ACTIVE ADAPTIVE MANAGEMENT IN INSECT PEST AND WEED CONTROL: INTERVENTION WITH A PLAN FOR LEARNING

Katriona Shea,[1,5,6] Hugh P. Possingham,[2,5] William W. Murdoch,[3,5] and Rick Roush[4]

[1]*Department of Biology, 208 Mueller Laboratory, Pennsylvania State University, University Park, Pennsylvania 16802 USA*
[2]*Departments of Zoology and Entomology and Mathematics, University of Queensland, St. Lucia QLD 4072, Australia*
[3]*Department of Ecology, Evolution and Marine Biology, University of California, Santa Barbara, California 93106 USA*
[4]*CRC for Weed Management Systems, University of Adelaide, SA 5005, Australia*
[5]*National Center for Ecological Analysis and Synthesis (NCEAS), 735 State Street, Suite 300,
Santa Barbara, California 93101-3351 USA*

Abstract. A major problem in insect pest and weed management is uncertainty. Managers are faced with three main types of uncertainty: uncertainty about biological and environmental processes, and observational uncertainty. Active adaptive management (AAM) is management with a deliberate plan for learning about the managed system, so that management can be improved in the face of uncertainty. We discuss the potential benefits of applying AAM to insect pest and weed control with reference to a number of examples. We first address the possible uses for AAM in biological control, with particular reference to agent selection and release. We also propose applying AAM methods to resistance management and to spatial strategies for pest control. We conclude with an overview of AAM, a discussion of some of the potential limitations to its use in pest management, and the possibilities for increased implementation of AAM in the future.

Key words: active adaptive management; applied ecology; biocontrol agent selection; biological control; experimental management; pest control; release strategies; resistance management; spatial management; weed control.

INTRODUCTION

Despite centuries of effort, we are no closer to winning the war on insect pests and weeds. Even as we bring some pests under control, others develop resistance to our efforts and new problem species arise (Gould 1991). The costs to agriculture, forestry, pasture and cropping industries, and natural ecosystems are huge. For example, the United States Department of Agriculture (USDA) estimates that native pests infest several million acres of forests in the United States alone (USDA Forest Service 2000). The estimated cost of weeds to Australia is over $3 billion per annum (Groves 1998). In the United States, Pimentel et al. (2000) have estimated losses of over $54 billion per annum to non-native insects and plants. The cost of non-native invasive species in terms of lost biodiversity is significant and rapidly increasing (Williamson 1996).

A major reason for the failure of scientists, farmers, managers, and politicians worldwide to control these pests is an obvious one: managing pests in an uncertain world is hard to do. Uncertainty rears its head in a variety of ways. For example, a farmer using a pesticide to manage the pests on a crop has to contend with uncertainty about how many pests are actually present, how they will respond to different levels of pesticide, and how unpredictable weather changes the effectiveness of pesticide application. Thus uncertainty can be

classified into three main types: uncertainty about the observations or measurements we make on the managed system (observation uncertainty), uncertainty about the underlying behavior of the system (model uncertainty), and uncertainty about the environment (process uncertainty) (Hilborn and Mangel 1997 and Parma et al. 1998).

Managers have a variety of responses to such uncertainty (Walker 1998). A few choose to ignore their uncertainty; they choose a management strategy, and stick to it no matter what happens. Luckily such nonresponsive management is rare. The next type of manager tends to be reactive. This ''fire-fighting'' approach involves reacting to events as they occur; for example, spraying pests only when outbreaks occur without adopting a preventative approach. The third type of manager uses a passive adaptive management approach. Such managers do learn from the results of previous management attempts, and attempt to predict the consequences of different strategies based on their experiences. This type of management is the most common. The final form of management, active adaptive management, includes the benefits of passive adaptive management with the addition of an actual plan for learning about the managed system, in order to improve the management at future times. This paper focuses on the latter two forms of management, and in particular the benefits offered by moving from a passive to an active adaptive management philosophy in pest control.

Adaptive Management

Passive adaptive management has long been a part of pest control. Observant humans have achieved improvements in their pest management practices in spite of the complexity of nature. However, there have been few deliberate plans to accelerate learning. Over the last century there has been an increased use of experiments in developing pest management practice, but experiments have generally been limited to relatively simple problems. Many of the remaining questions for pest management are simply seen as too complex given the resources available.

Active adaptive management recognizes that we are uncertain about our observations, biotic processes, and the future, and encourages us to learn about the system, bearing the uncertainty in mind and given other constraints. In this way, it forces us to acknowledge all forms of uncertainty. Parma et al. (1998) define active adaptive management (AAM) as "ecological intervention with a plan for learning about the system." In other words AAM involves "learning by doing and doing to learn" or "experimental management," here there is a deliberate, pro-active, plan to accelerate learning, and our decisions are modified as we learn about the system we are managing.

Learning about a managed system is only useful in cases where management decisions are repeated. If a management decision is to be made only once, then there is no practical value to learning. However, this is patently not the case in most areas of pest control; farmers, foresters, and other pest managers make decisions again and again, both temporally and spatially. The discipline of pest management provides an ideal arena for the use of active adaptive management and we believe that taking an AAM approach provides a way to reduce uncertainty and maximize net benefit. In this paper, we discuss four areas where pest management problems exist and where active adaptive management offers possible contributions to their resolution. We present these examples in a comparative fashion, to show the improvements that can be gained from using AAM rather than more conventional management approaches. The four examples are: biological control agent selection, release strategies for biocontrol agents, resistance management, and spatial aspects of pest management. We follow this with a review of the process of using AAM from the very beginning of a management program. We then address some potential limitations of AAM, before concluding with a discussion of how the shift to AAM at institutional and local scales might be encouraged and achieved.

Selection of Agents for Biological Control

While the release of one agent may seem isolated and irrelevant to the release of another, there is nevertheless scope for an adaptive management approach to the release of different agents for different pest species. Pest managers are likely to resist the idea of experimenting with biological control agents, yet the 100-yr history of classical biological control is one of uncontrolled and unmonitored experiments on a grand scale. For example, 52 species of predators and parasitoids were released in California over a period of 70 yr to control red scale in citrus (Clausen 1978). All except eight species failed to establish. It seems that in most places *Aphytis melinus* is now the main control agent (DeBach et al. 1971). But in any grove, several species usually are present. Could one or more of these 52 species have provided better control, earlier, in the absence of competitors that were present when they were released? Perhaps some of the releases that failed would have succeeded in the absence of earlier establishments. More importantly, surely we could have learned more systematically over the last 100 yr about what characterizes a successful agent? Unfortunately, it is still common practice to release agents, none evaluated for its probable population effects in a rigorous way, simply as they become available, on the assumption that they will sort themselves out to provide optimal control (McFadyen 1998). As recommended by Ehler (1990), we need to move from such "empirical" approaches to a more predictive mode of operation.

One possible source of a guiding framework for more predictive agent choice is ecological theory. The search for common "characteristics" of successful biocontrol agents has been going on for many years based on prior experience (e.g., Beddington et al. 1978, Waage and Mills 1992, Waage and Barlow 1993) and there may be common rules that would emerge with closer inspection (Shea et al. 2000). Ecological theory can also be used to address several strategic questions that face managers. For example, which is the best single species to release if we are going to release only one and have a choice among potential agents? Releasing only one species might minimize costs or the risk of non-target attacks, or the risk that agents might interact to reduce efficacy. Ecological theory indicates that the best single agent to release, all else being equal, produces the most female offspring per attacked pest individual (Murdoch and Briggs 1996). Furthermore, the best agent attacks the pest insect stage that is earliest in the life cycle, is vulnerable for the longest period, and suffers least attack from other natural enemies (Murdoch and Briggs 1996). Should we release more than one species? Which combination of species should we release if we are considering releasing more than one? A model by Briggs (1993) shows that a combination of agent species can provide worse control than one species on its own. Ecological theory suggests that the best combinations of control agents are those that exclude an agent that is good at competing with other agents yet decreases the degree of control. For example, a species that beats its competitors by suppressing a stage of the pest that does little damage (e.g., the egg stage), while

inducing increases in other more damaging stages, would be a poor choice.

The potential benefits of using active adaptive management (AAM) for biological control agent selection can be most easily illustrated by an example. Consider a newly arrived orchard pest that has been deemed a suitable target for biological control. Studies in its home range indicate that it has a suite of natural enemies, three of which pass stringent host specificity and other tests and are recommended for release. An "empirical" approach (Ehler 1990) would involve releasing all three, with the hope that they would provide some measure of control. A predictive approach, time permitting, would involve studies of the three species and their life histories, possibly development of models, and use of previously developed ecological insight to choose one or two to release. In the event that the resultant control is ineffectual, there still remains the option of releasing the other agents, with the hope that control might improve.

An AAM approach could involve aspects of both these approaches. Replicated sets of orchards, separated in space, could receive single, paired or all three species, or just the species combinations that are predicted as most likely to succeed. In this way, we can use ecological theory to predict the best combinations, but we do not need to assume that the theory is correct: the purpose of AAM is to improve any initial framework in the light of experience. Monitoring of pest densities over only two or so years would answer the question of which species or combinations of species provide better control. Combinations that failed to provide some measure of control could be abandoned, while those combinations that appeared most successful could be evaluated more closely in further trials, perhaps under different conditions. Over time, the three species would likely become mixed; however, this would have been the case anyway. The value is that we will have learned much more about our system; for example, which agents to augment and which to discourage. Furthermore, the results of repeated experiments of this type should lead to general rules of thumb for choosing between one and various combinations of multiple agents. Thus using a deliberate adaptive management approach and testing releases (that are going to happen anyway) in a rigorous experimental design provides invaluable information for managers.

RELEASE STRATEGIES FOR BIOLOGICAL CONTROL AGENTS

In biological control, an initial goal is to establish the agent efficiently and effectively in as many sites as possible. A fast and broad spread of the agent will bring rapid economic gains, whereas a slow spread may waste some of the growth potential of the biocontrol agent through intraspecific competition. The formal objective might be to minimize the time it takes to establish a certain number of agent populations, or max-imize the number of secure populations established within a finite time frame or budget. Given this objective, one of the decisions a release manager needs to make is this: given a fixed number of agents for release, how big should each release group (inoculum) be to maximize benefit? We will call the combination of number of inocula and their size the "release strategy." For example, given 1000 individuals, two possible release strategies would be ten groups of 100 individuals or twenty groups of 50 individuals each.

Shea and Possingham (2000) use a formal decision-making approach (Possingham 1997, Shea et al. 1998) to find the optimal release strategy. They show that the most efficient release strategy is relatively independent of many of the assumptions, relationships, and parameters in their model. For example, the growth and extinction probabilities of different populations make little difference to the optimal strategy. However, the relationship between the size of an inoculum and the probability that it establishes a population, has a major impact on the optimal strategy. Shea and Possingham (2000) found that a detailed knowledge of the shape of this relationship is essential for finding the most efficient release strategy—yet how can it be determined? What release strategy will simultaneously achieve the stated goal and improve our knowledge so that future efficiency can be increased?

At the start of a release strategy we might, either through knowledge of other releases of similar species under similar circumstances or through a model of the impact of release numbers on colonization success (e.g., Hopper and Roush 1993), be able to define a priori an inoculum size/inoculum success relationship. An optimal strategy could then be determined without assuming that this information is perfect. Within the active adaptive management (AAM) framework the best strategy would be different. Instead, we would choose a mixed strategy that gives a reasonable chance of successful establishment in at least one site but also refines our estimate of the inoculum size/inoculum success relationship. For example, if again there are 1000 insects, we might release six groups of 100 and eight groups of 50 insects. Such an approach fits within a Bayesian framework (Hilborn and Mangel 1997). The initial estimate of the success relationship is chosen to be the mean of some prior probability density function. In the event that we have little knowledge, our prior expectation might even be that the success of each release size is equally likely. The releases are then carried out and the results used to update the probability density function. The new best estimate can then be used to determine the best strategy as above, or to form the basis for further iterations, to try to focus in more closely on the optimal strategy.

A field analogy of this strategy has recently been used successfully (Memmott et al. 1998). Gorse thrips (*Sericothrips staphylinus*) was released as a biological control agent for gorse (*Ulex europaeus*) in New Zea-

land. Five release sizes, ranging from 10 to 810 (in multiples of three) thrips per bush were used at a gorse invasion front, and bushes were sampled for presence of the agent a year later. More of the smaller releases went extinct, but the larger three release sizes (90, 270, 810) had similar (low) extinction probabilities: the probability of establishment curve was approaching saturation. Nine times as many releases can be implemented with release sizes of 90 as with release sizes of 810, so Memmott et al. (1998) concluded that optimal release sizes would be less than 100 individuals per release. Given that the common strategy at the time was to release 1000 individuals per release site, this constituted an order of magnitude improvement in overall establishment rate of this agent. Only the active plan for learning made this improvement possible.

Such empirical and theoretical work, while it has been applied to the initial release stage of biological control programs, also has implications for the redistribution stage. This is the stage at which agents are being released all over the affected landscape in order to control the pest over as wide an area as quickly as possible. Again there is a constraint on the number of insects available and the money and time available for redistribution. While the initial investigations will have focused on the optimal number of insects to release in order to ensure a successful establishment of the agent at secure sites in the new country, the redistribution phase is concerned with the optimal release sizes for different circumstances; e.g., for different climates, or for different levels of pest infestation, or for different ecosystem types. The optimal release size for most situations in the initial establishment phase may not always be optimal in different parts of the country (e.g., lower net replacement rates for the biocontrol agent at sites with lower pest density or higher predation on the biocontrol agents themselves might imply the need for higher release rates; Hopper and Roush 1993). All these management possibilities need to be tested anyway; learning can be optimized at little or no extra cost, using an AAM approach (Freckleton 2000).

RESISTANCE MANAGEMENT

The broad scale use of chemical pesticides is often seen as a simple and reliable solution to pest control problems. Pesticide applications are made frequently in space and time, and some of the earliest uses of decision theory in pest management addressed the optimal timing and level of application of chemicals (Shoemaker 1982). Such relatively simple decisions are prime contenders for an extension to active adaptive management, especially in situations when their use is to be incorporated into an integrated pest management strategy. The development of pesticide resistance (see e.g., Gould 1991), however, provides managers with a moving target and makes a virtual necessity of the AAM approach (Roush and Powles 1996).

Chemical resistance management is perhaps most ad-

vanced for insects and mites, but is being developed increasingly for nematode parasites of animals, fungal diseases, and weeds. Most advances in field practice would be best described as a result of passive adaptive management. For insects, certain pesticides, and the way in which they were used, were observed to be associated with the rapid evolution of resistance. The use of relatively persistent pesticides, frequent insecticide use, and thorough coverage of the pest population (with few escapees) were generally found to produce rapid resistance, leading to recommendations to avoid persistent or frequent applications, and to treat only at those times, and on those portions of the crop, where the pests reached economically significant densities. This allows more individuals to escape from pesticidal selection. Areas or host plants where part of the population remains unexposed have been recognized as a key factor in delaying resistance to insecticides, and have come to be called refuges.

Small-scale laboratory and field experiments have been undertaken to explore resistance management since the 1940s and since the early 1970s there has been increasing use of models to evaluate resistance management options for insects (Tabashnik 1990; e.g., Gardner et al. 1998, Roush 1998). Such studies are echoed in the weed resistance management literature (Duke 1996, Gressel et al. 1996, Powles et al. 1997, Gressel 1999). However, given the complexities of population dynamics, pest movement, and the number of generations over which resistance typically evolves (10–30 generations; Mangel and Plant 1983, Plant et al. 1985, May and Dobson 1986), it has been very difficult to actually test models of resistance management strategies in the field.

For this reason, resistance management is an ideal candidate for AAM. For example, consider the need for refuges in insecticidal transgenic crops that use genes from *Bacillus thuringiensis* (Bt). Because the crops with Bt genes are genetically modified, the potential for resistance to these crops has attracted greater public attention than any other resistance management problem in history (Roush 1997). How big should refuges be, and are they optimal in size to restrain both resistance and pest population growth (Roush 1998)? Should they be contiguous or fragmented in spatial arrangement? Though models may allow some ranking of different strategies, in the absence of data on initial frequencies of resistance alleles, and more importantly, the survival on Bt transgenic plants of individuals heterozygous for one resistance allele, it is impossible to predict accurately whether any given strategy will last long enough, or to be certain that the best arrangement of refuges has been chosen. Rather than recommending a single ''best bet'' strategy for refuges, an AAM approach might involve the implementation of a series of alternative refuge arrangements and sizes in different areas. Monitoring for the appearance of resistance (frequency of observed alleles or resistant genotypes)

would provide information on the arrangements of refuges that best delay its evolution, of use in both this and other systems (Shea et al. 2000), and for future insecticidal toxins. The overall management program could then be altered as such new data become available (Andow and Hutchison 1998). Thus in this case the AAM approach would have the double benefit of narrowing in on the best strategy for a given time, but also being able to track evolutionary changes in the system, and adapt management practices to the changes relatively swiftly.

Spatial Strategies for Pest Control

Invading species, once they have established locally, undergo range expansion in their new environment. Range expansion can occur through two main modes, largely depending on the life history of the species in question (Shigesada and Kawasaki 1997). At one extreme, species spread in a locally contagious fashion, offspring settle near their parents and the invasion front can be characterized by wave-like spread. At the other extreme, offspring are dispersed long distances, and new source populations are set up far from the original population. Most species lie more centrally on this spectrum, combining local spread with occasional long distance dispersal events.

Whether the scale of the invasion relates to a new pest on a farm, or a new invasive species in a country, an important concern is the most appropriate management strategy to curtail spatial spread. Given constraints on time and funding, not all populations of the new pest can be accorded the same attention. Is it better to use those limited resources to attack isolated new populations or to attack core populations?

J. Moore and H. P. Possingham (*unpublished manuscript*) use control theory to determine the best spatial management strategy for invasive weeds with different life histories. They show that for a weed with a high colonization rate from core populations, like the bird-dispersed bridal creeper (*Myrsiphyllum asparagoides*), attacking the core (where there is a higher concentration of fruit where birds may aggregate) may be more successful overall than attacking isolated populations. For a species that colonizes in a spatially contagious fashion, spreading by mechanical means (e.g., *Watsonia bulbilifera*), attacking isolated populations appears to be more effective. However, the predicted best strategy does depend on the numbers of primary and satellite populations and is sensitive to variation in parameters that we often know little about. For example, our prospects for measuring parameters like probability and range of long-distance dispersal are poor. While the model may provide heuristic guidelines, there is clearly room here for an experimental approach to management.

A conventional management approach would be to use the best available information to develop a ''best-bet'' strategy for management of populations of the species in question. For example, based on the model above, resources would always be directed at core populations of bridal creeper, and small isolated populations would be ignored, unless they too became large or dense. There would be no scope to learn whether an alternative approach might be more effective.

An active adaptive management approach would involve testing both of the weed control strategies. The same total resources (time and money) would be used to treat either core or satellite populations in different areas (replicated invasions). A priori, we might still expect one strategy to be better. This approach would allow us to confirm or refute our prejudices, and importantly, would allow us to learn how much better the best strategy is. Careful monitoring could in turn lead to an unexpected refining of strategy that the original model might not directly address. For example, rate of spread might in fact be minimized by adopting a mixed strategy; expending most resources on core infestations, while also attacking the most distant and isolated satellites.

Using AAM appears to be a logical approach; however, as in all empirical ecology for management problems, there will be problems of replication in time and space. What is best in one place at one time may not be best in all places at all times. To test the two strategies properly, we would need several independent replicates of weed metapopulations. Spatial differences (e.g., in soil type, topography) will reduce the scope for suitable replication. The conditions in which weeds invade also show enormous temporal variation. Aside from normal year-to-year variability in climate there are the vast changes in the anthropogenic drivers that affect natural ecosystems. For example, the use of the bush land, the use of neighboring land, the mix of vertebrates and invertebrates, and other weeds are all changing rapidly and what is the best strategy today may not be so tomorrow. Nevertheless, these are commonly faced problems in larger scale applied ecology, and we are more likely to learn when changes in strategy are warranted using an adaptive rather than a fixed management approach.

Active Adaptive Management: An Overview

In the four examples explored here, we discussed AAM with reference to the benefit it would provide above and beyond a standard management approach. For managers interested in using AAM from the inception of a management project, we now outline the appropriate steps to follow to incorporate a deliberate plan for learning in the management strategy (Walters 1986, Parma et al. 1998).

Define the management objective.—What exactly are we trying to achieve? Are there multiple objectives that have to be ranked or weighted?

Describe what is known about the system.—Assemble all the relevant information that is known about the system. In some cases, this information may be incor-

porated into mathematical models; in other cases, verbal or conceptual models may be more appropriate.

Acknowledge uncertainties and formulate credible alternative model versions.—Sometimes very little is known about the system, especially in the case of a novel pest. Alternative scenarios (e.g., density dependence occurs in the juvenile or in the adult stages) may have very different management implications, yet be indistinguishable with current knowledge. These different possibilities should be given consideration, even if some seem more likely than others. Our belief in the possible scenarios will be updated as a result of the AAM approach.

Decide which system variables to measure.—This decision may be relatively straightforward. For example, in the case of choice of biocontrol agents or release strategies for agents, pest density seems the obvious measure. In the case of resistance management, however, should we monitor frequency of resistance alleles, or perhaps pest mortality rates?

Design alternative management options.—What are the possible management strategies we could use? Some strategies may be chosen because they correspond to current best practice, but others will be included if they seem likely to accelerate the rate of learning. For example, when trying to find optimal release strategies for biological control agents, we might make releases over a range around the estimated best strategy, but nevertheless focus more closely on release sizes near that putative best strategy, to learn quickly how to fine tune our estimate.

Predict outcomes.—What do we expect will happen as a result of those management options? The same management action may be predicted to generate different outcomes by the different models. These differences may allow us to distinguish between the models.

Try the management.—Management strategies should be implemented with as many replicates as feasible, given constraints. While it is still important to concentrate on management strategies that, a priori, appear most likely to succeed, focus should also be on treatments where most can be learned; for example, on management strategies that may allow us to distinguish between underlying models.

Monitor outcomes.—Failing to monitor management is the equivalent of failing to collect the results after doing an experiment. Only by comparing observed with predicted results of management can we learn to what degree our understanding of the system is correct.

Reassess and improve management in light of the new information gained.—The entire AAM process is iterative. Updating includes even the process of defining the management objective. For example, the initial objective may be to ''control pest densities,'' but new results might suggest that a better goal is to ''cause pest extinction'' or ''maintain pest densities below the economic threshold.'' Once we have learned that something does not work, or that something works unexpectedly well, we can update our understanding of the system itself, and the management we apply in the next iteration should reflect this improved knowledge. If our understanding of how the system works can be expressed as alternative process-based and/or statistical models, then our relative beliefs in these alternative models can be revised using ideas from Bayesian updating (Hilborn and Mangel 1997).

LIMITATIONS OF THE AAM APPROACH

There are a variety of issues that concern the adoption of AAM, and a number of limitations to the method, both fundamental and surmountable, depending on the circumstance.

Frequency of decision making

As stated in the Introduction, AAM improves with a higher number of replicates of decision-making events in space and time: it is not so useful when making only one decision, or if monitoring and assessment are costly. Given that most pest control decisions are repeated again and again, this is not often a limitation. Nevertheless, it is important to remember two things when making such decisions. First, AAM may be costly in the short term, but generate great savings in the longer term. It can be thought of as an investment in knowledge—much like paying university fees. Second, what may only be a single decision from one point of view is nevertheless a commonly made decision on a larger scale, from which someone would be wise to learn, as in our example for choice of biocontrol agents.

Importance of monitoring

Monitoring is clearly a vital part of an adaptive management approach. If you don't know the results of your experimental management how can you assess what has and has not worked, and improve your knowledge of the system and its operation? If you fail to monitor you will fail to learn about your system, even though the information is there for the taking.

There are two aspects to the issue of monitoring: the importance of monitoring, and the additional cost of monitoring in adaptive management, given that you believe monitoring is important anyway. Usually it is not much more costly to monitor an adaptively managed system than any other type of managed system, but often no monitoring is carried out in the first place, so the perceived increase is large.

Long response time

No matter how often decisions are made, or how much monitoring is carried out, there is no opportunity for learning in situations where the response time of the system is much longer than the frequency at which decisions are made. For example, the effects of large-scale environmental manipulations to control pests may not be evident for decades after their implementation; there is no information available with which to improve

decisions until the effects are known. Given the realities of economic discounting (see *Discounting and the value of information*) this long time frame may inhibit an early investment in experimentation.

Limitations to the competing model approach for process uncertainty

In situations where there is great uncertainty about the processes underlying our working models, we may have a problem learning much information, as we may have asked the wrong question. For example, we may develop several competing models, yet completely fail to incorporate an important process because we just don't realize it is going on. This is especially likely if there are underlying trends, such as global warming or the unexpected development of resistance to a chemical control. Underlying trends may mean the model premise is changing so that we are chasing a moving target: learning is easiest in a stable system. This, however, is a limit of any management approach, not just AAM. At least AAM forces us to recognize it as a possibility, and potentially will allow us to track the trend and modify management accordingly.

The costs of adaptive management

Adaptive management does involve some costs, though the amount depends on the system and the management options. There is a cost associated with the assembly of the system information (the development of conceptual or mathematical models of the system), and the synthesis and analysis of information. There may be a cost to designing well-replicated and controlled experiments, and some management options may be more expensive than the ''best bet/ status quo'' options. Monitoring is also cited as a major cost (see *Importance of monitoring.*)

However, adaptive management need not be expensive. If you are planning to do something anyway, often it is not much more costly to use a varied ''experimental'' approach than to do the same thing everywhere. This is certainly true, for example, of redistribution efforts for biocontrol agents. It would also be true for examining the effects of varying pesticide spraying rates in greenhouses.

In some situations, there is a need for a common effort to be made, which may increase perceived costs to an active adaptive manager. The question arises of how to compensate the managers who are trying out strategies that are, at least initially, expected to do worse. Such ethical issues mirror those faced by medical researchers with new medication for a life-threatening illness. Which patients get the control treatment in medical trials when this may be a death sentence? The advantage of using AAM in such cases is that as soon as there is convincing evidence that a management strategy is failing, management can be modified in response to the new information. It is less obvious what to do when some managers chose to opt out. For ex-

ample, adaptive resistance management would benefit the whole community, but usually with at least a minor cost to individual users. If a farmer makes efforts to avoid the development of resistance, but the neighboring farmers do not, the farmer may suffer increased resistance anyway. This will deter adoption of AAM practices. This is a ''Tragedy of the Commons''(Hardin 1968) reflected in other areas of common resource management; e.g., human disease vaccination programs, where high population immunity rates benefit even those who have not incurred the small risks associated with vaccination, leading to individuals opting out and thus increasing the chance of an outbreak.

Similarly, it is often the case that adaptive management incurs a high short-term cost for a long-term gain. In forestry and fisheries the costs incurred by an adaptive manager may not lead to benefits for a very long time. With large discounting rates this can make AAM uneconomic. However, in pest control far shorter life histories are involved (e.g., in univoltine or bivoltine insect pests, annual crops, annual or short-lived perennial weeds, fungi). This often means that short-term costs and long-term gains both occur on a time scale that would be perceived as ''short'' by a manager, and the eventual gain is more likely to accrue to the same manager that incurs the initial cost. If this is so it seems even more surprising that adaptive management is so little used in pest control.

The problem of irreversibility and the precautionary principle

Associated with costs are risks, and some risks may be felt to be too high, especially when a decision is irreversible. For example, the decision to release a new biocontrol agent is irreversible. It is hard to remove an already released insect if it is not successful, or even if it is harmful in some way. The best and most successful competitor may be the worst control agent, and prevent the establishment of a better agent. The non-target effects of already released biocontrol agents are nearly impossible to undo. In these situations the precautionary principle may limit the decisions being made. The precautionary principle involves avoiding management measures that could have major and unfavorable impacts (Parma et al. 1998).

Discounting and the value of information

When costs and benefits are subject to discounting (Clark 1990), then the advantages of taking an AAM approach are diminished. Discounting will favor the here and now and strategies that are our ''best bet,'' while learning can only enhance future benefits, which themselves are discounted. In the extreme case of very high discounting, there is no point in learning at all.

In a similar vein, if the system we are studying changes so that what we know now may not be true in the future, information gained about best management may decay in value as conditions change. In such sit-

uations learning is also not favored. This can be thought of as information discounting. While these temporal changes may at first seem daunting, we need to remember that active adaptive management is not an excuse to gather further information and delay management. The management is proceeding anyway within the framework of an experiment. So in a sense we lose very little by taking an AAM approach.

Institutional restrictions

Institutional problems or resistance to change may make it very hard to adopt or implement an adaptive approach (Walters 1986). Organizations and individuals may be loath to admit to mistakes or errors of judgment, or to alter previously advocated management approaches. This is what Walters (1997) calls "self-interest in research and management organizations."

Effecting a Shift to AAM: Research, Policy, Education, and Adoption

Active adaptive management can be used as a valuable, if not vital, approach at multiple scales of organization, from the individual farmer, through state and government organizations, to multinational pest control efforts. Individual farms can be managed adaptively, for example for threshold levels of pests in greenhouse crops. Local government and community organizations can use AAM, as can state agencies, for example to manage biological control agent redistribution efforts. Furthermore, such agencies are in the best position to learn from previous efforts by comparing successes across species, as well as for a particular species. National organizations, such as CSIRO in Australia or the United States Department of Agriculture in the United States, have the scope to use AAM for larger scale problems such as resistance management. There is also hope for multinational AAM efforts, for example, for release strategies and choice of biocontrol agents for globally problematic pests, and in general policy.

Effecting an increase in the use of AAM approaches will require change at all these levels. The work we have presented here is largely targeted at the larger scales of organization, in an attempt to inform the research and policy focus of national and international agencies, which in turn affect smaller, local agencies. However, while some areas, like biocontrol agent selection, fall exclusively under the aegis of larger bodies, the other three examples we have used can involve management both at large, and at far smaller scales. For example, our discussion of spatial strategies for pest control can apply equally well to an agency developing large scale control policy for an invading weed of national importance and to a farmer trying to decide how to control a weed spreading on a farm. To reach managers who operate at smaller scales, especially at the level of the individual farm or farmer, an education component to policy must also be developed.

Many farmers do manage adaptively, though often this is more passive than active, and options may not be well replicated. Our experience is that active adaptive management has intuitive appeal, and such cases seem especially ripe for conversion to more active management. Thus this shift to AAM could be in part effected using existing extension and outreach programs. For example, many integrated pest management programs already stress monitoring and passive learning, so the further shift to active learning would not require the development of new educational structures. Unfortunately most farmers are very risk averse. The experimental nature of AAM may make it appear riskier than using a single recommended "optimal" or "best bet" management approach, though often it is not because it spreads risk. What is needed is convincing evidence that any short-term costs will be fully allayed in the longer term. Concerns could be surmounted by using a finer scale of AAM than at the research stage; for example, a relatively slight variation on practices that research has shown to be good management practice, allowing fine tuning to particular farm conditions. Similarly, local evidence that AAM really does help track and even prevent shifts in the managed system (e.g., increased resistance), so that farmers can respond more quickly to changes, would also improve adoption rates. Thus adoption would be greatly facilitated by the establishment of learning collaboratives (Thrupp 1996, Röling and Wagemakers 1998, Jordan et al. 2000). Learning collaboratives are groups of farmers and other interested people that share information and collaborate on learning about common pest problems. Such collaboratives might also offer a way to distribute the costs and financial burden of risks associated with treatments having poorer expectation of success.

In this paper, we have focused primarily on the uses of adaptive management for insect pest and weed management. Surprisingly, adaptive management is far more commonly used in areas, like fisheries (Walters 1986, National Research Council 1998) and whole ecosystems (Holling 1978, Walters 1997), where it is far more difficult to get information about the system and its response to management actions. In population management, adaptive management approaches have been developed mainly for harvested systems (Parma et al. 1988). For example, the hunting of North American waterfowl is managed using an active adaptive approach (Nichols et al. 1995, Williams et al. 1999). Adaptive management is also being used for the control of vertebrate pests. For example, in Australia adaptive management is being used or considered for the control of feral pigs (Choquenot et al. 1996) and carp (Bomford and Tilzey 1996), among other species (Caughley and Sinclair 1994). Of all population management systems, pest control is arguably the easiest to monitor, yet active adaptive management has rarely been used. This is, in part, because the higher frequency of repetition of management actions has led to improvement by trial and error, so that there are more generic rules of thumb

than for other managed systems. Here we have focused on four examples where AAM could generate additional benefits, but there are many more. Almost any time a pest management decision is made there is scope for the use of an active adaptive management approach to the problem. Spatial and temporal replication of all facets of pest control is huge, and we hope that managers will seize the opportunity to improve their understanding, and hence the management of their systems, by adopting an active adaptive management framework.

LITERATURE CITED

Andow, D. A., and W. D. Hutchison. 1998. Bt corn resistance management. Pages 19–66 *in* M. Mellon and J. Rissler, editors. Now or never: serious new plans to save a natural pest control. Union of Concerned Scientists, Cambridge, Massachusetts, USA.

Beddington, J. R., C. A. Free, and J. H. Lawton. 1978. Characteristics of successful natural enemies in models of biological control of insect pests. Nature **273**:513–579.

Bomford, M., and R. Tilzey. 1996. Pest management principles for European carp. Pages 9–20 *in* J. Roberts and R. Tilzey, editors. Controlling carp: exploring the options for Australia. CSIRO Land and Water, Griffith, Australia.

Briggs, C. J. 1993. Competition among parasitoid species on a stage-structured host and its effect on host suppression. American Naturalist **141**:372–397.

Caughley, G., and A. R. E. Sinclair. 1994. Wildlife ecology and management. Blackwell Science, Oxford, UK.

Choquenot, D., J. McIlroy, and T. Korn. 1996. Managing vertebrate pests: feral pigs. Australian Government Publishing Service, Canberra, Australia.

Clark, C. W. 1990. Mathematical bioeconomics. Second edition. John Wiley and Sons, New York, New York, USA.

Clausen, C. P., editor. 1978. Introduced parasites and predators of arthropod pests and weeds: a world review. Agricultural Research Service, U. S. Department of Agriculture, Washington, D.C., USA.

DeBach, P., D. Rosen, and C. E. Kennett. 1971. Biological control of coccids by introduced natural enemies. Pages 165–194 *in* C. B. Huffaker, editor. Biological control. Plenum Press, New York, New York, USA.

Duke, S. O. 1996. Herbicide-resistant crops: agricultural, environmental, economic, regulatory, and technical aspects. CRC Press, Boca Raton, Florida, USA.

Ehler, L. E. 1990. Introduction strategies in biological control of insects. Pages 111–134 *in* M. Mackauer, L. E. Ehler, and J. Roland, editors. Critical issues biological control. Intercept, Andover, Hants, UK.

Freckleton, R. P. 2000. Biological control as a learning process. Trends in Ecology and Evolution **15**:263–264.

Gardner, S. N., J. Gressel, and M. Mangel. 1998. A revolving dose strategy to delay the evolution of both quantitative vs. major monogene resistances to pesticides and drugs. International Journal of Pest Management **44**:161–180.

Gould, F. 1991. The evolutionary potential of crop pests. American Scientist **79**:496–507.

Gressel, J. 1999. Tandem constructs: preventing the rise of superweeds. Trends in Biotechnology **17**:361–366.

Gressel, J., L. Segel, and J. K. Ransom. 1996. Managing the delay of evolution of herbicide resistance in parasitic weeds. International Journal of Pest Management **42**:113–129.

Groves, R. H., editor. 1998. Recent incursions of weeds to Australia 1971–1995. CRC for weed management systems. Technical series Number 3. CRC for Weed Management Systems, Adelaide, Australia.

Hardin, G. 1968. The tragedy of the commons. Science **162**:1243–1247.

Hilborn, R., and M. Mangel. 1997. The ecological detective: confronting models with data. Princeton University Press, Princeton, New Jersey, USA.

Holling, C. S. 1978. Adaptive environmental assessment and management. John Wiley and Sons, London, UK.

Hopper, K. R., and R. T. Roush. 1993. Mate finding, dispersal, number released, and the success of biological control introductions. Ecological Entomology **18**:321–331.

Jordan, N., S. White, J. Gunsolus, R. Becker, and S. Damme. 2000. Learning groups developing collaborative learning methods for diversified, site-specific weed management: a case study from Minnesota, USA. Pages 85–95 *in* M. Cerf, D. Gibbon, B. Hubert, R. Ison, J. Jiggins, M. Paine, J. Proost, and N. Röling, editors. Cow up a tree: knowing and learning for change in agriculture. INRA, Paris, France.

Mangel, M., and R. E. Plant. 1983. Multiseasonal management of an agricultural pest. I. Development of the theory. Ecological Modelling **20**:1–19.

May, R. M., and A. P. Dobson. 1986. Population dynamics and the rate of evolution of pesticide resistance. Pages 170–193 *in* Committee on strategies for the management of pesticide resistant pest populations, Board on Agriculture, National Research Council, editors. Pesticide resistance: strategies and tactics to management. National Academy Press, Washington, D.C., USA.

McFadyen, R. E. C. 1998. Biological control of weeds. Annual Review of Entomology **43**:369–393.

Memmott, J., S. V. Fowler, and R. L. Hill. 1998. The effect of release size on the probability of establishment of biological control agents: gorse thrips (*Sericothrips staphylinus*) released against gorse (*Ulex europaeus*) in New Zealand. Biocontrol Science and Technology **8**:103–115.

Murdoch, W. W., and C. J. Briggs. 1996. Theory for biological control: recent developments. Ecology **77**:2001–2013.

National Research Council. 1998. Improving fish stock assessments. National Academy Press, Washington, D.C., USA.

Nichols, J. D., F. A. Johnson, and B. K. Williams. 1995. Managing North American waterfowl in the face of uncertainty. Annual Review of Ecology and Systematics **26**:177–199.

Parma, A. M., P. Amarasekare, M. Mangel, J. Moore, W. W. Murdoch, E. Noonburg, M. A. Pascual, H. P. Possingham, K. Shea, C. Wilcox, and D. Yu. 1998. What can adaptive management do for our fish, forests, food and biodiversity? Integrative Biology, Issues, News, and Reviews **1**:16–26.

Pimentel, D., L. Lach, R. Zuniga, and D. Morrison. 2000.

Environmental and economic costs of nonindigenous species in the United States. BioScience **50**:53–64.

Plant, R. E., M. Mangel, and L. E. Flynn. 1985. Multiseasonal management of an agricultural pest. II. The economic optimization problem. Journal of Environmental Economics and Management **12**:45–61.

Possingham, H. P. 1997. State-dependent decision analysis for conservation biology. Pages 289–304 *in* S. T. A. Pickett, R. S. Ostfeld, M. S. Shachak, and G. E. Likens, editors. The ecological basis of conservation: heterogeneity, ecosystems and biodiversity. Chapman and Hall, New York, New York, USA.

Powles, S. B., C. Preston, I. B. Bryan, and A. R. Jutsum. 1997. Herbicide resistance: impact and management. Academic Press, San Diego, California, USA.

Röling, N. G., and M. A. E. Wagemakers, editors. 1998. Facilitating sustainable agriculture. Cambridge University Press, Cambridge, UK.

Roush, R. T. 1997. Bt-transgenic crops: just another pretty insecticide or a chance for a new start in resistance management? Pesticide Science **51**:328–334.

Roush, R. T. 1998. Two-toxin strategies for management of insecticidal transgenic crops: can pyramiding succeed where pesticide mixtures have not? Philosophical Transactions of the Royal Society of London series B **353**:1777–1786.

Roush, R. T., and S. B. Powles. 1996. Pesticide resistance: why be concerned? Pages 3–16 *in* G. W. Bourdot and D. M. Suckling, editors. Pesticide resistance: prevention and management. New Zealand Plant Protection Society, Rotorua, New Zealand.

Shea, K., P. Amarasekare, P. Kareiva, M. Mangel, J. Moore, W. W. Murdoch, E. Noonburg, A. M. Parma, M. A. Pascual, H. P. Possingham, C. Wilcox, and D. Yu. 1998. Management of populations in conservation, harvesting and control. Trends in Ecology and Evolution **13**:371–375.

Shea, K., and H. P. Possingham. 2000. Optimal release strategies for biological control agents: an application of stochastic dynamic programming to population management. Journal of Applied Ecology **37**:77–86.

Shea, K., P. H. Thrall, and J. J. Burdon. 2000. An integrated approach to management in epidemiology and pest control. Ecology Letters **3**:150–158.

Shigesada, N., and K. Kawasaki. 1997. Biological invasions: theory and practice. Oxford University Press, Oxford, UK.

Shoemaker, C. A. 1982. Optimal integrated control of univoltine pest populations with age structure. Operations Research **30**:40–61.

Tabashnik, B. E. 1990. Modeling and evaluation of resistance management tactics. Pages 153–182 *in* R. T. Roush and B. E. Tabashnik, editors. Pesticide resistance in arthropods. Routledge, Chapman and Hall, New York, New York, USA.

Thrupp, L. A., editor. 1996. New partnerships for sustainable agriculture. World Resources Institute, Washington, D.C., USA.

USDA (United States Department of Agriculture) Forest Service. 2000. Forest insect and disease conditions in the United States 1999. [Online, URL: ⟨http://www.fs.fed.us/foresthealth/annual_i_d_conditions/index.html⟩.]

Waage, J. K., and N. D. Barlow. 1993. Decision tools for biological control. Pages 229–246 *in* G. A. Norton and J. D. Mumford, editors. Decision tools for pest management. CAB International, Wallingford, UK.

Waage, J. K., and N. J. Mills. 1992. Biological control. Pages 412–430 *in* M. J. Crawley, editor. Natural enemies: the population biology of predators, parasites and diseases. Blackwell Science, Oxford, U.K.

Walker, B. 1998. The art and science of wildlife management. Wildlife Research **25**:1–9.

Walters, C. J. 1986. Adaptive management of renewable resources. MacMillan, New York, New York, USA.

Walters, C. 1997. Challenges in adaptive management of riparian and coastal ecosystems. Conservation Ecology [Online, URL: ⟨http://www.consecol.org/vol1/iss2/art1⟩.]

Williams, B. K., M. D. Koneff, and D. A. Smith. 1999. Evaluation of waterfowl conservation under the North American waterfowl management plan. Journal of Wildlife Management **63**:417–440.

Williamson, M. 1996. Biological invasions. Chapman and Hall, London, UK.