Raising the bar for systematic conservation planning

William T. Langford[a*], Ascelin Gordon[a], Lucy Bastin[b], Sarah A. Bekessy[a], Matt D. White[c], Graeme Newell[c]

[a]School of Global Studies, Social Science & Planning, RMIT University, GPO Box 2476, Melbourne, 3001 Australia.

[b]School of Engineering and Applied Science, Aston University, Birmingham, B4 7ET, UK (currently at the Joint Research Centre of the European Commission, Ispra, Italy)

[c]The Arthur Rylah Institute for Environmental Research, Department of Sustainability and Environment, PO Box 137, Heidelberg 3084, Australia.

Corresponding author: Langford, W.T. (bill.langford@rmit.edu.au)

Abstract

Mathematical methods in systematic conservation planning (SCP) represent a significant step toward cost-effective, transparent allocation of resources for biodiversity conservation. However, research demonstrates important consequences of uncertainties in SCP. Current research often relies on simplified case studies with unknown forms and amounts of uncertainty and low statistical power for generalizing results. Consequently, conservation managers have little evidence for the true performance of conservation planning methods in their own complex, uncertain applications. SCP needs to build evidence for predictive models of error and robustness to multiple, simultaneous uncertainties across a wide range of problems of known complexity. Only then can we determine true performance rather than how a method appears to perform on data with unknown uncertainty.

Systematic Conservation Planning: background and definition

Widespread loss of biodiversity is commonly addressed by attempts to reserve, protect, and manage habitat for species at risk. Making good choices for these actions and reserves in a non-static, spatial and temporal context is an extremely difficult problem when there are many species and many locations involved. This leads to problems that are often not amenable to solution by rules of thumb or exactly solvable by analytic means.

Over the past 25 years, a family of mathematical approaches has evolved to explicitly define criteria and computationally solve for near-optimal prioritizations of conservation actions. A primary focus has been on mathematical methods for spatial allocation of conservation reserves [1-3] under the umbrella of systematic conservation planning (SCP) [4-6]. In recent years, research in this area has also evolved toward a broader emphasis on prioritizing conservation actions in general through the lens of decision theory [7]. In this paper, we examine the collision between these high-precision methods and complex, highly uncertain data.

The ideas behind SCP have much to offer conservation managers in moving beyond ad-hoc conservation planning, including the promise of quantitative, repeatable, and transparent decision-making. This is a significant advance given the inscrutable and idiosyncratic nature of conservation planning and investment across the globe. The resulting methods are powerful tools that have been used in numerous real-world conservation efforts with significant biodiversity implications, for example, selecting reserves for Madagascar [8], the Great Barrier Reef [9], and South Africa [10].

In spite of its successes and broad application, various authors have noted that SCP still encounters significant obstacles in bridging the gap from academic research to application. For example, Prendergast et al.[11] found that many conservation managers were not implementing SCP methods simply because they were unaware of them. A more vexing problem comes from the difficulty of implementing suggested actions within a complex web of socio-political constraints [12]. Although these issues are equally important and substantial challenges for SCP research, we restrict our focus here to problems associated with mathematical aspects of SCP. Specifically, we discuss the lack of evidence for approaches to addressing the complexities and large uncertainties that are associated with all data and models used in SCP.

Can we predict the performance of SCP methods under uncertainty?

While current SCP methods are mathematically sophisticated and highlight many important factors such as complementarity, risk, and uncertainty, there are important mathematical difficulties in applying these results to real problems. In particular, research has focused on studies conducted in simplified circumstances where most real-world complications are either poorly understood or abstracted away to make the problem mathematically tractable [13]. Unfortunately, uncertainties and approximations in data and models are ubiquitous in SCP, significantly affecting reliability of information about factors like: costs and budgets; land availability; species vulnerabilities, presence, abundance, and interactions; as well as large-scale effects of climate, economics, land use change, and politics. These and numerous other complexities violate the assumptions of methods and effectively eliminate any theoretical guarantees of finding the best solution, or possibly even a good solution. This is true even for methods specifically aimed at dealing with uncertainty.

Many papers in the field do acknowledge the existence of multiple types of uncertainties and complications and propose methods for dealing with some of them [14-29]. However, these methods are only evaluated on case studies that provide little evidence for how they will perform in different and more complex circumstances. While these studies are useful in highlighting the fact that a particular complication *can* have an effect on outcomes, this is of limited utility to practitioners; they only warn practitioners of the possibility of various problems arising, but give no generalizable result to predict the likelihood or degree to which these problems will apply in their particular situation. In fact, nearly every study very carefully states that their result is *not* generalizable beyond the current case study.

The inability to estimate the likelihood and degree of error in SCP outcomes leaves conservation planners with the knowledge that there are things that they should worry about and things they should strive for, but it also leaves them with a range of important questions that in most cases are currently unanswerable, including: Given uncertainties in underlying data, can they have confidence in a conservation planning method's outcomes and defend it in a politically charged decision making environment? And, how can they be sure that a method that excelled in a static, simplified case study with unknown uncertainties will suit their dynamic, complex situation, which may not share the characteristics that determined the performance documented in the case studies?

One of the differences between traditional ecological research and SCP that makes dealing with uncertainty unusually important is that SCP results need to be more than another brick in the wall of science. In particular, SCP methods are intended for use in real-world situations where a decision must be made, regardless of the current state of the science. While much ecological research is focussed on trying to *explain* what factors might influence a process, SCP that is safe to use in the real world needs to reliably *predict* something about how a method will perform to be of genuine use in real world situations.

This element of prediction requires a different research emphasis. It means that we need to pay much more attention to deriving and conveying bounds on the degree and likelihood of error when SCP methods are applied to conditions well beyond the scope of a case study. Another equally important distinction of SCP is the focus on efficiency and optimality. Optimization can have the unfortunate side-effect of producing brittle solutions that are not robust to uncertainty as they intently rely on the details of the input data, which are known to be uncertain.

While we raise many issues here about the accuracy of SCP methods, not all errors are equally important. For a user making a decision, what matters is not the exact *amount* of error in the output. Rather, the question is whether the decision and outcome would change if we could reduce the error, for example, by gathering more information. However, current SCP research does not enable us to reliably predict or even bound either the level of error or the likelihood of decision change.

Underlying problems

Many of the mathematical problems underlying these issues relate to three general problems that we will refer to as: *Unknown amounts of error, the Generalization Problem,* and *Reliance on post-hoc sensitivity analysis.*

Unknown amounts of error: Apparent vs. True values

The first fundamental problem is that it is impossible to quantify the error in case studies using real data. . The problem here is that data inputs to SCP such as the distribution of species habitat or costs nearly always contain unknown or unknowable amounts of error. Users must pretend that input data are correct when evaluating model performance, hence only seeing the *apparent* results of the techniques of interest. Consequently, studies comparing methods or rules of thumb on *apparent* data may provide meaningless and/or misleading results.

The use of apparent data rather than true data also raises significant issues in the application of existing research. That research tells us that things like complementarity and cost affect outcomes, but it tells us that based on true complementarity and true cost. What does it tell us about apparent complementarity and apparent cost in real cases where the values used to compute these measures are all uncertain?

The Generalization Problem: Reliance on case studies

A second fundamental problem is that the SCP literature relies almost exclusively on case studies as opposed to proofs or experiments across many types of problems. This means that most SCP research lacks statistical power to control for problem characteristics that drive the performance of SCP methods. Importantly, only a few studies attempt to characterize problems in a way that might allow users to determine whether a given method will perform well in their local situation; that is, whether results are generalizable (Box 1).

In 2009, we demonstrated the importance of case study specificity by exploring a number of interactions between uncertainty and problem characteristics [30]. We showed examples where applying SCP methods on the same landscapes, the same number of species, the same costs and the same input uncertainties yielded very different performance as a function solely of the structure of species distributions. That study highlighted how the intrinsic level of difficulty of a particular case study can have a major effect on the relative and absolute performance of a method, as well as on how deceptive its *apparent* performance is compared to its *true* performance (Figure 1). Problem characteristics such as whether the target species are clumped onto a few hotspots or spread evenly across the landscape may completely determine whether a problem is easy or difficult, that is, whether a simple method can solve the problem or whether no method can possibly satisfy constraints. These characteristics determine the likely quality and accuracy of a method's outcomes but are almost never mentioned. For example, studies rarely express problem characteristics such as species rarity distributions and cost distributions that would allow users to discern whether the characteristics of their problem (and the gaps in their data, or their knowledge of that data) are similar to those of published case studies.

This general lack of controls and statistical power means that there is little or no evidence for generalization. While authors nearly always honestly state that their study does not generalize, it means that there is little evidence to show that methods espoused in specific case studies will exhibit similar performance in a user's own situation with its associated uncertainties and complications. This is important because most real-world decisions are conducted in an environment where there is little time, expertise, and resource for local verification of method performance. Since SCP results, unlike pure research, are intended as the basis for action, it is vital that method developers explore and give rigorous evidence for, the range and types of situations where a proposed method will perform well.

Reliance on post-hoc sensitivity analysis

The primary way that uncertainty is addressed in SCP applications is to do a sensitivity analysis on a proposed solution after it has been derived. It is based around the idea that if we perturb the inputs to a method and there is little variation in the results, then the method is reasonable. While this is a useful way to quickly identify fragile solutions, there are three major problems with relying on it as the sole evidence for reliability. First, our results can be stable, but wrong. A small variance may be a necessary condition for a good solution, but it tells us nothing about how close the solution is to being correct, i.e., its bias. Second, the perturbations are generally done one variable at a time, in spite of research detailing problems with ignoring interactions among many uncertain variables [31]. While sensitivity analysis in higher dimensions is more difficult, there is significant research that makes this approach more feasible. Third, the choices of parameters, models, and perturbations are generally based on the investigator's opinions about what is reasonable rather than on empirical evidence. For example, cost is frequently included as an important feature in SCP [32-36] and there is research on methods to estimate cost data [35, 36], but error estimates on costs are almost never given even though costs can be a primary driver for outcomes. Consequently, like other variables, when sensitivity analysis is applied to costs, it is generally based on opinion rather than evidence, in spite of the significant literature reflecting the common overconfidence of experts in their own opinions [37-39].

The user's dilemma

To our knowledge there are *no* studies examining ways to characterise SCP problems that allow defensible bounds to be placed on a method's performance under real-world conditions. Similarly, there is little software support for testing proposed solutions under complex combinations of local conditions and uncertainties or for sharing models of behavior, processes, and uncertainties. Some may claim that generalization is in fact impossible because the real world is too complex. However, our central argument is that it can't go both ways; we must either generalize rigorously or test much more comprehensively. If the problem is so complex that reliable bounds on a method's performance in a new, unseen situation are impossible, then it is also impossible to claim a priori that the proposed method will give reliable performance there without extensive testing.

Recommendations

We believe that several positive steps can be taken to reduce the effects of these underlying problems. We detail these below and provide a summary and template for implementing them in Text Box 2.

1) *Test SCP methods on multiple problems using correct data, and control for complexity and uncertainty*

Understanding the impacts of uncertainty in real data necessitates the use of simulations and simulated errors. Without simulation we can only test how a method *appears* to perform under uncertainty, rather than test its *true* performance. For many ecologists, "simulation" is a dirty word, but in this context it is an indispensable adjunct to field data, providing another experimental environment for collecting evidence about the behavior of methods under uncertainty [40-43]. Clearly, simulation must be grounded in links to the real world, but it is the only way that we can accurately gather mathematical evidence and statistical power for the simultaneous effects of uncertainty and complexity, given our limited ability to sample and experiment on the real world.

Other authors have raised the need for an evidence base for real-world conservation practice [44-46]. We believe this is vitally important and our suggestions regarding the use of simulation complement this approach by providing evidence for the robustness of quantitative SCP approaches to complexity and uncertainty. This is not possible with real-world data containing unknown amounts of error (see Box 2).

Another advantage of simulation is that it allows us to explore the representational power of the mathematical methods themselves under uncertainty. By this we mean that SCP methods must *at least* be able to represent and perform well in simpler, simulated worlds if they are to perform well in the more complex and uncertain real world. As long as our simulated worlds have behaviors that are structurally similar to things that we want our methods to be able to handle, then we can use them to help explore a method's performance, investigate the consequences of uncertainties and complexities, and most importantly, weed out methods that are not robust to them.

2) Explicitly model error on SCP inputs

To simulate error and perform sensitivity analysis we must know the magnitude of errors in models and data, as well as the distributions of the errors. For example, if errors in cost or species input maps are distributed uniformly across a study area, they will have different consequences for a reserve selection algorithm or metapopulation model than if the errors are spatially correlated with factors like soil type and patch boundaries. Unless we know the distributions, biases, and magnitudes of these errors, we have no evidence for choosing bounds or distributions of scenarios to test. Consequently, our sensitivity analyses and simulations can be looking at the wrong parts of the model input space and mislead us. Unfortunately, error models for SCP inputs, particularly for spatial error and cost error, have received almost no attention in the literature. They require much more research if we are to accurately evaluate and generalize SCP performance.

3) More rigorous expectations for publication and funding

Finally, editors, reviewers, and funding agencies would do well to insist that research goes beyond case studies and mathematical novelty and the impact of a single type of complexity or uncertainty in a single spatial distribution in a single location. Ginzburg and Jensen have made a similar point in relation to theoretical ecology [47]:

> "An engineering firm that builds a faulty bridge based on an overfitted model will be sued or fined out of existence; to date, we know of no ecological theorist whose similarly overfitted model has evoked comparable penalties. Because society demands little from theoretical ecology, one can have a successful lifetime career in the field without any of one's theories being put to the practical test of actual prediction."

True progress in SCP methods and outcomes requires a culture that expects new studies to control for the structure of problems and methods known to affect performance. We especially need to evaluate methods on more than one problem and on problem formulations that reflect the world as it is, rather than as it would be if it were mathematically subservient to our favorite technique.

Open questions

One issue in our suggestions is that we have advocated providing evidence for the models and bounds on errors used in sensitivity analysis. While some evidence, such as error in fitted cost models, is available but seldom used, other evidence such as the spatial variation in the errors for cost or species distribution models is generally not accessible now. Similar issues exist with respect to which types of uncertainty to include and how many uncertainties to explore at once. This lack of existing predictive information on relative importance and interactions among uncertainties is exactly why we advocate moving beyond case studies to studies with statistical power and the use of true rather than apparent data. As these kinds of studies begin to appear, we can build reliable knowledge about the magnitude and distribution of errors in the mathematical methods underpinning SCP and use them to improve both the performance and the error bounds on our methods.

As SCP methods have developed they have extended their utility beyond reserve selection to the choice of conservation actions in general, such as strategies for restoration [48, 49], invasive species control [50, 51], adaptive monitoring and management [52, 53], and conservation on private land [54, 55]. Some of these methods may appear not to have the problems described in this paper as they derive solutions directly from equations rather than through search algorithms. However, many of these equations hinge on the probabilities and rewards associated with different actions and outcomes. These values are generally *chosen* based on expert opinion and are therefore, uncertain. Research has shown that even though these calculations are designed to help with uncertainty, getting decision-theoretic probability and reward estimates wrong can lead to making a bad decision [56]. Consequently, it is important to have evidence and models for the structure and magnitude of those errors as well.

Conclusion

SCP is undoubtedly a useful and important advance in conservation decision-making. However, for SCP to be truly useful for conservation managers, the reliability of its outputs must be honestly characterized. A more rigorous typology and quantification of problem characteristics and error will also create potential for systematic meta-analysis and meaningful comparison of results.

No matter how we arrive at a proposed conservation plan, we need to know: i) the risks and rewards of attempting to use the proposed method or strategy in a particular location and ii) the likelihood of it achieving its claimed outcomes. Both users and SCP itself will benefit greatly if we raise the bar and undertake more research that builds evidence for method performance in a way that reflects the uncertainties and complexities of the real world rather than over-simplified case studies on data containing unknown amounts of error. Given that SCP outcomes may determine the fate of species, this problem is not “just academic”.

Acknowledgements

We would like to thank Iris Bergmann, Ben Cooke, Alex Lechner, and Katelyn Samson for their helpful comments on the manuscript. This research was funded by the Australian Research Council through Linkage Project LP0882780, and the Applied Environmental Decision Analysis research hub (through the Australian Commonwealth Environment Research Facilities programme).

Box1 - Generalization and problem characterization

When a user approaches their own conservation task and looks to the SCP literature for help, several questions arise in determining whether the results and method apply to their situation. In particular, they need to know which studies:

1) Use data where true outcomes are/can be known;
2) Use multiple geographic locations;
3) Use multiple distributions of species co-occurrence, costs, threats, etc.;
4) Explore multiple uncertainties simultaneously;
5) Characterize problem attributes (i.e., explain the test problem in a way that enables the user to understand how similar it is to their own problem).

A number of studies do address single uncertainties, but only use case studies without problem characterization to give users evidence for their situation. Below we describe four studies that take positive steps toward characterizing problem structure and performance bounds, though there are others that take positive steps as well (e.g., [20-22]).

- The best, and perhaps the only, example of putting rigorous bounds on expected performance under an uncertainty is given by Moilanen et al. [57]. Here a worst-case style analysis is used to mathematically guarantee a lower bound on species representations in Zonation outputs over input habitat maps assuming a given upper bound on input error. This is a positive step but still does not address more complex uncertainties or uncertainties where it is difficult or impossible to determine the worst-case situation.

- Pressey et al. [17] address problem characterization by demonstrating variation in outcomes resulting from changes of data set size, site size, rarity of features, and nestedness of features in replicated synthetic data sets. All the data sets, however, were variations derived from a single original data set, consequently only exposing the variability of outcomes from one small corner of the problem domain.

- Drechsler [18] addresses the uncertain dynamics of land acquisition through simulations that synthesise different combinations of species counts, species occupancy levels, and nestedness. While there is explicit uncertainty in the land acquisition, the method assumes that probabilities are known and correct, which is unlikely and known to bring other risks [56].

- Turner and Wilcove [19] also examine uncertainty in site availability, this time with a ten year time frame and three different real-world data sets, budget constraints and loss of sites to development. However, they do not characterize the structure of the species sets to control for those effects and they ignore other complications, including uncertainty in the species data.

Figure 1 - Problem difficulty and *Apparent* vs. *True* performance

This figure shows one of the results from Langford et al. [30] to illustrate both the difficulties of relying on case studies and the utility of using simulated data to examine method performance under uncertainty. The objective was to find the least-cost reserve network that contains at least one representation of each species using two common reserve selection rules of thumb in the presence of error, which in this case was a 30% overestimate of habitat. The results are shown for three different distributions of species richness:

- "Hot spots", where species tend to co-occur on the same patch;
- "Victorian", where the distribution of co-occurrences matches a real distribution in Victoria, Australia;
- "Uniform", where species locations are uncorrelated.

The bar chart on the left shows the *apparent* costs of a reserve network that *appears* to represent each species at least once based on the erroneous maps. The bar chart on the right shows the *true* costs required (the cost is measured as a proportion of total landscape cost). The dashed box around the *apparent* Victorian results highlight what would have been found in a single case study using "real" data.

These results illustrate four important points discussed throughout this paper:

1. *Problem difficulty*: Even though the landscapes were identical and the number of patches occupied by each species was identical, controlling for the spatial distribution of the species showed a wide range of performance for both methods.

2. *Misleading ranking of methods*: Based on a*pparent* data, the Unprotected Richness rule of thumb appears to be far more efficient than the Simple Richness rule of thumb even though the results were approximately equal on the *true* data.

3. *Misleading absolute performance*: Using the *apparent* maps alone, one would grossly underestimate the cost required to achieve the conservation goal using Unprotected Richness. Interestingly, even though Simple Richness never appeared to perform as well as Unprotected Richness, its *apparent* performance was always similar to its *true* performance.

4. *Error amplification*: There is often a sense that all input data has errors, but the errors in the outputs will probably have similar magnitudes to those in the inputs. These experiments show this is not something that can be safely assumed.

Box 2 - Summary of specific suggestions for improving SCP studies under uncertainty

Here we provide a summary of specific recommendations for improving the utility and accuracy of SCP studies in the presence of uncertainty and real-world complications.

1. **Move beyond case studies** The problem is not so much that case studies are done; rather it is that virtually no research that goes beyond case studies to anything more comprehensive. Developing libraries of studies that includes multiple problem structures and multiple interacting uncertainties will enable more predictive results.

2. **Evaluation** When evaluating or comparing methods or studying uncertainties the following 3 steps should be included: (i) Testing using data where the true values are known, rather than with data containing unknown amounts of error (see below); (ii) Testing behavior under multiple uncertainties simultaneously, rather than one at a time; (iii) Characterization of problem structure (e.g. the number of species, landscape configuration, spatial co-occurrence of species or distributions of costs) and testing on multiple problems with different structures.

3. **Case studies** Sensitivity analyses should be done by simultaneously varying multiple factors known to influence outcomes rather than studying each factor in isolation. Where possible, evidence should be given for the range of errors used in the sensitivity analysis. For example, if a model has been used to generate costs, sensitivity analysis should be based on evidence such as mean and variation for the model's error and for how it is distributed spatially.

To make the method of testing with true versus apparent values more tangible, we outline the sequence of steps for this approach below (more detail and examples of use are given in [30]):

- We must first define a dataset as being a true representation of the world. This data may be synthetic or real, and could represent any or all of the inputs to an SCP problem such as species habitat maps, cost maps, etc. With synthetic data, direct control over the input data is possible, or real-world data can be used from multiple locations where problem characteristics differ.

- Secondly, we can degrade these true inputs using models representing our beliefs about possible real-world forms of error, for example, over or under-estimation of costs or spatial bias in error in predicting species habitat.

- Thirdly, SCP analysis should then be carried out in parallel on both true and degraded data. The impact of errors being studied can then be determined by comparing differences between the SCP outcomes in the true and degraded data.

References

1. Williams, J.C., *et al.* (2005) Spatial attributes and reserve design models: a review. *Environmental Modeling and Assessment* 10, 163-181
2. Sarkar, S., *et al.* (2006) Biodiversity Conservation Planning Tools: Present Status and Challenges for the Future. *Annual Review of Environment and Resources* 31, 123-159
3. Vanderkam, R.P.D., *et al.* (2007) Heuristic algorithms vs. linear programs for designing efficient conservation reserve networks: Evaluation of solution optimality and processing time. In *Biological Conservation*, 349-358
4. Kirkpatrick, J. (1983) An iterative method for establishing priorities for the selection of nature reserves: An example from Tasmania. *Biological Conservation* 25, 127-134
5. Margules, C.R., and Pressey, R.L. (2000) Systematic conservation planning. *Nature* 405, 243-254
6. Pressey, R.L., *et al.* (1993) Beyond opportunism: Key principles for systematic reserve selection. In *Trends in Ecology & Evolution*, 124-128
7. Wilson, K.a., *et al.* (2009) Setting conservation priorities. *Annals of the New York Academy of Sciences* 1162, 237-264
8. Kremen, C., *et al.* (2008) Aligning conservation priorities across taxa in Madagascar with high-resolution planning tools. *Science* 320, 222-226
9. Fernandes, L., *et al.* (2005) Establishing Representative No-Take Areas in the Great Barrier Reef: Large-Scale Implementation of Theory on Marine Protected Areas. *Conservation Biology* 19, 1733-1744
10. Cowling, R. (2003) A conservation plan for a global biodiversity hotspots in the Cape Floristic Region, South Africa. *Biological Conservation* 112, 191-216
11. Prendergast, J.R., *et al.* (1999) The Gaps between Theory and Practice in Selecting Nature Reserves. *Conservation Biology* 13, 484-492
12. Knight, A.T., *et al.* (2006) Designing Systematic Conservation Assessments that Promote Effective Implementation: Best Practice from South Africa. *Conservation Biology* 20, 739-750
13. Moilanen, a. (2008) Two paths to a suboptimal solution – once more about optimality in reserve selection. *Biological Conservation* 141, 1919-1923
14. Regan, H.M., *et al.* (2002) A Taxonomy and Treatment of Uncertainty for Ecology and Conservation Biology. *Ecological Applications* 12, 618-628
15. {Ascough II}, J., *et al.* (2008) Future research challenges for incorporation of uncertainty in environmental and ecological decision-making. *Ecological Modelling* 219, 383-399
16. Moilanen, A., *et al.* (2006) Uncertainty analysis for regional-scale reserve selection. *Conservation biology : the journal of the Society for Conservation Biology* 20, 1688-1697
17. Pressey, R.L., *et al.* (1999) Effects of data characteristics on the results of reserve selection algorithms. *Journal of Biogeography* 26, 179-191
18. Drechsler, M. (2005) Probabilistic approaches to scheduling reserve selection. *Biological Conservation* 122, 9
19. Turner, W.R., and Wilcove, D.S. (2006) Adaptive decision rules for the acquisition of nature reserves. *Conservation Biology* 20, 527-537
20. Costello, C., and Polasky, S. (2004) Dynamic reserve site selection. *Resource and Energy Economics* 26, 157-174
21. Moilanen, a., and Cabeza, M. (2007) Accounting for habitat loss rates in sequential reserve selection: Simple methods for large problems. *Biological Conservation* 136, 470-482

22. Visconti, P., *et al.* (2010) Habitat vulnerability in conservation planning–when it matters and how much. *Conservation Letters*
23. Polasky, S., and Solow, A.R. (2001) The value of information in reserve site selection. *Biodiversity and Conservation* 10, 1051-1058
24. Polasky, S., *et al.* (2000) Choosing reserve networks with incomplete species information. *Biological Conservation* 94
25. Polasky, S., *et al.* (2005) Conserving Species in a Working Landscape : Land Use with Biological and Economic Objectives. *Ecological Applications* 15, 1387-1401
26. Rae, C., *et al.* (2007) Implications of error and uncertainty for an environmental planning scenario: A sensitivity analysis of GIS-based variables in a reserve design exercise. *Landscape and Urban Planning* 79, 210-217
27. Beech, T., *et al.* (2008) A stochastic approach to marine reserve design: Incorporating data uncertainty. *Ecological Informatics* 3, 321-333
28. Nicholson, E., and Possingham, H.P. (2007) Making conservation decisions under uncertainty for the persistence of multiple species. *Ecological Applications* 17, 251-265
29. Leroux, S.J., *et al.* (2007) Accounting for System Dynamics in Reserve Design. *Ecological Applications* 17, 1954-1966
30. Langford, W.T., *et al.* (2009) When do conservation planning methods deliver ? Quantifying the consequences of uncertainty. *Ecological Informatics* 4, 123-135
31. Saltelli, A., and Annoni, P. (2010) How to avoid a perfunctory sensitivity analysis. *Environmental Modelling & Software* 25, 1508-1517
32. Bode, M., *et al.* (2008) The Cost of Conservation. *Science* 321, 340
33. Ando, A., *et al.* (1998) Species Distributions, Land Values, and Efficient Conservation. *Science* 279, 2126-2128
34. Shogren, J.F., *et al.* (1999) Why economics matters for endangered species protection. *Conservation Biology* 13, 1257-1261
35. Naidoo, R., *et al.* (2006) Integrating economic costs into conservation planning. *Trends in ecology and evolution* 21, 681-687
36. Naidoo, R., and Iwamura, T. (2007) Global-scale mapping of economic benefits from agricultural lands: Implications for conservation priorities. *Biological Conservation* 140, 40-49
37. Henrion, M., and Fischhoff, B. (1986) Assessing uncertainty in physical constants. *American Journal of Physics* 54, 791-798
38. Kynn, M. (2008) The ‘heuristics and biases’ bias in expert elicitation. *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 171, 239-264
39. Speirs-Bridge, A., *et al.* (2010) Reducing overconfidence in the interval judgments of experts. *Risk analysis : an official publication of the Society for Risk Analysis* 30, 512-523
40. Peck, S.L. (2004) Simulation as experiment: a philosophical reassessment for biological modeling. *TRENDS in Ecology and Evolution* 19, 530-534
41. Austin, M.P., *et al.* (2006) Evaluation of statistical models used for predicting plant species distributions: Role of artificial data and theory. In *Ecological Modelling*, 197-216
42. Meyer, K.M., *et al.* (2009) The power of simulating experiments. *Ecological Modelling* 220, 2594-2597
43. Hoffman, J.D., *et al.* Use of simulated data from a process-based habitat model to evaluate methods for predicting species occurrence. *Ecography*
44. Sutherland, W.J., *et al.* (2004) The need for evidence-based conservation. *Trends in ecology & evolution (Personal edition)* 19, 305-308
45. Segan, D.B., *et al.* (2010) Using Conservation Evidence to Guide Management. *Conservation Biology*, no-no

46. Ferraro, P.J., and Pattanayak, S.K. (2006) Money for Nothing? A Call for Empirical Evaluation of Biodiversity Conservation Investments. *PLoS Biology* 4, 482-488
47. Ginzburg, L.R., and Jensen, C.X.J. (2004) Rules of thumb for judging ecological theories. *Trends in Ecology and Evolution* 19, 121-126
48. Crossman, N.D., *et al.* (2007) Systematic landscape restoration in the rural–urban fringe: meeting conservation planning and policy goals. *Biodiversity and Conservation* 16, 3781-3802
49. Dorrough, J., *et al.* (2008) Integrating ecological uncertainty and farm-scale economics when planning restoration. *Journal of Applied Ecology* 45, 288 -295
50. Regan, T.J., *et al.* (2006) Optimal eradication: when to stop looking for an invasive plant. *Ecology letters* 9, 759-766
51. Burgman, M.a., *et al.* (2010) Reconciling uncertain costs and benefits in Bayes nets for invasive species management. *Risk analysis : an official publication of the Society for Risk Analysis* 30, 277-284
52. Runge, M.C., *et al.* (2011) Which uncertainty? Using expert elicitation and expected value of information to design an adaptive program. *Biological Conservation*
53. Wintle, B.a., *et al.* (2010) Allocating monitoring effort in the face of unknown unknowns. *Ecology Letters*
54. Drechsler, M., *et al.* (2007) A model-based approach for designing cost-effective compensation payments for conservation of endangered species in real landscapes. *Biological conservation* 140, 174-186
55. Gordon, A., *et al.* (2011) Modelling trade offs between public and private conservation policies. *Biological Conservation* 144, 558-566
56. Regan, H.M., *et al.* (2005) Robust Decision-Making Under Severe Uncertainty for Conservation Management. *Ecological Applications* 15, 1471-1477
57. Moilanen, A., *et al.* (2006) Uncertainty Analysis for Regional-Scale Reserve Selection. *Conservation Biology* 20, 1688-1697