The value of information for spatial conservation planning

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Abstract

Spatial conservation plans are typically based upon uncertain inputs and may benefit from additional data to inform them.However, the toolset of spatial prioritization does not yet contain a method for assessing the value of new information to a spatial conservation plan. If the value of information were to be calculated, then conservation plans would more effective, benefiting from a more optimal amount of information. Here, for the first time we demonstrate how a formal value of information analysis can be applied to a spatial conservation plan. We show how a value of information analysis can be combined with traditional conservation planning tools to map species distributions and optimize a reserve network to protect them. We incorporate uncertainty into conservation planning with Monte Carlo sampling of the planning inputs and then test the effects of uncertainty reduction to calculate the value of additional information to a conservation plan. The impact of optimally incorporating additional information into conservation plans, will be more effective plans where additional information is beneficial, and avoiding the loss of resources to uneccessary information gathering where new data has no benefit to the fundemental objectives of the plan.

Introduction

Spatial conservation planning is the field of science that focuses on developing methods to select candidate sites for protection and other conservation actions (Moilanen et al., 2009). Spatial conservation plans are complex and their inputs are commonly uncertain because they are generally based on few data. The outcomes of spatial conservation plans could be improved if they incorporated additional information. For example, additional occurrence data could be included for species of concern to the conservation planner so that the input layers of the spatial plan were more precise. But additional information comes as at cost. And that cost may have to be traded-off against implementing the conservation plan itself. Therefore, it is crucial to measure the value of potential new information to the conservation plan. If the value of new information is too low, that is, it does not significantly improve the conservation outcome, it may be better to implement a plan based on the original information alone.

Spatial conservation planning and imperfect information

Nearly all conservation actions include a spatial component: that is, decisions about where to act. Spatial conservation planning originally focused on designing networks of conservation reserves [**cite**], but has since then expanded to also cover other conservation actions and multi-action planning (e.g., Kujala et al., 2015). An aim of conservation planning is to preserve a comprehensive, adequate and representative subset of a region's biota by separating its constituents from threatening processes. Conservation does not occur in a vacuum. States and non-state actors practicing conservation do so with limited budgets and resources. Also, previous conservation actions need to be accounted for to target resources where they are most critically needed. Therefore, conservation planning must be systematic (Margules and Pressey, 2000)

A typical (systematic) spatial conservation plan will assess a pool of candidate locations for reservation (or some equivalent action). The planner will either find a set of locations that maximize conservation benefits within a given budget, or prioritize locations in order to meet a conservation target as cost effectively as possible. These are called maxmial benefit or minimal set problems respectively [**cite**].

The information needed to make a spatial conservation plan

A systematic spatial conservation conservation plan is in essence a classic decision analysis requiring optimization. Like any decision analysis it first requires a comprehensive problem definition. In defining the problem the conservation planner requires five types of information to proceed [**cite**].

- **Objectives**: The objective may be a target (e.g., protect 20% of the habitat of a set of species) or a goal to maximize some gain or minimize some loss (e.g. protect locations so as to minimize the average loss of habitat for a set of species.)
- **Constraints**: The bounds in which the plan operates. Including but not limited to, the spatial and temporal frame the plan will operate in, and the resources (e.g., monetary) available to the planner.
- **Actions**: The actions the planner can take (e.g., protect, not protect, restore habitat, etc.) to meet their objectives within the given constraints.
- **State variables**: The components of the system in which the plan will operate that planner seeks to effect and against which, the performance of the plan will be measured. In a spatial conservation plan the state variables are typically the distribution of a set of species the plan is seeking to protect.
- **System models**: A system model links the actions the planner will take and the state variables. With a system model the planner can predict what the outcome of any given plan will be with respect to the state variables of interest (e.g., what will be the effect of protecting certain areas on the distribution of species).

Uncertainty in spatial conservation planning.

Of the components in the list above, it is the last two, state variables and system models, where the most critical uncertainty lies. By critical, here we mean that uncertainty which could, once addressed, change the decision being made and the decision outcome. Here we focus on the uncertainty in state variables and leave the treatment of system model uncertainty for another forum. While in some sense, there may be uncertainty in objective, constraints and actions, these cannot be critical (in the strict sense we use the term above) as these components define the decision problem itself and thus addressing them is not directly changing the decision and its outcome, it is changing the framework under which the decision maker is operating.

State variables (typically modeled species distributions) are almost always based on imperfect knowledge. Conservation planners do not know with certainty where the species they seek to protect occur and must rely on models to predict there occurrence and abundance. Such models may themselves be based on uncertain and imperfect inputs (e.g., the distribution of a species may be predicted from a climate envelope that is based on uncertain climate data)(Guillera-Arroita et al., 2015). Uncertainty also arises in state variables such as species distribution maps because the models used to build them are trained with few data points. For example, a common approach to predicting the distribution of species is to use so called presence-only species distribution models (often with the software MaxEnt [**cite**]). In such models, the environment of locations where a species is known to occur, is compared to the environment overall. Ignoring for a moment any uncertainty in the nature of the environment, the fewer locations a species is known to be present at, the more imprecise and uncertain the predictions of its overall distribution from such models will be.

State variable uncertainty matters to conservation planning because the uncertainty will propagate from inputs all the way through the planning algorithm to the output, the conservation plan. This happens regardless of whether or not the uncertainty is accounted for explicitly.

Accounting for uncertainty in spatial conservation planning

Ultimately a conservation planner, like any decision maker, can do one of two things in the face of uncertainty. They can make a decision (formulate a plan) with the uncertainty or try to reduce the uncertainty. Even if they take the second option, rarely is uncertainty completely resolved and the plan must be made with imperfect information. More often than not, spatial conservation planning is done in spite of uncertainty rather than by taking any uncertainty into account. Uncertainty, whether or not explicit acknowledged, is not often quantified for state variables or any of the other decision components. For example, a set of predictive species distribution maps will be produced on top of which a spatial plan is built. However, only one map per species is typically produced and these maps will be implicitly treated as the true state of the system. When in reality the maps represent one possible, and at best average or most likely (though typically not both and perhaps not either), version of the system state under the assumption that the data used to produce them was unbiased. If instead, a set of maps was produced that reflected the uncertainty (multiple maps for each species) then a complementary set of plans could be produced from them, that reflected the uncertainty in state variables. It is only at this point having quantified uncertainty, that uncertainty can truly be addressed and an assessment made of whether and/or how to reduce it by acquiring addition additional information. To know whether or how to reduce uncertainty a conservation planner must measure the value of information.

The value of information

Value of information analysis is a tool used to quantify how much reducing the uncertainty in a predictive model is worth to a decision maker. The value of information is the difference between the final outcome of a decision (or plan) with or without additional information. Value, in and of itself, cannot be known in advance of any decision problem, including a spatial conservation plan, playing out. Therefore, decision theorists work with expected value. Expected value is the mean of all possible outcomes weighted by their probability of occurring. For example, if a person will earn a dollar when a fair coin toss is heads, and nothing if it is tails, the expected value of the toss is 50 cents. When making a decision with multiple alternatives, assuming the decision maker is risk neutral, it is always best to take the action that maximizes the expected value.

The expected value with original information

The expected value (see Box 1) with original information, EVWOI, is the maximum expected value if no additional information is gathered before a decision is made. In the case of spatial conservation planning, EVWOI is the default. Typically, a conservation plan maximizes the expected value using the information at hand. For example, species occurrence data (point locations of places where each species of concern has been observed) is used to build a set of species habitat suitability maps, using a species distribution modelling algorithm such as MaxEnt. A second algorithm, such as Zonation or Marxan [**cite**], is used to construct a plan that maximizes (or approximately maximises) the expected outcome with respect to some objective/target. The key, is that in the default case there is only one map used per species. The one-per-species map set represents the expected outcome under this level of uncertainty. Any uncertainty is averaged over and the map delineating the spatial conservation plan will indicate the expected value with original information.

The expected value with perfect information

Having perfect information is to have complete knowledge—no uncertainty. While in practice this is unlikely to ever occur, the expected value with perfect information (EVWPI, see Box 1 for a formal definition) is a useful construct as it allows to calculate the expected value of information

The expected value of perfect information

If the conservation planner can estimate the value of having perfect information, that is knowing what it is worth to resolve all uncertainty before enacting a conservation plan, then they will have an idea of the upper bound on what they should be willing to do to reduce uncertainty. If the expected value of perfect information is relatively small then it is less likely to be worth resolving uncertainty than if the value of perfect information was relatively large.

Box 1: A simple example: value of information for a plan to protect one species at two properties

A conservation planner can afford to protect one piece of land to help save an endangered species from extinction. Two properties are available.

The planner's aim is to maximise the area of habitat protected for the endangered species. The planner is uncertain about each property's **habitat suitability**. A property's habitat suitability can be either one (suitable) or zero (unsuitable). The first property has a 50% chance of being suitable (a 50% chance that habitat suitability is one, and a 50% chance that it is zero). But the planner knows that the second property has a slightly better chance (60%) of being suitable (i.e., a 40% chance it's unsuitable). The properties are identical in all other ways. A property can be protected **with original information** (i.e., choosing a property while still ignorant of the habitat suitabilities) or **with perfect information** (i.e., knowing the actual habitat suitabilities of each property in advance). The **value** of protecting a property is the same as its habitat suitability (i.e., the value can be zero or one). Regardless of they habitat suitability, an unprotected property has no value to the planner. The conservation planner must decide which property to protect.

Expected value

The **expected value** (EV) is the value the planner expects (but not necessarily what they get), given the outcome of their decision is uncertain. An **expected value** is a value weighted (multiplied) by a probability. Before they make a decision, the planner can work out the **expected value with original information** (EVWOI) or the **expected value with perfect information** (EVWPI). The **expected value of perfect information** (EVPI) is the difference between the EVWPI and the EVWOI. If the EVPI is positive, it means it is worth (up to a point) learning before making a decision. For this example, if the EVPI is large enough, it is worth the planner working out what the habitat suitabilities of the two properties are, before they decide which one to protect. But if the EVPI is too low (when there is little difference between EVWOI and EVWPI) they should just decide which one to protect straightaway.

Expected value with original information

The EVWOI is the highest value the planner expects they could get, on average (the **maximum expected value**), by protecting a property with only the information they have on habitat suitability at hand. To work out the expected value of protecting a property, the planner weights (i.e., multiplies) the values that are possible by their probabilities and adds them together.

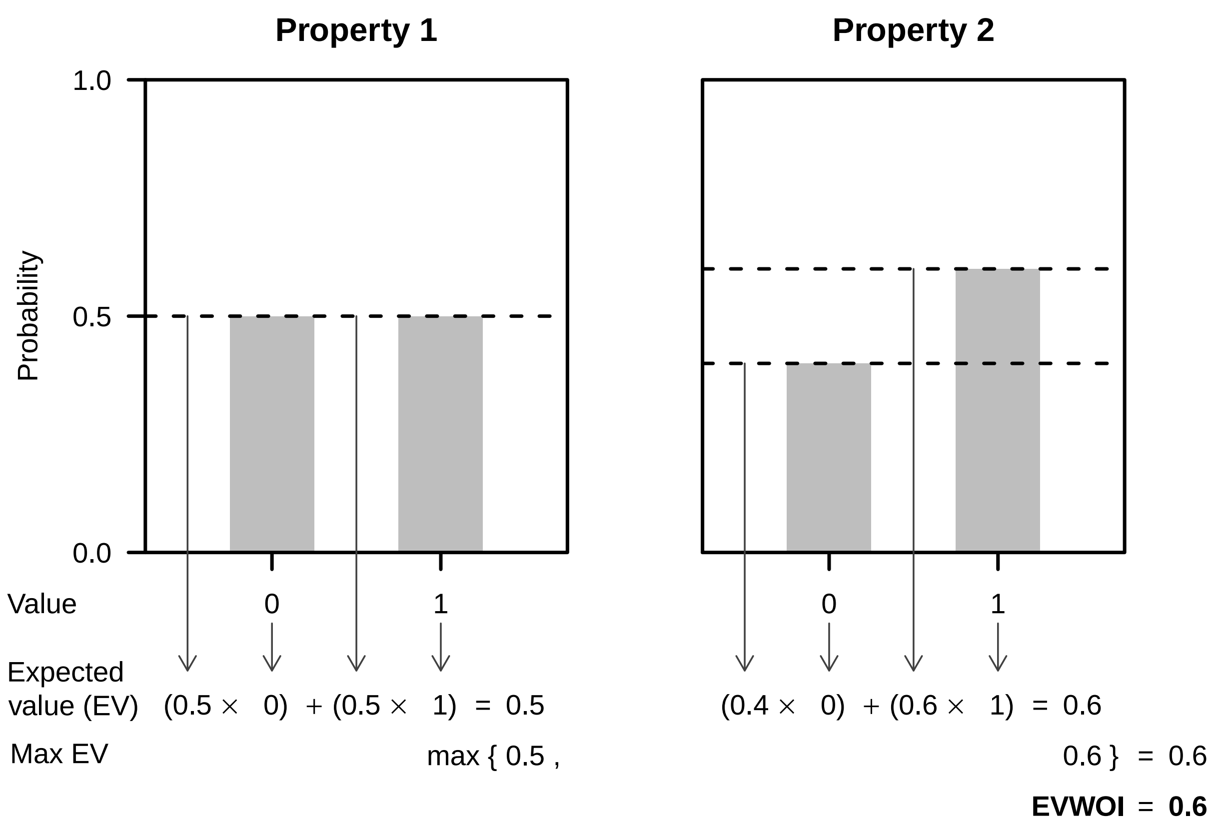

Figure 1: How to calculate EVWOI. First calculate the expected value of choosing to protect each property separately. The expected value of protecting a property is the values (the grey bars) that are possible, multiplied by their respective probabilities (the height of the grey bars) and then added together. EVWOI is the greatest (maximum) of the expected values. In this case, the EVWOI is the expected value of protecting property 2 is **0.6**.

In this case, protecting the first property has a 0.5 probability of having a value of 1, and a $1 - 0.5 = 0.5$ probability of having a value of 0. So, the expected value is:

$$1 \times 0.5 + 0 \times (1 - 0.5) = 0.5.$$

The calculation for the second property is:

$$1 \times 0.6 + 0 \times (1 - 0.6) = 0.6,$$

meaning the maximium expected value, EVWOI, is also **0.6**. Formally, using mathematical notation, the calculation can be expressed as:

$$\text{EVWOI} = \max_{a} \mathbb{E}_s[U(a, s)]. \tag{1}$$

Where a represents the **action** taken by the conservation planner, s represents a **state** (or scenario) (i.e., in this case it decscribes the information the planner has on the properties' habitat suitabilities), U represents the **utility** (or the value to the planner) of taking action a, and $\mathbb{E}$ is the mathematical symbol for **expectation**.

Expected value with perfect information

The EVWPI is the value the planner expects if they knew the properties' habitat suitabilities before deciding which one to protect.

In this case, there are four possible scenarios:

1. both properties are suitable,
2. the first is suitable while the second is not,
3. the second is suitable while the first is not, and
4. neither is suitable.

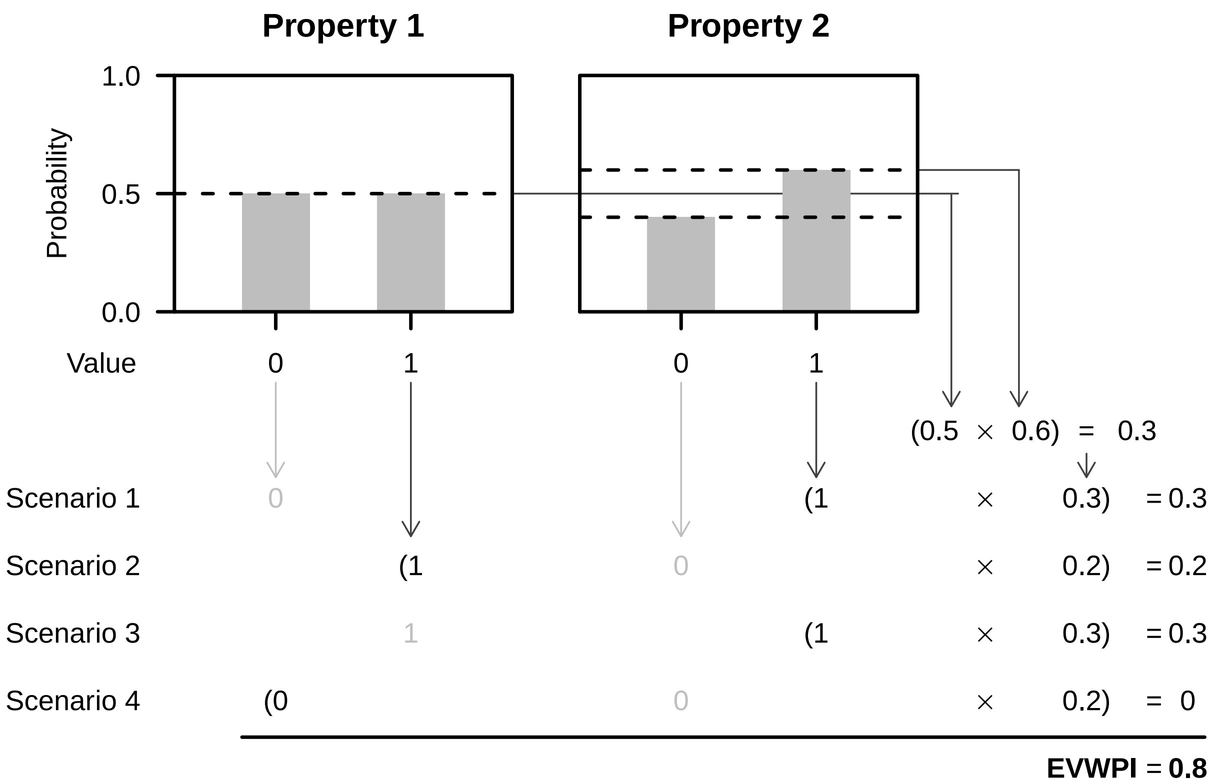

Figure 2: How to calculate EVWPI. First work out the scenarios that are possible. Then choose the property to protect in each possible scenario. When the properties have equal value it doesn't matter which one is selected (e.g., in scenarios 3 & 4). Next calculate the probability that the scenario occurs by multiplying the probabilities of the property habitat suitabilities (e.g., for scenario 1, the probability is $0.5 \times 0.6 = 0.3$, see the rightmost arrows). Next multiply the scenario probabilties by the value of the properties selected in each scenario. Finally, sum the weighted scenario values (rightmost values). In this case the EVWPI is **0.8**.

Because the planner is only protecting one property, the value the planner gets from any one of these scenarios is the highest of the values of the two properties for that scenario (i.e., the value for scenarios 1, 2 and 3 is one, since there is at least one suitable property, while the value for scenario 4 is zero, since neither property is suitable). To work out the EVWPI, the planner takes the four maximum values (one for each scenario), and sums them, weighted by the scenarios' respective probabilities. The probability of a given scenario is the probability that the first property has the suitability stated in the scenario, multiplied by the probability that the second property has the suitability stated in the scenario. For scenarios 1 and 3, where the second property is suitable, the probability of the scenario is $0.5 \times 0.6 = 0.3$, irrespective of whether the first property is suitable or not. This is because the probability of the first property being suitable is the same as the probability that it is unsuitable (i.e., 0.5). Similarly, for scenarios 2 and 4, where the second property is unsuitable, the probability is $0.5 \times 0.4 = 0.2$. So, the weighted values for scenarios 1 to 4, respectively, are:

$$\begin{aligned}
&1 \times (0.5 \times 0.6) = 1 \times 0.3 = 0.3, \\
&1 \times (0.5 \times 0.4) = 1 \times 0.2 = 0.2, \\
&1 \times (0.5 \times 0.6) = 1 \times 0.3 = 0.3, \text{ and} \\
&0 \times (0.5 \times 0.4) = 0 \times 0.2 = 0.
\end{aligned} \tag{2}$$

The EVWPI is the sum of these weighted values, $0.3 + 0.2 + 0.3 + 0 = \mathbf{0.8}$. In mathematical notation this can be expressed as:

$$\text{EVWPI} = \mathbb{E}_s[\max_a U(a, s)]. \tag{3}$$

Here the symbols have the same meaning as in equation 1. But notice that instead of calculating the **action that maximises the expected value** as in EVWOI, EVWPI is the **expected maximum value of action**. In other words, the order of maximisation and expectation has been reversed.

Expected value of perfect information

As noted above, the expected value of perfect information (EVPI) is the difference between the EVWPI and the EVWOI. Combining equations 1 and 3, the EVPI can be expressed as:

$$\text{EVPI} = \mathbb{E}_s[\max_a U(a,s)] - \max_a \mathbb{E}_s[U(a,s)]. \tag{4}$$

In the conservation planner's case, EVPI is $0.8 - 0.6 = \mathbf{0.2}$, meaning that if they could express habitat value as money, they should be willing to spend up to 20% of the price of a property, but no more, on learning about habitat suitabilty, before they decide what to protect, because if the expense of gathering the information is greater than the expected benefit from acting on the accumulated information(new information plus original).

As indicated above, spatial conservation planners rarely explicitly address uncertainty in state variables. This presents a problem, as without measuring uncertainty a conservation planner cannot know whether uncertainty is worth addressing. Without doubt there is a motive to reduce uncertainty in general, as decisions made with less uncertainty, all else being equal, will be better ones than decisions made with relatively more uncertainty. In light of these facts we propose that the field of spatial conservation planning should absorb the decision theoretic tools of value of information analyses. However, introducing a new tool into to an established framework is by no means trivial. As such here we seek to incorporate the concepts of value of information in harmony with the norms of systematic spatial conservation planning. In doing so, we outline what we think is the first example of a robust and comprehensive method of calculating the value of information for a spatial conservation plan for the first time. Our approach in the following work has to been to balance simplicity with realism. While our central case study is contrived, it uses real (not simulated) data in a plan to protect species of conservation concern in a region in need of systematic planning [**cite**]. To perform our analysis we combine the use of established software packages MaxEnt (Phillips and Dudík, 2008) and Zonation (**?**), which are well known to conservation planners, with Monte Carlo sampling methods and value of information analysis. The rest of this text is organized as follows. We introduce the case study briefly and then demonstrate how, within the context of spatial conservation planning, the value of information can be calculated using Monte Carlo methods. To aid understanding we interweave the case study with toy, low resolution examples so that reader may gain a deeper understanding of the method we are proposing.

Case study: a spatial conservation plan for the Hunter region, NSW, Australia

To demonstrate how to incorporate the value of information in a systematic spatial conservation plan, we now turn to a case study on prioritizing the Hunter region for the conservation of threatened plants and animals. For the case study we make the simplifying assumptions that the entire region is an original position where no area is protected but the entire region is available for protection in a conservation plan. While this is entirely unrealistic, it would be unnecessary to complicate the demonstration with a more realistic scenario as the complication would only serve to distract the reader from the key components of the method we outline here.

Study area

The Hunter is a biodiverse region of north-eastern New South Wales, Australia. The region is home to many threatened species of plants and animals. There are multiple threats to biodiversity in the region. The Hunter is under is under active development and the area's land users utilize it's resources for mining, agriculture, transport, urban infrastructure and conservation. For the the analyses we present here, we consider the Hunter region to include the local government areas of Cessnock, Dungog, Gloucester, Gosford, Greater Taree, Great Lakes, Lake Macquarie, Maitland, Musselbrook, Newcastle, Port Macquarie-Hastings, Port Stephens, Singleton, Upper Hunter and Wyong, an area of 38,296 km^2.

Study species

The Hunter is home to many species of national conservation significance. Here we consider six species: two birds, two mammals and two plants. For the following analyses we build conservation plans that aim to maximise the average relative carrying capacity of these six species across the hunter region. Table 1 outlines these six species and an estimate of their maximum carrying capacity (see supplement for more details) as well as their conservation status according to the *NSW Threatened Species Conservation Act 1995* (TSC), *Commonwealth Environment Protection and Biodiversity Conservation Act 1999* (EPBC) and the IUCN Red list (IUCN).

Common Name	Scientific Name	$\bar{K}^{\max}$	TSC	EPBC	IUCN
Powerful Owl	*Ninox strenua*	0.1	V	-	LC
Spotted-tailed Quoll	*Dasyurus maculatus*	0.2	V	E	NT
Regent Honeyeater	*Anthochaera phrygiam*	2.0	CE	CE	CE
Squirrel Glider	*Petaurus norfolcensis*	150.0	V	-	LC
Bynoe's Wattle	*Acacia bynoeana*	250.0	E	V	
Charmhaven Apple	*Angophora inopina*	18000.0	V	V	

Table 1: Species used in the conservation plan for the Hunter region. LC = Least Concern; NT = Near Threatened; V = Vulnerable; E = Endangered; CE = Critically Endangered. $\bar{K}^{\max}$ = Estimated maximum carrying capacity (no individuals per square kilometre).

Input data for the conservation plan

Predictors of species distributions

We summarise the environment of the Hunter region with six data layers: annual mean solar radiation, annual mean temperature, annual precipitation, precipitation seasonality (coefficient of variation), inherent soil fertility, and topographic wetness index (Figure ?). Each layer is a 297 by 324 grid of 1 km^2 cells. We chose this set of variables as they are publicly available (see supplement for sources), are biologically plausible drivers of the distribution of many taxa, have previously been shown to predict the distributions of the study species in the region [**cite**] and are relatively uncorrelated with one another (maximum Pearson correlation coefficient = 0.54).

Species occurence data

We obtained 30 random occurrence records within the boundaries of the Hunter region (as defined above) and within the date range, 1996 to 2016, for each of the six study species from the Atlas of Living Australia database [**cite**]. We chose this relatively low sample-size random subset to ensure that subsequent modelling would have an initial level of uncertainty large enough for us to demonstrate how to calculate the value of information.

Box 2: A slightly less simple example: value of information for a plan to protect one species at two properties with continuous uncertainty

In Box 1 we demonstrated how to calculate the value of information when the uncertainty in value was discrete (value of property could be zero or one). In the following example we increase the complexity slighlty and demonstrate how to calculate EVPI when uncertainty is continuous. Otherwise the problem remains the same. A planner has the budget to protect one property for the conservation of an endangered species and there are two properties available.

Here again, the planner's aim is to maximise the area of habitat protected. And again, the planner is uncertain about the habitat suitability of both properties. This time however, the uncertainty in habitat suitability is continuous. Now planner thinks that the habitat suitability of both properties can be **any value** between zero and one, whereas before the planner thought the value could be **either** zero or one.

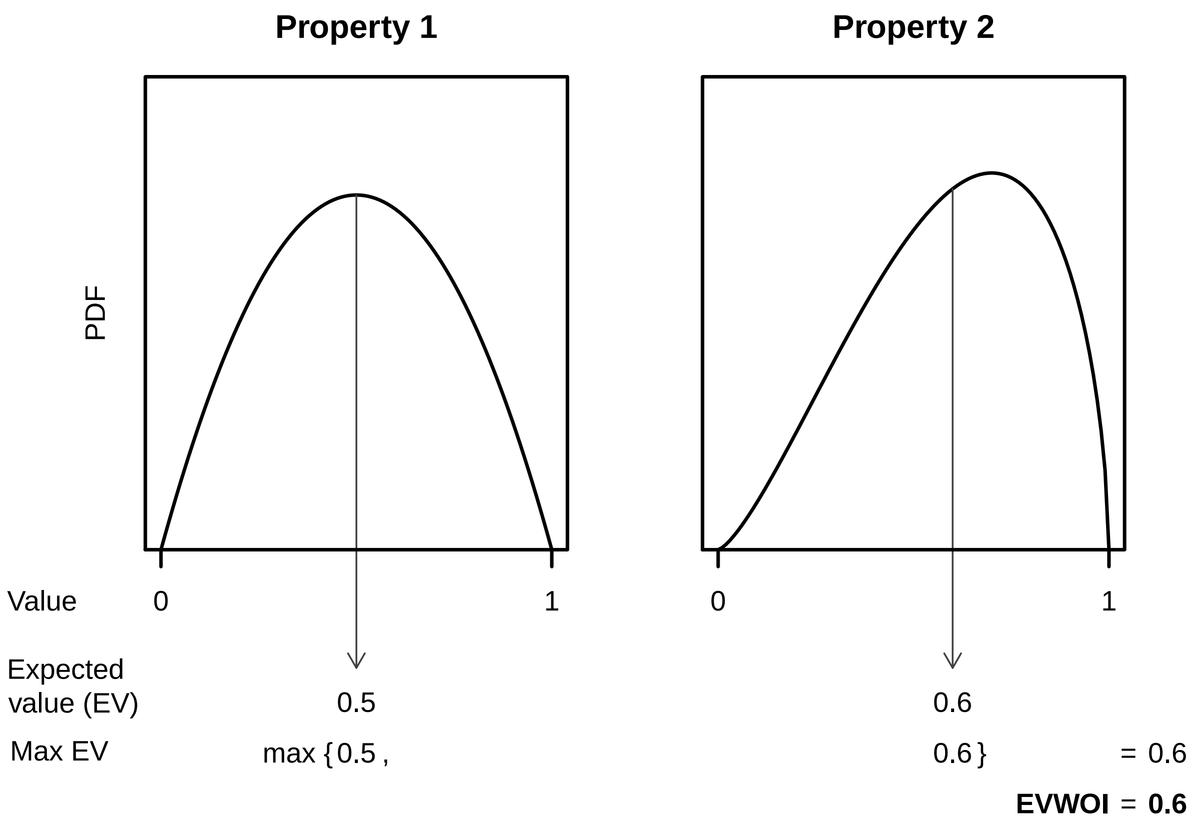

Figure 3: How to calculate EVWOI with continuous uncertainty. The EVWOI in this case is even simpler than for the discrete case (Figure 2). Simply take the expected value of each properties' distribution of value, the maximum of which, is the EVWOI (note that for property 2, which has an asymmetrical distribution, the expected value, its mean, is a little lower than its most probable value, the mode).

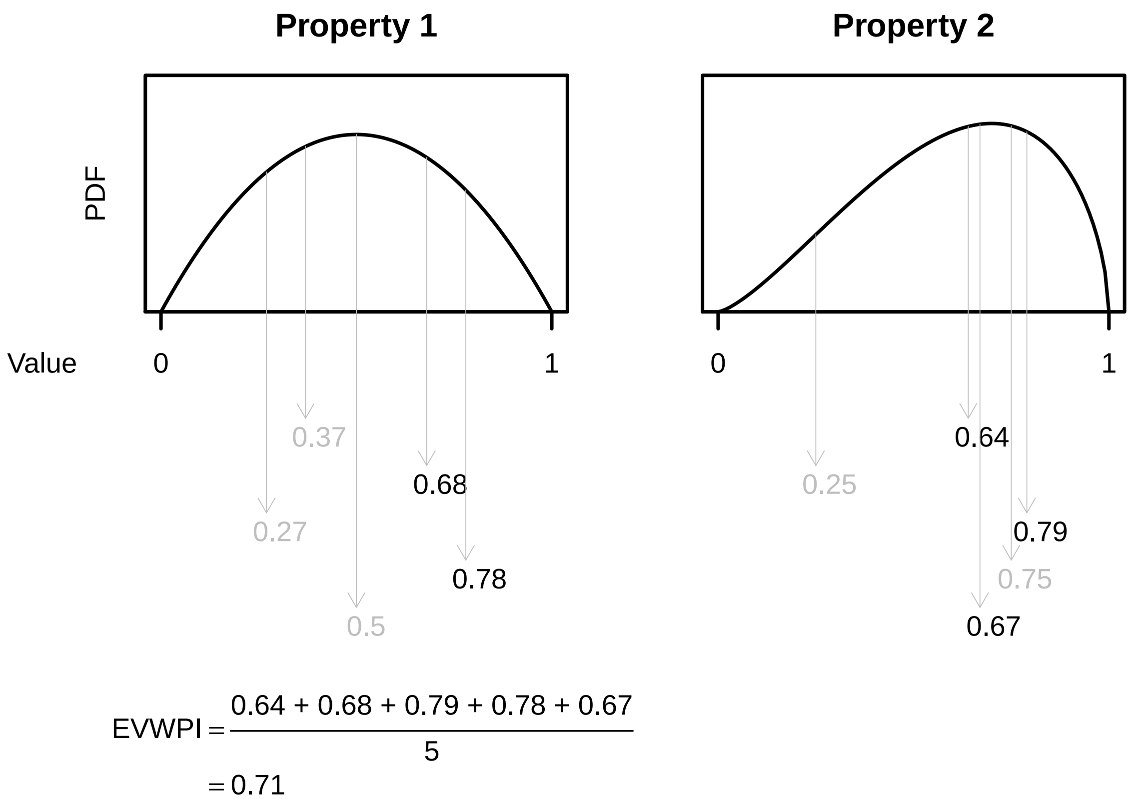

Figure 4: How to calculate EVWPI with Monte Carlo sampling. For continuous uncertainty, unlike discrete uncertainty the number of possible outcomes/scenarios are infinite. Any combination of values between 0 and 1 for each property (though some values are more likely than others). One solution is to use Monte Carlo sampling. For example we can estimate the EVWPI by selecting random pairs from the distribution of property values (numbers at the end of arrows above), selecting the maximum in each case (numbers in black text) and averaging by dividing by the number of samples. By selecting each pair in proportion to the probability distribution functions (PDFs) as we take more Monte Carlo samples the estimate of EVWPI approaches its true value. With the five samples above we estimate an EVWPI of .72 (which is close to the true value of .69, which we would get it if used a large number of samples.

Modelling species distributions using MaxEnt

We used the software MaxEnt [**cite**] to create species distribution maps on which to base the conservation plan. MaxEnt can be used to describe the potential distribution of species with occurrence records alone. The algorithm does this by comparing the distribution of occurrence records in covariate space to the distribution of covariate space as a whole, also known as the background (see below). We fit MaxEnt models to each species with only linear and quadratic features enabled.

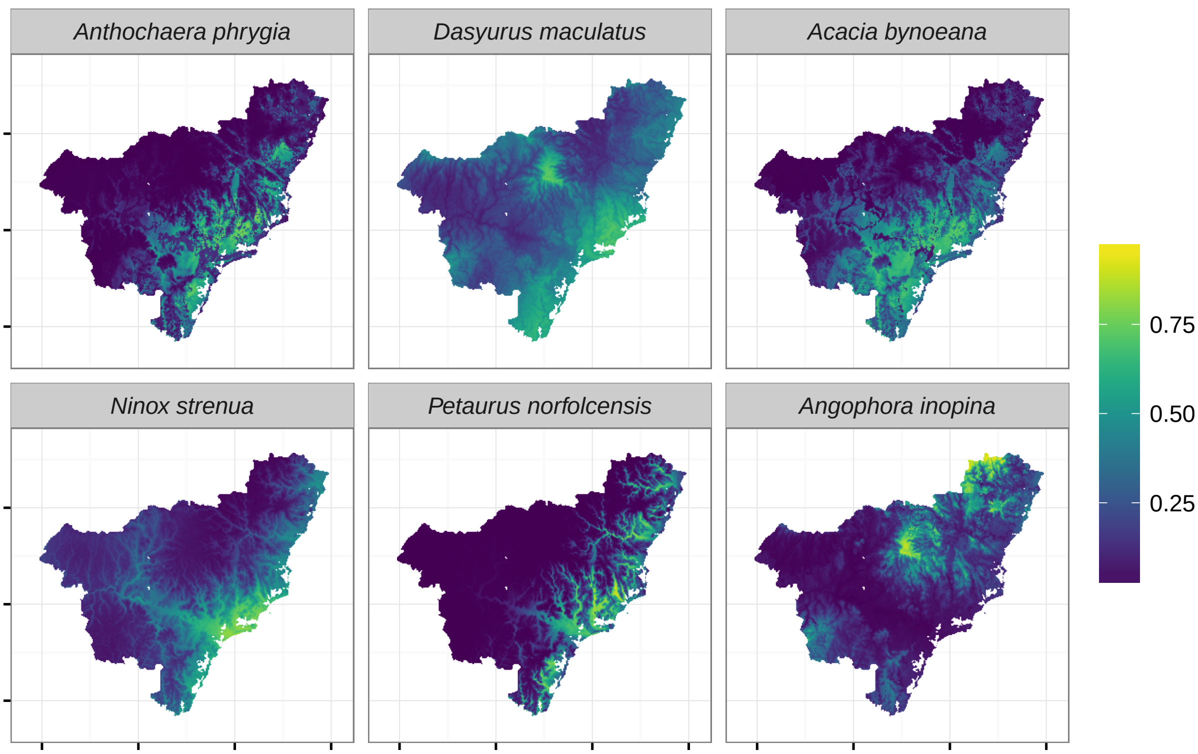

Figure 5: Distribution of study species in the Hunter region. Maps show the relative carrying capacity (logistic output) of each species estimated by fitting Maxent models to the occurrence data in Figure ? using the predictor set in Figure ? and background data in Figure ?.

Background geographic data

To fit distribution models with the occurrence records and environmental predictors we used a set of background points selected so as to minimise sampling bias in the occurrence points. For each higher taxonomic group (birds, mammals and plants) the background points were selected by randomly sampling 10,000 occurrence records of all taxa belonging to each group for the same spatial and temporal extent indicated above.

Intepreting the output of MaxEnt

Interpreting MaxEnt output in both it's native formats (raw and logistic) has in the past proved problematic and controversial. It has been shown that it equally problematic to interpret MaxEnt output as either relative occurrence rate or probability of presence it is legitimate to interpret MaxEnt output as an indicator of relative habitat suitability. Here we chose to interpret the logistic output of MaxEnt as a rough indicator of relative carrying capacity. Where the logistic output is zero, the carrying capacity should be zero (or close enough to zero) and where the output is one, the carrying capacity should be close to the maximum attainable for the species. When the output is some fraction of one then we assume the carrying capacity is that fraction of the maximum. The important caveat here is that the relationship between MaxEnt logisitic output and carrying capacity is linear. While there is no prima facie region that it should, be it is seems the most logical assumption and any conceivable deviation from lineararity should not matter too much in the present case as the species of interest here have carrying capacities that vary over many orders of magnitude. The benefit of intepreting the MaxEnt output in such a way is that we can use the distribution maps to calculate an estimate of total potential population size for each species. And subsequently once we have a conservation plan, we can calculate the potential impact on population size of the plan or other competing plans.

Incorporating uncertainty

Simply fitting a MaxEnt model with a set of occurrence points does not by itself account for the uncertainty in species

Prioritizing with Zonation

Box 3: A simple example of calculating the value of information for a conservation plan using Zonation

	Species 1					Species 2					Rank				
	20	76	17	34	72	26	59	51	25	47	25	3	21	24	7
	38	76	47	34	64	54	18	33	86	50	15	14	17	6	10
E[K]	42	64	77	74	28	27	39	71	42	40	19	13	1	9	20
	50	62	36	56	20	80	78	32	60	47	4	2	23	8	22
	41	12	61	88	55	72	78	52	37	20	12	16	11	5	18
Total			1244					1224							
	10	93	22	65	58	39	40	35	40	49	24	5	23	15	14
	62	82	78	40	35	64	26	50	92	39	8	13	6	7	20
k_1	9	61	87	81	44	0	56	82	35	74	25	10	1	9	11
	10	50	61	33	21	78	98	54	40	54	17	2	12	22	21
	33	0	61	89	52	52	89	79	47	25	18	16	3	4	19
Total			1237					1337							
	30	59	12	3	85	13	78	66	9	45	21	5	16	25	8
	13	70	16	28	94	44	10	15	80	61	20	17	22	11	3
k_2	75	66	66	67	12	54	22	60	49	7	7	14	9	10	24
	90	74	10	79	20	81	58	10	81	40	1	6	23	2	19
	48	23	61	87	58	92	66	25	27	15	4	13	15	12	18
Total			1246					1108							

$$\mathrm{EVWOI} = \frac{\frac{77}{1244} + \frac{71}{1224}}{2} = 0.06$$

$$\mathrm{EVWPI} = \frac{\frac{\frac{87}{1237}+\frac{82}{1337}}{2} + \frac{\frac{90}{1246}+\frac{81}{1108}}{2}}{2} = 0.07$$

$$\begin{aligned}\mathrm{EVPI} &= \mathrm{EVWPI} - \mathrm{EVWOI} \\ &= 0.07 - 0.06 \\ &= 0.01\end{aligned}$$

Figure 6: How to calculate the value of information for a conservation plan for 2 species, 25 cells and a budget large enough to purchase 1 cell, using zonation. First calculate the EVWOI (top row). With original information we rank each cell using the maps of expected carrying capacity (top left quadrant). For the highest rank cell (greyed out cell, top right quandrant) take the average proportion of carrying capacity remaining with all other unprotected cells are removed (top equation. Next calculate EVWPI. For each set of bootstrapped species carrying capacity maps k_1 and k_2 rank each cell and calcualte the average proportion of carrying capacity remaining. The EVWPI is the average of the average proportion of carrying capacity remaining for each bootstrap sample k_1 and k_2 (middle equation). Finally we calculate EVPI which is the difference between the EVWOI and EVWPI (bottom equation)

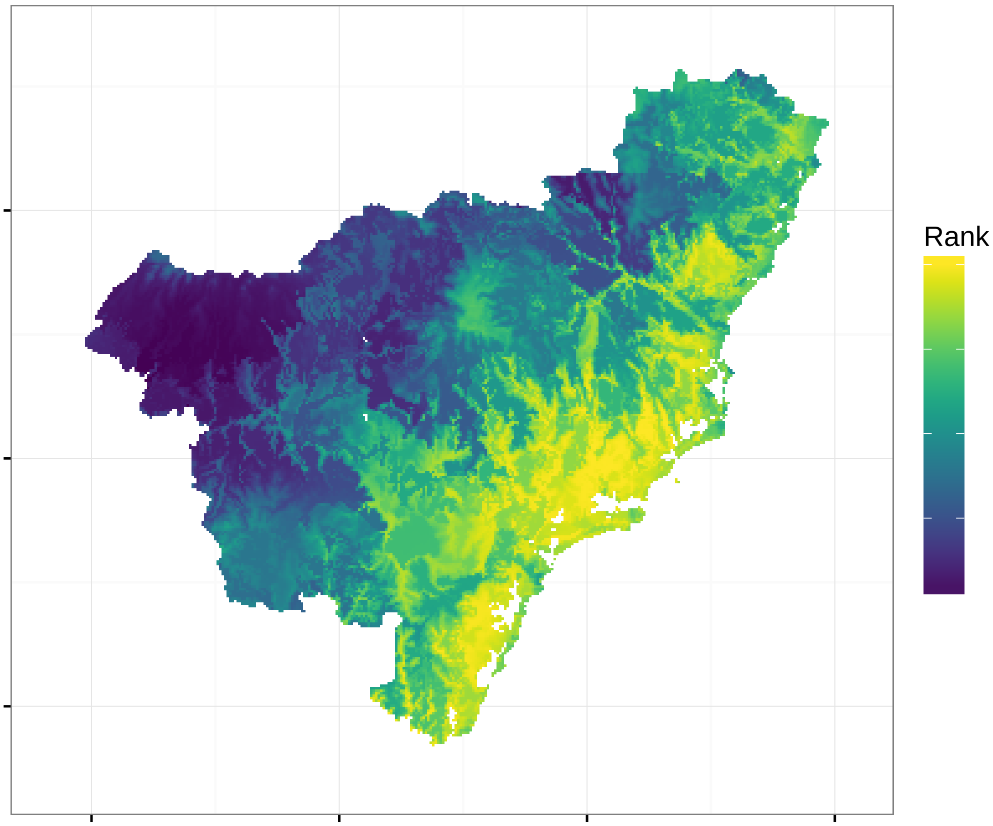

Figure 7: Priority map for the Hunter region. Pixels have been ranked from lowest priority (blue) to highest priority (yellow) using the Zonation greedy algorithm. The additive benefit function was used to iteratively remove cells with the lowest marginal benefit. In calculating marginal benefit each species was weighted equally. The map can be used to calculate the expected value with original information for a fixed budget (number of cells protected) with value measured as the average proportion of species total carrying capacity remaining if all unprotected cells were removed.

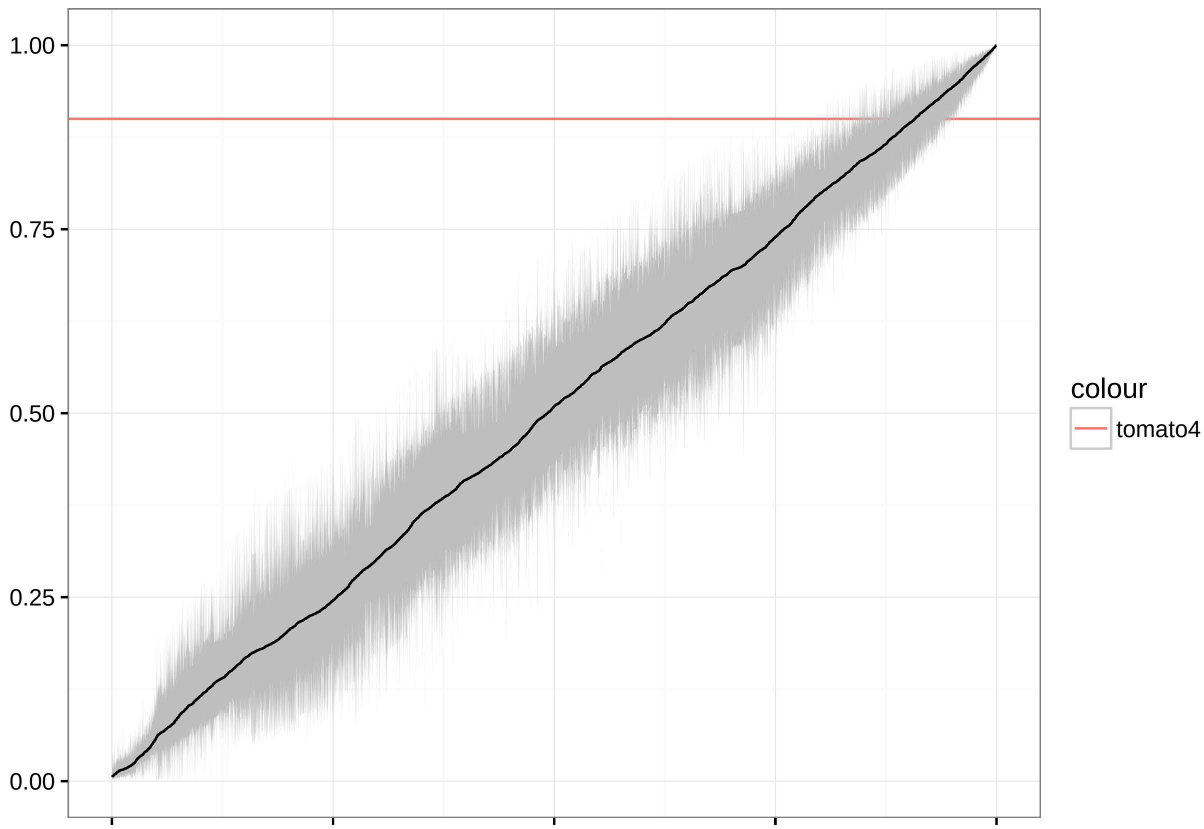

Figure 8: Uncertainty in pixel ranks. Ten thousand random pixels have been selected and displayed in order of their priority rank (black line). Grey bars indicate the 95% inner quantile of the priority rankings based on the bootstrapped maps. Pixels which have mean values above the red horizontal line are included in the conservation plan under original information.

Expected value	Average proportion of carrying capacity remaining
EVWOI	25.5
EVWPI	26.5
EVPI	1.0

Table 2: Something

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