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Where and how much? A spreadsheet that allocates surveillance effort for a weed

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Summary
In this paper I present a spreadsheet that implements the spatial surveillance prioritization methodology developed by Hauser and McCarthy (2009). They couch surveillance planning within a cost-benefit framework to identify both how much investment is justifiable to detect a weed and how that investment should be distributed across a heterogeneous landscape. The methodology partitions the landscape into homogenous sites with the optimal allocation depending on the probability that the weed is present, the ease of weed detection, and the benefits of weed detection at each site. A surveillance plan can be calculated for an arbitrarily large number of sites, limited only by the spreadsheet's row capacity.

Introduction
Early detection of and response to weeds is crucial for their feasible eradication or containment (Panetta and Timmins 2004, Cacho *et al.* 2006, 2008). However it is only recently that the cost of surveillance has been traded against its inherent consequences, such as the probability of successful eradication or the damage caused by the weed (Regan *et al.* 2006, Mehta *et al.* 2007, Bogich *et al.* 2008, Rout *et al.* 2009). Increased investment in surveillance is expected to increase the proportion of weeds detected and thus, decrease the impact of the weed. Though the rate of weed detection is rarely well understood, these studies highlight its importance for planning cost-effective surveillance; furthermore, methods exist to estimate detection rates (Garrard *et al.* 2008).

Hauser and McCarthy (2009) model the surveillance of a weed that is thought to be at a low density in a heterogenous landscape. In such circumstances, strategic planning is vital for identifying where and how much surveillance effort is justified. By partitioning the landscape into homogeneous sites, Hauser and McCarthy determine the survey intensity at each site that (A) optimally trades the surveillance cost against the expected benefits of early detection, and (B) minimizes expected weed impact subject to a fixed surveillance budget.

Although Hauser and McCarthy's equations appear complicated, it is possible to implement them in a spreadsheet to obtain the optimal solution. In this paper I present such a spreadsheet.

Materials and methods
Hauser and McCarthy (2009) modelled a heterogeneous landscape as set of n contiguous sites, each of equal area, with the weed being either present or absent within each site. Each site can be searched, with the probability of detecting the weed depending on the presence or absence of the weed, the search effort invested, and the local terrain. This search effort incurs a cost. Weed detections trigger control efforts in the neighbourhood of the incursion, which may continue over some time. In this way, weed detections also incur a cost. The failure to detect a weed in some sites is expected to incur the greatest costs of all, given that the weed is expected to spread and cause further damage before being detected and controlled at some later date.

Selecting an objective
Hauser and McCarthy (2009) consider two surveillance planning scenarios. First, they assume that the impacts of the weed can be measured in the same currency as surveillance effort. In this case it is possible to identify an optimal trade-off between the surveillance costs and weed impacts (objective A); as surveillance investment increases, we expect successful weed detections to increase and weed impacts to decrease.

The second scenario assumes that a non-negotiable surveillance budget is available; then the objective is to distribute that budget amongst the n sites such that the expected weed impacts are minimized (objective B). In this scenario it is not necessary that the surveillance costs and weed impacts be expressed in the same currency, and it is possible to calculate the expected impacts under a range of budgets to assess the trade-off between unlike currencies.

Partitioning a landscape into sites
To maintain consistency of results, Hauser and McCarthy's model requires that all sites be of the same area. Thus, dividing the landscape into a square grid can be convenient. It is important to select an appropriate spatial scale upon which to

plan surveillance. This model assumes the size of a single weed infestation is substantially smaller than the size of the site. However, it is also important that sites are sufficiently small to capture variation in habitat suitability, search terrain, and value across the landscape.

For example, Hauser and McCarthy (2009) used a 20 m × 20 m grid to define sites in their case study of orange hawkweed surveillance on the Bogong High Plains of Victoria. This was the scale at which input data (vegetation type, predicted probability of weed occurrence) were provided. Furthermore, individual orange hawkweed infestations on the High Plains were expected to cover no more than 5 m^2, less than 2% of the area of one site. If infestations were expected to cover a substantially larger area (say, 100 m^2) then the input data could be aggregated to define larger sites (say, 100 m × 100 m), such that the ratio of expected infestation area to site area is small.

The probability of weed presence

Hauser and McCarthy's model supports the common intuition that surveillance should be conducted where the weed is most likely to be. Thus, an efficient surveillance plan requires a predicted probability of weed presence at each site. These probabilities should be expressed as values between 0 and 1, with 0 indicating that weed presence is impossible (surveillance effort will never be allocated to such a site) and 1 indicating that the weed is known with certainty to be present at the site. These probabilities can be estimated subjectively, though several authors have developed models that predict the probability of weed, pest or disease presence over a landscape (Buchan and Padilla 2000, Underwood *et al.* 2004, Inglis *et al.* 2006, Williams *et al.* 2008). The predicted probability of weed presence in each site should take into account factors such as habitat suitability, possible dispersal from known weed incursions, and any history of weed presence within the site.

Weed detectability

The probability of detecting the weed in a site depends on the presence or absence of the weed, the search effort invested, and the local terrain. Hauser and McCarthy assume that when a weed is present at a site, the probability of failing to detect an infestation declines exponentially with surveillance effort. The rate of decline may vary from site to site; that is, some sites may be more difficult to search than others due to differences in terrain. To reflect this variation, a search efficiency parameter, λ_i, must be estimated for each site. The parameter must be non-negative, with $\lambda_i = 0$ indicating that it is impossible to detect the weed at site i using the given surveillance method, and large values of λ_i indicating that surveillance can detect the weed at site i with high efficiency.

Garrard *et al.* (2008) present an experimental method for estimating the detection function and search efficiency parameter. The reciprocal of this parameter, $1/\lambda_i$, can be interpreted as the mean amount of surveillance effort required to first detect a weed at an infested site. For example, Hauser and McCarthy (2009) assumed that $\lambda_i = 0.6020$ per minute for shrubby sites. Thus, the average time taken to first discover a weed at an infested shrubby 20 m × 20 m site was estimated to be 1.66 minutes.

Hauser and McCarthy's model is flexible regarding the currency used to measure surveillance effort. Money invested, time spent searching, or the proportion of area covered may be appropriate currencies for measuring weed search effort.

Detection benefit

Differing land uses or biodiversity values across a landscape should influence the prioritization of surveillance effort. Some infested sites may also be easier or cheaper to treat than others. Thus, Hauser and McCarthy's model requires a measure of the expected (mean) benefits of weed detection for each site. Some factors to consider in estimating these benefits are:

- the likely spread and future damage that will be prevented by successfully detecting a weed during this survey;
- the saved costs of monitoring, controlling and/or eradicating this potential larger future incursion, less the cost of monitoring, controlling and/or eradicating that is triggered by detecting a weed during this survey; and
- the ease or difficulty of successfully treating an infestation in the neighbourhood of one site compared to another (based on accessibility, land use, etc.).

The benefits measured for a site may include costs that would be incurred outside the site in the instance that the incursion is not rapidly contained. Ideally, the measure of expected benefits would average over all possible invasion trajectories over the lifetime of the weed incursion although this will rarely be possible. An alternative approach is to consider the benefits of weed detection at a site between the current and next planned survey.

Under objective A, the benefits must be measured in the same currency as surveillance effort. Only then can the two commodities be directly traded to calculate an optimal surveillance investment. Under objective B, it is sufficient that the relative benefit between sites be estimated. However, a thorough estimate of surveillance benefits can allow the exploration of performance over a range of different surveillance budgets.

Surveillance budget (objective B only)

Objective B requires the specification of a total budget for surveillance effort. The currency of the budget is flexible, though it must obviously be measured in the same units as the surveillance effort allocated to each site.

Calculating the optimal surveillance allocation

Hauser and McCarthy (2009) provide the equations that optimally allocate surveillance effort under objectives A and B. These equations can be solved as formulae in the spreadsheet presented here.

Results

The spreadsheet workbook described here is available at no charge via email request (chauser@unimelb.edu.au).

Selecting an objective Objectives A and B are treated in separate sheets within the surveillance planning workbook, titled Unconstrained Optimization and Budget-Constrained Optimization, respectively.

Partitioning a landscape into sites The selection of site size and location is to be carried out prior to use of this spreadsheet, as described in the Materials and methods. Each site in the landscape is represented by a row in the Data Entry sheet, and there are cells available for entering an individual identifier for each site (column A), as well as spatial co-ordinates (columns B–C, Figure 1).

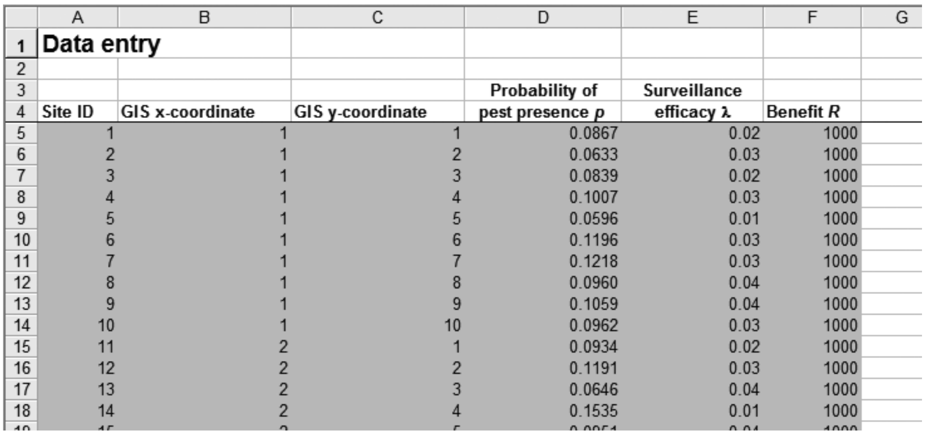
The probability of weed presence The probability of weed presence for each site is entered into column D of the Data Entry sheet (Figure 1).

Weed detectability The value of the ease of detection parameter is not intuitive. Thus a Detection Function sheet is available, where a detection parameter value can be entered and the consequent detection response to surveillance effort is plotted (Figure 2). The value of the detection parameter for each site is entered into column E in the Data Entry Sheet (Figure 1).

Detection benefit The benefit of successful detection at each site is entered into column F in the Data Entry Sheet (Figure 1).

Surveillance budget Since the surveillance budget parameter applies only to objective B, it is entered at the top of the sheet optimizing objective B, called Budget-Constrained Optimization (Figure 3).

Calculating the optimal surveillance allocation Under objective A, where the costs and benefits of weed surveillance are traded directly, the optimal surveillance effort for each site is treated independently. Data are transferred from the Data Entry sheet,



	A	B	C	D	E	F	G
1	Data entry						
2							
3				Probability of	Surveillance		
4	Site ID	GIS x-coordinate	GIS y-coordinate	pest presence *p*	efficacy λ	Benefit *R*	
5	1	1	1	0.0867	0.02	1000	
6	2	1	2	0.0633	0.03	1000	
7	3	1	3	0.0839	0.02	1000	
8	4	1	4	0.1007	0.03	1000	
9	5	1	5	0.0596	0.01	1000	
10	6	1	6	0.1196	0.03	1000	
11	7	1	7	0.1218	0.03	1000	
12	8	1	8	0.0960	0.04	1000	
13	9	1	9	0.1059	0.04	1000	
14	10	1	10	0.0962	0.03	1000	
15	11	2	1	0.0934	0.02	1000	
16	12	2	2	0.1191	0.03	1000	
17	13	2	3	0.0646	0.04	1000	
18	14	2	4	0.1535	0.01	1000	

Figure 1. A screen capture of the Data Entry sheet in the surveillance planning workbook. Columns denote Site ID (A), optional GIS x- and y-coordinates (B, C), probability of pest presence (D), surveillance efficacy (E) and benefit (F).

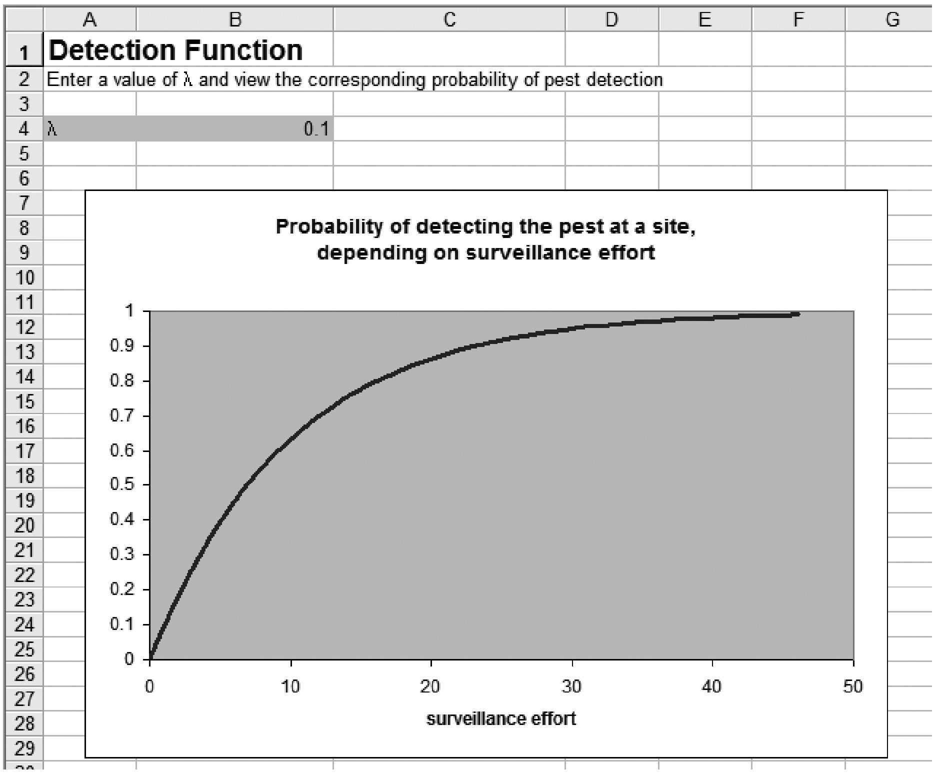


Figure 2. A screen capture of the Detection Function sheet in the surveillance planning workbook. A value of detection parameter λ is entered, generating a plot of the probability of detection as a function of surveillance effort.

and the optimal surveillance allocation is calculated in column H (Figure 4).

Under objective B, sites must be prioritized as a function of their properties. The Budget-Constrained Optimization sheet features a 'Prioritize sites' button to sort site data appropriately, and an error check that alerts the user to unsorted data. Once data are sorted, the surveillance allocation is presented in column W (Figure 3).

Visualizing results Though the spreadsheet does not include automatic plotting features, results can be exported in a number of formats for plotting and/or mapping. For example, Hauser and McCarthy (2009) exported surveillance plans as comma-separated value (.csv) files, then imported the files into ArcGIS for mapping.

Discussion

Hauser and McCarthy's (2009) model provides guidance for planning cost-efficient weed surveillance, and is especially useful for heterogeneous landscapes where weed habitat suitability, dispersal, detection and impact are expected to vary across space. The spreadsheet described in this paper is an accessible medium for using that model.

Sites that are recommended for surveillance effort generally have a high probability of weed presence, terrain that facilitates rapid detection, and large benefits associated with detection during the planned survey. The amount of survey effort recommended increases with probability of presence and with detection benefits, but in a nonlinear manner. Sites that are very difficult to search will be prioritized for survey only if the expected benefits are very high; in this case a thorough search will be recommended. Sites that are easy to search are more likely to be prioritized for survey, though only at a low effort; this will assure a sufficiently high probability of weed detection.

While Hauser and McCarthy's model provides new insight into how cost-effective weed surveillance should be planned, it requires input data that may not always be available. Site-specific probabilities of occurrence (including those derived from species distribution modelling), detection probabilities, weed impacts and control costs are unlikely to be estimated with high confidence. It is therefore important to perform sensitivity analyses; fortunately optimizations within this spreadsheet are performed rapidly so it is feasible to investigate multiple parameter sets and observe changes in the optimal surveillance plan. A more thorough uncertainty analysis of Hauser and McCarthy's surveillance model is planned as a future study.

Surveillance is a vital component of successful weed management, yet rigorous methods for planning and implementing surveillance are only recently emerging. The spreadsheet presented in this study demonstrates how ecological and economic modelling can be utilized for planning cost-effective surveillance.

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	B	C	D	E	F	G	H	W
1	**Budget-constrained optimisation**			Budget B	2000		Prioritise sites	Reset
2	Allocate a surveillance budget efficiently							
3				Probability of	Surveillance		Prioritisation score	Optimal surveillance effort
4	Site ID	GIS x-coordinate	GIS y-coordinate	pest presence p	efficacy λ	Benefit R	$pxRx\lambda$	x (units = 1/[λ units])
48	58	6	8	0.0559	0.04	3000	6.71	13.59
49	45	5	5	0.0725	0.03	3000	6.53	17.20
50	79	8	9	0.1293	0.01	5000	6.47	50.68
51	32	4	2	0.1051	0.02	3000	6.31	24.10
52	99	10	9	0.0614	0.02	5000	6.14	22.76
53	75	8	5	0.0604	0.02	5000	6.04	21.94
54	53	6	3	0.0978	0.02	3000	5.87	20.50
55	87	9	7	0.0585	0.02	5000	5.85	20.34
56	50	5	10	0.0971	0.02	3000	5.83	20.14
57	27	3	7	0.1395	0.04	1000	5.58	8.99
58	67	7	7	0.1104	0.01	5000	5.52	34.88
59	81	9	1	0.1099	0.01	5000	5.50	34.43
60	84	9	4	0.0534	0.02	5000	5.34	15.78
61	86	9	6	0.104	0.01	5000	5.20	28.91
62	41	5	1	0.0539	0.03	3000	4.85	7.32
63	23	3	3	0.12	0.04	1000	4.80	5.23
64	72	8	2	0.095	0.01	5000	4.75	19.86
65	31	4	1	0.0728	0.02	3000	4.37	5.74
66	91	10	1	0.0861	0.01	5000	4.31	10.02
67	9	1	9	0.1059	0.04	1000	4.24	2.10
68	17	2	7	0.1309	0.03	1000	3.93	0.28
69	8	1	8	0.096	0.04	1000	3.84	0.00
70	15	2	5	0.0951	0.04	1000	3.80	0.00
71	48	5	8	0.0623	0.02	3000	3.74	0.00
72	16	2	6	0.0917	0.04	1000	3.67	0.00

Figure 3. A screen capture of the Budget-Constrained Optimization sheet in the surveillance planning workbook. The surveillance budget is entered into cell F1. Columns B-G summarize data from the Data Entry sheet, column H gives the prioritization score for each site, and column W presents the optimal surveillance allocation under objective B.

	A	B	C	D	E	F	G	H
1	**Unconstrained optimisation**							
2	Trade the costs of surveillance against the benefits.							
3							Prioritisation score	Optimal surveillance effort
4	Site ID	GIS x-coordinate	GIS y-coordinate	Probability of pest presence p	Surveillance efficacy λ	Benefit R	$p \times \lambda \times R$	x (units = 1/[λ units])
5	1	1	1	0.0867	0.02	1000	1.73400	27.52
6	2	1	2	0.0633	0.03	1000	1.89900	21.38
7	3	1	3	0.0839	0.02	1000	1.67800	25.88
8	4	1	4	0.1007	0.03	1000	3.02100	36.85
9	5	1	5	0.0596	0.01	1000	0.59600	0.00
10	6	1	6	0.1196	0.03	1000	3.58800	42.59
11	7	1	7	0.1218	0.03	1000	3.65400	43.19
12	8	1	8	0.096	0.04	1000	3.84000	33.64
13	9	1	9	0.1059	0.04	1000	4.23600	36.09
14	10	1	10	0.0962	0.03	1000	2.88600	35.33
15	11	2	1	0.0934	0.02	1000	1.86800	31.24
16	12	2	2	0.1191	0.03	1000	3.57300	42.45
17	13	2	3	0.0646	0.04	1000	2.58400	23.73
18	14	2	4	0.1535	0.01	1000	1.53500	42.85
19	15	2	5	0.0951	0.04	1000	3.80400	33.40
20	16	2	6	0.0917	0.04	1000	3.66800	32.49
21	17	2	7	0.1309	0.03	1000	3.92700	45.60
22	18	2	8	0.1019	0.02	1000	2.03800	35.60
23	19	2	9	0.088	0.04	1000	3.52000	31.46
24	20	2	10	0.0625	0.03	1000	1.87500	20.95

Figure 4. A screen capture of the Unconstrained Optimization sheet in the surveillance planning workbook. Columns A–F summarize data from the Data Entry sheet, column G gives the prioritization score for each site, and column H presents the optimal surveillance allocation under objective A.

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