



Info-gap theory and robust design of surveillance for invasive species: The case study of Barrow Island

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ABSTRACT

Surveillance for invasive non-indigenous species (NIS) is an integral part of a quarantine system. Estimating the efficiency of a surveillance strategy relies on many uncertain parameters estimated by experts, such as the efficiency of its components in face of the specific NIS, the ability of the NIS to inhabit different environments, and so on. Due to the importance of detecting an invasive NIS within a critical period of time, it is crucial that these uncertainties be accounted for in the design of the surveillance system. We formulate a detection model that takes into account, in addition to structured sampling for incursive NIS, incidental detection by untrained workers. We use info-gap theory for satisficing (not minimizing) the probability of detection, while at the same time maximizing the robustness to uncertainty. We demonstrate the trade-off between robustness to uncertainty, and an increase in the required probability of detection. An empirical example based on the detection of *Pheidole megacephala* on Barrow Island demonstrates the use of info-gap analysis to select a surveillance strategy.

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1. Introduction

The introduction of non-indigenous species (NIS) to natural environments can impact on the structure and function of established ecosystems if such species establish and proliferate in the new environment. In the case of previously un-invaded environments with high conservation value, the consequences of introduced species cannot always be predicted. Species not recognised as pests may exhibit “invasive” qualities, and therefore it is necessary in the context of conservation and natural biodiversity to prevent all introductions of NIS to the extent practicable, whether declared to be invasive or not.

Surveillance programs exist to detect the presence of NIS against a background of endemic and naturalised species, early enough to

consider eradication without significant damage to the environment in which it is discovered. For the situation which is the case study of this paper, a proposed industrial development on an island nature reserve, this includes pre-border, border and post-border surveillance activities.

Despite their obvious value, surveillance programs to prevent impacts to conservation values can be problematic. Firstly, significant effort is invested to prevent introduction of the NIS, and then the surveillance strategy must detect the remaining very rare events. Secondly, ongoing surveillance over large areas can be prohibitively costly if traditional sampling grids and transects are adopted, requiring large resources to implement, monitor and diagnose the results. Thirdly, over-zealous or indiscriminate sampling may produce a quantity of diagnostic work that overwhelms scarce taxonomic resources. Fourthly, an over-zealous surveillance program could have conservation consequences in itself by impacting on the abundance of native species. Finally, when a surveillance program does not report an incursion over a period of time, how do we know whether a surveillance system “zero” (an NIS is not detected) is a real zero (i.e. the organism is truly not present), or the presence of

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NIS is simply below the detection limit of the system (an “operational zero”)?

A further problem posed by the zeroes collected by a surveillance system, which attempts to detect rare events, is how to maximize the efficiency of the locations of the surveillance system components¹ (SSCs) to some acceptable standard. Surveillance efficiency can be enhanced through an iterative refinement of SSC placement, based on reviews of previous SSC indications. However, if all earlier surveillance effort has yielded zero indications, when zeros were expected (i.e. a very rare likelihood of introduction), then it is difficult to determine how effectively the SSCs have been placed. SSC placement efficiency is desirable not only to maximize the chances of intercepting an introduction, but also to ensure that ineffective SSCs are not contributing to the cost and other resource demands of the surveillance program.

An opportunity, on the other hand, is to empower non-scientists to participate in surveillance, in a manner that augments more structured scientific sampling approaches. There are numerous examples of property owners and industrial workers contributing to the detection of NIS (ABC News, 2008; Delaney et al., 2008). Harnessing the capacity of a large population of “eyes and ears” to participate in a surveillance program is an attractive proposition, although there has not been a quantitative interpretation of their role in a surveillance program that combines observations with more structured scientific surveillance.

We use Barrow Island as a case study. Barrow Island is an island of the coast of North West Australia and a proclaimed nature reserve. A government approval for industrial development of part of the island requires that prevention of introducing NIS be demonstrated by a surveillance program with an appropriate statistical power of detection. We choose to address some of the problems associated with ongoing surveillance on a larger scale outlined above using a novel mathematical approach known as *info-gap decision theory* (Ben-Haim, 2006). Info-gap theory is an approach which models and manages non-probabilistic uncertainty in data (that is, gaps in information) and calculates the robustness of decisions that are made using these uncertain data. A surveillance program which is highly robust to uncertainty is preferred over a strategy which has low robustness. This info-gap analysis forms the basis for improving the design of the surveillance.

In the case of a surveillance program on Barrow Island to accommodate a large industrial development, we wish to:

1. Aggregate diverse sources of data, of varying quality, such as non-scientific observations by a large workforce concurrently with structured scientific sampling;
2. Decide if additional training or motivation will improve the efficiency of observations relative to structured scientific sampling, given an interpretation of the value of non-scientific observations (and the human limitations of recognizing target taxa);
3. Determine how best to place SSCs to maximize surveillance efficiency in view of an uncertainty in the spatial distribution of target taxa for detection of NIS, given a practical number of SSCs which can be implemented with available scientific expertise on the island (this paper does not address this issue directly); and
4. Evaluate the effect of changing SSCs density and deployment on the robustness of the surveillance program.

This research focuses on detection of the bigheaded ant, *Pheidole megacephala*. This ant was selected as an exemplar species of

potential NIS for Barrow Island, due to its known invasiveness and its proximity on the Australian mainland. It was considered that surveillance for *P. megacephala* would be likely to detect it if it was present in an SSC, as it would be for many other tramp ant species, making it a suitable exemplar.

This case study is an early application of info-gap decision theory to surveillance. (For an economic perspective of detecting invasive NIS, see Moffitt et al., 2008.) While the study is specific to activities on Barrow Island and to the characteristics of *P. megacephala*, we believe that the methodology has applicability to other biosecurity efforts, such as the detection of epidemics with low clinical profile (Ranta et al., 2001), or the fine-tuning of surveillance systems (Areal et al., 2008).

The paper is organized as follows. Section 2 describes the biosecurity imperatives for Barrow Island and outlines the surveillance methodology used. Section 3 summarizes the relevant characteristics of *P. megacephala*. Section 4 briefly describes how info-gap theory is used to robustly *satisfice* a requirement—that is, striving for a *good enough* result in the presence of severe uncertainty. Section 5 presents a model to estimate the efficiency of the biosecurity efforts at Barrow Island, at this stage without referring to the uncertainties in the basis of the model. Section 6 uses info-gap decision theory to inform the choice of preferred biosecurity strategies, based on the model introduced in Section 5. A concluding discussion appears in Section 7. Mathematical derivations are presented in the Appendix.

2. Barrow Island

2.1. Background

Chevron Australia has been the operator of an oilfield and marine terminal for crude oil transport vessels on Barrow Island since the 1960s, and has managed quarantine to prevent the establishment of non-indigenous species (NIS) as an important part of its environmental responsibilities.

Barrow Island was proclaimed a Class A Nature Reserve in 1910 for its conservation value, and has a land area of about 26,000 hectares. The island is about 70 km off the coast of North West Australia and has been separated from the mainland for some 8000 years. It is the home for at least 24 terrestrial species that do not occur elsewhere, and another five terrestrial species with restricted distribution elsewhere. Barrow Island has a semi-arid climate, punctuated with heavy rainfall almost exclusively associated with cyclonic events.

The existing oilfield operation consists of more than 800 wells, 200 km of roads, 250 accommodation units, recreational facilities, a barge landing with marine infrastructure, and an active airport that accommodates commercial jets and helicopters servicing offshore activities. There are constant movements of a workforce of several hundred people and goods between the mainland and the island. To date, more than 10,000 cargo landings and several hundred thousand personnel transfers have been potential pathways for the introduction of NIS. Although the threat of incursions exists from oilfield operations, very few introductions have occurred. No significant impacts to the conservation values of the island have been detected as a consequence of accidental introductions.

Barrow Island has been exposed to NIS from visits by pearlers dating back to the late 1800s, and more recently by occasional trespassers who have landed on the island and non-Chevron transit passengers arriving at the airport for helicopter transfers to other offshore facilities. Six non-indigenous plant species are being monitored and eradicated through a weed management program undertaken by Chevron in consultation with government, although

¹ SSCs include traps, surveys, baits, and so on.

it is not possible to identify the source of these incursions. Similarly, one tramp ant and 11 other invertebrate species have been confirmed as NIS to date, as a result of comprehensive invertebrate baseline surveys of the island (Majer et al., 2006, 2007). An introduced black rat population was successfully eradicated from the southern end of the island by 1998 (Burbridge and Morris, 2002; Morris, 2002). In contrast to other islands in the vicinity, Barrow Island is now free of non-indigenous rodents and the uncontrolled proliferation of weed species, although continued vigilance is necessary to prevent future introductions.

2.2. Quarantine surveillance of a proposed liquefied natural gas plant

Chevron and its Joint Venture Partners (ExxonMobil and Shell Australia) have proposed the construction and operation of a 15 million tonne per annum liquefied natural gas (LNG) plant on Barrow Island, known as the Gorgon Project. The construction site, accommodation village and other land disturbance are limited to 300 hectares, to be concentrated on the eastern end of the island. The construction site will be contiguous with a material offloading facility, which will be licensed by the government as a “Quarantine Approved Premises” to allow importation of material directly to Barrow Island as a first port of entry in Australia.

The proposal will greatly increase the frequency and volume of material and people arriving on the island, especially during a four-year construction period when about three million freight tonnes of material will be delivered to a construction site employing thousands of people. The increased quarantine threat has been subject to a rigorous risk assessment process (Whittle et al., 2008), which has identified a number of introduction pathways, with quarantine barriers developed that have been independently judged by experts to reduce the likelihood of introduction to a very rare event.

The significant emphasis on preventing introductions must be backed up, however, by an on-island detection program that will detect introductions early enough to enable the option of eradication without significant ecological collateral damage, in the event that eradication is determined to be the appropriate response. “Early enough” detection is the overarching objective of the detection program, recognizing that different taxa will require appropriate temporal and spatial scales of detection to meet this objective.

The detection program for NIS will rely on three components, each of which has some likelihood of detecting NIS if one is indeed present:

- **Observation:** un-structured, opportunistic visual and auditory observation and reporting of suspect organisms at the point of arrival and on the construction site. Both trained biologists and personnel with little or no formal biological training contribute to observation. It is noteworthy that the majority of the historical observations of NIS on Barrow Island (and elsewhere) have been reported by persons with little or no formal biological training, which indicate the potential usefulness of un-structured observation.
- **Surveillance:** structured and un-structured surveillance at the point of arrival, on the construction site, and in the “transition zone” around the proposed land disturbance. Surveillance is the domain of trained biologists. Structured surveillance could include sampling traps and lures, recording devices, and remote sensing. Un-structured surveillance could include random or targeted inspection of sites to detect NIS based on visual observation or indirect evidence (e.g. droppings, discolorations of vegetation, tracks, boreholes/nests, or auditory signals). The areal extent of the transition zone requires definition for different taxa, based on their initial dispersal

capability and temporal aspects of their reproductive biology and mechanisms of establishment.

- **Monitoring:** ecological monitoring of the island for change which has been predicted to occur or might be induced by the construction and operation of the LNG plant, including changes that might be detected due to the presence of NIS (among other potential environmental stressors).

“Surveillance system” in the context of this paper includes the observation and surveillance components of the detection program. The ecological monitoring element of the detection program is not explicitly included in this discussion of surveillance, since the robustness of the surveillance effort should be measured against the objective of early detection, to prevent establishment that might otherwise be detected later through broad-scale ecological monitoring activities.

The detection program is backed up with diagnostic capabilities and immediate response plans to control the spread of NIS, while rapidly seeking longer-term eradication advice.

3. *Pheidole megacephala*

3.1. Background

P. megacephala (also known as coastal brown ant, bigheaded ant, brown house ant, Madeira ant, Grosskopfameise, lion ant, tramp ant) was selected as an exemplar species for Barrow Island, where it has not been detected in baseline surveys, due to its known invasiveness and to its proximity on the Australian mainland. It was considered that *P. megacephala* is likely to be detected by surveillance, and therefore would be representative of many other tramp ant species, making it a suitable exemplar. *P. megacephala* is one of about 150 ant species known as “tramp ants”, that have become widely distributed in the world due to human activity, with seven being invasive worldwide (Holway et al., 2002).

P. megacephala is one of the world’s worst invasive species (Walker, 2006), having achieved a global distribution in a wide range of habitats. This ant forms very extensive colonies and displaces many native invertebrate species directly through aggression, and as such is a serious threat to biodiversity. Evidence also exists of reductions in vertebrate populations where this ant is extremely abundant. Effects on plants and horticultural crops can be direct through seed-harvesting, or indirect through tending phytophagous insects which reduce plant productivity. It will chew on irrigation pipes, telephone cabling and electrical wires and is a domestic pest, scavenging in bathrooms, kitchens and elsewhere.

Other invasive ant species in the Pacific area bear similar risk profile with regards to Barrow Island (PIAG, 2004). These include the tropical fire ant (*Solenopsis geminata*), yellow crazy ant (*Anoplolepis gracilipes*), Singapore ant (*Monomorium destructor*), ghost ant (*Tapinoma melanocephalum*), Papuan thief ant (*Solenopsis papuana*), crazy ant² (*Paratrechina longicornis*), little fire ant (*Wasmannia auropunctata*), Argentine ant (*Linepithema humile*), Pharaoh ant (*Monomorium pharaonis*), and white-footed ant (*Tecnomyrmex albipes*).

3.2. General description

P. megacephala is a small ant (minor workers approximately 2 mm long and major workers 3–4 mm long), ranging in colour from a pale yellow to a very dark brown (Walker, 2006). Major workers have distinctive large heads and comprise about 1 percent

² *P. longicornis* has been detected in baseline surveys on Barrow Island.

of the population. The ant usually does not bite and does not sting (Warner and Scheffrahn, 2007).

P. megacephala may occur and be found foraging in warm temperate, tropical and subtropical areas in a great variety of habitats, including gardens, houses and natural environments. Nests may be found in exposed soil with loose soil around the centre, or under cover and in rotting wood, often around drippers or in the bottom of pot plants as they are water-loving (CSIRO, 2003). Nests may appear similar to termite residues (Warner and Scheffrahn, 2007).

The behaviour of *P. megacephala* in a monsoonal tropical rainforest in northern Australia in 1996 was described by Hoffmann et al. (1999), who demonstrated that the abundance of both native ants and other invertebrates was inversely proportional to the abundance of *P. megacephala*. This ant spread in a rainforest by 12 m average in the wet season and contracted by 7 m average in the dry season (Hoffmann et al., 1999). *P. megacephala* is more likely to invade closed vegetation formations (Hoffmann et al., 1999; Hoffmann and Parr, 2007; Majer, 1985), but may also invade open vegetation formations (Wetterer, 2007).

4. Info-gap decision theory – Précis

Decision-making may be viewed as choosing a decision q from a set Q of possible decisions that will enhance a reward. This reward may be monetary profit, utility, probability of success, or some scale for grading the “successfulness” of the outcome. However, more often than not, the reward must take into account factors which are unknown to the decision maker, for instance the values of parameters, or the relation between the decision q and the reward (the structure of the model itself). We will refer to these parameters and models as the state of the world. We shall denote the reward function as $R(q, u)$, where $u \in U$ is the state of the world, and U the set of possible states of the world. We may have a best estimate \tilde{u} of the state of the world, but our uncertainty around the true state of the world is non-probabilistic. That is, we simply do not know a probability distribution of u , or if we have an estimated probability distribution with no confidence in its accuracy. In many cases the uncertainty is also unbounded, meaning that we do not know the worst case for u .

Info-gap models are used to quantify non-probabilistic “true” (Knightian) uncertainty (Ben-Haim, 2006). An info-gap model is an unbounded family of nested sets, $u(\alpha, \tilde{u})$. At any level of uncertainty α , a non-negative scalar, the set $u(\alpha, \tilde{u})$ contains possible realizations of u . As the horizon of uncertainty α gets larger, the sets become more inclusive. The info-gap model expresses the decision maker’s beliefs about uncertain variation of u around \tilde{u} .

Info-gap models obey two axioms:

$$\text{Contraction: } u(0, \tilde{u}) = \{\tilde{u}\} \quad (1)$$

$$\text{Nesting: } \alpha < \alpha' \text{ implies } u(\alpha, \tilde{u}) \subseteq u(\alpha', \tilde{u}) \quad (2)$$

The contraction axiom asserts that \tilde{u} is the only possibility when there is no uncertainty ($\alpha = 0$). The nesting axiom asserts that the range of possible realizations increases as the level of uncertainty increases.

Suppose the decision maker wishes the reward to be large, and has some notion of a critical value r_c . This means that a reward higher than r_c would be appreciated, but a reward smaller than r_c cannot be tolerated.

The *robustness function* $\hat{\alpha}(q, r_c)$ is the greatest horizon of uncertainty α which still guarantees a reward no smaller than r_c :

$$\hat{\alpha}(q, r_c) = \max \left\{ \alpha : \left(\min_{u \in u(\alpha, \tilde{u})} R(q, u) \right) \geq r_c \right\} \quad (3)$$

The inner minimum states that for any realization u within the given horizon of uncertainty the reward is no less than r_c . *Robust-satisficing* decision-making maximizes the robustness and satisfies the reward at the value r_c , without specifying a limit on the level of uncertainty:

$$\hat{q} = \operatorname{argmax}_{q \in Q} \hat{\alpha}(q, r_c) \quad (4)$$

A similar concept may be used to measure *opportuneness*. Here we define a critical value r_w , which represents a better result than r_c . Since $r_w > r_c$, worse outcomes than r_w may be accepted, but an outcome of r_w is considered a windfall success. The opportuneness of an alternative q is the minimal amount of change to the model that will yield a result at least as good as r_w :

$$\hat{\beta}(q, r_w) = \min \left\{ \alpha : \left(\max_{u \in u(\alpha, \tilde{u})} R(q, u) \right) \geq r_w \right\} \quad (5)$$

The inner maximum states that for some realization u within the given horizon of uncertainty the reward is no less than r_c . Note, that for robustness *bigger is better*, meaning that if $\hat{\alpha}(q, r_c) > \hat{\alpha}(q', r_c)$, then q is more robust than q' in respect of r_c . However, for opportuneness *smaller is better*, meaning that if $\hat{\beta}(q, r_w) < \hat{\beta}(q', r_w)$, then q is more opportune than q' in respect of r_w .

It can readily be shown that there is an inherent trade-off between robustness (or opportuneness) and reward. Since robustness is the *immunity to failure*, the robustness decreases as the performance requirement r_c becomes more demanding (decreases). Similarly, opportuneness is the *immunity to success*, and thus the opportuneness function $\hat{\beta}(q, r_w)$ increases (becomes worse, because $\beta(q, r_w)$ is the immunity to windfall) as the windfall criterion r_w becomes more demanding (decreases). Another immediate result is that the robustness of the *optimal* result—the maximal reward under our best estimate \tilde{u} —is not robust. In fact, it has zero robustness, meaning that a slight deviation from our estimation \tilde{u} may prevent us from meeting the requirement r_c . Note that the optimal result also has zero opportuneness, since it is achieved without deviating from the estimate. This is illustrated in Section 6.

Info-gap theory has been applied extensively in ecological analysis and planning, in conservation management (Regan et al., 2005; Burgman et al., 2005; Crone et al., 2007; Nicholson and Possingham, 2007), managing environmental risks (Levy et al., 2000), economic analysis (Knoke, 2008), and even detection for invasive species (Moffitt et al., 2008).

5. Probability of missed detection

The goal of the surveillance system is to detect an incursion of an NIS “early enough” (see above). We will denote the critical time by t . Note that the critical time may be taxon specific, and that critical time may be driven by a spatial distribution of establishment for some taxa which is not considered explicitly here.

The surveillance system is based on two methods for detecting an incursive NIS discussed in Section 2.2: surveillance and observation. Under surveillance, we count both structured and un-structured sampling. We will denote the probability of the taxon to be detected in a (given) random sample by p if the NIS is present within the active area of the surveillance system. Note that a single sample may be comprised of multiple elements, such as pitfall traps, visual surveys, and more. If random sampling occurs at

a rate of θ samples per time unit, then the probability that the taxon will be *undetected* for a critical time (given its incursion of the island and assuming independence) is:

$$(1 - p)^{\theta t} \tag{6}$$

It is quite straightforward that p increases as the number of invading individuals increases. Since we are aiming for the detection of a rare event of invasion, we will refer to the probability of detecting a minimal “critical” population (such as a single colony).

By observation we refer to “incidental surveillance”. The worker population of Barrow Island may be used as sensors, while going about their normal routine: should they encounter an NIS, and if they identify it as such, they will be encouraged to report the incident. These encounters have a random nature. We will therefore assume that incidents of reporting an incursive NIS by the working population of Barrow Island behaves like a Poisson process, with some characteristic rate of reporting λ (which may be taxon dependent), hence the time between events is assumed to have an exponential distribution. For example, if there are expected to be seven events of detection per year (given the presence of the NIS), the rate would be $\lambda = 7$, and the probability of one or more incidental detection in the duration of a single year would be $1 - e^{-7}$. The workers are not present throughout the entire island: only a small portion of the island contains workers on a regular basis. The area occupied by the workers may or may not be suitable for incursion by the NIS. We represent this by a probability, z . Let z denote the probability that the taxon will establish in the area occupied by the workers, if the taxon actually reaches the site. The probability of the taxon to go *undetected* by the working population for a critical time (given its incursion of the island) is therefore:

$$ze^{-\lambda t} + (1 - z) \tag{7}$$

Notice that if part of the surveillance system is ongoing trapping (stationary traps which are placed throughout the entire critical time period), the probability of detection (or missed detection) for such traps is better explained by the incidental observation model than the random sampling model. That is, there is a certain probability that the taxon is within the effective radius of the trap, and if so the probability of detecting it increases with time.

The overall probability of an incursive NIS to go undetected for a critical time is obtained by multiplying Eq. (6) by Eq. (7):

$$\bar{P}_d(p, \lambda, z, \theta) = z(1 - p)^{\theta t} e^{-\lambda t} + (1 - z)(1 - p)^{\theta t} \tag{8}$$

Eqs. (6)–(8) are all probabilities conditioned on the presence of the NIS. We do not know the prior probability of any given taxon actually being present. Consequently, we cannot calculate the total probability of any incursive taxon to go undetected for a critical time.

The above model can be used to choose between strategies of surveillance. By strategies, we will refer to the setting of the sampling rate, θ , the probability of detection per sample, p , and the rate of detection by the worker population, λ . All three parameters can be either directly chosen or indirectly influenced by the decision maker. For instance, increasing the number of SSCs (or their quality) may increase p . Awareness programs for the working population, or other strategies such as the use of packaging color that will contrast expected NIS, may increase λ . It is reasonable to assume that z is uninfluenced by the surveillance strategy.

This model is quite simplistic. It does not take into account, for instance, probable nodes of arrival or habitat preference of the invading taxon. Rather, it assumes that the planners of the

surveillance system incorporate the above information into the parameters of the model, especially p and z .

6. Info-gap analysis

The conditional probability of missed detection described in Eq. (8) could be used for choosing a strategy if we could be certain of its parameters. Unfortunately, most of the parameters are based on informed expert judgement, as is typical of any surveillance program which is designed to detect taxa which have not been previously detected, and which have a very rare likelihood of being present. Since it is hard to predict the “invasion pattern” of an incursive NIS, it is hard to estimate the probability p of detecting such a taxon in an SSC. It is even harder to estimate the detection rate λ by the working population: this rate is a function of the rate of encounters between the NIS and the working population, the probability that a worker who encounters an NIS will notice and recognize it, and the probability that the worker is motivated to report the encounter. The detection model may be probabilistic, but the uncertainties regarding its parameters do not have a probabilistic nature. We will use info-gap analysis to estimate “how wrong can we be?”, or how wrong can the estimates be, and still allow us to obtain an acceptable probability of detection.

6.1. Info-gap model of uncertainty

We will use an info-gap model to describe these non-probabilistic uncertainties. Due to severe lack of information, we will use a very simple info-gap model: a fractional error info-gap model. Let \tilde{p} , $\tilde{\lambda}$ and \tilde{z} denote our best estimates for the probabilities of detection by sampling, p , the rate of detection by the working population, λ , and the probability of establishment within the working area, z , for *P. megacephala*. Then the info-gap model (Ben-Haim, 2006) may be defined as the following unbounded family of nested sets of values of p , λ and z :

$$u(\alpha, \tilde{p}, \tilde{\lambda}, \tilde{z}) = \left\{ p, \lambda, z : \begin{cases} \left| \frac{p - \tilde{p}}{\tilde{p}} \right| \leq \alpha, & 0 \leq p \leq 1 \\ \frac{\lambda - \tilde{\lambda}}{\tilde{\lambda}} \leq \alpha, & \lambda \geq 0 \\ \left| \frac{z - \tilde{z}}{\tilde{z}} \right| \leq \alpha, & 0 \leq z \leq 1 \end{cases} \right\}, \quad \alpha \geq 0 \tag{9}$$

This info-gap model is quite uninformative and represents great uncertainty. Specifically, it assumes that all the uncertain parameters are “just as uncertain”. For instance, a 10% estimation error to the probability of detection by sampling corresponds to the same horizon of uncertainty as a 10% estimation error to the rate of detection by the working population. In cases where more information is available (for instance, standard deviation of the different parameters from several other sites), it is possible to calibrate the info-gap model accordingly. Since we do not incorporate experts’ estimates of the uncertainty weights, the above info-gap model represents an uncertainty which is greater than the actual uncertainty.

6.2. Robustness and opportuneness

Suppose the surveillance system designer is facing the following criterion: an incursive NIS must be detected (within the critical time for that taxon) with probability of at least π_c . This criterion can be used to formulate the robustness function defined in Eq. (3), which is the greatest horizon of uncertainty, α , up to which the probability of detection exceeds the critical threshold, π_c :

$$\hat{\alpha}(\theta, \tilde{p}, \tilde{\lambda}, \tilde{z}, \pi_c) = \max \left\{ \alpha : \left(\min_{p, \lambda, z \in u(\alpha, \tilde{p}, \tilde{\lambda}, \tilde{z})} [1 - \bar{P}_d(p, \lambda, z, \theta)] \right) \geq \pi_c \right\} = \max \{ \alpha : \mu(\alpha) \geq \pi_c \} \quad (10)$$

which defines the function $\mu(\alpha)$. An explicit expression is:

$$\mu(\alpha) = 1 - (1 - \alpha)\tilde{z} \left(1 - (1 - \alpha)\tilde{p} \right)^{\theta t} e^{-(1-\alpha)\tilde{\lambda}t} - \left(1 - (1 - \alpha)\tilde{z} \right) \times \left(1 - (1 - \alpha)\tilde{p} \right)^{\theta t} \quad (11)$$

This definition of $\mu(\alpha)$ assumes that $\alpha \leq 1$. When $\alpha > 1$, we define $\mu(\alpha) = 0$. A derivation of $\mu(\alpha)$ can be found in an Appendix.

An opportuneness function, as defined in Eq. (5), can be formulated in a similar fashion. Here, the criterion is an “optimistic” probability of detection π_w . We refer to π_w as optimistic if it is larger than π_c and hence considered by the decision maker as a windfall. Not reaching this probability of detection would not be considered a failure. The opportuneness function is therefore:

$$\hat{\beta}(\theta, \tilde{p}, \tilde{\lambda}, \tilde{z}, \pi_w) = \min \left\{ \alpha : \left(\max_{p, \lambda, z \in u(\tilde{p}, \tilde{\lambda}, \tilde{z})} [1 - \bar{P}_d(p, \lambda, z, \theta)] \right) \geq \pi_w \right\} = \min \{ \alpha : \eta(\alpha) \geq \pi_w \} \quad (12)$$

which defines $\eta(\alpha)$ whose value is:

$$\eta(\alpha) = 1 - h \left((1 + \alpha)\tilde{z} \right) h \left(1 - (1 + \alpha)\tilde{p} \right)^{\theta t} e^{-(1+\alpha)\tilde{\lambda}t} - h \left(1 - (1 + \alpha)\tilde{z} \right) h \left(1 - (1 + \alpha)\tilde{p} \right)^{\theta t} \quad (13)$$

$$h(x) = \begin{cases} 0, & \text{if } x < 0 \\ 1, & \text{if } x > 1 \\ x, & \text{if } 0 \leq x \leq 1 \end{cases} \quad (14)$$

A derivation of $\mu(\alpha)$ can be found in an Appendix.

6.3. Numerical example

Our numerical example focuses on *P. megacephala*, and is based on Whittle et al. (2008). We will assume that there is only a single colony of the species present. This is expected to be the case soon after a single introduction event.

6.3.1. Model parameters

Our model contains six types of “standard” surveillance system components (SSCs). These are described in Table 1. Each SSC type is characterized by a footprint area, and probability of detection when the NIS is within the footprint of the SSC. The fraction of sample frame refers to the fraction of the risk regions (defined shortly) which are contained within the SSC’s footprint. Thus, for instance, a single pitfall trap has a footprint of 80 m², which covers a fraction of 0.0002 of the risk region, and a probability of 0.4 of detecting an NIS if it is present within the footprint. Hence the probability that a single pitfall trap will detect the NIS if it is present in the risk region is 0.0002 × 0.4 = 0.00008.

The SSCs are not used to survey the entire area of the island. A risk analysis (Whittle et al., 2008), taking into account the preferred habitat of the *P. megacephala* and the locations where the species could be introduced to the island through project activities, mapped the island and identified several risk regions. Taking a practical view that sampling is only of practical benefit in regions with

Table 1

Surveillance system components (SSCs) characteristics. Pitfall traps are passive, relying on ants falling in as they forage.

SSC	Footprint area (m ²)	Fraction of sample frame within footprint	Probability of detection
Pitfall trap	80	0.00020	0.4
Barrier pitfall trap	40	0.00010	0.5
Food baits – carb/oil/protein	100	0.00024	0.6
Vacuuming of shrubs	120	0.00029	0.9
Litter extraction	5	0.00001	1
Visual survey	5000	0.01225	0.7 ^a

With no attractant their footprint is limited to the foraging range from the ant nest. A barrier trap is a type of pitfall trap, placed at the boundary fence, hence its footprint is a semicircle. The fence will guide animals in, so footprint is half that of a pitfall trap, but the probability of detection is increased slightly. Food baits require separate baits for each of three food types, placed together in one petri dish. Visual survey is undertaken by a biologist in a strip 100 m long and 5–10 m wide. (Whittle et al., 2008).

^a Whittle et al. (2008) distinguish between two areas: area of medium risk (Z2) and area of medium-high to high risk (Z1). The probability of detection by visual survey is 0.9 for area Z1, and 0.1 for Z2. Following Whittle et al. (2008), we assume similar proportions of visual survey for both areas, and therefore the (geometric) average probability of detection per survey is 0.7.

medium-high to high invasion risk, the total area of the medium-high to high risk regions is approximately 0.4 km² (Fig. 1). Now, for example, the probability of detecting a single colony using a single randomly located pitfall is $(80/400,000) \times 0.4 = 8 \times 10^{-5}$, where 80 m² is the footprint area of the pitfall (Table 1), 400,000 is the total area of the risk zones, and 0.4 is the probability of detection when the colony is within the footprint of the pitfall (Table 1). This probability includes both the probability that the colony would be within the footprint of the pitfall, and the probability of detection.

The “non-standard” SSC is the incidental detection by the workers. The “footprint” of this SSC is the intersection between the area where workers are present, and the area in which the *P. megacephala* is likely to establish. Whittle et al. (2008) estimate the area where the workers are present to be approximately 0.08 km². This is a very conservative assumption, since the area of the accommodation camp in itself is approximately 0.06 km², and most of its area is within the risk zone (see Fig. 1). We will assume that the area where the workers are present is twice this estimate. Thus our estimate of the probability that the NIS will establish itself in the workers’ area is $\tilde{z} = 0.16/0.4 = 0.4$, where the numerator is the area where workers are present and the denominator is the total area of the risk zones. We estimate that it would take approximately six months for a single colony to reach a size that is noticeable by workers. After that, the expected time for detection is estimated as three months ($\tilde{\lambda} = 12/3 = 4$ detection events expected per year). However, now the probability for incidental detection over a period t , given establishment, is calculated by:

$$1 - \left(z e^{-\lambda(t-(6/12))} + (1 - z) \right) \quad (15)$$

Under the above assumptions, the probability of incidental detection by the workers within critical time is approximately 0.35.

The critical time for detection is any time before eradication would result in unacceptable impacts to the native flora and fauna. We assume that the critical time for *P. megacephala* is one year (that is, $t = 1$).

We will compare two strategies of detection, where the aim of the analysis is to choose between them. The first strategy, denoted by s_1 , is based on the allocation of SSCs suggested in Whittle et al. (2008). The number of units of each type in a single “sample” is detailed in Table 2. We assume here that the rate of sampling for this strategy is $\theta = 8$. That is, the sampling detailed in Table 2 is repeated eight times per year. The combination of the SSCs within a single sample (Table 2) and the (overall) probability of detection

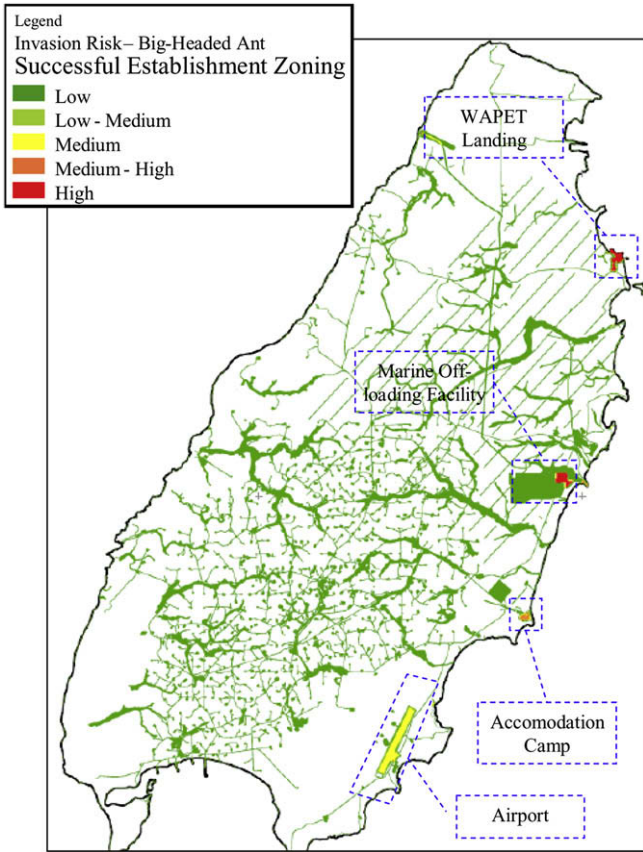


Fig. 1. Risk map for the invasion of *P. megacephala* (Whittle et al., 2008).

by a single SSC (Table 1) gives an estimate for the probability of detection by a single sample, $\bar{p} = 0.22^3$.

The second strategy gives more weight to incidental detection by workers. Firstly, this strategy, denoted by s_2 , assumes that $\bar{z} = 0.8$. This assumption may be the result of operative actions intended to increase the alertness of the workers for the presence of *P. megacephala* in the area where the ant could have been released, or from workers periodically scanning the surrounding environment. We will also assume that awareness seminars and motivational initiatives increase the rate of incidental detection to $\tilde{\lambda} = 8$. Now the probability of an incidental detection by a worker is approximately 0.8. This increase in the surveillance abilities of the workers allows a substantial decrease in the frequency of the structured sampling. We assume a decrease in the frequency, setting $\theta = 4$.

The above assumptions enable us to estimate the probability of detecting a colony in the critical period of time, which is 1 minus the probability of missed detection, \bar{P}_d , defined in Eq. (8). We will denote this probability by $\tilde{\pi}$. Under the first strategy, s_1 , we have a best estimate of $\tilde{\pi} = 0.91$. Under the second strategy, s_2 , we have $\tilde{\pi} = 0.92$. Remember that these are the nominal estimates, that is, the estimates under the nominal model, so they are subject to severe uncertainty.

³ The estimate of the probability of detection is calculated by $\bar{p} = 1 - \prod_i (1 - \tilde{f}_i \tilde{p}_i)$, where \tilde{f}_i is the estimated fraction of the sample frame within the footprint for the i th SSC, and \tilde{p}_i is the estimated probability of detection for the same SSC.

Table 2
Number of SSC units per sample

SSC	Units
Pitfall trap	26
Barrier pitfall trap	20
Baits/Lures	29
Vacuuming shrubs	14
Litter extraction	15
Visual survey	28 ^a

^a Includes surveys in both zones Z1 and Z2.

6.3.2. Results

Fig. 2 presents the robustness and opportuneness curves, under the above assumptions. We will show how comparison of these two robustness curves helps the planner choose between the two corresponding surveillance strategies, which entail different allocations of resources between casual (worker) surveillance and professional surveillance. The horizontal axis is the critical probability of detecting the invasion within the critical time, π_c . Higher values of the detection probability represent a better result (or a higher requirement).

The robustness curves illustrate the immunity of the two alternatives to failure due to errors. Therefore, bigger robustness is

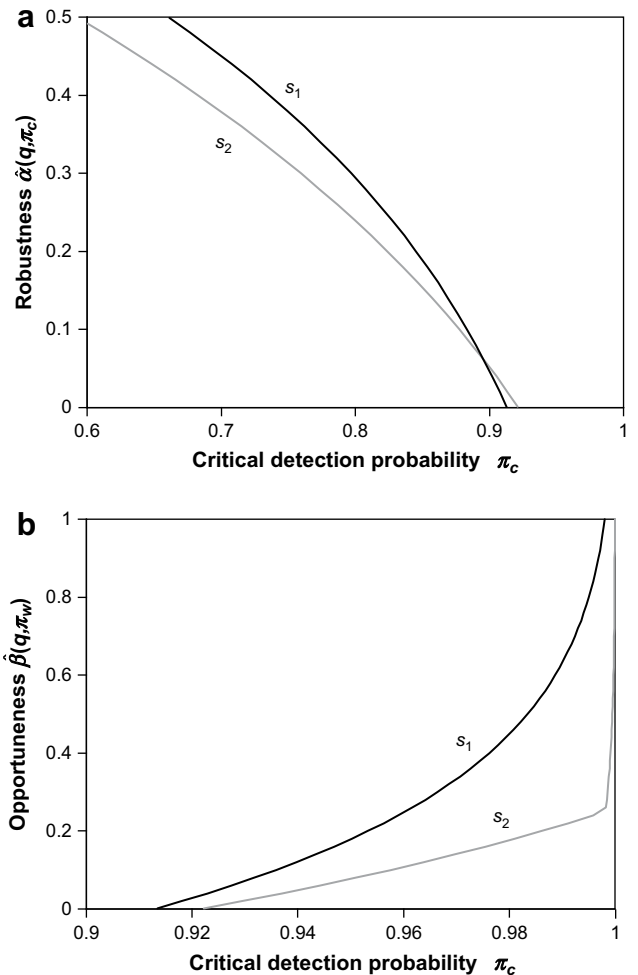


Fig. 2. Robustness and opportuneness curves for the two strategies of the numerical example.

preferred. From Fig. 2a it is evident that neither of the alternatives is strictly more robust: the robustness curves cross one another. While for critical detection probabilities greater than 0.9 strategy s_2 is more robust, strategy s_1 is more robust for critical detection probabilities smaller than 0.9. This means that the choice of a robust-satisficing decision maker depends on the choice of critical detection probability: while an “optimistic” decision maker who sets a critical detection probability higher than 0.9 would prefer strategy s_2 , a more pessimistic (or realistic) decision maker with a critical probability smaller than 0.9 would prefer s_1 .

The absolute value of the robustness is interesting by itself. For both strategies, the robustness is very low for reasonable critical detection probabilities. For instance, for critical detection of 0.85, the robustness is only 0.15. This means that if the estimates are prone to errors of up to 15%, the strategies cannot guarantee a detection probability of more than 85%. If the estimated parameters are highly uncertain, this robustness may be deemed insufficient by the decision maker. In this case, the decision maker has three alternatives. The first is to choose lower (less demanding) critical detection probabilities. This may be undesirable, since the aim of the surveillance system is to detect incursive NIS with high probabilities. A second alternative is to try and diminish the uncertainty. This may be done by conducting surveys and experiments, or by comparing results from similar sites. And finally, the decision maker can view both strategies as being unacceptable, and request that a third, more robust, strategy be devised. Examples of such strategies include increasing the number or range of traps, or increasing or improving the effectiveness of worker surveillance.

Another straightforward result is that, for both strategies, the robustness of the nominal estimates is zero. This is since the slightest deviation from the assumptions of the model may cause a failure. This result is typical of all info-gap analyses.

The opportuneness measures the immunity to windfall success. Therefore, we would prefer smaller values of the opportuneness function. Fig. 2b shows that strategy s_2 has better (lower) opportuneness than strategy s_1 , regardless of the windfall detection probability. However, decision makers tend to be risk averse, so it is unlikely that the superior opportuneness of strategy s_2 will be a dominant factor. The opportuneness may be factored into the decision when the robustness of the two strategies is close, that is, for $\pi_c \approx 0.9$.

Note that the kink in the opportuneness curve occurs for strategy s_2 when $\hat{\beta}(s_2, \pi_w) = 0.25$. This is since $\tilde{z} = 0.8$, and from Eq. (9) it is evident that when the horizon of uncertainty α is greater than 0.25, the most optimistic value of z remains 1, and does not increase with α . Therefore, a greater windfalling error in the other uncertain parameters is needed to get the same increase in the most optimistic probability of detection. Thus, the slope of the opportuneness curve increases dramatically.

7. Conclusion

Detecting the incursion of an NIS is a critical component in different quarantine contexts. In addition to protocols to prevent such incursions, we would like to identify an incursion in a reasonable time, which will make feasible eradication without significant environmental consequences. Since no surveillance system can guarantee such identification, we settle for high probabilities of detection. The probability of detection for a specific surveillance system is often based on the characteristics of both the system and the expected incursive NIS. However, severe uncertainties cause the calculations of detection probabilities to be based on rough estimates. Lack of comparable data, lack of information regarding the NIS, and even uncertainty

regarding which NIS is of interest, all contribute to the severe uncertainty surrounding the probabilities of detection.

We focused on the problem of choosing between surveillance strategies in light of the great uncertainty accompanying estimates of the surveillance system and incursive NIS characteristics. The implication of a missed detection, along with the inherent uncertainties, causes one to favor a strategy which will be robust to these uncertainties.

We presented a simple model which combines the contribution of incidental detection by workers, along with more structured sampling. This model enables us to estimate the effect of training and motivation on the probability of detecting an incursive NIS. That is, we have compared alternative strategies with the aim of prioritizing them.

This paper has developed a robust-satisficing methodology for choosing between strategies of surveillance when the interaction of the incursive NIS with the surveillance system is highly uncertain. We have used info-gap theory for satisficing (not minimizing) the probability of detection. We have demonstrated the trade-off between robustness to uncertainty on the one hand, and probability of detection. Attempting to maximize the probability of detection has zero robustness to uncertainty in the interaction of the incursive NIS with the surveillance system. Since this interaction is highly uncertain, low robustness is undesirable. Greater robustness is obtained only by aiming at a detection probability which is lower than the estimated maximum. The robust-satisficing strategy chooses a surveillance strategy which guarantees an acceptable detection probability (which usually will not be the estimated maximum), for the largest possible range of error in the estimated parameters of interaction. The robustness analysis enables the decision maker to evaluate surveillance strategies in terms of whether they promise adequate improvements in detection probabilities, at plausible levels of immunity to error in the interaction parameters. Combined with a search over the possible set of strategies—strategies including, for instance, the spatial spreading of given SSCs—this method enables to optimize, robustness-wise, the strategy chosen.

We have presented an empirical example based on the detection of incursive *P. megacephala* in Barrow Island. We demonstrated that the robustness curves of different strategies may intersect, indicating that none of the strategies is strictly more robust. Rather, in this situation the more robust (and therefore, preferred) strategy is a function of the critical value chosen. We also demonstrated how robustness curves may be used to determine if surveillance strategies are “robust enough”, and that even if the estimated probability of detection has a considerable factor of safety over a critical probability of detection, it does not necessarily mean that the strategy is robust enough.

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Appendix A. Mathematical details

We will now show how to derive $\mu(\alpha)$ and $\eta(\alpha)$ of Eqs. (11) and (13), respectively.

Consider Eq. (8). Since $0 \leq z \leq 1$, $\bar{P}_d(p, \lambda, z, \theta)$ is monotonic decreasing in p and in λ . Since $\lambda \geq 0$, $(1-p)^{\theta t} e^{-\lambda t} \leq (1-p)^{\theta t}$, and therefore $\bar{P}_d(p, \lambda, z, \theta)$ is also monotonic decreasing in z .

From Eq. (9) we have:

$$\min\{p \in u(\alpha, \tilde{p}, \tilde{\lambda}, \tilde{z})\} = \begin{cases} (1 - \alpha)\tilde{p}, & \alpha \leq 1 \\ 0, & \alpha > 1 \end{cases} \quad (16)$$

$$\max\{p \in u(\alpha, \tilde{p}, \tilde{\lambda}, \tilde{z})\} = \begin{cases} (1 + \alpha)\tilde{p}, & \alpha \leq (1 - \tilde{p})/\tilde{p} \\ 1, & \alpha > (1 - \tilde{p})/\tilde{p} \end{cases} \quad (17)$$

The same holds for z. For λ :

$$\max\{\lambda \in u(\alpha, \tilde{p}, \tilde{\lambda}, \tilde{z})\} = (1 + \alpha)\tilde{\lambda} \quad (18)$$

From the above it follows that when $\alpha \leq 1$, we have:

$$\begin{aligned} \mu(\alpha) &= \min_{p, \lambda, z \in u(\alpha, \tilde{p}, \tilde{\lambda}, \tilde{z})} [1 - \bar{P}_d(p, \lambda, z, \theta)] \\ &= 1 - \bar{P}_d((1 - \alpha)\tilde{p}, (1 - \alpha)\tilde{\lambda}, (1 - \alpha)\tilde{z}, \theta) \\ &= 1 - (1 - \alpha)\tilde{z} \left(1 - (1 - \alpha)\tilde{p}\right)^{\theta t} e^{-(1 - \alpha)\tilde{\lambda} t} \\ &\quad - \left(1 - (1 - \alpha)\tilde{z}\right) \left(1 - (1 - \alpha)\tilde{p}\right)^{\theta t} \end{aligned} \quad (19)$$

When $\alpha > 1$ we have:

$$\mu(\alpha) = 1 - \bar{P}_d(0, 0, 0, \theta) = 0 \quad (20)$$

Similarly, we have:

$$\begin{aligned} \eta(\alpha) &= \max_{p, \lambda, z \in u(\alpha, \tilde{p}, \tilde{\lambda}, \tilde{z})} [1 - \bar{P}_d(p, \lambda, z, \theta)] \\ &= 1 - \bar{P}_d(h((1 + \alpha)\tilde{p}), h((1 + \alpha)\tilde{\lambda}), h((1 + \alpha)\tilde{z}), \theta) \\ &= 1 - h((1 + \alpha)\tilde{z}) h(1 - (1 + \alpha)\tilde{p})^{\theta t} e^{-(1 + \alpha)\tilde{\lambda} t} \\ &\quad - h(1 - (1 + \alpha)\tilde{z}) h(1 - (1 + \alpha)\tilde{p})^{\theta t} \end{aligned} \quad (21)$$

References

ABC News, 2008. Queenslanders enlisted as fire ant bounty hunters. ABC News. Australian Broadcasting Corporation. <http://www.abc.net.au/news/stories/2008/04/29/2230486.htm> (last updated: April 29, 2008).

Areal, F.J., Touza, J., Macleod, A., Dehnen-Schmutz, K., Perrings, C., Palmieri, M.G., Spence, N.J., 2008. Integrating drivers influencing the detection of plant pests carried in the international cut flower trade. *Journal of Environmental Management* 89, 300–307.

Ben-Haim, Y., 2006. In: *Info-Gap Theory: Decisions Under Severe Uncertainty*, second ed. Academic Press, London.

Burbridge, A.A., Morris, K., 2002. Introduced mammal eradications for nature conservation on Western Australian islands: a review. In: Veitch, C., Clout, M. (Eds.), *Turning the Tide: The Eradication of Invasive Species*. International Union for the Conservation of Nature. Invasive Species Specialist Group, Gland, Switzerland, pp. 64–70.

Burgman, M.A., Lindenmayer, D.B., Elith, J., 2005. Managing landscapes for conservation under uncertainty. *Ecology* 86, 2007–2017.

Crone, E.E., Pickering, D., Schultz, C.B., 2007. Can captive rearing promote recovery of endangered butterflies? An assessment in the face of uncertainty. *Biological Conservation* 139, 103–112.

CSIRO, 2003. *The Big Headed Ant (Pheidole megacephala)*. CSIRO Centre for Arid Zone Research, Alice Springs, NT, p. 2.

Delaney, D.G., Sperling, C.D., Adams, C.S., Leung, B., 2008. Marine invasive species: validation of citizen science and implications for national monitoring networks. *Biological Invasions* 10, 117–128.

Hoffmann, B.D., Andersen, A.N., Hill, G.J.E., 1999. Impact of an introduced ant on native rain forest invertebrates: *Pheidole megacephala* in monsoonal Australia. *Oecologia* 120, 595–604.

Hoffmann, B.D., Parr, C.L., 2007. An invasion revisited: the African big-headed ant (*Pheidole megacephala*) in northern Australia. *Biological Invasions*. Available from: <<http://www.springerlink.com/content/a06103j220n232g000/>>.

Holway, D.A., Lach, L., Suarez, A.V., Tsutsui, N.D., Case, T.J., 2002. The causes and consequences of ant invasions. *Annual Review of Ecology and Systematics* 33, 181–233.

Knoke, T., 2008. Mixed forests and finance – methodological approaches. *Ecological Economics* 65, 590–601.

Levy, J.K., Hipel, K.W., Kilgour, D.M., 2000. Using environmental indicators to quantify the robustness of policy alternatives to uncertainty. *Ecological Modelling* 130, 79–86.

Majer, J.D., 1985. Recolonization by ants of rehabilitated mineral sand mines on North Stradbroke Island, Queensland, with particular reference to seed removal. *Australian Journal of Ecology* 10, 31–48.

Majer, J.D., Callan, S., Graham, R., 2006. Report on the Preliminary Survey of Terrestrial Invertebrates for the Proposed Gorgon Gas Processing Facility on Barrow Island. Curtin University of Technology, for Chevron Australia Pty. Ltd.

Majer, J.D., Callan, S., Graham, R., 2007. Report on the Baseline Survey of Terrestrial Invertebrates and Non-indigenous Species for the Gorgon Gas Development on Barrow Island – Revision A. Curtin University of Technology, for Chevron Australia Pty. Ltd.

Moffitt, L.J., Stranlund, J.K., Osteen, C.D., 2008. Robust detection protocols for uncertain introductions of invasive species. *Journal of Environmental Management* 89, 293–299.

Morris, K.D., 2002. The eradication of the black rat (*Rattus rattus*) on Barrow and adjacent islands off the northwest coast of Western Australia. In: Veitch, C., Clout, M. (Eds.), *Turning the Tide: The Eradication of Invasive Species*. International Union for the Conservation of Nature. Invasive Species Specialist Group, Gland, Switzerland, pp. 219–225.

Nicholson, E., Possingham, H.P., 2007. Making conservation decisions under uncertainty for the persistence of multiple species. *Ecological Applications* 17, 251–265.

PIAG, 2004. Pacific ant protection plan. Proposal prepared for the Pacific Plant Protection Organisation and Regional Technical Meeting for Plant Protection. Pacific Invasive Ant Group (PIAG) – IUCN/SSC Invasive Species Specialist Group (ISSG).

Ranta, J.O., Hovi, T., Arjas, E., 2001. Poliovirus surveillance by examining sewage water specimens: studies on detection probability using simulation models. *Risk Analysis* 21, 1087–1096.

Regan, H.M., Ben-Haim, Y., Langford, B., Wilson, W.G., Lundberg, P., Andelman, S.J., Burgman, M.A., 2005. Robust decision making under severe uncertainty for conservation management. *Ecological Applications* 15, 1471–1477.

Walker, K., 2006. Coastal Brown-ant, *Pheidole megacephala* (Fabricius). Available from: Pest and Disease Image Library <http://www.padil.gov.au/viewPestDiagnosticImages.aspx?id=645>.

Warner, J., Scheffrahn, R.H., 2007. Featured creatures: bigheaded ant, *Pheidole megacephala*. Available from: In: Fasulo, T. (Ed.), *Featured Creatures*. University of Florida http://creatures.ifas.ufl.edu/urban/ants/bigheaded_ant.htm.

Wetterer, J.K., 2007. Biology and Impacts of Pacific Island Invasive Species. 3. The African big-headed ant, *Pheidole megacephala* (Hymenoptera: Formicidae). *Pacific Science* 61, 437–456.

Whittle, P., Barrett, S., Mengersen, K., Hardie, D., Nietrzeba, A., Stoklosa, R., Majer, J., 2008. Design of Detection Program for Non-Indigenous Species of Terrestrial Invertebrates on Barrow Island: Proof of Concept Using Exemplar Species The Big-Headed Ant, *Pheidole megacephala*. Queensland University of Technology, and CRC for National Plant Biosecurity, for Chevron Australia Pty. Ltd.