79.398711	$220,000.00	$214,000.00	43.43	17.57	12176.88	$266,372.00	2017
79	43.1574	-79.9249	9179 Airport Road, Mount Hope	212 Butter Road East,	43.165978	-79.961277	$330,000.00	$276,000.00	41.75	16.89	16336.76	$395,000.00	2017
80	42.91329	-80.69026	224950 Otterville Road, SpringfoRoad	34532 Quaker Street	42.999408	-80.65746	$144,000.00	$118,547.00	43.41	17.57	6748.43	$400,000.00	2016

81	43.06116	-80.46987	141 Harley Road, Harley	6 Eleventh Concession Road	43.047949	-80.476343	$110,000.00	$81,500.00	50.73	20.53	3969.54	$20,000.00	2004
82	42.99524	-79.4902	74298 Side Road 42, Wellandport	74298 Side Road 42	42.985307	-79.505487	$148,000.00	$148,000.00	30.09	12.18	12154.07	$2.00	1981
83	43.05376	-79.59533	7441 Silver St, Smithville	1446 Allen Road	43.053569	-79.62143	$37,000.00	$37,000.00	18.73	7.58	4882.20	$54,500.00	2006
84	43.15538	-79.8169	1246 Fletcher Road, Hannon	1112 Westbrook Road	43.138819	-79.719113	$205,000.00	$186,000.00	10.04	4.06	45783.05	$385,000.00	2017
85	43.15741	-80.03295	1303 Butter Road W, Ancaster	1097 Hwy 2	43.138568	-79.720043	$271,000.00	$240,000.00	44.74	18.11	13254.95	$9,320.00	2015
86	42.58033	-80.58487	1644 Lakeshore Road, Port Rowan	1921 Lakeshore Road	42.579564	-80.559578	$213,000.00	$153,500.00	24.72	10.01	15342.26	$135,000.00	2016
87	42.57701	-80.47141	342 Hastings Drive, Port Rowan	162 Hunter Drive N	42.625396	-80.472494	$317,000.00	$292,000.00	15.27	6.18	47243.35	$150,000.00	1991
88	43.012	-80.58085	793615 Slant Road, Norwich	77350 Highway 59	43.014601	-80.608223	$20,500.00	$17,950.00	12.62	5.11	3514.41	$180,000.00	2016
89	42.96687	-80.46075	885 Highway 24	885 Highway 24	42.966872	-80.460752	$4,107,000.00	$3,480,155.00	793.74	321.22	10834.34	$2.00	1992
90	42.66022	-80.48024	Backus Woods	Backus Woods	42.660218	-80.40239	$1,032,000.00	$686,000.00	540.52	218.74	3136.16	$5,372,500.00	2011
91	42.88758	-79.5703	1098 North Shore Drive	1098 North Shore Drive	42.887584	-79.570301	$969,000.00	$759,500.00	840.87	340.29	2231.95	$610,000.00	1994
92	42.97463	-79.81716	0 Brooks Road	0 Brooks Road	42.974634	-79.817158	$611,000.00	$520,000.00	407.90	165.07	3150.19	$750,000.00	2012
93	42.62962	-80.55716	200 4th Concession Road, Walsingham	200 4th Concession Road	42.629617	-80.55716	$321,000.00	$221,500.00	396.28	160.37	1381.20	$93,750.00	1987
94	42.67014	-80.49267	Backus Woods II	Backus Woods II	42.670143	-80.492669	$1,921,000.00	$1,810,500.00	853.72	345.49	5240.42	$500.00	1912
95	42.67023	-80.4964	Backus Woods III	Backus Woods III	42.670231	-80.4964	$314,500.00	$225,250.00	336.12	136.02	2312.14	$5,372,500.00	2011
96	42.79372	-80.58396	5 Byerlay Side Road	5 Byerlay Side Road	42.79372	-80.583963	$522,000.00	$353,500.00	233.77	94.60	5517.85	$75,000.00	1989
97	42.64242	-80.5642	316 Regional Road 60	316 Regional Road 60	42.642415	-80.564198	$198,000.00	$147,000.00	215.00	87.01	2275.65	$2.00	1955
98	42.77417	-80.4521	482 Mcdowell Road E	482 Mcdowell Road E	42.77417	-80.452103	$461,000.00	$357,000.00	205.78	83.28	5535.69	$2,800.00	1937
99	42.64849	-80.62452	915 6th Concession Road Enr	915 6th Concession Road Enr	42.648485	-80.624523	$496,000.00	$337,000.00	207.25	83.87	5913.81	$2.00	1967
100	42.74794	-80.4165	1164 Charletteville West	1164 Charletteville West	42.747941	-80.4165	$473,000.00	$363,500.00	204.39	82.71	5718.44	$6,500.00	1965
101	42.80723	-80.60331	566 2nd Concession Road Street	566 2nd Concession Road Street	42.807226	-80.603305	$496,000.00	$337,000.00	202.15	81.81	6062.98	$1,000.00	1992
102	42.80072	-80.44906	375 Yuell Road	375 Yuell Road	42.800718	-80.449057	$463,000.00	$356,500.00	192.99	78.10	5928.40	$2.00	1978
103	42.72141	-80.33029	61 Mole Side Road	61 Mole Side Road	42.721412	-80.330285	$225,000.00	$208,500.00	192.17	77.77	2893.14	$2.00	1979
104	43.02312	-79.69807	Caistorville Road	Caistorville Road	43.023124	-79.698067	$160,000.00	$1,205,000.00	176.27	71.33	2242.96	$1.00	1963
105	42.75642	-80.42536	1284 Char'ville West 1/4	1284 Char'ville W 1/4	42.756422	-80.425359	$412,000.00	$323,000.00	159.47	64.53	6384.23	$14,700.00	1996
106	42.66495	-80.64018	921 4th Concession Road Enr	921 4th Concession Road Enr	42.664954	-80.640182	$414,000.00	$283,500.00	157.54	63.75	6493.86	$2.00	1964
107	42.69691	-80.42157	141 Charlotteville 2 Road	141 Charlotteville 2 Road	42.69691	-80.421571	$372,000.00	$2,965,000.00	136.72	55.33	6723.42	$3,000.00	1970
108	42.72597	-80.30185	109 Fishers Glen Road	109 Fishers Glen Road	42.725973	-80.301848	$118,000.00	$114,000.00	130.30	52.73	2237.72	$30,000.00	1970
109	42.78713	-80.3601	1371 Charlotteville Road 7	1371 Charlotteville Road 7	42.787133	-80.360103	$370,000.00	$295,000.00	133.14	53.88	6867.13	$924,000.00	2008
110	42.71586	-80.3631	906 Charlotteville Road 2	906 Charlotteville Road 2	42.715858	-80.363104	$350,000.00	$282,000.00	130.87	52.96	6608.81	$1.00	1963

111	42.79952	-80.42146	1905 Regional Road 10	1905 Regional Road 10	42.799521	-80.421455	$354,000.00	$301,000.00	120.53	48.78	7257.68	$363,101.00	2016
112	42.8108	-80.36433	1486 McDowell Road E	1486 McDowell Road E	42.810801	-80.364326	$337,000.00	$273,000.00	116.68	47.22	7137.00	$2,000.00	1929
113	42.67992	-80.38794	521 Front Road	521 Front Road	42.679922	-80.387937	$344,000.00	$278,000.00	114.61	46.38	7416.96	$0.00	1992
114	42.63851	-80.54152	820 W Quarter Line Road	820 W Quarter Line Road	42.638514	-80.541515	$408,000.00	$267,000.00	108.85	44.05	9262.28	$65,000.00	1986
115	42.71042	-80.59209	1950 West Quarter Line	1950 West Quarter Line	42.710418	-80.592091	$326,000.00	$257,902.00	108.90	44.07	7397.07	$2.00	1953
116	42.78875	-80.44857	555 Regional Road 1	555 Regional Road 1	42.788751	-80.44857	$313,000.00	$257,500.00	110.12	44.56	7023.80	$600.00	1925
117	42.90364	-80.06279	354 Conc 8 Walpole	354 Conc 8 Walpole	42.903644	-80.06279	$98,000.00	$95,500.00	6.80	2.75	35591.31	$1.00	1986
118	42.92628	-80.39143	1881 Windham East	1881 Windham East	42.926283	-80.391429	$31,500.00	$29,250.00	4.92	1.99	15814.34	$1.00	1985
119	42.97869	-80.41192	2631 Windham East Quarter Line	2631 Windham East Quarter Line	42.978692	-80.411921	$34,000.00	$31,750.00	6.35	2.57	13230.84	$21,700.00	2015

APPENDIX D – R CODE

I. Single Species

```
## Single Objective VOI Calculations ##
# Raymond et al., 2018 #
-----------------------------------------------------------------
library(raster)

## DATA PREPARATION ##

## Read in raster data

## Probability data
        fra.raster <- raster("NAME OF FILE.tif")
        fra <- extract(fra.raster, extent(fra.raster), cellnumbers
        = TRUE)

## Cost data
        cost.raster <- raster("Price_Per_Hectare.tif")
        cost <- extract(cost.raster, extent(fra.raster),
        cellnumbers = TRUE)

## Specify species data here ##
        plant <- fra

## Create a table combining data
        prob.cost <- cbind(plant, cost)
        prob.cost <- na.omit(prob.cost)

## vectorize data to increase speed
        cell.v  <- as.vector(prob.cost[,1])
        prob.v  <- as.vector(prob.cost[,2])
        cost.v <- as.vector(prob.cost[,4])
        vect  <- cbind(cell.v , prob.v, cost.v)

## remove values ~ 0
        data  <- subset(vect , prob.v  > 0.05)

### START VOI CALCULATIONS ###

##  Create a consequence table with the possible benefits ##
        conseq.table <- data.frame(c(1,0), c(0,0))
        rownames(conseq.table) <- c("protect", "d.protect")
        colnames(conseq.table) <- c("present", "absent")
```

```
## Specify variables ##
        cell  <- data [ ,1]
        prob.pres  <- data [ ,2]
        prob.abs  <- 1 - prob.pres
        cost <- data[ ,3]

## expected values for actions with current info
        ex.val.protect  <- prob.pres  * conseq.table["protect",
        "present"] + prob.abs  * conseq.table["protect", "absent"]

        ex.val.d.protect  <- prob.pres  * conseq.table["d.protect",
        "present"] + prob.abs  * conseq.table["d.protect","absent"]

        ex.val.all.uncert  <-cbind(ex.val.protect,ex.val.d.protect)

## next, determine the decision under uncertainty, by looking at the max value ##
        ex.val.dec.uncert  <- apply(ex.val.all.uncert , 1, max)

## all values should be the same as their original poc, since they are being multiplied by 1 ##

## now for values under certainty
        ex.val.all.cert  <- cbind(ex.val.protect ,ex.val.d.protect)
        ex.val.dec.cert  <- rowSums(ex.val.all.cert)

## initially will be the same as values under uncertainty, but now lets update for monitoring

## loop to cover a range of monitoring accuracies
        acc.levels <- seq(0.05, 0.95, 0.05)
## cost of monitoring
        cost.mon <- 750

updated.info = NULL
value = NULL
n <- length(acc.levels)

for(i in 1:n) {

  true.pos <- acc.levels[i]
  false.neg <- 1 - true.pos
  mon.acc <- data.frame(c(true.pos, false.neg), c(0, 1))
  rownames(mon.acc) <- c("found", "n.found")
  colnames(mon.acc) <- c("present", "absent")
  acc <- rep(true.pos, length(cell ))

## can now update the prior poc values
```

```
## if we find the plant
        p.pres.if.found <- mon.acc["found", "present"] * prob.pres/
        ((mon.acc["found", "present"] * prob.pres)
        +(mon.acc["found", "absent"] * prob.abs))

         p.abs.if.found <- (1 - p.pres.if.found)

## if we don't find it
        p.pres.if.n.found <- mon.acc["n.found", "present"] *
        prob.pres / ((mon.acc["n.found", "present"] * prob.pres) +
        (mon.acc["n.found", "absent"] * prob.abs))

        p.abs.if.n.found <- (1 - p.pres.if.n.found)

## Updated info

## Total probabilities for present/absent
        prob.found <- (mon.acc["found", "present"] * prob.pres) +
        (mon.acc["found", "absent"] * prob.abs)

        prob.n.found <- (1 - prob.found)

        updated.info <- rbind(updated.info, data.frame(cell , acc, p.pres.if.found, p.abs.if.found,
        p.pres.if.n.found, p.abs.if.n.found, prob.found, prob.n.found)) ###

}

## Updated Expected Value

## If found
        ex.val.protect.found <- updated.info[,3] *
        conseq.table["protect", "present"] + updated.info[,4] *
        conseq.table["protect", "absent"]

        ex.val.d.protect.found <- updated.info[,3] *
        conseq.table["d.protect", "present"] + updated.info[,4] *
        conseq.table["d.protect", "absent"]

        ex.val.found <- cbind(ex.val.protect.found,
        ex.val.d.protect.found)

## If not found
        ex.val.protect.n.found <- updated.info[,5] *
        conseq.table["protect", "present"] + updated.info[,6] *
        conseq.table["protect", "absent"]
```

```
        ex.val.d.protect.n.found <- updated.info[,5] *
        conseq.table["d.protect", "present"] + updated.info[,6] *
        conseq.table["d.protect", "absent"]

        ex.val.n.found <- cbind(ex.val.protect.n.found,
        ex.val.d.protect.n.found)

## Optimal outcomes

## If found
        optimal.outcome.found <- apply(ex.val.found, 1, max)

## If not found
        optimal.outcome.n.found <- apply(ex.val.n.found, 1, max)

## Expected Value 2 - After Monitoring
        ex.val.dec.after.mon <- (optimal.outcome.found *
        updated.info[,7])

## Results of the loops
        prob.found <- updated.info[,7]

        value <- rbind(value, data.frame(cell, updated.info[,2],
        optimal.outcome.found, optimal.outcome.n.found, prob.found,
        ex.val.dec.after.mon))

### Cost effectiveness 1 --> Decision before monitoring
        ex.cost.dm <- ((prob.pres * cost) + (prob.abs * cost))

        ex.cost.dm.rep <- rep(ex.cost.dm, length(acc.levels))

        ex.val.dec.uncert.rep <- rep(ex.val.dec.uncert,
        length(acc.levels))

        cost.eff.current <- (ex.val.dec.uncert.rep/ex.cost.dm.rep)

## Cost effectiveness 2 --> After monitoring, assuming we protect only if and occurence is found

        ex.cost.m.pif <- (prob.found * cost + cost.mon)

        cost.eff.m.pif <- ex.val.dec.after.mon/ex.cost.m.pif


## Combining the two, to make the monitor vs don't decision
```

```
## Cost effectiveness table
        cost.eff.table <- cbind(cost.eff.current, cost.eff.m.pif)

## Expected Cost of actions table
        ex.cost.table <- cbind(ex.cost.dm, ex.cost.m.pif)

## Optimal cost effective value --> maximum cost effectiveness
        max.cost.eff <- apply(cost.eff.table, 1, max)

## Expected Value of actions table
        ex.val.table <- cbind(ex.val.dec.uncert.rep,
        ex.val.dec.after.mon)

        colnames(ex.val.table) <- c("ex value of dec uncertainty",
        "ex value of dec after mon")

dec.table = NULL
mon.decision = NULL
ex.cost.t = NULL
ex.val.t = NULL

## Monitoring Decision

        mon.decision <- ifelse (cost.eff.table[ ,1] >=
        cost.eff.table[ ,2], "N", "Y")

levels <- as.factor(updated.info[ ,2])

## table with the monitoring choice, decision value and cell number

        dec.table <- rbind(dec.table, data.frame (updated.info[
        ,1], updated.info [,2], mon.decision))
        colnames(dec.table) <- c("cell", "acc", "mon.decision")

dec.table2 = NULL

## Select appropriate values based on monitoring decision

        ex.cost.t <- ifelse (dec.table[ ,3] == 'Y', ex.cost.t <-
        ex.cost.table[ ,2], ex.cost.t <- ex.cost.table[ ,1])

        ex.val.t <- ifelse(dec.table[ ,3] == 'Y', ex.val.t <-
        ex.val.table[ ,2], ex.val.t <- ex.val.table[ ,1])
```

```
dec.table2 <- rbind(dec.table2, data.frame
(updated.info[,1], updated.info[,2], max.cost.eff,
        mon.decision, ex.cost.t, ex.val.t))

colnames(dec.table2) <- c("cell","accuracy","maximum cost eff value", "monitoring decision",
"expected cost", "expected value")

## Ranking management units by highest cost effectiveness value
        ranks  <- dec.table2[order(dec.table2[,2],
        -dec.table2[,3]), ]

        factor <- levels(as.factor(ranks$accuracy))

## Set budget value here
        budget <- 100000

selected.properties.table = NULL
add.value.table = NULL

## Loop for picking the most 'cost effective' management units up to the budget, at each
accuracy level

for (i in 1:length(factor)) {

  c.fact <- factor[i]

  properties.acc.level <- subset(ranks, accuracy == c.fact)
  selected.properties <- subset(properties.acc.level,

        # Selects management units up to the budget
        cumsum(properties.acc.level[,5]) <= budget)


        # Separate out remaining management units
        leftover.properties<-properties.acc.level[!(cumsum(properties.acc.level[,5]) <= budget), ]

        additive.cost <- sum(selected.properties[,5])
        remaining.budget <- budget - additive.cost

        o.leftover.properties  <- leftover.properties[order(-leftover.properties[,3],
        leftover.properties[,5]), ]

        so.leftover.properties <- subset(o.leftover.properties, o.leftover.properties[,5] <=
        remaining.budget)
```

```
        add.properties <- subset(so.leftover.properties, cumsum(so.leftover.properties[,5]) <=
        remaining.budget)

        total.properties <-  rbind(selected.properties,
        add.properties )

  additive.cost2 <- sum(total.properties[,5])
  additive.value <- sum(total.properties[,6])

selected.properties.table <- rbind(selected.properties.table,
total.properties)

add.value.table <- rbind(add.value.table, data.frame(c.fact, additive.value, additive.cost2))

}

## End cost effective loop
## End of monitoring accuracy loop
colnames(add.value.table) <- c("accuracy", "additive value", "additive cost")

## separating by accuracy level
sorted.table <- split(selected.properties.table, as.factor(selected.properties.table$accuracy))
```

Multiple Species:

```
## Multiple Objective VOI Calculations ##
# Raymond et al., 2018 #
-----------------------------------------------------------------
library(raster)

## DATA PREPARATION ##

## First read in raster data

## Probability data

  PTB <- raster("Purple_twayblade_Halidmand-Norfolk1.tif")
  plot(PTB)
  summary(PTB)
  ptb.data <- extract(PTB, extent(PTB), cellnumbers = TRUE)

  FRA <- raster("False_rue-anemon_Haldimand-Norfolk1.tif")
  plot(FRA)
  summary(FRA)
  fra.data <- extract(FRA, extent(FRA), cellnumbers = TRUE)

  CT <- raster("Cucumber_Tree_Halidmand-Norfolk1.tif")
  plot(CT)
  summary(CT)
  ct.data <- extract(CT, extent(CT), cellnumbers = TRUE)

## Cost data
  cost.raster <- raster("Price_Per_Hectare.tif")
  cost <- extract(cost.raster, extent(cost.raster), cellnumbers
  = TRUE)

## Combine the cell number and the probabilities for each cell and the cost of that cell
        all.data <- cbind(ptb.data, fra.data[,2], ct.data[,2],
        cost[,2])

        colnames(all.data) <- c("cell", "prob.ptb", "prob.fra",
        "prob.ct", "Cost")

## Remove NA values, and any cells that have values <0.05 for ANY plant. This specification
can be modified depending on your management goals.
        all.data <- na.omit(all.data)
        all.data <- all.data[apply(all.data[, -1], MARGIN = 1,
        function(x) all(x > 0.05)), ]

## vectorize data to increase speed
```

```
  cell.v <- as.vector(all.data[,1])
  prob.v.ptb <- as.vector(all.data[,2])
  prob.abs.v.ptb <- 1 - prob.v.ptb
  prob.v.fra <- as.vector(all.data[,3])
  prob.abs.v.fra <- 1 - prob.v.fra
  prob.v.ct <- as.vector(all.data[,4])
  prob.abs.v.ct <- 1 - prob.v.ct
  cost.v <- as.vector(all.data[,5])

vect <- cbind(cell.v, prob.v.ptb, prob.v.fra, prob.v.ct, cost.v)
## Calculate probability of finding none on a plot

        prob.none <-  (prob.abs.v.ptb * prob.abs.v.fra *
        prob.abs.v.ct)

## Probability of finding at least one target - Can be modified depending on the management
goals. Here we are interested in finding areas where any of the three plants occur.

        prob.alo <- 1 - prob.none

#######################################################################

## START VOI CALCULATIONS

## Create a consequence table with possible values associated

        conseq.table <- data.frame(c(1,0), c(0,0))
        rownames(conseq.table) <- c("protect", "d.protect")
        colnames(conseq.table) <- c("present", "absent")

## Specify the cost of actions here - in our case the only action considered is monitoring

        cost.mon <- 750
```

```
########### PURPLE TWAYBLADE ###########

######## DON'T MONITOR ########

	cell <- vect[ ,1]

	## Select PTB probability out of original table
		prob.pres <- vect[ ,2]
		prob.abs <- 1 - prob.pres

	## expected values for actions with current info
		ex.val.protect <- prob.pres * conseq.table["protect",
		"present"] + prob.abs * conseq.table["protect",
		"absent"]

		ex.val.d.protect <- prob.pres *
		conseq.table["d.protect", "present"] + prob.abs *
		conseq.table["d.protect", "absent"]

		ex.val.all.uncert <- cbind(ex.val.protect,
		ex.val.d.protect)

## next, will look at decision under uncertainty, by looking at the max value
	ex.val.dec.uncert <- apply(ex.val.all.uncert, 1, max)

## all values should be the same as their original poc, since they are being multiplied by 1

 ######## MONITOR ########

	ptb.acc.level <- 0.6

	updated.info = NULL
	value = NULL

	## Plug in survey accuracy value

	acc.level <- ptb.acc.level
	true.pos <- acc.level
	false.neg <- 1 - true.pos

	mon.acc <- data.frame(c(true.pos, false.neg), c(0, 1))
	rownames(mon.acc) <- c("found", "n.found")
	colnames(mon.acc) <- c("present", "absent")
	acc <- rep(true.pos, length(cell))

	## can now update the prior poc values
```

```
## if we find the plant
p.pres.if.found <- mon.acc["found", "present"] * prob.pres
/ ((mon.acc["found", "present"] * prob.pres) +
(mon.acc["found", "absent"] * prob.abs))

p.abs.if.found <- (1 - p.pres.if.found)

## if we don't find it
p.pres.if.n.found <- mon.acc["n.found", "present"] *
prob.pres / ((mon.acc["n.found", "present"] * prob.pres) +
(mon.acc["n.found", "absent"] * prob.abs))

p.abs.if.n.found <- (1 - p.pres.if.n.found)

## Updated info
## Total probabilities for present/absent

prob.found <- (mon.acc["found", "present"] * prob.pres) +
(mon.acc["found", "absent"] * prob.abs)

prob.n.found <- (1 - prob.found)

updated.info <- rbind(updated.info, data.frame(cell, acc,
p.pres.if.found, p.abs.if.found, p.pres.if.n.found,
p.abs.if.n.found, prob.found, prob.n.found))

## Updated Expected Value

## If found
ex.val.protect.found <- updated.info[,3] *
conseq.table["protect", "present"] + updated.info[,4] *
conseq.table["protect", "absent"]

ex.val.d.protect.found <- updated.info[,3] *
conseq.table["d.protect", "present"] + updated.info[,4] *
conseq.table["d.protect", "absent"]

ex.val.found <- cbind(ex.val.protect.found,
ex.val.d.protect.found)

## If not found
ex.val.protect.n.found <- updated.info[,5] *
conseq.table["protect", "present"] + updated.info[,6] *
conseq.table["protect", "absent"]
```

```
ex.val.d.protect.n.found <- updated.info[,5] *
conseq.table["d.protect", "present"] + updated.info[,6] *
conseq.table["d.protect", "absent"]

ex.val.n.found <- cbind(ex.val.protect.n.found,
ex.val.d.protect.n.found)

## Optimal outcomes ##

## If found
optimal.outcome.found <- apply(ex.val.found, 1, max)

## If not found
optimal.outcome.n.found <- apply(ex.val.n.found, 1, max)

## Optimal action will always be to protect

## Expected Value after Monitoring
ex.val.dec.after.mon <- (optimal.outcome.found *
updated.info[,7])
```

Here we are calculating the value of a single decision without expected cost. We assume that if the plant is found, we will protect it. If the plant is not found, we will move on to another management unit. Therefore the expected value of a decision after monitoring will be protect, multiplied by the probability that it is found

```
##### PTB RESULTS #####

ptb.results <- rbind(value, data.frame(cell, ex.val.dec.uncert, updated.info[,2],
ex.val.dec.after.mon, updated.info[,7]))

colnames(ptb.results) <- c("cell", "ex.val.dm.ptb", "survey accuracy", "ex.val.after.mon.ptb",
"prob.found")

#write.csv(ptb.results, file = "ptb.results.60.csv")
```

```
########### FALSE RUE ANEMONE ###########

######## DON'T MONITOR ########

	cell <- vect[ ,1]

	## Select FRA probability out of original table
		prob.pres <- vect[ ,3]
		prob.abs <- 1 - prob.pres

	## expected values for actions with current info
		ex.val.protect <- prob.pres * conseq.table["protect",
		"present"] + prob.abs * conseq.table["protect",
		"absent"]

		ex.val.d.protect <- prob.pres
		conseq.table["d.protect", "present"] + prob.abs *
		conseq.table["d.protect", "absent"]

		ex.val.all.uncert <- cbind(ex.val.protect,
		ex.val.d.protect)

## next, will look at decision under uncertainty, by looking at the max value
	ex.val.dec.uncert <- apply(ex.val.all.uncert, 1, max)

## all values should be the same as their original poc, since they are being multiplied by 1

######## MONITOR ########

	fra.acc.level <- 0.7

	updated.info = NULL
	value = NULL

	## Plug in survey accuracy value
	acc.level <- fra.acc.level

	true.pos <- acc.level
	false.neg <- 1 - true.pos

	mon.acc <- data.frame(c(true.pos, false.neg), c(0, 1))
	rownames(mon.acc) <- c("found", "n.found")
	colnames(mon.acc) <- c("present", "absent")
	acc <- rep(true.pos, length(cell))

	## can now update the prior poc values
```

```
## if we find the plant
p.pres.if.found <- mon.acc["found", "present"] * prob.pres
/ ((mon.acc["found", "present"] * prob.pres) +
(mon.acc["found", "absent"] * prob.abs))

p.abs.if.found <- (1 - p.pres.if.found)

## if we don't find it
p.pres.if.n.found <- mon.acc["n.found", "present"] *
prob.pres / ((mon.acc["n.found", "present"] * prob.pres) +
(mon.acc["n.found", "absent"] * prob.abs))

p.abs.if.n.found <- (1 - p.pres.if.n.found)

## Updated info
## Total probabilities for present/absent
prob.found <- (mon.acc["found", "present"] * prob.pres) +
(mon.acc["found", "absent"] * prob.abs)

prob.n.found <- (1 - prob.found)

updated.info <- rbind(updated.info, data.frame(cell, acc,
p.pres.if.found, p.abs.if.found, p.pres.if.n.found,
p.abs.if.n.found, prob.found, prob.n.found))

## Updated Expected Value

## If found
ex.val.protect.found <- updated.info[,3] *
conseq.table["protect", "present"] + updated.info[,4] *
conseq.table["protect", "absent"]

ex.val.d.protect.found <- updated.info[,3] *
conseq.table["d.protect", "present"] + updated.info[,4] *
conseq.table["d.protect", "absent"]

ex.val.found <- cbind(ex.val.protect.found,
ex.val.d.protect.found)

## If not found
ex.val.protect.n.found <- updated.info[,5] *
conseq.table["protect", "present"] + updated.info[,6] *
conseq.table["protect", "absent"]

ex.val.d.protect.n.found <- updated.info[,5] *
```

```
conseq.table["d.protect", "present"] + updated.info[,6] *
conseq.table["d.protect", "absent"]

ex.val.n.found <- cbind(ex.val.protect.n.found,
ex.val.d.protect.n.found)

## Optimal outcomes ##

## If found
optimal.outcome.found <- apply(ex.val.found, 1, max)

## If not found
optimal.outcome.n.found <- apply(ex.val.n.found, 1, max)

## Optimal action will always be to protect

## Expected Value after Monitoring
ex.val.dec.after.mon <- (optimal.outcome.found *
updated.info[,7])
```

Here we are calculating the value of a single decision without expected cost. We assume that if the plant is found, we will protect it. If the plant is not found, we will move on to another management unit. Therefore the expected value of a decision after monitoring will be protect, multiplied by the probability that it is found

```
##### FRA RESULTS #####

fra.results <- rbind(value, data.frame(cell, ex.val.dec.uncert, updated.info[,2],
ex.val.dec.after.mon,  updated.info[,7]))

colnames(fra.results) <- c("cell", "ex.val.dm.fra", "survey accuracy", "ex.val.after.mon.fra",
"prob.found")

write.csv(fra.results, file = "fra.results.70.csv")
```

```
########### CUCUMBER TREE ###########

######## DON'T MONITOR ########

	cell <- vect[ ,1]

	## Select CT probability out of original table
	prob.pres <- vect[ ,4]

	prob.abs <- 1 - prob.pres

	## expected values for actions with current info
	ex.val.protect <- prob.pres * conseq.table["protect",
	"present"] + prob.abs * conseq.table["protect", "absent"]

	ex.val.d.protect <- prob.pres * conseq.table["d.protect",
	"present"] + prob.abs * conseq.table["d.protect", "absent"]

	ex.val.all.uncert <- cbind(ex.val.protect,ex.val.d.protect)

## next, will look at decision under uncertainty, by looking at the max value

	ex.val.dec.uncert <- apply(ex.val.all.uncert, 1, max)

## all values should be the same as their original poc, since they are being multiplied by 1

######## MONITOR ########

	ct.acc.level <- 0.9

	updated.info = NULL
	value = NULL

	## Plug in survey accuracy value
	acc.level <- ct.acc.level

	true.pos <- acc.level
	false.neg <- 1 - true.pos

	mon.acc <- data.frame(c(true.pos, false.neg), c(0, 1))
	rownames(mon.acc) <- c("found", "n.found")
	colnames(mon.acc) <- c("present", "absent")

	acc <- rep(true.pos, length(cell))

	## can now update the prior poc values
```

```
## if we find the plant
p.pres.if.found <- mon.acc["found", "present"] * prob.pres
/ ((mon.acc["found", "present"] * prob.pres) +
(mon.acc["found", "absent"] * prob.abs))

 p.abs.if.found <- (1 - p.pres.if.found)

## If we don't find it
p.pres.if.n.found <- mon.acc["n.found", "present"] *
prob.pres / ((mon.acc["n.found", "present"] * prob.pres) +
(mon.acc["n.found", "absent"] * prob.abs))

p.abs.if.n.found <- (1 - p.pres.if.n.found)

## Updated info
## Total probabilities for present/absent
prob.found <- (mon.acc["found", "present"] * prob.pres) +
(mon.acc["found", "absent"] * prob.abs)

prob.n.found <- (1 - prob.found)

updated.info <- rbind(updated.info, data.frame(cell, acc,
p.pres.if.found, p.abs.if.found, p.pres.if.n.found,
p.abs.if.n.found, prob.found, prob.n.found))

## Updated Expected Value

## If found
ex.val.protect.found <- updated.info[,3] *
conseq.table["protect", "present"] + updated.info[,4] *
conseq.table["protect", "absent"]

ex.val.d.protect.found <- updated.info[,3] *
conseq.table["d.protect", "present"] + updated.info[,4] *
conseq.table["d.protect", "absent"]

ex.val.found <- cbind(ex.val.protect.found,
ex.val.d.protect.found)

## If not found
ex.val.protect.n.found <- updated.info[,5] *
conseq.table["protect", "present"] + updated.info[,6] *
conseq.table["protect", "absent"]

ex.val.d.protect.n.found <- updated.info[,5] *
```

```
        conseq.table["d.protect", "present"] + updated.info[,6] *
        conseq.table["d.protect", "absent"]

        ex.val.n.found <- cbind(ex.val.protect.n.found,
        ex.val.d.protect.n.found)

        ## Optimal outcomes ##

        ## If found
        optimal.outcome.found <- apply(ex.val.found, 1, max)

        ## If not found
        optimal.outcome.n.found <- apply(ex.val.n.found, 1, max)

        ## Optimal action will always be to protect

## Expected Value after Monitoring
        ex.val.dec.after.mon <- (optimal.outcome.found *
        updated.info[,7])

## Here we are calculating the value of a single decision without expected cost. We assume that
if the plant is found, we will protect it. If the plant is not found, we will move on to another
management unit. Therefore the expected value of a decision after monitoring will be protect,
multiplied by the probability that it is found

##### CT RESULTS #####
ct.results <- rbind(value, data.frame(cell, ex.val.dec.uncert, updated.info[,2],
ex.val.dec.after.mon, updated.info[,7]))

colnames(ct.results) <- c("cell", "ex.val.dm.ct", "survey accuracy", "ex.val.after.mon.ct",
"prob.found")

write.csv(ct.results, file = "ct.results.90.csv")
```

```
### CUMULATIVE CALCULATIONS ###

## Dont Monitor

## Expected Value Don't Monitor
        all.ex.val.dm <- cbind(cell, ptb.results[ ,2], fra.results[
        ,2], ct.results[ ,2])

        colnames(all.ex.val.dm) <- c("cell", "ptb", "fra" , "ct")

        all.ex.val.dm <- cbind(all.ex.val.dm, total.val.dm =
        rowSums(all.ex.val.dm[ ,2:4]))

## Expected Cost Don't monitor
        all.ex.cost.dm <- cbind(cell, cost.v)

## Monitor

## Updated Probability found
        all.prob.found <- cbind(cell, ptb.results[ ,6],
        fra.results[,6], ct.results[ ,6])

        colnames(all.prob.found) <- c("cell","p.ptb","p.fra",
        "p.ct")

## Probability NOT found
        pn.ptb <- 1 - ptb.results[ ,6]
        pn.fra <- 1 - fra.results[ ,6]
        pn.ct <- 1 - ct.results[ ,6]

        p.none.updated <- (pn.ptb * pn.fra * pn.ct)

        p.alo.updated <- (1 - p.none.updated)

## Expected Value - Monitor
        all.ex.val.m <- cbind(cell, ptb.results[ ,4], fra.results[
        ,4], ct.results[ ,4])

        colnames(all.ex.val.m) <- c("cell", "ptb","fra", "ct")

        all.ex.val.m <- cbind(all.ex.val.m, total.value.mon =
        rowSums(all.ex.val.m[ ,2:4]))

        write.csv(all.ex.val.m, file = "all.mon.csv")

## Expected cost - Monitor
```

```
        all.ex.cost.m <- cbind(cell, p.alo.updated, cost.v)
        colnames(all.ex.cost.m) <- c("cell", "probability alo
        updated", "cost")

        all.ex.cost.m <- cbind(all.ex.cost.m, ex.cost.m =
        (all.ex.cost.m[ ,2] * all.ex.cost.m[,3] + cost.mon ))

## Cost Effectiveness

        cost.eff.current <- (all.ex.val.dm[,5]/all.ex.cost.dm[,2])

## Cost effectiveness 2 --> After monitoring, protect only if found
        cost.eff.m.pif <- all.ex.val.m[,5]/all.ex.cost.m[,4]

## Combining the two, to make the monitor vs don't decision
## Cost effectiveness table
        cost.eff.table <- cbind(cost.eff.current, cost.eff.m.pif)

## Expected Cost of actions table
        ex.cost.table <- cbind(all.ex.cost.dm[,2],
        all.ex.cost.m[,4])

        colnames(ex.cost.table) <- c("DM", "M")

## Optimal cost effective value- max cost effectiveness value
        max.cost.eff <- apply(cost.eff.table, 1, max)

## Expected Value of actions table
        ex.val.table <- cbind(all.ex.val.dm[,5], all.ex.val.m[,5])
        colnames(ex.val.table) <- c("ex value of dec uncertianty",
        "ex value of dec after mon")

####

dec.table = NULL
mon.decision = NULL
ex.cost.t = NULL
ex.val.t = NULL

## Identify monitoring decision
        mon.decision <- ifelse (cost.eff.table[ ,1] >=
        cost.eff.table[ ,2], "N", "Y")

## table with the monitoring choice, decision value and cell
        dec.table <- rbind(dec.table, data.frame (updated.info[,1],
        mon.decision))
```

```
        colnames(dec.table) <- c("cell", "mon.decision")

dec.table2 = NULL

## Select appropriate values based on monitoring decision
        ex.cost.t <- ifelse (dec.table[ ,2] == 'Y', ex.cost.t <-
        ex.cost.table[ ,2], ex.cost.t <- ex.cost.table[ ,1])

        ex.val.t <- ifelse(dec.table[ ,2] == 'Y', ex.val.t <-
        ex.val.table[ ,2], ex.val.t <- ex.val.table[ ,1])

        dec.table2 <- rbind(dec.table2, data.frame (updated.info[,1], max.cost.eff, mon.decision,
        ex.cost.t, ex.val.t))

        colnames(dec.table2) <- c("cell", "maximum cost eff value", "monitoring decision",
        "expected cost", "expected value")

## Ranking cells by highest cost effectiveness value
        ranks  <- dec.table2[order( -dec.table2[,2]), ]

## Set budget value here ##
        budget <- 100000

selected.properties.table = NULL
add.value.table = NULL

        selected.properties <- subset(ranks, cumsum(ranks[,4]) <= budget)   #selects properties
        up to the budget
        leftover.properties <- ranks[!(cumsum(ranks[,4]) <= budget), ]

        additive.cost <- sum(selected.properties[,4])
        remaining.budget <- budget - additive.cost

## At the point where the next property is more expensive than the remaining budget, we remove
any properties that are > than the remaining budget, and re-rank

        o.leftover.properties <- subset(leftover.properties, leftover.properties[,4] <=
        remaining.budget)
        add.properties <- subset(o.leftover.properties, cumsum(o.leftover.properties[,4]) <=
        remaining.budget)

## These properties are then added to properties selected in the first pass to give the total of
properties selected within the budget

        total.properties <- rbind(selected.properties,
```

```
        add.properties)

        additive.cost2 <- sum(total.properties[,4])
        additive.value <- sum(total.properties[,5])

        selected.properties.table <-
        rbind(selected.properties.table, total.properties)

        add.value.table <- rbind(add.value.table,
        data.frame(additive.value, additive.cost2))

##FINAL RESULTS ##

        print(selected.properties.table)
        print(add.value.table)

        write.csv(selected.properties.table, file =
        "selected.properties.multi.csv")

        write.csv(add.value.table, file =
        "add.value.table.multi.csv")
```