Raising the bar for systematic conservation planning

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Abstract

Systematic conservation planning (SCP) represents a significant step toward cost-effective, transparent allocation of resources for biodiversity conservation. However, research demonstrates important consequences of uncertainties in SCP and of basing methods on simplified circumstances involving few real-world complexities. Current research often relies on single case studies with unknown forms and amounts of

uncertainty as well as 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. To build effective and reliable methods in SCP, we need more challenging and integrated testing of their robustness to uncertainty and complexity and much greater emphasis on generalization to real-world situations.

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 in a dynamic, spatial and temporal context is a difficult problem when there are many species, candidate actions, and locations involved. This leads to problems that are often not amenable to solution by rules of thumb or exactly solvable by analytic means [1].

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 [2-4] under the umbrella of Systematic Conservation Planning (SCP) [5-7]. 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 [8]. In this paper, we examine the collision between these high-precision methods and complex, highly uncertain data and discuss strategies for improving the utility and reliability of these methods.

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 [9-13], the Great Barrier Reef [14], and South Africa [15].

In spite of its successes and broad application, various authors have noted that conservation planning still encounters significant obstacles in bridging the gap from academic research to application. For example, a number of authors describe problems related to undertaking and implementing conservation planning within a complex web of social, economic, and political constraints[16-18]. Although these issues are at least as important, our focus here is on problems associated with mathematical aspects of SCP. Specifically, we discuss issues in addressing the effects of complexities and large uncertainties that are associated with most data and models used in SCP.

Making conservation decisions under uncertainty

While current SCP methods are mathematically sophisticated and highlight many important factors such as complementarity and risk, there are important mathematical difficulties in applying these results to real problems. In particular, much SCP research has focused on case studies conducted in simplified circumstances where most real-world uncertainties and complications are either poorly understood or abstracted away to make the problem mathematically tractable [19]. Unfortunately, uncertainties and approximations in data and models are ubiquitous in SCP, significantly affecting reliability of information about factors such as: 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 [20].

In recent years, numerous papers have explored this issue and demonstrated consequences of multiple types of uncertainties and complications as well as proposing methods for dealing with some of them [20-36]. However, the conclusions (including our own work [20]) are only evaluated on case studies or problem sets with limited scope that provide little evidence for how they will carry over to different and more complex circumstances. More importantly, they do not provide explicit predictive models for the robustness of their conclusions to previously unseen situations and uncertainties. In fact, many studies carefully state that their results do *not* generalize beyond the current case.

While we raise questions here about the accuracy of SCP methods under uncertainty and complexity, not all errors are equally important. For a user making a decision, what matters is not just the exact amount of error in the output. Instead, the question is whether the decision and outcome would change if we could reduce the error, for example, by gathering more information [30]. Current SCP research would have much greater utility to practitioners if it could provide predictive models and evidence for estimating the amount, structure, and probability of error necessary for knowing whether decisions should change. In Box 1, we give an example of the consequences of this lack of predictive estimation.

In the rest of this paper, we suggest immediate solutions to parts of the problem and outline a research agenda to fill the gaps in building a better, more predictive understanding of the robustness of SCP methods that goes well beyond the scope of current studies. This understanding would in turn, lead to improving SCP methods and outcomes.

Underlying problems

Deciding whether the application of a given SCP method is acceptable in a particular situation requires knowledge of a) the errors in the inputs (i.e., the range and probability distribution of possible input errors), and b) how and when those errors are likely to affect the outputs of the given SCP method. We believe that three specific issues significantly undercut a decision maker's ability to reliably estimate the distribution of these errors and their effects on predicted outcomes. These issues are: *Lack of predictive modelling and generalization*, *Unknown amounts of error, and Lack of good input error models.*

Lack of predictive modelling and generalization for SCP outputs

The first fundamental problem is that the SCP literature relies almost exclusively on case studies or problem sets with very limited scope as opposed to studies across many types of problems leading to a testable prediction of the generality of the result. This means that most SCP research lacks statistical power to control for problem characteristics that drive the performance of SCP methods (Box 2). Varying these characteristics across studies is important because even applying SCP methods to the same landscapes, the same number of species, the same costs and the same input uncertainties can yield very different performance as a function solely of a single characteristic such as the structure of species distributions (Figure 1).

To our knowledge there are currently no studies that explicitly state and test a mathematical or verbal prediction of the size, probability, and spatial distribution of errors in SCP outputs on previously unseen problems. Predictions are not even made and tested over the typical range of the simplest and most ubiquitous variables such as the number of species and number of planning units. While many authors honestly state that their studies do not generalize, this means that there is little evidence to show that conclusions in specific case studies will hold in a user’s own situation with its associated uncertainties and complications.

Unknown amounts of error: Apparent versus True values

A second fundamental problem is that **it** is impossible to measure the true amount of error at any specific pixel, polygon, or map in both inputs and outputs of SCP studies that use real data. This is a result of the fact that data inputs to SCP are usually the result of a chain of sampling and model-fitting transformations. While we can improve the quality of SCP inputs through better field sampling, cost and time constraints mean that intensive sampling is often not an option. More importantly, for many inputs to SCP, it is impossible for sampling to identify the true value of that input. For example, even if we know exactly where every true location of a species is, an infinite number of distributions could have generated that sample (e.g., the uniform distribution). Consequently, when evaluating a conclusion, users must assume that input data are correct, meaning that they only see what we will refer to as the *apparent* performance of the techniques of interest (Figure 2).

This masking of the *true* performance means that studies comparing methods or rules of thumb on *apparent* data may provide meaningless and/or misleading results. For example, many papers emphasize the importance of including costs in conservation planning [10, 37-40], but those conclusions are based on *true* costs. What do they tell us about using *apparent* costs in real cases where the values used to compute these measures are all uncertain? Adams et al. [41] give an example that raises the question of whether “using partial estimates of costs might produce less efficient outcomes than assuming homogeneous costs”. While there is no question about the usefulness of *correct* costs in choosing actions, how do users like those in the Madagascar example (Box 1) make sure their decisions are robust to errors in costs? The problem with ignoring cost is that it implicitly assumes homogeneous costs, and this usually represents a large amount of error with respect to the true costs. This suggests that questions about ignoring costs in SCP are better seen as questions about the consequences of *error* in cost. Therefore, just as with species data, we need to pay attention to determining when the use of apparent values rather than true values will lead to a change of decision.

Lack of good error models for SCP inputs

The third problem is that even when we can know true error values, we have little evidence for the correlation structure and distribution of the set of errors (Figure 2). Both sensitivity analysis and efforts at generalization under uncertainty rely on the correctness of the *error models* assumed to generate or describe the amount, structure, and probability of errors in inputs to the SCP process. However, there is currently so little testing of inputs to SCP methods with known amounts and structures of error that there is very little evidence for these generative error models. Instead, errors or perturbations are generated based on opinion rather than evidence, in spite of the significant literature reflecting the common overconfidence of experts in their own opinions [42-44]. Given the spatial, sequential and combinatorial nature of SCP, an important missing aspect of error models is the spatial and temporal specificity and interactions of different types of errors.

Recommendations

We believe that several steps can be taken to make it easier for SCP users to know the risks and rewards associated with a particular decision. These steps do not require new mathematical techniques; rather, they require a shift in the culture and orientation of SCP research. In short, we believe that large improvements can be made simply by moving away from the descriptive, anecdotal, case study culture to one that is predictive and evidence-based, striving to support generalizable results. The essence of the strategy we support is simply to augment the many small-scale studies that currently exist by testing explicit, predictive claims about the performance and error in SCP methods on a statistically powerful variety of problems, using data with known amounts of error and controlling for problem complexity and uncertainty. We give more detail below and provide a summary in Figure 2.

Explicitly predict probability, structure, and amount of SCP output error and test generalization of predictions

We need to learn predictive models that map problem characteristics to probability distributions of errors in SCP output. We also need to make their predictions explicit and test them on problems that cover the space of SCP problems and input errors and where we can know the true answer. The space that we refer to here includes factors such as number of species, number of planning units, correlations of species co-occurrence, species rarity, cost, etc.

As a simple example, we would like to be able to predict the following: given the environmental, economic, and ecological samples used in solving a specific reserve selection problem using apparent data, what are the confidence intervals on the estimated i) true representation achieved, ii) true cost of achieving representation goals, and iii) the decrease in outcome quality resulting from using apparent rather than true data (also known as the *regret*). We would actually like to know the distributions of these errors as well as the downstream effects that we really care about such as persistence or vegetation condition. For now though, even simple aggregate measures like variance or a confidence interval would be a useful first step.

Challenge problems

Faced with problems of similarly daunting complexity, ecologists often conduct controlled experiments where they create their own communities and manipulate them to gain information about real systems. We suggest that in a similar way, we can build families of challenge problems that act as surrogate systems to understand and learn to predict the reliability of SCP methods. While we do not understand the world well enough to build a model of it that mirrors its complex and stochastic behavior, we do understand many drivers that lead to complex behavior in environmental and economic systems. With existing knowledge and techniques, we can generate families of similarly dynamic, complex, and plausible situations spanning the space of SCP problems.

Linking multiple generative models to build families of SCP problems of varying difficulty and complexity would give us both true and apparent data as well as sufficient statistical power and control for training and for independent test examples to estimate generalization. Having control over problem structure would also make it possible to build benchmark problems of varying difficulty, which would allow tests to screen for the relative power of different methods. While this is not sufficient to predict exactly how conclusions will hold in new situations, one necessary condition for a useful conclusion is that it hold on simpler problems than the ones where we want to apply it.

Active learning

One problem with learning to predict is that there is a huge range of problem structures and uncertainties to consider. One way to make this more tractable is to use techniques such as active learning to reduce the total number of experiments required. The intuition here is that we need not explore every region of the problem space with equal effort if we are doing well in certain parts of the space with little sampling. In active learning, an algorithm asks for new samples as it learns rather than specifying the complete sample set beforehand as might be done using optimal experimental design. The choice of the next sample can then be based on where the algorithm most needs information to improve its predictions. This may save considerable resources compared to preselecting all sample points before simulation.

Explicitly seek and test for robustness to unknown uncertainties

Since we can never know all of the factors and uncertainties to include in our models, our goal should be to mitigate this kind of model error by designing and demonstrating robustness to these unknown factors. By definition, we cannot know what these unknown unknowns are. However, the current literature has already given us a large catalog of uncertainties that we can use to explore and expand the robustness of methods and beliefs. We can do this in much the same way that we use bootstrap sampling to estimate the variance of samples where the true distribution is unknown. For example, if a method or proposition is tested on a number of uncertainties that it has made no attempt to address, then that gives us information on its robustness to unseen uncertainties.

Measure results on data with known amounts of error

The only way to know a method's true performance under uncertainty (as opposed to its apparent performance), is to generate the errors ourselves and apply them to data that we define or generate as correct (Figure 2). Clearly, the results of simulation are only as useful as their match to reality, but it is the only way that we can accurately measure the consequences of error given our limited ability to sample and experiment on the real world. It is important to note that while "real" data may appear to be more valid than simulations, studies that use real data still include unknown amounts of error and therefore, have the same problems with being approximations to reality as modelled results. Moreover, any real data can be used in a simulation as well, so simulations represent a superset of what can be done solely with real data. Simulation is not the only answer to all problems in SCP, but it is a necessary adjunct to field data by providing another experimental environment for collecting evidence about the behavior of methods under uncertainty [45-48].

Learn error models predicting probability, structure, and amount of input errors for SCP

To perform sensitivity analysis on SCP outputs we must learn models to generate the magnitude and distribution of errors that occur in inputs to SCP such as habitat suitability and cost models. For example, if errors in cost or species input maps are distributed uniformly across a study area, they will have different consequences for the results of a spatially explicit reserve selection algorithm than if the errors are spatially correlated with factors like soil type and patch boundaries (Figure 2).

We can develop much better error models than are currently available simply by applying known uncertainties and biases to input data and then propagating those effects through the SCP process [48], as described in Challenge Problems above. As a simple example, we know that there is often sampling bias in inputs to habitat models. This bias is easy to simulate and propagate through the habitat modelling. We can then test the robustness of SCP to this kind of error. If we know distributions, biases, and magnitudes of these errors, then we have evidence for choosing bounds or distributions of scenarios to test as well as the ability to investigate the value of gathering more information to reduce uncertainty [29-30].

Raising the bar

Finally, editors, reviewers, and funding agencies would aid practitioners by insisting that research goes beyond case studies, mathematical novelty, and the impact of a single type of complexity or uncertainty in a single distribution in a single location. Ginzburg and Jensen have made a similar point in relation to theoretical ecology [49]:

> "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 make and test predictions and to control for the structure of problems and methods known to affect performance.

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. No matter whether a conservation plan is the result of a negotiation or the output of an algorithm, 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 probability of it achieving its claimed outcomes.

SCP will benefit greatly if we raise the bar and undertake research that builds predictive models and evidence for method performance rather than over-simplified case studies on data containing unknown amounts of error. The more rigorous quantification of problem characteristics and error that we propose will also create potential for systematic meta-analysis and meaningful comparison of results.

Some may claim that performance prediction is in fact impossible because the real world is too complex, but our central concern is that it cannot go both ways. *If the problem is so complex that reliable bounds on a proposed SCP 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 in new unseen situations.*

Given that SCP outcomes may determine the fate of some species, addressing this problem is not “just academic”.

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Box 1 – What is the evidence for a plan's likely performance?   A large-scale example

An exchange in the journal *Science* in 2008 illustrates the dilemma faced by potential users of SCP methods. Kremen et al. [9] used Zonation reserve selection software [50] to determine the best 10% of Madagascar to reserve for biodiversity conservation, based on data from six taxonomic groups. Later, Coetzee [12] criticized the plan for not incorporating costs, well-known taxa (e.g., birds), and effects of climate change. Bode et al. [10] further criticized the exclusion of costs from the prioritization, claiming that the plan included expensive areas and suggesting that a better solution would favor low cost areas. In reply, Kremen et al. [11] pointed out that the costs in Bode et al. were based on global data that was inaccurate, at the wrong scale, and based solely on agriculture and livestock opportunity costs. Furthermore, they had addressed taxonomy and climate change through their choice of species and were unable to get appropriate bird data for their procedures.

Two years later, Fiorella et al. [13] applied Zonation to two different versions of a subset of the Madagascar data (52 lemur species). As in range studies with other species [51-54], they found large overestimation of habitat in the original maps. After using species knowledge to restrict the maps and re-running Zonation they found that 65% to 68% of locations that were in the original top 10% (i.e., areas to be reserved) were no longer in the top 10%. This suggests that the original study could contain large errors, but SCP users still have no evidence for how likely that is, since the input maps for Zonation in the original study were generated using a different method.

Unfortunately for conservation managers needing to know the consequences of following the plan, both the discussion and the research conclude with an unresolved exchange of opinions. Even given the entire SCP literature, there is no evidence or predictive model that would allow either side to put mathematically supported arguments for whether the decisions should be changed.

Our intention here is not to single out this work as problematic. Rather, we chose it because of its importance and the unique exchange of letters and follow-on study. Taken together, they encapsulate the state of SCP and point out that nearly all work in SCP, even high profile, expert work such as this, stops short of giving users the evidence they need to estimate the decision consequences of their uncertainty in the real world.

Box 2 - Generalization and problem characterization

When a practitioner with a conservation task looks to the SCP literature, several questions arise in determining whether the results apply to their situation. In particular, they need to know which studies:

- make explicit performance predictions and test them on previously unseen problems;
- use data where true outcomes can be known;
- use broad problem sets that give statistical power and are representative of real applications (multiple distributions, costs, threats, etc.);
- explore multiple uncertainties simultaneously;
- include correlation and spatial structure in the errors..

Numerous studies address single uncertainties but only use case studies lacking 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 (see [20,27-29] for other examples).

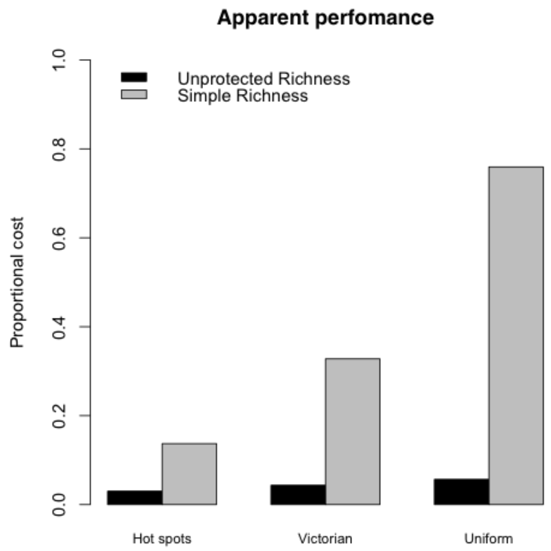
- A good example of putting rigorous bounds on expected performance under an uncertainty is given by Moilanen et al. [23]. Here, a worst-case analysis is used to guarantee a lower bound on species representation in outputs assuming a given worst-case input map error. This is a positive step but it is still conditioned on having a good input error model, for which we currently lack evidence. It also does not address *regret*, that is, the loss in method performance compared to what would have been achieved using the true data.

- Pressey et al. [24] 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 outcomes from one corner of the problem domain.

- Drechsler [25] addresses uncertain dynamics of land acquisition through simulations synthesizing different combinations of species counts, 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 [55].

- Turner and Wilcove [26] 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 presents results from [20] illustrating 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 heuristics based on species richness. The "simple richness" rule picks patches in order according to the number of species on each patch. "Unprotected richness" picks according to the number of species on each patch that have not already been reserved (complementarity). Cost is measured as a proportion of total landscape cost.

Error was introduced in the form of a 30% overestimate of suitable habitat since overestimation is common [51-54]. 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 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 revealed a wide range of costs from both methods.

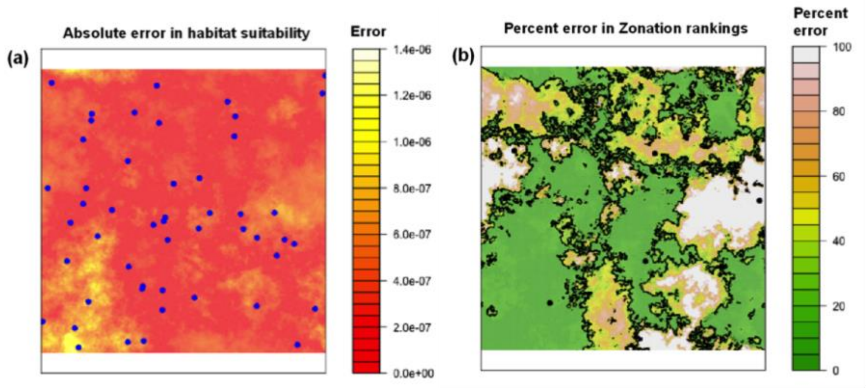
2. *Misleading ranking of methods*: Based on a*pparent* data, the Unprotected Richness approach appears to be far more efficient than the Simple Richness approach, even though the results were approximately equal on the *true* data.

3. *Misleading performance measurements*: Using the *apparent* maps alone, one would grossly underestimate the cost required to achieve the conservation goal using the Unprotected Richness approach. 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*: Results here and in [20] show how SCP methods can strongly amplify their input errors: a*pparent* input habitat area is only 1.3 times *true* area, but *true* costs for Unprotected Richness were 4.6, 6.2, and 14.1 times their *apparent* costs.

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



Here we summarize specific recommendations for improving SCP studies in the presence of uncertainty and real-world complications.

1. **Building and testing predictive models of error** Explicitly state predictions for the probabilities and structure of error for any study's conclusions. Test predictions on multiple problems including interacting uncertainties on out-of-sample data. The two images above illustrate the kind of spatial correlation in error that must be accounted for. The left-hand image shows error in output of a habitat suitability model with simulated species presence locations. The right-hand image shows percent difference in priority rankings for a reserve selection method (Zonation) between using true suitability probabilities and corresponding erroneous probabilities from the habitat suitability model.

2. **Evaluation** When evaluating or comparing methods or studying uncertainties the following 3 steps should be included: (i) Measuring performance on data where true values are known, rather than on data containing unknown amounts of error; (ii) Measuring performance under many uncertainties simultaneously, rather than one at a

time; (iii) Characterization of problem structure (e.g. the number and spatial co-occurrence of species, landscape configuration, distribution of costs) and measuring performance on multiple problems with different structures.

3. **Sensitivity Analysis** Sensitivity analyses should be done by simultaneously varying multiple factors rather than studying each factor in isolation. Evidence should be given supporting the range and structure of errors used in the sensitivity analysis.

To make the method of measuring true versus apparent performance more concrete, we outline steps for this approach below (more details and examples are given in [20]):

- First, we define a dataset to be the true conditions in our modelled 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 characteristics is possible, or real-world data can be used from multiple locations where problem characteristics differ.

- Second, we can inject error into these true inputs to create apparent inputs by applying models representing our beliefs about real-world forms of error, for example, over or under-estimation of costs or spatial bias in error in predicting species habitat.

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

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