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Author for correspondence:
Sam Nicol
e-mail: sam.nicol@csiro.au

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Adapting environmental management to uncertain but inevitable change

Sam Nicol[1], Richard A. Fuller[2], Takuya Iwamura[3] and Iadine Chadès[1]

[1]Land and Water, Ecosciences Precinct, CSIRO, Dutton Park, Queensland 4102, Australia
[2]School of Biological Sciences, University of Queensland, Brisbane, Queensland 4072, Australia
[3]Department of Biology, Stanford University, Stanford, CA 94305, USA

Implementation of adaptation actions to protect biodiversity is limited by uncertainty about the future. One reason for this is the fear of making the wrong decisions caused by the myriad future scenarios presented to decision-makers. We propose an adaptive management (AM) method for optimally managing a population under uncertain and changing habitat conditions. Our approach incorporates multiple future scenarios and continually learns the best management strategy from observations, even as conditions change. We demonstrate the performance of our AM approach by applying it to the spatial management of migratory shorebird habitats on the East Asian–Australasian flyway, predicted to be severely impacted by future sea-level rise. By accounting for non-stationary dynamics, our solution protects 25 000 more birds per year than the current best stationary approach. Our approach can be applied to many ecological systems that require efficient adaptation strategies for an uncertain future.

1. Introduction

Species' distributions and abundances are shifting as a result of climate change [1,2]. Much work has been done to predict future long-term climate trends and their associated impacts on ecological systems. Some species are colonizing new areas, while other species are threatened with extinction by the warming climate [2]. Despite the potential implications of the changing climate, scientists hesitate to convert climate predictions into actionable decisions about where and when to act to achieve a management objective in the uncertainty of a changing environment [3,4]. Predicting the best management strategy in systems subject to long-term trends in threat (non-stationary systems) is difficult because the impact of future climate cannot be inferred from existing data with certainty [5,6]. A common approach is to generate a range of plausible scenarios to cover a suite of possible futures [7–9], but this provides little guidance for managers because the likelihood of each scenario is unknown [10]. Although they acknowledge the uncertainty, managers need not just data but processed information that can be used to make better decisions in a changing world [4,6,10]. Scientists need to provide managers with actionable guidance for immediate decisions using the best information available [11], while also providing reasonable estimates of how uncertain they are about their predictions [12]. Adaptive management (AM), or learning by doing, is recognized as the best management principle to manage systems under uncertainty in ecology [13,14] and natural resource economics [15,16] but suffers from a lack of solution methods [14,17].

Here, we address this problem by showing for the first time how to derive AM strategies that maximize the probability of achieving a management objective over time and across space in a changing climate. We use a partially observable Markov decision process (POMDP) [18] and build on an optimization method from artificial intelligence [17,19] to develop a decision tool to manage non-stationary systems. Using a predefined set of models of climate change impacts, our approach uses feedback from management actions to detect the most likely impacts of climate change over time. We calculate active adaptive strategies that provide the best actions given the current uncertainty, so actions can be taken to manage populations while further learning occurs [13].

Using our approach, we demonstrate how to determine where and when to protect habitats for migratory shorebirds using the East Asian–Australasian (EAA) flyway given uncertainty about the impacts of future sea-level rise (SLR) on shorebird habitats. The EAA flyway is a major migratory shorebird route; each year after breeding in eastern Siberia and Alaska, the birds undertake a return migration through Asia to Australasia. To complete their migration, the shorebirds depend on intertidal mudflats as stopover sites [20], which have been subject to extensive loss and degradation in the past [21,22] and are acutely vulnerable to further loss through SLR in the future [23].

Mean global sea level is predicted to rise between 0.75 and 1.90 m by 2100 [24,25]. As sea level rises, intertidal areas that are critical habitats for migrating shorebirds will be inundated, and their ability to shift inland in response to SLR depends on the upshore habitat being protected from development [24]. The extent of population losses will depend on the magnitude of SLR, creating further uncertainty [23]. Furthermore, the rate of SLR has accelerated over the past century [26], indicating that the rate of SLR can change over a short time period. Stochastic systems with underlying probability distributions that change over time are termed non-stationary. Non-stationary systems with an uncertain rate of change are challenging to manage because more data will not necessarily lead to reduced uncertainty if the trend changes with time. For the shorebirds of the EAA flyway, our objective is to choose where and when to avert habitat losses caused by uncertain, non-stationary impacts of SLR to maximize the expected breeding population size, less the costs of management.

A recent attempt to manage non-stationary systems using AM approximated change by assuming no trend (stationarity) to choose actions for short periods, and using the observations from the short period to learn a new stationary model at the end of each period [27]. However, the short time horizon means that the approach cannot anticipate long-term future change. An alternative approach assumes models of the future with constant rates of change [28,29]. If the rate of change is not constant, as in the case of SLR [26], then this approach may lead to poor management recommendations. By contrast, our POMDP approach improves AM by optimizing the long-term management of systems where the best predictive model of the system may change at any time. We demonstrate that our method can be used to simultaneously make optimal management decisions given current information and also to learn as climate change occurs. Accounting for scenario uncertainty in this way can identify management decisions that protect network populations in anticipation of future impacts of SLR and outperforms the recently published 'bottleneck index' network metric [23].

2. Material and methods

(a) Modelling the flyway as a network

For 10 shorebird taxa (bar-tailed godwit [*Limosa limosa baueri*; *Limosa limosa menzbieri*], curlew sandpiper [*Calidris ferruginea*], eastern curlew [*Numenius madagascariensis*], great knot [*Calidris tenuirostris*], grey-tailed tattler [*Tringa brevipes*], lesser sand plover [*Charadrius mongolus*], red knot [*Calidris canutus piersmai*; *Calidris canutus rogersi*] and terek sandpiper [*Xenus cinereus*]), the routes taken through the flyway are modelled as weighted directed graphs [23,30] (e.g. figure 1). Nodes represent regional groups of internationally important shorebird sites and are assumed to be at carrying capacity. Inundation by SLR decreases carrying capacity at a non-breeding node in proportion to the area lost. Lines represent the flow of birds migrating between nodes [23,30]. We assume that birds migrate deterministically through the network from a single breeding node (the method could accommodate stochastic migration if sufficient data existed).

(b) Management objective

The management objective is to maximize the expected population size at the breeding node over time less management penalties. Management penalty refers to the cost of protecting habitat (see §2e for details). If the sea level rises, then habitat in the non-breeding nodes is inundated, restricting how many birds can pass through the impacted nodes and return to the breeding node. Each year, one non-breeding node can be protected to prevent or offset the local habitat loss caused by SLR. Our goal is to find the best places in the network to protect over time to achieve the management objective. The challenge is that SLR is a non-stationary process, and we do not know when SLR will occur or what its effect on bird populations will be. We need models to describe the flyway network as the impacts of SLR change through time. To do this, we create different flyway network models that represent our best guesses about how SLR will impact bird populations for discrete values of SLR (0, 1 and 2 m), then use feedback from observed bird population data to determine the probabilities that each impact model is correct at any given time.

(c) Flyway responses to sea-level rise scenarios

We model three alternative future flyway networks corresponding to the impacts of habitat loss on bird populations under three SLR scenarios (0, 1 or 2 m) for each taxon (e.g. figure 1 and electronic supplementary material, S1, for networks for all taxa). To compute the expected habitat loss, we assume that the proportion of a non-breeding node inundated by an SLR scenario is equivalent to the proportional reduction in the carrying capacity at the node. Reducing the non-breeding node capacity constricts flow through the network and reduces the number of birds that return from the migration. For each SLR scenario, the amount of shorebird habitat required to offset the losses caused by rising sea levels at each non-breeding node is calculated from elevation models, bathymetry, tidal information and existing impermeable surfaces. See [23] for details of calculating areas of inundation and impermeable surfaces.

After returning to the breeding node, the surviving population undergoes stochastic breeding before the next annual migration begins. We estimate the annual change in population size after breeding for all taxa using a stochastic Gompertz model (electronic supplementary material, S2) and population data from Moreton Bay, Australia [31].

(d) Management actions to prevent sea-level rise impacts

Management actions in our model protect land to allow upshore habitat movement in response to SLR. Actions can protect a non-breeding node against the habitat loss caused by 0, 1 or 2 m of SLR. If the realized SLR is greater than the existing protection level, then we assume habitat loss will occur, reducing the carrying capacity of the node. The extent of habitat lost at the node is determined using the realized impact of SLR model (§2c). If a node is protected against the realized SLR, there will be no habitat loss. Birds arriving at a non-breeding node already at carrying capacity are assumed to die. Protection actions may be implemented successfully or may fail each year after

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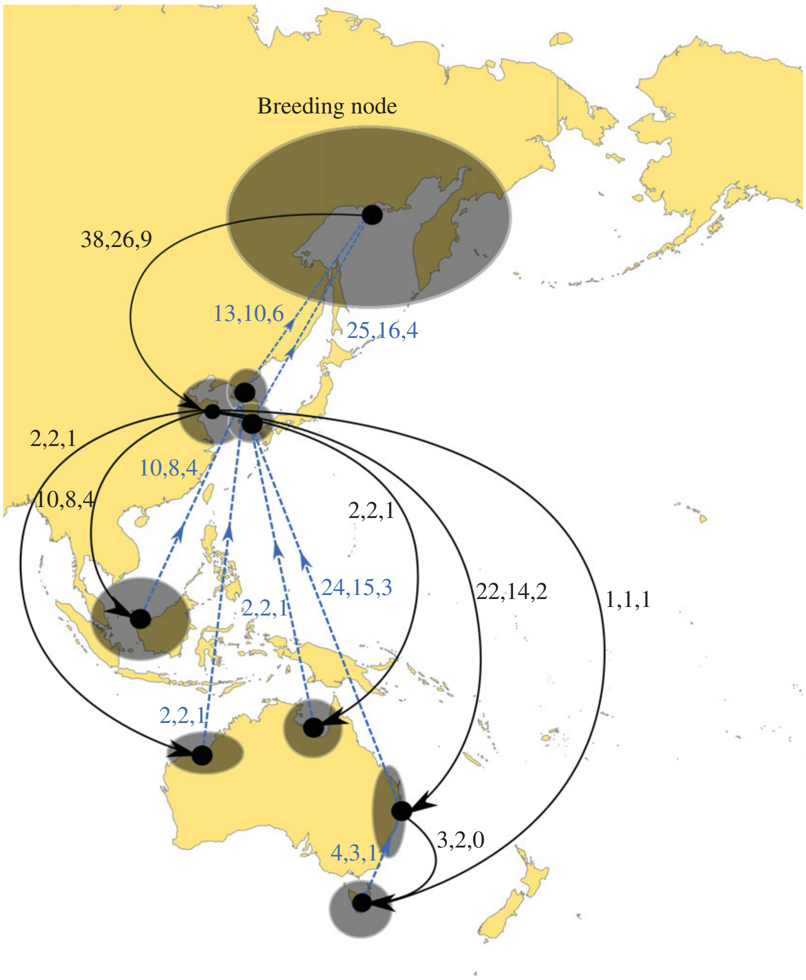

Figure 1. Network representation of the migratory flyway of the eastern curlew [23]. Shaded nodes represent the key staging, breeding and non-breeding nodes used by the curlew. Southward migration is depicted by the solid black arrows, and northward migration is depicted using dashed blue lines. Flows through the nodes decrease as the habitat of each node inundated by SLR increases. Numbers adjacent to lines show the maximum flows ($\times 10^3$) through the network under SLR scenarios of 0, 1 and 2 m, respectively. In each year, managers can counteract habitat loss at a single non-breeding node, preventing the loss of population flow through that node. (Online version in colour.)

implementation with fixed probabilities (electronic supplementary material, S3.2). We allow for management at one non-breeding node in each time step, but our approach can accommodate several actions per time step (although note that increasing the number of actions per time step exponentially increases the number of combinations that must be considered, limiting the number of actions that can be included during optimization). Actions are not taken at the breeding node because breeding takes place in the Siberian and Alaskan tundra for most taxa, and these inland areas are less likely to be affected by SLR than intertidal habitat in the non-breeding nodes.

(e) Reward function

We find the optimal AM strategy by maximizing the expected sum over time of a discounted reward function. The reward function specifies the quality of a state relative to the objective and is the mechanism for deciding which actions perform optimally over time. In this flyway example, the reward function is equal to the population size at the breeding node minus a management penalty for action in the current step (electronic supplementary material, S3.2). The one-time management penalty to protect a non-breeding node against an SLR impact scenario is calculated as the number of birds that would be lost owing to inundated habitat in that node if the SLR impact scenario were realized (i.e. the management penalty is proportional to the node area protected, which is proportional to the carrying capacity of the node in the event of SLR). Protecting against higher SLR impact at a node requires protecting more habitat and is more expensive than protecting against lower SLR impact scenarios. While in reality, management penalties would vary by node, measuring management penalties in terms of number of birds enables direct comparison between the penalties and rewards as they are in the same units. A more advanced management penalty would require study to equate the value of birds (reward) to the cost metric (e.g. land value). We include a discount factor (0.95) that allows managers to specify the relative value of birds in the present compared with birds in the future.

(f) Adaptive management with non-stationary dynamics

Recall that management of the flyway network is difficult because the correct network population model is uncertain and can change over time (non-stationary). Achieving the management objective requires making management decisions based on predicting the future breeding population size, but if the network model used for prediction can change at any time then we need to learn the probability that each network model represents reality at each time step.

We propose to learn the probabilities that each network model represents reality over time using AM, an iterative process of reducing uncertainty by learning the true system model from management outcomes [13,32,33]. The impact of SLR on bird populations at any time is assumed to be one of a suite of alternative models. We model the AM problem as a POMDP where the system model is unobservable but all other variables are completely observable, improving the method proposed in [17]. Specifically, we relax the standard assumption of stationarity in the unobserved state and instead allow the network population model of SLR impacts to change over time. We do this by specifying a probability of transition between network population models, so there is a changing belief (i.e. probability) that each candidate model is true at a given time (here we use a probability of transition of 0.05 between network population models, or an increase in SLR of 1 m every 20 years). In so doing, we demonstrate that we can solve AM problems when the stationarity assumption is not valid (electronic supplementary material, S3). Framing the non-stationary AM problem as a POMDP is key to our approach because POMDPs can be solved efficiently using advanced methods from artificial intelligence (e.g. [34,35]).

An additional complexity comes from the size of the flyway networks. Many ecological networks are large, and the computational complexity grows exponentially with the number of network nodes. The computational complexity of large networks can be addressed by modelling the system as a factored POMDP [36]. Factored POMDPs simplify the joint transition probability between states by specifying the conditional independence between system variables. Dependencies between variables can be represented using an influence diagram (electronic supplementary material, S4). Exploiting this independence structure reduces the problem complexity by storing only the information that is required to find an optimal solution [34].

(g) Learning and optimization

We build a factored POMDP model for each of 10 flyway networks representing 10 taxa that use the EAA flyway (electronic supplementary material, S3). Each factored POMDP represents a model of how a bird population may respond to changing SLR. Deterministic SLR information (e.g. depth and bathymetry) were used to create plausible models (§2c), but once the models were created, physical SLR data were not used to learn the most likely model. Instead, we observed the response of the bird population and learned the best management action directly from the population observed at the breeding node.

The state-based probability that a model of SLR impacts is correct (belief) is learned based on observations of the population at the breeding node and the protection levels of the non-breeding nodes. Belief states are sufficient statistics to summarize the observable history of the POMDP [37]. At each time step, observations are used to update the belief of each state using Bayes' rule (electronic supplementary material, equation S8). The optimal strategy matches each belief state with an optimal management action.

We solve the optimization problem using the point-based solver Symbolic Perseus [34]. Although point-based methods are not theoretically guaranteed to return optimal solutions, they provide near-optimal solutions in practice [17].

(h) The bottleneck heuristic

We compare the POMDP solution with a bottleneck heuristic [30,38] that combines connectivity with the proportion of population flow passing through node n for a given SLR scenario. The bottleneck heuristic is calculated using $b = \max_n(c_n p_n)$, where c_n is the betweenness centrality (proportion of flow through node n), and p_n is the proportion of the area of node n inundated by the SLR scenario (details of the computation of inundated area are in [23]). Nodes with higher b values are assumed to be priorities for management.

3. Results

Although the impact of SLR on bird populations is uncertain, our approach learns the probabilities that each of the migratory network population models best represent reality over time while managing optimally to maximize the breeding population of a shorebird taxon (less management penalties). We simulated an increasing impact of SLR on bird populations while tracking (i) the population size at the breeding node, (ii) the belief (i.e. the probability that each bird population network model is correct, obtained by comparing expected model outcomes and simulated observations), and (iii) the management action recommended by the POMDP strategy (figure 2). We programmed the simulation model to increase the expected impact of SLR by 1 m every 10 years, starting from the 0 m SLR impact scenario in the initial year (i.e. the expected impact of SLR is the 0 m bird population network model for years 0–10, the 1 m model for years 11–20 and the 2 m model for years 21–30). While this rate of change is faster than the predicted rate of SLR [24], it illustrates how our method learns uncertain dynamics. With a slower rate of change, we found similar results over a longer timescale (electronic supplementary material, S5). Our simulation approach meant that at each simulated time step, there was a 'realized' scenario (i.e. a correct network model of the bird population) that was known to us but had to be learned from system feedback by our approach. When the realized SLR increased in the simulation, the belief in the bird population model corresponding to the increased SLR scenario increased, and the management actions were adjusted to align with the realized scenario (figure 2). Because we controlled the simulated rate of change between population network models, we could evaluate how well our approach learned in an uncertain domain. Although our AM approach did not know the realized population network model at any time, it adapted and correctly learned the most probable population model even when the realized population model changed (figure 2*b*; see electronic supplementary material, S1 and figures S1–S10, for results across all taxa).

In our simulations of non-stationary SLR impacts, identifying the probability that a network population model represents reality and implementing the POMDP management strategy lead to significantly smaller decreases in average population size for all taxa, except the terek sandpiper, in comparison to taking no action (figure 3). Average gain in population size relative to doing nothing ranged between 2 and 29%, corresponding to between 1140 (*rogersi* red knot) and 14 500 (curlew sandpiper) additional birds in the breeding population (figure 3, and electronic supplementary material, S6, for comparison with a random strategy).

Based on simulations of the impacts of SLR models, our results significantly outperformed ($p < 0.05$) a recently proposed 'bottleneck index' network metric management strategy, which assumes a stationary scenario of the effect of SLR on bird populations [30]. Performance results for both the bottleneck index and the POMDP solution were generally superior to doing nothing, however the POMDP solution always equalled or outperformed the bottleneck strategy in our trials (percentage improvement of the POMDP compared with the bottleneck strategy ranged from 0 to 11.6% over the 10 taxa, and the POMDP strategy protected a total of 25 000 more birds per year than the bottleneck strategy over the 10 taxa; figure 3). Because it is given an estimate of the rate of change between models of SLR impacts, the POMDP strategy is able to use more information than the bottleneck strategy. However, although our approach assumed a fixed probability of the rate of change between models of SLR impacts, sensitivity analysis

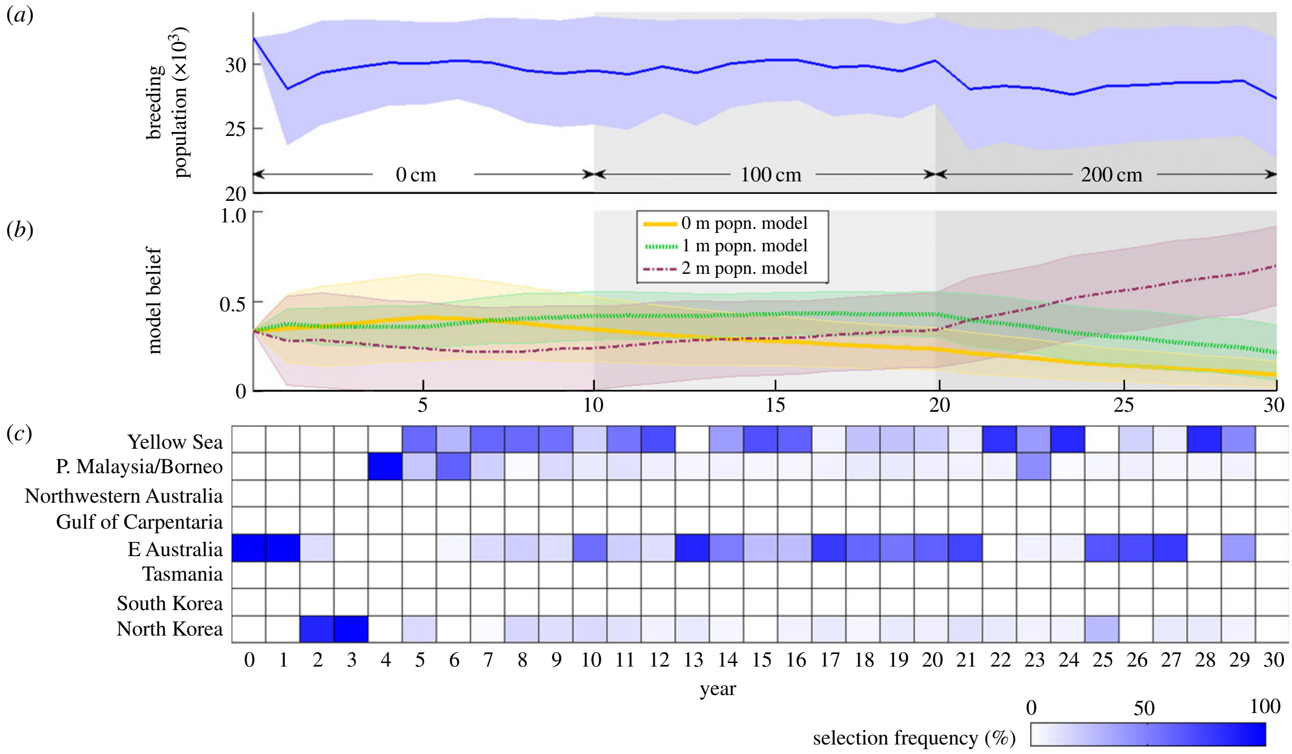

Figure 2. AM strategy for eastern curlew over 100 simulations. (*a*) Simulated breeding population over time. There are three network models of the population, created from three SLR predictions (0, 1 or 2 m). The true model is uncertain. (*b*) Simulated belief in the network models over time. The most likely network model has the highest belief. We assumed initial beliefs were equal. Using population observations (*a*), the probability that a network model represents reality can be learned over time (*b*). In these simulations, we know the true model but our approach does not. We programmed the simulation to increase the SLR impact model by 1 m every 10 years. The approach learns the most likely network model as the SLR scenario changes. (*c*) Location and timing of optimal actions. Darker colours represent locations that were selected more frequently during the simulations. Shaded areas in (*a*,*b*) depict 1 s.d. (Online version in colour.)

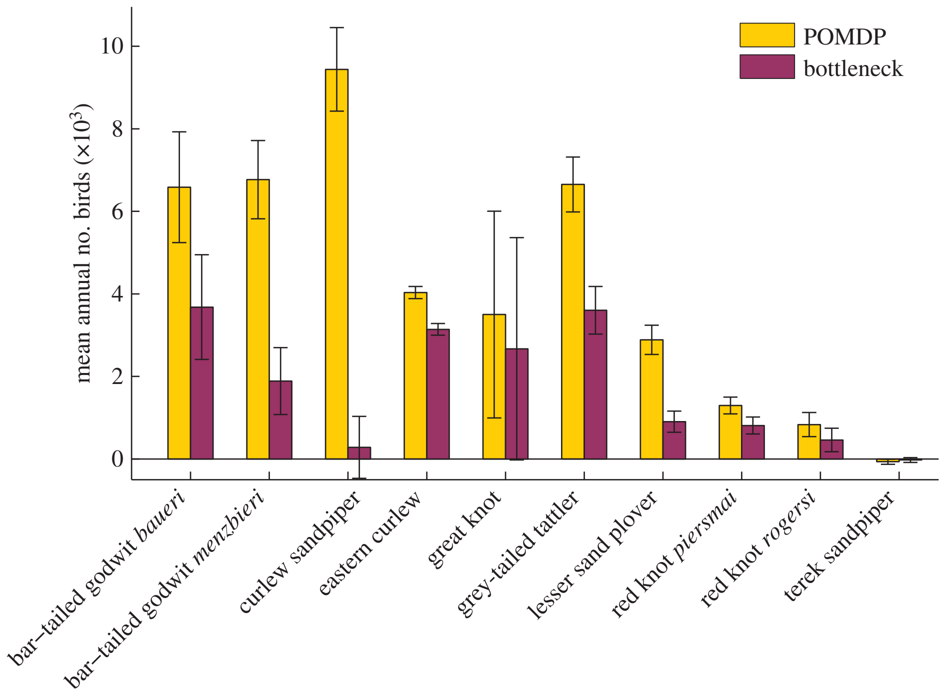

Figure 3. Additional birds protected by implementing the POMDP solution or a 'bottleneck' heuristic management strategy (§2h) compared with no management, simulated over a 50-year period. During the simulations, the predicted impacts of 0 m SLR were applied for years 1–10; 1 m SLR from years 11–30 and 2 m SLR from years 30–50. The POMDP strategy learns which population model is closest to the simulated impacts of SLR; the bottleneck strategy assumed a fixed 1 m SLR. The number of birds is the increase in mean annual breeding population (in thousands) compared with no management, computed over 100 simulations. The POMDP strategy protects a total of 25 000 more birds per year than the bottleneck strategy over the 10 taxa. Error bars depict 1 s.d. For most taxa, the POMDP strategy significantly outperforms ($p < 0.05$) the bottleneck strategy. (Online version in colour.)

showed that the POMDP strategy outperformed the bottleneck strategy even when the time interval between changes in models of SLR impacts varied (electronic supplementary material, figures S12 and S13). The bottleneck strategy assumed a single model of the impacts of SLR that did not change over time. By contrast, our POMDP solution allowed for multiple network population models, allowing it to detect the changing environment and select management actions accordingly, leading to improved performance.

Correctly identifying the probabilities of impact of SLR prevents wasting resources on ineffective action by assuming the 'wrong' model. The results of the bottleneck strategy we present here are calculated for a 1 m SLR, but if the realized SLR has impacts different from those predicted by the 1 m population model, the actions recommended by the bottleneck strategy may cost more than doing nothing without delivering any benefit. For the curlew sandpiper, the bottleneck strategy selects northwestern Australia and Southern China for protection, as this pathway supports 58% of the population in the 1 m SLR impact model (see electronic supplementary material, figure S3). However, if the impacts of 2 m SLR are realized, then the population flow through this pathway is constricted even if the bottleneck management strategy is followed. This occurs because an additional 20% of the usable habitat of an upstream node (SE Asia) is lost if the SLR impacts increase from those predicted by the 1 m model to the 2 m model, preventing many birds from ever reaching the protected nodes. If the wrong population network model is used, then even if the actions recommended by the bottleneck strategy are followed, the flow will be restricted because actions have been taken in the wrong regions to prevent the worst effects of the SLR. In this case, taking no action would have a greater net benefit than the bottleneck strategy as the penalty for action would be avoided (different penalty assumptions will make the bottleneck strategy more or less cost-effective). By contrast, the POMDP strategy correctly protects SE Asia, outperforming the bottleneck strategy (figure 3).

Across the 10 shorebird taxa, the regions most frequently prioritized for protection were the Yellow Sea, northeastern Australia and Korea (electronic supplementary material, figure S14). Offset action was also required in peninsular Malaysia, Japan, Tasmania and New Zealand. Two factors drive whether a site is selected for protection: the population flow through the node, and the extent of SLR impacts expected at the node. The Yellow Sea is not predicted to suffer such vast habitat inundation owing to SLR as other sites such as northeastern Australia, but the Yellow Sea is an important stopover region for seven of the 10 taxa studied [23]. Any habitat loss at this site reduces flow to many downstream sites in the network, so protecting this node is often prioritized. However, sites with small flows in the current scenario can become key sites in the future, and some of these sites also require protection. For eastern curlew under the 0 m SLR population network model, peninsular Malaysia receives 26% of the population (about 10 000 birds) on the southward migration. However, under the impacts of the 2 m SLR model, 44% of the population (4000 birds) use peninsular Malaysia, making this pathway the most significant under the 2 m SLR impact scenario (figure 1). As the belief in the population model associated with an SLR scenario increases, it can become optimal to act in places that currently seem to be low priorities.

4. Discussion

Uncertainty hinders management decisions [11], especially when the future is expected to be markedly different from the present or the rate of change is unpredictable [26]. The consequences of mis-management can be dire when the range of uncertainty is high, as demonstrated by the range of predicted outcomes from climate scenarios [39]. Under dynamic uncertainty, decision-making tools that predict the future using existing conditions or static single-scenario projections may mislead managers and scientists [40,41]. By improving the AM approach [13] to account for uncertain future scenarios, our approach simultaneously learns the probability that a model of change best represents reality and provides the best management action given the current uncertainty about the future. In our simulations, the method learned a new most likely population network model within a few years after the true model changed. Even when the true population model associated with an SLR scenario changed over time, as observed during the twentieth century [26], the approach learned the most likely model and altered the management strategy to be optimal for the new scenario (figure 2). Learning the probability that a scenario represents reality was valuable (protecting between 1140 and 14 500 birds for nine of 10 taxa) and gave better results than heuristic management assuming a fixed future climate scenario (figure 3). Accounting for the uncertain environment led to surprising recommendations to act in locations that do not carry much network flow under current conditions. This is the strength of our approach: adaptive learning predicts that these locations can become valuable nodes as the environment changes. Our approach anticipates the risk of severe environmental change impacts and recommends protecting these nodes before change occurs to ensure they are intact (e.g. peninsular Malaysia in figure 1).

As a general rule, managing nodes that carry high flow (e.g. the Yellow Sea) is critical to preserving network flow. Similarly, nodes that are vulnerable to detrimental change (e.g. habitat loss caused by SLR in northeastern Australia (electronic supplementary material, S7)) should be managed. The trade-off between these two potentially conflicting strategies depends on how the flows change between network models and the likelihood of changing network models. Consequently, the belief in a network model has an important role in effective management. Although heuristic management of 'bottleneck' nodes with high flows and high predicted habitat loss performed reasonably well, it was outperformed by the POMDP solution that accounted for changing uncertainty (figure 3). Employing the bottleneck heuristic may be a sound strategy if the timing of action is not important, but if it matters when protection is implemented (e.g. if development threatens certain sites) then the POMDP strategy is superior.

The approach we present differs from sensitivity analysis approaches that evaluate multiple climate scenarios [7] because we maintain a probability that each network model is correct. Knowing the probability of each network model means that we can recommend the best management actions given our uncertainty about the true impact of non-stationary environmental change. While other studies used Markov Chain Monte Carlo approaches to estimate the uncertainty in climate models [42,43], our approach is the first to adaptively learn and predict the probability of impacts of climate while also providing the best management responses given the existing and future uncertainty. However, AM approaches that assume a predefined set of scenarios require that the true scenario be close to a scenario in the set [17]. If the model set does not approximate the true scenario, then our approach might not provide the best solutions. Because our method uses the fastest computational methods to solve AM problems (POMDP), our approach can accommodate a large number of models, if available [17].

However, as the number of possible future models increases, it might become more difficult to distinguish between models. Models must be similar enough to provide sufficient resolution but different enough to require alternative optimal management strategies; there is no need to distinguish between models if the management response is the same [44]. Finding the minimum set of models to include in AM problems is an unsolved optimization problem that requires further research.

Our approach requires an estimate of the probability of transition between models of SLR impacts [24]. This estimate provides additional information to the decision-making process that improves management performance compared with a static estimate of future SLR impacts (electronic supplementary material, S5). Our approach can be adapted to remove this assumption by treating the rate of change between models of SLR impacts as a hidden probability that can take discrete values (electronic supplementary material, S8). This comes at an additional computational cost because additional hidden parameters must be learned. For the tests that we completed on the EAA flyway networks, we found that removing this assumption had no significant impact on the number of birds protected (electronic supplementary material, S8), however it may be important in other applications. An alternative approach is to solve the problem using passive rather than our active AM approach. Solving the problem with passive AM means that we would not manage the system based on anticipating future learning opportunities, making the solution reactive rather than proactive [32].

Our model learns the best management actions for bird populations in a changing environment based on the assumption that changes in SLR directly reduce the population of breeding birds. The learning model uses the breeding population as the observed variable. This approach has the advantage of directly observing the variable of interest to managers (i.e. the number of birds), but we do not learn about the assumed relationship between habitat loss from SLR and changes in bird populations (note that recent research suggests that there may be a simple relationship between population size and habitat loss [45]). An extension of our model could incorporate observations of SLR as well as breeding population. This extension would require an additional unobserved parameter to learn the relationship between the habitat loss from SLR and the changes in bird populations. Learning the additional parameter would increase the time and data required to resolve uncertainty among the models.

SLR is only one of many factors affecting shorebird populations in the EAA flyway. Coastal development and changes in sedimentation regimes have caused the loss of 65% of tidal flats in the Yellow Sea in the past 50 years [21], and a number of other threats from harvesting and disturbance to climate change on the breeding grounds are operating [46]. Our manuscript focuses on the threat of SLR as an illustration of non-stationary change, but additional threats could be incorporated by our approach if state-transition models of the response of bird populations to threats could be articulated. While research on the rate of habitat loss is ongoing [21], we do not yet have models of how multiple threats are interacting. If hypotheses considering multiple threats could be articulated, these could be incorporated without additional computational complexity.

We have demonstrated the benefit of our approach on one of the most difficult decision problems to date: managing networks that change over time and space. Our approach is not limited to decisions about climate change and can help solve any non-stationary AM problem. Problems involving networks of uncertain structure occur in many situations [47,48]. For example, our method could be used to manage invasive species across space and time with uncertain dispersal probabilities [49,50], similarly it could be used to best manage disease outbreak [36], the management and surveillance of hard-to-detect species [51], or uncertain dynamic interactions between species assembled in foodwebs [52,53].

Implementation of adaptation actions to protect biodiversity has perhaps been limited by uncertainty about the future. One reason for this could be the myriad models and future scenarios presented to decision-makers [4,6,10,11]. Our method is a way to empirically evaluate models for the decision-maker while also providing a management recommendation for immediate action, taking uncertainty into account. Decision-makers can see the current probability that a model is correct, as well as a recommended management action based on that belief (figure 2). SLR and other non-stationary processes will affect many biological and human systems [54], and our method provides a way to manage this uncertain but inevitable change.

Data accessibility. The datasets supporting this article are available at: (doi:10.5061/dryad.hr05m).

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Authors' contributions. S.N., I.C. and R.A.F. conceived and designed the study. T.I. and R.A.F. collected the flyway network data. S.N. prepared the POMDP model and carried out analysis. S.N. and I.C. wrote the draft manuscript. All authors contributed substantially to manuscript revisions.

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References

1. Parmesan C, Yohe G. 2003 A globally coherent fingerprint of climate change impacts across natural systems. *Nature* **421**, 37–42. (doi:10.1038/nature01286)
2. Thomas CD *et al*. 2004 Extinction risk from climate change. *Nature* **427**, 145–148. (doi:10.1038/nature02121)
3. Hulme PE. 2005 Adapting to climate change: is there scope for ecological management in the face of a global threat? *J. Appl. Ecol.* **42**, 784–794. (doi:10.1111/j.1365-2664.2005.01082.x)
4. Kerr RA. 2011 Time to adapt to a warming world, but where's the science? *Science* **334**, 1052–1053. (doi:10.1126/science.334.6059.1052)
5. Conroy MJ, Runge MC, Nichols JD, Stodola KW, Cooper RJ. 2011 Conservation in the face of climate change: the roles of alternative models, monitoring, and adaptation in confronting and reducing uncertainty. *Biol. Conserv.* **144**, 1204–1213. (doi:10.1016/j.biocon.2010.10.019)

6. Pidgeon N, Fischhoff B. 2011 The role of social and decision sciences in communicating uncertain climate risks. *Nat. Clim. Change* **1**, 35–41. (doi:10.1038/nclimate1080)
7. Moss RH *et al*. 2010 The next generation of scenarios for climate change research and assessment. *Nature* **463**, 747–756. (doi:10.1038/nature08823)
8. Dickinson R. 2012 Proceed with planning despite multiple models. *Science* **335**, 539. (doi:10.1126/science.335.6068.539)
9. Ritten JP, Frasier WM, Bastian CT, Gray ST. 2010 Optimal rangeland stocking decisions under stochastic and climate-impacted weather. *Am. J. Agric. Econ.* **92**, 1242–1255. (doi:10.1093/ajae/aaq052)
10. Kerr RA. 2011 Vital details of global warming are eluding forecasters. *Science* **334**, 173–174. (doi:10.1126/science.334.6053.173)
11. Lemos M, Rood R. 2010 Climate projections and their impact on policy and practice. *Wiley Interdiscip. Rev. Clim. Change* **1**, 670–682. (doi:10.1002/wcc.71)
12. Smith LA, Stern N. 2011 Uncertainty in science and its role in climate policy. *Phil. Trans. R. Soc. A* **369**, 4818–4841. (doi:10.1098/rsta.2011.0149)
13. Walters CJ. 1986 *Adaptive management of renewable resources*. New York, NY: Macmillan Press.
14. Williams BK. 2011 Resolving structural uncertainty in natural resources management using POMDP approaches. *Ecol Model.* **222**, 1092–1102. (doi:10.1016/j.ecolmodel.2010.12.015)
15. Fackler P, Pacifici K. 2014 Addressing structural and observational uncertainty in resource management. *J. Environ. Manage.* **133**, 27–36. (doi:10.1016/j.jenvman.2013.11.004)
16. Springborn M, Sanchirico JN. 2013 A density projection approach for non-trivial information dynamics: adaptive management of stochastic natural resources. *J. Environ. Econ. Manage.* **66**, 609–624. (doi:10.1016/j.jeem.2013.07.003)
17. Chades I, Sabbadin R, Carwardine J, Martin TG, Nicol S, Buffet O. 2012 MOMDPs: a solution for modelling adaptive management problems. In *Proc. association for the advancement of artificial intelligence* (*AAAI-12*) (eds B Selman, J Hoffman), pp. 267–273. Palo Alto, CA: The AAAI Press.
18. Monahan GE. 1982 Survey of partially observable Markov decision processes: theory, models and algorithms. *Manage. Sci.* **28**, 1–16. (doi:10.1287/mnsc.28.1.1)
19. Ong SCW, Png SW, Hsu D, Lee S. 2010 Planning under uncertainty for robotic tasks with mixed observability. *Int. J. Robot. Res.* **29**, 1053–1068. (doi:10.1177/0278364910369861)
20. Myers JP *et al*. 1987 Conservation strategy for migratory species. *Am. Sci.* **75**, 19–26.
21. Murray NJ, Clemens RS, Phinn SR, Possingham HP, Fuller RA. 2014 Tracking the rapid loss of tidal wetlands in the Yellow Sea. *Front. Ecol. Environ.* **12**, 267–272. (doi:10.1890/130260)
22. Murray NJ, Ma Z, Fuller RA. 2015 Tidal flats of the Yellow Sea: a review of ecosystem status and anthropogenic threats. *Austral Ecol*. (doi:10.1111/aec.12211)
23. Iwamura T, Possingham HP, Chades I, Minton C, Murray NJ, Rogers DI, Treml EA, Fuller RA. 2013 Migratory connectivity magnifies the consequences of habitat loss from sea-level rise for shorebird populations. *Proc. R. Soc. B* **280**, 20130325. (doi:10.1098/rspb.2013.0325)
24. Vermeer M, Rahmstorf S. 2009 Global sea level linked to global temperature. *Proc. Natl Acad. Sci. USA* **106**, 21 527–21 532. (doi:10.1073/pnas.0907765106)
25. Pfeffer WT, Harper JT, O'Neel S. 2008 Kinematic constraints on glacier contributions to 21st-century sea-level rise. *Science* **321**, 1340–1343. (doi:10.1126/science.1159099)
26. Church JA, White NJ. 2006 A 20th century acceleration in global sea-level rise. *Geophys. Res. Lett.* **33**, L01602. (doi:10.1029/2005GL024826)
27. Nichols JD *et al*. 2011 Climate change, uncertainty, and natural resource management. *J. Wildl. Manage.* **75**, 6–18. (doi:10.1002/jwmg.33)
28. Martin J, Fackler PL, Nichols JD, Lubow BC, Eaton MJ, Runge MC, Stith BM, Langtimm CA. 2011 Structured decision making as a proactive approach to dealing with sea level rise in Florida. *Clim. Change* **107**, 185–202. (doi:10.1007/s10584-011-0085-x)
29. McDonald-Madden E, Runge M, Possingham H, Martin T. 2011 Optimal timing for managed relocation of species faced with climate change. *Nat. Clim. Change* **1**, 261–265. (doi:10.1038/nclimate1170)
30. Iwamura T. 2012 *Spatial conservation prioritisation under global threats*. Brisbane, Australia: University of Queensland.
31. Wilson H, Kendall BE, Possingham HP. 2010 Variability in population abundance and the classification of extinction risk. *Conserv. Biol.* **25**, 747–757. (doi:10.1111/j.1523-1739.2011.01671.x)
32. Williams BK, Szaro RC, Shapiro CD. 2009 *Adaptive management: the U.S. department of the interior technical guide*. Washington, DC: U.S. Department of the Interior.
33. Williams BK. 2009 Markov decision processes in natural resources management: observability and uncertainty. *Ecol. Model.* **220**, 830–840. (doi:10.1016/j.ecolmodel.2008.12.023)
34. Poupart P. 2005 *Exploiting structure to efficiently solve large scale partially observable Markov decision processes*. Toronto, Canada: University of Toronto.
35. Hoey J, St-Aubin R, Hu AJ, Boutilier C. 1999 *SPUDD: stochastic planning using decision diagrams*. Stockholm, Sweden: Proceedings of Uncertainty in Artificial Intelligence.
36. Chades I, Martin TG, Nicol S, Burgman MA, Possingham HP, Buckley YM. 2011 General rules for managing and surveying networks of pests, diseases, and endangered species. *Proc. Natl Acad. Sci. USA* **108**, 8323–8328. (doi:10.1073/pnas.1016846108)
37. Astrom KJ. 1965 Optimal control of Markov decision processes with incomplete state estimation. *J. Math. Anal. Appl.* **10**, 174–205. (doi:10.1016/0022-247X(65)90154-X)
38. Iwamura T, Fuller RA, Possingham HP. 2014 Optimal management of a multispecies shorebird flyway under sea-level rise. *Conserv. Biol.* **28**, 1710–1720. (doi:10.1111/cobi.12319)
39. Stocker T, Dahe Q, Plattner G. 2013 Climate change 2013: the physical science basis: technical summary. Intergovernmental Panel on Climate Change.
40. Lempert R, Schlesinger M, Bankes S, Andronova N. 2000 The impacts of climate variability on near-term policy choices and the value of information. *Clim. Change* **45**, 129–161. (doi:10.1023/A:1005697118423)
41. Costello C, Polasky S. 2004 Dynamic reserve site selection. *Resour. Energy Econ.* **26**, 157–174. (doi:10.1016/j.reseneeco.2003.11.005)
42. Katz R. 2002 Techniques for estimating uncertainty in climate change scenarios and impact studies. *Clim. Res.* **20**, 167–185. (doi:10.3354/cr020167)
43. New M, Hulme M. 2000 Representing uncertainty in climate change scenarios: a Monte-Carlo approach. *Integr. Assess.* **1**, 203–213. (doi:10.1023/A:1019144202120)
44. Nicol S, Chadès I. 2012 Which states matter? An application of an intelligent discretization method to solve a continuous POMDP in conservation biology. *PLoS ONE* **7**, e28993. (doi:10.1371/journal.pone.0028993)
45. He F. 2012 Area-based assessment of extinction risk. *Ecology* **93**, 974–980. (doi:10.1890/11-1786.1)
46. MacKinnon J, Verkuil Y, Murray N. 2012 *IUCN situtation analysis on East and Southeast Asian intertidal habitats, with particular reference to the Yellow Sea* (*including the Bohai Sea*). Occasional paper of the IUCN Species Survival Commission No. 47. Cambridge, UK: IUCN.
47. May R. 2006 Network structure and the biology of populations. *Trends Ecol. Evol.* **21**, 394–399. (doi:10.1016/j.tree.2006.03.013)
48. Montoya JM, Pimm SL, Solé RV. 2006 Ecological networks and their fragility. *Nature* **442**, 259–264. (doi:10.1038/nature04927)
49. Regan TJ, McCarthy MA, Baxter PWJ, Panetta FD, Possingham HP. 2006 Optimal eradication: when to stop looking for an invasive plant. *Ecol. Lett.* **9**, 759–766. (doi:10.1111/j.1461-0248.2006.00920.x)
50. Regan TJ, Chades I, Possingham HP. 2011 Optimal strategies for managing invasive plants in partially observable systems. *J. Appl. Ecol.* **48**, 76–85. (doi:10.1111/j.1365-2664.2010.01915.x)
51. Chades I, McDonald-Madden E, McCarthy MA, Wintle B, Linkie M, Possingham HP. 2008 When to stop managing or surveying cryptic threatened species. *Proc. Natl Acad. Sci. USA* **105**, 13 936–13 940. (doi:10.1073/pnas.0805265105)
52. Fahimipour AK, Hein AM. 2014 The dynamics of assembling food webs. *Ecol. Lett.* **17**, 606–613. (doi:10.1111/ele.12264)
53. May RM. 2009 Food-web assembly and collapse: mathematical models and implications for conservation. *Phil. Trans. R. Soc. B* **364**, 1643–1646. (doi:10.1098/rstb.2008.0280)
54. Dasgupta S, Laplante B, Meisner C, Wheeler D, Yan J. 2009 The impact of sea level rise on developing countries: a comparative analysis. *Clim. Change* **93**, 379–388. (doi:10.1007/s10584-008-9499-5)