ROBUST.PRIORITIZR: ROBUST SYSTEMATIC CONSERVATION PRIORITIZATION

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ABSTRACT

1. Climate change poses significant threats to biodiversity. To ensure the long-term persistence of species, protected areas must be established in locations that will safeguard suitable habitats in the future. Although statistical models can predict where such habitats may occur under different future scenarios, designing protected areas that can effectively protect these habitats across a wide range of futures remains challenging.
2. We present the `robust.prioritizr` `R` package as a decision support tool for systematic conservation planning. This tool is designed to identify priority areas for establishing protected areas that are robust against uncertainty. Using advances in robust optimization, this tool identifies priority areas that can achieve conservation objectives cost-effectively under a wide range of plausible future scenarios. Our novel approach a) allows users to flexibly specify their desired level of robustness to explore trade-offs between risk reduction and solution cost; b) does not make assumptions about the statistical distribution of uncertainty; and c) uses exact solvers for mixed-integer linear programming problems to guarantee solution optimality.
3. We examine a case study based in Victoria, Australia, to showcase the tool. This case study involved 872 native species, 12,988 candidate areas for selection, and four climate change scenarios across five time steps. Using this tool, we identified priority areas for cost-effectively meeting representation target thresholds for each species under various future scenarios in the region. Additionally, compared with prioritization generated using conventional approaches, prioritizations generated with the tool were better able to achieve conservation objectives across multiple future scenarios.
4. *Synthesis and applications.* Our study allows conservation scientists and practitioners to create conservation plans that are robust to uncertainties. The tool was developed as an open-source `R` package to enhance the `prioritizr` `R` package and is available on the Comprehensive R Archive Network (CRAN). By explicitly considering multiple future scenarios during priority setting, conservation plans can be made more resilient to the impacts of climate change on biodiversity.

Keywords systematic conservation planning, reserve selection, climate change, scenario analysis, robust optimization

1 Introduction

Climate change is a major threat to global biodiversity (Arneth *et al.*, 2020; Araújo and Rahbek, 2006). As climate regimes shift, many species will need to move to new locations to survive (Pecl *et al.*, 2017; Montràs-Janer *et al.*, 2024). Shifts in climate regimes mean that as governments act on their pledges to establish protected areas to cover 30% of the planet by 2030 under the Global Biodiversity Framework (CBD, 2018), they must ensure that their plans for establishing protected areas (hereafter, prioritizations) account for both the current and future distribution of species' suitable habitats (Hannah, 2008; Carroll and Ray, 2021; Dreiss *et al.*, 2022). However, accounting for the future distribution of even a single species is challenging because predictions may vary considerably depending on the underlying assumptions about future climate regimes and land-use activities (such as those characterized by alternative Shared Socioeconomic Pathway – Representative Concentration Pathway (SSP-RCP) scenarios; van Vuuren *et al.*, 2011). Consequently, there is a need for practitioners to produce prioritizations that are robust to uncertainty (Ando and Mallory, 2012; Knoke *et al.*, 2016; Rutschmann *et al.*, 2025).

Finding an approach to successfully address climate change uncertainty has been a long-standing obstacle to effective spatial prioritization (Reside *et al.*, 2018). For example, one approach (hereafter, the fully robust approach) involves considering a set of plausible scenarios to characterize alternative future distributions and generating a prioritization to adequately represent each species across every scenario (Levin *et al.*, 2015; Levy and Ban, 2013). Although conceptually simple, this approach can produce prioritizations with high implementation costs that hinder its feasibility (Levin *et al.*, 2015). Another approach involves calculating the probability that a particular species will occur at a particular location across multiple scenarios and then discounting (penalizing) this probability based on the degree of uncertainty across scenarios (for example, available via `Zonation`; Moilanen *et al.*, 2006). Although its solutions might be more cost-effective, it requires distributional assumptions regarding uncertainty. For example, if standard errors are used for discounting uncertainty (i.e., uncertainty is assumed to be normally distributed), then prioritization may not achieve high species representation when scenarios form multiple distinct groups (i.e., uncertainty is multimodal or has fat-tailed distributions). Modern Portfolio Theory-based methods would similarly require the estimation of the covariance matrix of returns across planning units, a data-intensive process that makes strong distributional assumptions about uncertainty (Dunkel and Weber, 2012; Popov *et al.*, 2022). Finally, the `Marxan with Probability` tool (Watts *et al.*, 2021) explicitly accounts for the probability that each species will be adequately represented under each scenario, overcoming the limitations of the previous approaches. However, this tool relies on meta-heuristic algorithms that produce suboptimal prioritizations (Schuster *et al.*, 2020; Beyer *et al.*, 2016).

The field of robust optimization in operations research is dedicated to addressing the challenge of decision-making under uncertainty (Ben-Tal *et al.*, 2009; Bertsimas and Sim, 2004). Similar to existing approaches that account for uncertainty in conservation prioritization settings (Popov *et al.*, 2022), robust optimization approaches aim to identify solutions that remain feasible and effective across a range of uncertain scenarios. For example, the chance-constrained approach (Charnes and Cooper, 1959) ensures that the probability that a solution meets its constraints exceeds a predefined threshold. Additionally, the Conditional Value-at-Risk (CVaR) approach provides a computationally efficient formulation to identify solutions that are robust to uncertainty by focusing on and reducing negative outcomes at the tail of the uncertainty distribution. This finds solutions that effectively minimize downside risk, which are negative consequences that could occur from rare, yet severely negative, events, and are effective even when the uncertainty distribution is non-normal. Although previous studies have also applied robust optimization, downside risk, and CVaR techniques in conservation and land-use prioritization (Knoke *et al.*, 2016; Shah and Ando, 2015; Husmann *et al.*, 2022; Cho *et al.*, 2025a), previous applications are not easily generalizable to other contexts and do not allow users to easily customize their desired level of robustness to uncertainty.

Here, we introduce the `robust.prioritizr R` package (hereafter, the package) to provide general-purpose robust optimization approaches for systematic conservation planning. The package enhances the `prioritizr R` package (Hanson *et al.*, 2025) and provides a flexible interface for generating spatial prioritizations that are robust to uncertainties. To achieve this, the package leverages novel applications of chance constraints and CVaR approaches for reserve selection. We provide an overview of the package, explain its mathematical formulation, and detail its usage with a case study involving 872 native species in Victoria, Australia, across four climate scenarios and five time steps until 2090. We compared the prioritizations generated using the chance-constrained, CVaR, and fully robust approaches and a prioritization that did not account for uncertainty. Our findings highlight the untapped potential of robust optimization techniques for environmental decision-making.

2 Methods

2.1 Package description

The `robust.prioritizr R` package (hereafter, the package) extends the open-source `prioritizr R` package (Hanson *et al.*, 2025) by implementing systematic conservation planning problems characterized by uncertain constraints, as shown in Figure 1.

A robust systematic conservation planning problem is similar to a systematic conservation planning problem, except that it contains uncertain data described by a finite set of data realizations. Each realization describes one plausible state of the world, and the decision-maker does not know which state of the world will be realized. Climate scenarios are examples of realizations: decision-makers do not know which climate scenario will turn out to be “true,” and the distribution of species in space may differ across each climate scenario. The decision-maker’s goal is to design a protected area system that meets their targets across most climate scenarios.

In Step 1, users can define a conservation planning problem, detailing the planning units and the region in which prioritization needs to be made. For example, these planning units can be grid cells or polygons of administrative boundaries. In this step, the user also defines the features to be used for prioritization, which are usually maps of biodiversity and the cost of establishing, acquiring, and restoring protected areas. In a typical conservation prioritization workflow in `prioritizr`, the user can only specify one realization of the data layer, such as the species distribution of one particular species under one projection. In contrast, the `robust.prioritizr R` framework allows users to specify multiple realizations of the data.

In Step 2, users define a mathematical objective, which describes the user’s conservation goals quantitatively. Among the variations of mathematical objectives used, the minimum set objectives and minimum shortfall objectives are among the most widely used in conservation planning exercises. Accordingly, both were selected for implementation in the framework. The minimum set objective seeks to find a solution that minimizes the total cost while ensuring that all species representation targets (e.g., the proportion of a species’ range represented within the protected area) are met (Rodrigues and Gaston, 2002). The minimum set objective has been widely used in various conservation planning examples, such as for the conservation of migratory species (Schuster *et al.*, 2019), protecting biodiversity hotspots at risk of deforestation (Struebig *et al.*, 2015), and identifying priorities for nature’s contributions to people (Neugarten *et al.*, 2024). The minimum shortfall objective minimizes the total shortfall between a species’ representation and its respective targets (Arponen *et al.*, 2005), and has been used previously in examples such as identifying global priorities for biodiversity, carbon, and water quality goals (Jung *et al.*, 2021), analyzing countries’ responsibilities for Global Biodiversity Framework targets (Shen *et al.*, 2023), and improving protected area connectivity (Sacre *et al.*, 2025).

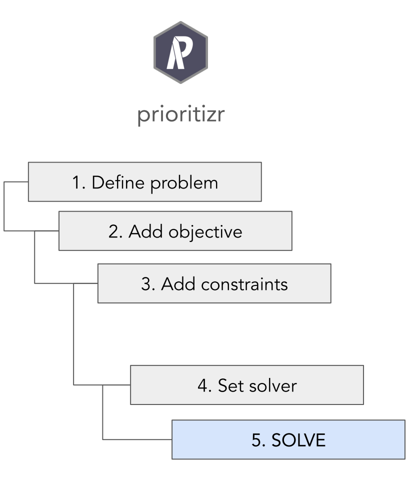
In Step 3a, the users specify the constraints that represent a robust optimization approach to account for uncertainty. Users of the package will still have access to all of the flexible preconfigured constraints in `prioritizr`, such as the “Management Zones” functionality and neighbor contiguity constraints (similar to Watts *et al.*, 2009; Beyer *et al.*, 2016).

Adding robust constraints (Step 3b) is an additional step specific to the `robust.prioritizr` framework. Whereas a standard constraint implemented in `prioritizr` is only represented using one data realization, a robust constraint is represented by grouping several data realizations, each collectively known as a "feature group.” In this step, users specify which data realizations correspond to the same robust constraint by specifying the feature group. After the user groups these data realizations into feature groups, they can then customize the approach they would like to use to deal with uncertainty and the level of robustness they require. These options are explained in detail in the next section.

Steps 4 and 5 are equivalent across the packages, allowing users to use a mixed-integer linear programming solver of their choice, such as Gurobi (Gurobi Optimization, LLC, 2024), CPLEX (IBM, 2009), CBC solver (Forrest *et al.*, 2024), HiGHS (Huangfu and Hall, 2018), and SYMPHONY (Ralphs and Güzelsoy, 2006). The use of these solvers provides mathematical guarantees of the optimality of the solution (Rodrigues and Gaston, 2002; Beyer *et al.*, 2016), making them more desirable than heuristic algorithms or simulated annealing approaches used by decision-support software such as Zonation and Marxan, which do not offer similar guarantees.

2.2 Robust objectives and constraints

We designed the package to provide a flexible interface for specifying uncertainty in terms of discrete realizations, where each realization is assumed to have an equal probability of occurring, explicitly accounting for uncertainty through the use of these realizations. Consider the function $f_k(x)$, where the feature representation of the protected area x under realization k is calculated using f. The user’s objective is to find the x that ensures that $f_k(x) \geq T$, where T is the species representation target. Importantly, this constraint must hold across a large proportion of possible discrete realizations k.



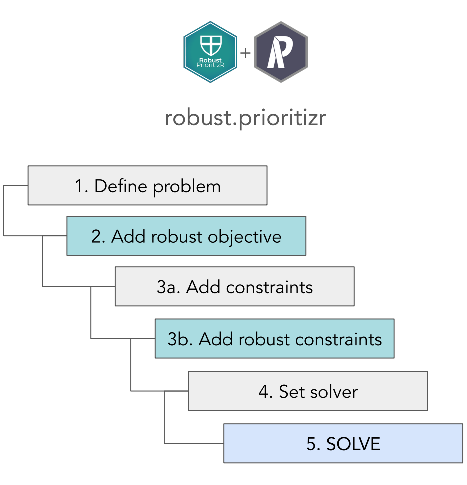


Figure 1: Prioritization workflow: "prioritizr" (non-robust) versus "robust.prioritizr" (robust)

We use a stylized version of the distribution of $f_k(x)$ across k in Figure 2 to illustrate the constraints available in this package.

We first describe a fully robust constraint, as shown in Figure 2A. To satisfy this fully robust constraint, the feature representation must exceed its target across all realizations. This provides the strongest protection against uncertainty, as it means that the target is met regardless of which realization is realized. However, in some cases, the fully robust constraint can be too strict, which can heavily restrict the space of feasible solutions to the problem. For example, consider a planning problem in which the range of a threatened species is projected to shrink dramatically under an extreme climate scenario to the point where there are no more suitable habitats for that species within the planning region. In this case, if a fully robust constraint is used, the entire problem will be infeasible because the target cannot be met even if all planning units are set aside as protected areas.

Figure 2B can help relax the strictness of the constraint by allowing a part of the probability distribution to fall below its target using chance constraints. Doing so would broaden the solution space and enable the user to find more feasible solutions, but comes at the expense that the solution will no longer be fully robust to all realizations of the data. The package enables the user to choose how tolerant they are towards violations of the constraint by specifying the confidence level parameter α. α can be interpreted as the probability that the constraint will be met, and the solution will ensure that the proportion of realizations that meets the constraint always exceeds α. In other words, the $1-\alpha$ quantile of the probability distribution always exceeds the target.

Figure 2C extends this further by implementing the Conditional Value-at-Risk (CVaR), or Expected Shortfall, metric for optimization (Rockafellar and Uryasev, 2000; Bertsimas *et al.*, 2004). CVaR is a metric that originates from quantitative finance and is used to measure the risk of any given random probability distribution. It is typically considered a superior risk measure compared to alternatives, such as quantile-based measures or standard deviation, as it satisfies a set of axioms that make it a “coherent" risk measure in financial economics (Artzner *et al.*, 1999; Rockafellar and Uryasev, 2002). For the purposes of optimization, CVaR also benefits from established linear programming formulations that make its optimization more computationally efficient than chance constraints (Rockafellar and Uryasev, 2000). The CVaR constraint ensures that the expected value of the tail of the distribution exceeds the target, where the tail is defined as the values in the distribution that fall below a specified quantile. In Figure 2C, the values that fall below the $(1-\alpha)$ quantile of the probability distribution are colored blue and red, and the CVaR calculates the expected value in the tail of that distribution.

In the Supplementary Information, we provide an accessible explanation of the mathematical intuition behind these constraints and the full mathematical formulation of the planning problems implemented in this package.

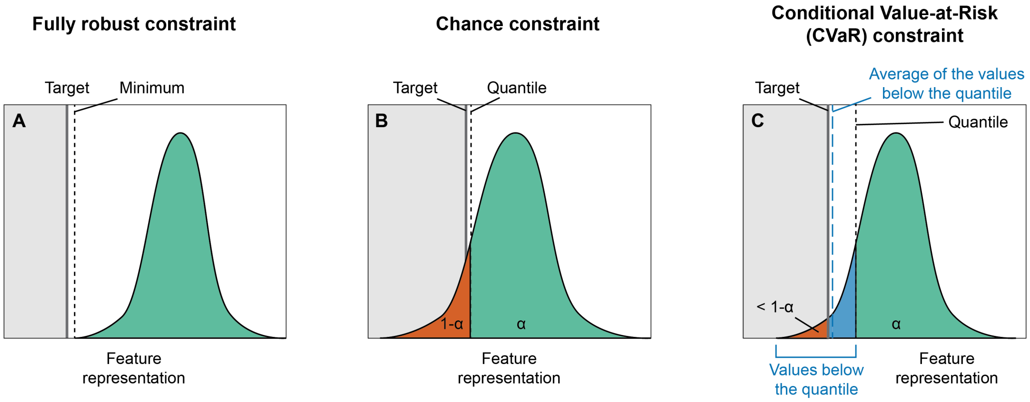


Figure 2: Distribution of uncertain features in relation to the specified target. (A) Fully robust constraint, (B) Chance constraint with the confidence level α, and (C) CVaR constraint with the confidence level α

2.3 Case study in Victoria, Australia

2.3.1 Study system and data

To illustrate our approach, we applied the package to a spatial conservation planning problem in Victoria, Australia. The state of Victoria, covering a region of 237,117 km^2, is a critical part of the Australian government's strategy for achieving an ambitious protected area expansion under the Global Biodiversity Framework's targets of protecting 30% of land and seas by the year 2030. Achieving the ambitious 30% targets set out in this plan requires decision-support tools that can ensure that landscape-scale conservation remains effective under future climate change. To formulate the planning problem, we divided the state of Victoria into 12,988 discrete planning units, each approximately 18 km^2 in size.

We obtained current and future species occurrence data from Archibald *et al.* (2024). Briefly, these data provide projections of future species distribution under climate scenarios evaluated under the Coupled Model Intercomparison Project 6 (CMIP6). We used the spatial distribution of 872 species, including the threatened brush-tailed rock-wallaby (*Petrogale penicillata*), Snowy Mountains skink (*Liopholis guthega*), and the orange-bellied parrot (*Neophema chrysogaster*). The occurrence data consisted of habitat suitability projections spanning four distinct CMIP6 climate change scenarios (including SSP1–RCP2.6 and SSP5–RCP8.5) and five temporal milestones: a historical baseline representing 1990, alongside future projections for 2030, 2050, 2070, and 2090.

We also obtained additional data to guide the selection of reserves. The Collaborative Australian Protected Area Database (DCCEEW, 2024) was used to characterize existing protected areas; planning units with at least 50% area covered by existing protected areas were classified as current protected areas. The 2013 Human Footprint Index (Williams *et al.*, 2020) was used as a proxy for the protected area cost.

2.4 Planning problem formulation

The overall objective of the planning problem is to find the set of planning units to include in the protected area, such that the total cost (summed across selected planning units) is minimized. To illustrate our approach, we solved the following minimum set problem for our case study area in Victoria:

$$\min \sum_{i=1}^{I} x_i c_i \tag{1}$$

$$\text{subject to} \quad \Pr_k \Big(\sum_{i=1}^{I} x_i R_{ijk} \geq T_j \Big) \geq \alpha \qquad \forall \quad j = 1, ..., J \tag{2}$$

$$x_i = 1 \qquad \forall \quad i \in L \tag{3}$$

$$x_i \in \{0, 1\} \qquad \forall \quad i = 1, ..., I \tag{4}$$

In the first line, the objective function seeks to minimize the total socioeconomic cost of the reserve network, calculated as the sum of the costs (c_i) across all I planning units, where the binary decision variable x_i indicates whether the planning unit is selected. This optimization problem is subject to a robust constraint, which ensures that the probability (Pr) of the selected planning units containing sufficient suitable habitat (R_{ijk}) to meet or exceed the spatial representation target (T_j) for species j across all uncertain future climate scenarios and time steps is at least at the specified confidence level (α). Additionally, a locked-in constraint ensures that all existing protected areas within set L are selected ($x_i = 1$). Finally, the decision variable for each planning unit is enforced to be strictly binary, either entirely selected or not selected ($x_i \in \{0, 1\}$).

We developed four prioritizations by varying the robustness constraint to evaluate the impact of robustness on the outcomes of the prioritization process.

A. **Non-robust solution:** A non-robust baseline model that is optimized solely on historical (1990) species distributions, ignoring future climate change trajectories. This prioritization is solved using only `prioritizr` and does not use the additional features in this package.

B. **Fully robust**: α is set to 1, meaning that the target is projected to be met even when the protected area is evaluated against the worst possible climate realisation and time-step in the dataset.

C. **Partially robust - Chance Constraint:** A chance-constrained model implementing a 75% confidence level ($\alpha = 0.75$). This approach treated the combined future climate scenarios and time steps as discrete data realizations, demanding that species representation targets be met in at least 75% of these future realizations.

D. **Partially robust - CVaR constraint:** A model that minimises downside risk by ensuring that the average feature representation across the worst 25% of climate realisations ($\alpha = 0.75$) meets or exceeds the target.

We present generalized versions of the mathematical formulation for each of these four prioritization problems in Supplementary Information.

2.5 Optimization analysis

We generated four prioritizations based on the problems described above (A-D), solving each using the Gurobi solver version 12.0 (Gurobi Optimization, LLC, 2024). For all four problems, species representation targets were set at 30% of each species' historic/baseline (1990) representation area (presence or absence) within the planning region. To ensure feasibility, we capped the target at the maximum achievable target. This adjustment was necessary because under certain climate scenarios, some species' ranges would contract dramatically, and the uncapped 30% target could not be met even if the entire planning region was selected for prioritization.

To evaluate the performance of the solution identified for each problem formulation, we computed four indicators. First, we recorded the representation of the critically endangered orange-bellied parrot (textitNeophema chrysogaster) endemic to southern Australia. These representations were calculated as the areas where species were predicted to be present within the prioritized protected area. Second, we recorded the size of the additional protected area of the protected area found to be optimal by each formulation. Third, we recorded the total estimated cost of creating a new protected area, represented by a unitless cost metric. Fourth, we recorded the computational solve time for each of the four problem formulations.

To illustrate the difference in each problem formulation, we recorded the number of decision variables, the number of constraints, and the proportion of binary variables from the full mixed-integer linear programming problem generated by `robust.prioritizr`, which provides a rough indication of the size and computational requirements for solving other problems of this type.

We also conducted an extensive computational speed test of the problem to provide users with an indication of the scalability and trade-offs of each problem formulation for increasing problem sizes. We ran the same problem

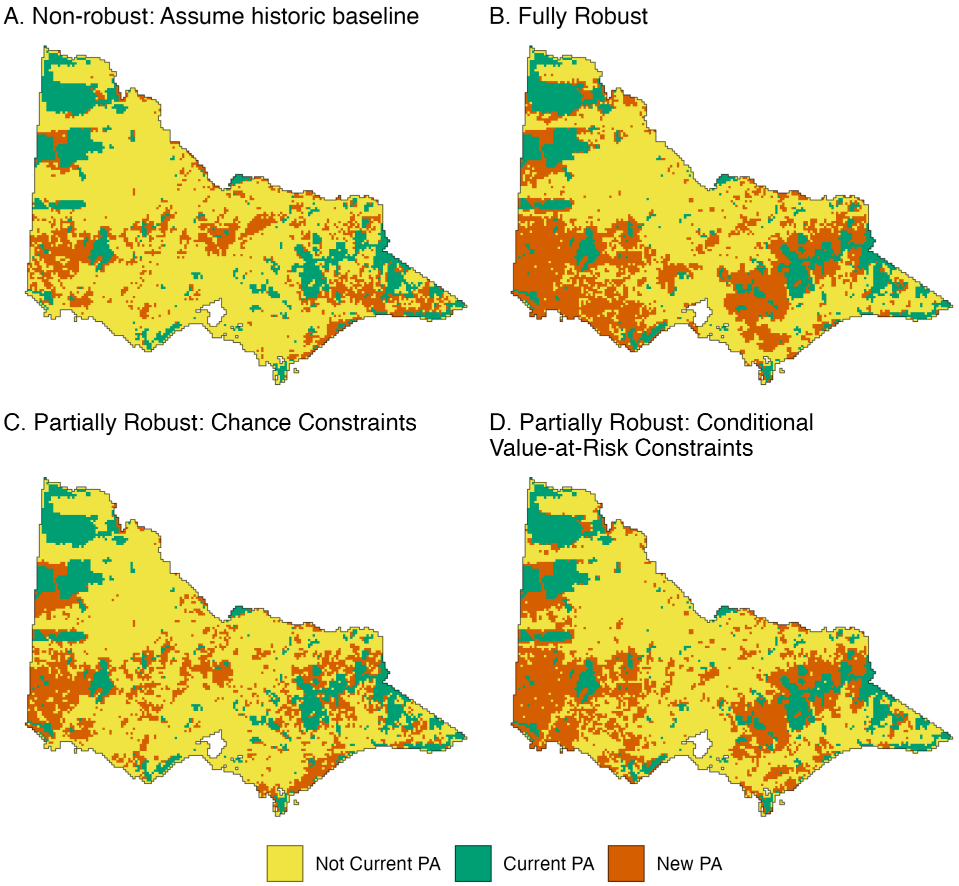


Figure 3: Prioritization solutions that robustly protect 30% of the ranges of 50 native species under climate change uncertainty in the Victoria case study: A. Non-robust: assume historic baseline, B. Fully Robust, C. Partially Robust: Chance Constraints, and D. Partially Robust: Conditional Value-at-Risk (CVaR) constraints

formulation for different sizes (number of species, from 18 to 872 total species) to test the approach under increasing problem size. Computational speed tests were conducted in a high-performance computing (HPC) environment to evaluate the scalability of our framework for larger problems, and our findings are presented in Supplementary Information Table 7.

3 Results

3.1 Spatial prioritization outcomes

Our results show that moving to a fully robust approach that accounts for climate change increases the protected area size from 75,000 km^2 (A: non-robust) to 112,000 km^2 (B: fully robust), an almost 50% increase (Figure 3A). This larger protected area network identified using the fully robust approach captured 47% of the planning area, including parts of the south-west and eastern parts of the state not captured under the non-robust approach.

In Figures 3C and 3D, we observe that for the partially robust problems formulated using Chance and CVaR constraints, meeting those constraints would only require increasing the protected area to 84,656 km^2 (13% more than the non-robust solution) and 102,730 km^2 (37% more than the non-robust solution, respectively).

3.2 The trade-off of making solutions robust

We observed that making prioritizations fully robust increased the total cost, whereas partially robust formulations were a middle ground between robustness and cost (Figure 4). Compared to the cost of non-robust prioritization

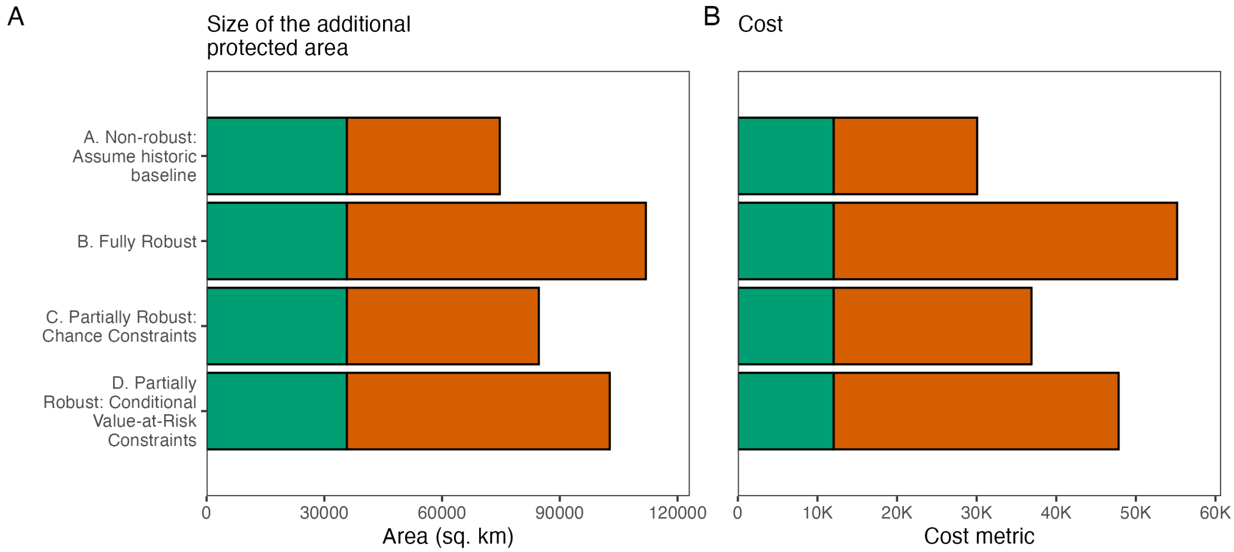


Figure 4: A: Size of the protected area, and B: the Cost of the protected area of the four prioritization solutions

(30,062), the fully robust prioritization increases the cost to 55,186, an 83% increase in the cost metric. In contrast, the partially robust formulations do not increase costs as much, only increasing costs to 36,891 (chance constraints) and 47,836 (CVaR constraints). Compared to the cost of the non-robust solution, these are 22% and 59% increases in costs, respectively.

3.3 Species representation across climate futures and time-steps

The prioritizations that are explicitly robust to uncertainty can represent the ranges of the orange-bellied parrot (*Neophema chrysogaster*), a critically endangered parrot endemic to southern Australia, across a much wider range of climate scenarios and time steps (Figure 5). We evaluated the representation of all species in our dataset across four different future Shared Socioeconomic Pathway (SSP)–Representative Concentration Pathway (RCP) combinations and show results for all species in Supplementary Information Table 6.

Under a high-emissions scenario (SSP5-RCP8.5) projection into 2090, the species range of the orange-bellied parrot is expected to contract dramatically, making it substantially harder to meet its target (target set at 15,270 km^2). Because the non-robust solution does not account for climate change, it is only able to meet the targets under the historical species ranges and fails to meet the targets across many other SSP-RCP combinations, particularly the projection under a high-emissions storyline, SSP5-RCP8.5 (Figure 5), where species representation falls to only 5,021km^2. In contrast, the fully robust prioritization accounts for all climate scenarios and time-steps and guarantees that the target is met across all scenarios and time-steps by dramatically increasing the number of planning units included in the new protected areas. Partially robust solutions attempt to take the middle ground. They restricted the total number of climate scenarios and time-steps that breached the biodiversity target by no more than 25% (i.e., four climate scenario/time-step combinations). As shown in Figure 5, although the target is still breached in the far future under high-emission storylines SSP3-RCP7.0 and SSP5-RCP8.5, it at least ensures that the target is still met in the near future, restricting these breaches to the far future. The partially robust chance constraints and CVaR problem protected 7,357km^2 and 10,753km^2 of the species' range under SSP5-RCP8.5, respectively. Although this still falls below the target, it improves the representation of the prioritization identified using the non-robust approach.

3.4 Computational considerations

The problem size and solution time are key considerations for practitioners with limited computational resources. The fully and partially robust problems have larger computational requirements and thus require more time to solve than the non-robust problems, as shown in Table 1. When tested using the commercial Gurobi solver (Gurobi Optimization, LLC, 2024), the non-robust solutions took only 0.3 s to find a solution. All robust solutions were slower, with solve times of 3.96, 31.04, and 5.95 s for the fully robust solution, partially robust solution with chance constraints, and partially robust solution with CVaR constraints, respectively. The chance-constrained problem was substantially slower than the CVaR

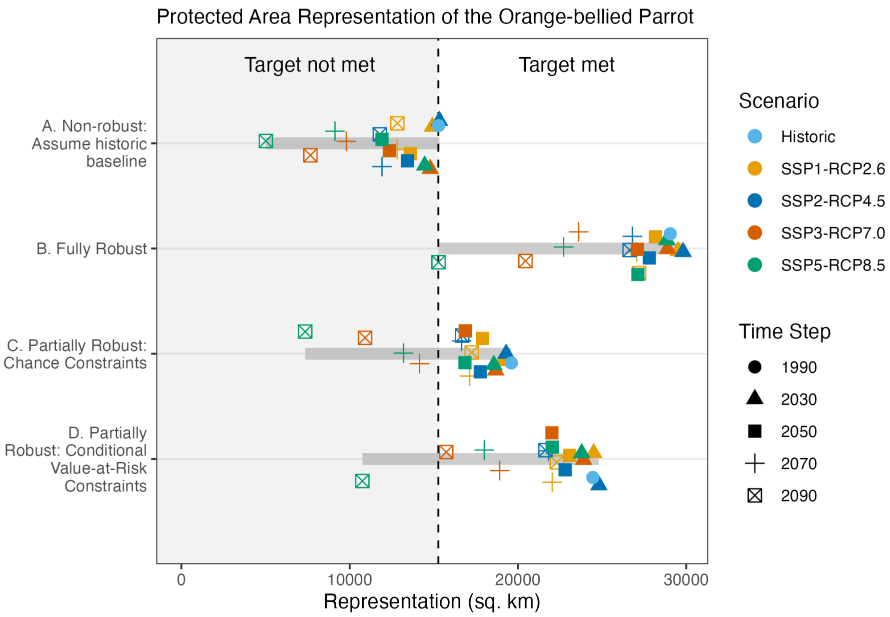


Figure 5: The protected area representation of a selected species (Orange-bellied Parrot) across different climate scenarios (SSP–RCP storylines) and time-steps.

problem because the CVaR constraints can be formulated through continuous rather than integer variables required by the Chance Constraints; they preserve the convexity of the problem and allow the problem to benefit from a wider range of solution methods for optimization compared to the problem with chance constraints that rely on integer variables (Rockafellar and Uryasev, 2000). The computational efficiency of the CVaR constraint relative to the Chance Constraint is also supported by the analysis of the constraint matrix size presented in Supplementary Information Table 3 and the results of the computational speed test across different problem sizes in the Supplementary Information (Section 5.5).

Table 1: Solver time (seconds) for a single replicate with 50 species under each planning approach (device: Apple Macbook Pro with M4 Pro)

Planning approach	Solve time (s)
A. Non-robust	0.30
B. Fully Robust	3.96
C. Chance Constraints	31.04
D. CVaR Constraints	5.95

4 Discussion

Plans for establishing and expanding protected areas must account for uncertainties driven by climate change (Hannah, 2008; Reside *et al.*, 2018). In this study, we introduced the `robust.prioritizr` `R` package as an accessible, transparent, and open-source decision-support tool that can explicitly account for climate-change uncertainty in conservation planning. Our case study showed that existing protected areas are insufficient for robust, long-term biodiversity protection. We also found that failing to account for climate change uncertainty during the prioritization process resulted in priority areas with a limited ability to represent species under plausible future scenarios. Moreover, by comparing prioritizations based on different approaches to account for uncertainty, we found that a conventional prioritization approach that ignores climate change uncertainty is unable to meet the species representation target for a large number of native species under some high-emission climate scenarios (Supplementary Information Table 6). In contrast, a fully robust approach can successfully meet the species representation target for the orange-bellied parrot across all climate scenarios and time steps, albeit at the expense of elevated costs. Meanwhile, the partially robust approaches (chance constraints and CVaR) achieved relatively high robustness in their targets (at least 75%) at lower overall costs. Our findings underscore the urgent need to consider climate change uncertainty in environmental decision-making (Pecl *et al.*, 2017; Archer *et al.*, 2025), particularly in actions guided by the Global Biodiversity Framework.

Importantly, our results indicate that explicitly considering climate uncertainty significantly influences the selection of priority areas for conservation. This is because the fully robust, chance constraint, and CVaR approaches implement a “bet-hedging" strategy, which involves deliberately selecting areas for protected area establishment that may become redundant, depending on future events (Schloss *et al.*, 2011). This strategy helps ensure that conservation objectives are met even under the catastrophic outcomes predicted in species projections. Implementing this bet-hedging strategy increases robustness by requiring protected area systems that cover larger land areas, which can increase overall opportunity costs. This finding echoes previous studies that have found similar trade-offs with bet-hedging strategies (Schloss *et al.*, 2011; Gillson *et al.*, 2013; Tobias *et al.*, 2025; Cho *et al.*, 2025b). This highlights the need for decision-makers to carefully evaluate and weigh the trade-offs between uncertainty reduction and cost minimization.

The `robust.prioritizr` package opens new possibilities for practitioners to apply and benefit from bet-hedging strategies in conservation prioritization. For example, Ando and Mallory (2012) found that efficient diversification can effectively reduce correlation in the uncertainty across planning units and quantitatively explored how to navigate trade-offs between the need to maximize expected benefits and reduce uncertainty through an “efficient frontier.” Following similar techniques, the `robust.prioritizr` framework allows users to specify their desired level of robustness, enabling them to explore optimal trade-offs between robustness and expected benefit/cost optimization through an “efficient frontier” (Ando *et al.*, 2018; Liang *et al.*, 2018; Runting *et al.*, 2018).

The package can help inform the implementation of management actions to achieve targets under the Global Biodiversity Framework (CBD, 2018). For example, the package can help identify priority areas for protected area establishment under Target 3, where governments have pledged to establish protected areas and other effective area-based conservation measures to cover 30% of the planet. Governments and non-governmental organizations can also leverage this package to inform integrated spatial planning under Target 1. As the package was developed as an extension of the `prioritizr` `R` package, it can be used to identify priority areas for multiple sectors (e.g., conservation, agriculture, and forestry) in the same framework as Watts *et al.* (2009), enabling decision-makers to implement management zones to plan and account for uncertainty in land and sea use across multiple management objectives (e.g., uncertainties in agricultural yield for meeting food supply objectives and uncertainties in timber harvest for production objectives; (Giakoumi *et al.*, 2025; Law *et al.*, 2017)). Furthermore, under Targets 4 and 8, governments seek to prevent species extinction and minimize the impacts of climate change. The package can identify priority areas for implementing policies to ensure that habitat destruction and degradation in the near future do not impact habitats that may be important for species survival in the more distant future.

The `robust.prioritizr` framework offers substantial advances over current methods for dealing with uncertainty in prioritization, providing users with a framework that a) does not require users to aggregate across uncertain species/features of interest, b) does not make distributional assumptions about uncertainty, and c) uses mixed-integer linear programming solvers with known optimality. To use many portfolio analysis conservation prioritization frameworks (e.g. Ando and Mallory, 2012; Cho *et al.*, 2025a; Runting *et al.*, 2018), practitioners must aggregate uncertain species/ ecosystem services values into a single benefit metric to be used for prioritization (such as unit-less benefit metrics, benefit-cost ratios, or monetary net present values). This aggregation can mask hidden trade-offs across species and features, where the representation of one species could be compromised by the need to maximize the overall score of the indicator. By eliminating the need for this aggregation, `robust.prioritizr` addresses this major gap by allowing users to simultaneously address uncertainty across many species and other features (e.g., predictions of ecosystem services). Moreover, while Zonation allows for uncertainty for each species/feature layer, the `robust.prioritizr` framework relaxes the distributional assumptions that Zonation relies on, allowing for the proper handling of uncertainty that may exhibit non-normal distributions or fat-tailed (low-probability, high-consequence) downside risks. The `robust.prioritizr` method also allows users to specify targets for each species/feature individually and enforce targets to be robustly met, which is not a feature within Zonation. Although Marxan with Probability overcomes the limitations of the need for aggregation and distributional uncertainty, it relies on meta-heuristic algorithms that do not guarantee optimal solutions.

Our work complements existing frameworks for climate-smart planning, as reviewed by Buenafe *et al.* 2025. Climate-smart planning involves identifying areas that provide suitable habitats in the future (climate refugia), conditions for fostering adaptive evolutionary processes (adaptation hotspots), and connectivity between present-day and future suitable habitats (climate corridors) (Ranius *et al.*, 2023; Sun *et al.*, 2025). Although various frameworks have been developed to identify such areas (for example, Buenafe *et al.*, 2023), they often involve identifying a set of climate refugia, adaptation hotspots, and/or climate corridors for each species (separately) based on multiple climate scenarios, and then identifying priority areas that aim to adequately represent each species across every scenario (Liczner *et al.*, 2023; Graham *et al.*, 2019) using a fully robust approach. By leveraging such data with the package, decision-makers can identify priority areas that strategically reduce redundancy and increase cost efficiency, as planning units that are important only in a few climate scenarios are selected to promote resilience against unexpected changes. However, `robust.prioritizr` does not evaluate connectivity across the new protected areas and the species' existing habitats and does not explicitly target climate corridors that lie between species' current and future predicted habitats. Practitioners interested in operationalizing this package to protect species with restricted ability to migrate can incorporate spatial information about the location of climate corridors by setting these as planning unit features that need to be explicitly protected, while also factoring in uncertainty about whether these climate corridors will be effective.

Our work addresses the critical gap between robust optimization and the practical needs of the conservation community, underscoring the need for a data-driven, systematic, and transparent approach to integrating uncertainty into systematic conservation planning. As climate change continues to threaten biodiversity, the framework we have made openly available for research (`https://cran.r-project.org/package=robust.prioritizr`) gives practitioners user-friendly access to robust approaches to secure a more resilient future for biodiversity.

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4.2 Author Contributions

FHTC and JOH contributed to the conceptualization, methodology, data curation, and software of the manuscript. FHTC completed the validation, formal analysis, and visualization tasks for the manuscript and wrote the original draft. FHTC and JOH reviewed and edited the draft before submission.

4.3 Artificial Intelligence (AI) use declaration

AI was **not** used to write the code and documentation for the open-source package (`robust.prioritizr`) available on CRAN. AI was **not** used to write the initial draft of the manuscript.

Generative AI tools were used to improve the human-written R code to produce supplementary analyses of the package presented in this paper from the open-source package, including (a) writing HPC code for running speed tests and (b) improving scientific figures based on the human-written R code. AI was used to assist with human proofreading and manuscript formatting.

4.4 Data availability

The core R package (v1.1.0) is available on CRAN (`https://cran.r-project.org/web/packages/robust.prioritizr/index.html`). The data used to illustrate the package, including R code used to process the dataset, are available on GitHub (`https://github.com/jeffreyhanson/robust.prioritizr.data`). The scripts used to process and create the results of this paper are available on GitHub (`https://github.com/frankiecho/robust.prioritizr.paper`).

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5 Supplementary Information

5.1 Glossary of terms

Table 2: Key terms in the systematic conservation planning process

Terminology	Description
Planning region	A spatially delineated region of where prioritization occurs; systematic conservation planning exercises generally do not account for biodiversity/features outside the planning region
Reserve	An area of land or water that is set aside for the preservation of natural values.
Prioritization	Plans for expanding protected area systems to fulfill conservation objectives that account for costs and land-use requirements in the planning region. All prioritization solutions here assume that if the area is not selected for prioritization, its habitat values would be “lost".
Planning units/ candidate areas	Spatially delineated areas within the planning region where decisions over its management are made
Features	Biotic elements of conservation interest, such as measures of biodiversity, ecosystem services, or other elements of the environment.
Objective function	A mathematical function specifying the metric to be maximized or minimized when identifying prioritizations, which is used to compare and evaluate different prioritizations.
Target	A quantitative threshold specifying the minimum level of representation that a prioritization must achieve for each feature (up to a specified confidence level).
Constraint	A mathematical rule that defines the requirements that a prioritization must meet. The targets can be specified as constraints.
Feasibility	Whether or not the prioritization satisfies all constraints in a problem.
Confidence level	The minimum probability that a prioritization will satisfy a target when specified as a constraint.
Uncertainty	In this context, the lack of sure knowledge about the quantitative value of the features.
Scenario	A specific, plausible alternative outcome or the state of the world, such as a climate change projection, species distribution model output, or ecosystem model prediction. For the purposes of this software, it is assumed that the "true" state of the world is one of the scenarios contained in the set.
Data realization	A set of data that jointly characterizes the same scenario for the same feature, such that one feature can be characterized by multiple data realizations.
Feature grouping	Grouping that is used to associate different data realizations of the same feature together, such that the solver does not interpret different data realizations as different features.
Worst-case outcome	The data realization that produces the largest gap between the feature representation and its targets, or the lowest possible value in the objective in a maximization objective, and vice versa.

5.2 Methodological intuition

In this formulation, we focus on the intuition behind the chance-constrained problem and the CVaR formulation of uncertain constraints in a stylized format, before presenting its full formulation. We first focus on the case of a problem with one decision variable and one uncertain data variable before generalizing to the formulation with an arbitrary number of decision variables and uncertain data variables. Consider a decision problem with a simple constraint as follows:

$$\min_{x} xc \tag{5}$$

$$\text{subject to} \quad xr \geq T \tag{6}$$

where x is the total area to protect (decision variable), c is the cost per hectare to protect, r is a feature of interest (e.g., species abundance per hectare or ecosystem service values per hectare), and T is a target. The expression xr represents the number of features that can be represented in the protected area, which is referred to as feature representation. The solution to the problem requires choosing x such that the feature representation xr is above the target T.

The formulation of the above problem becomes more complex as r is a random variable that is affected by uncertain factors, such as climate change, measurement errors, and temporal variability. Now, consider r as a non-negative random variable being a random draw from a set of possible data realizations $k \in \{1, ..., K\}$, where each realization represents one draw from the uncertain distribution of r. The probability of each state k is p_k.

Many forms of modifications can be made to the original constraint, considering these uncertainties. In this section, we provide an overview of three approaches: a "fully robust" approach that ensures that the target is held across all sample realizations, a "chance constrained" approach that ensures that the target is held given a certain confidence level/ probability, and a CVaR approach that also ensures that the target is held at a certain confidence level, that, while giving a constraint that is tighter than the "chance constrained" problem, preserves the convexity of the problem, if the problem is originally convex.

5.2.1 Fully robust constraint

In this context, a fully robust problem formulation must satisfy the following set of constraints:

$$xr_k \geq T \quad \forall \quad k = 1, ..., K$$

which states that x must be chosen to be greater than T for all possible data realizations of k. This constraint has the same effect as ensuring that the chosen decision (habitat variable) exceeds the target, even if the minimum of r_k is realized:

$$x \min_k (r_k) \geq T \tag{7}$$

If r has a lot of variability, x might need to be very large to ensure that the minimum value of its product with x is still greater than the target T.

5.2.2 Chance constrained problem

Now consider a "Chance Constrained" approach to specifying this constraint (Charnes and Cooper, 1959). The chance-constrained problem relaxes the above specification by ensuring that the probability that the constraint is met is guaranteed to be equal to or greater than a "confidence level.” In this context, the following is ensured:

$$\Pr_k \big(xr_k \geq T \big) \geq \alpha \tag{8}$$

where $\alpha \in [0, 1]$ is the confidence level parameter selected by the user. Holding this constraint is equivalent to holding the constraint that the quantile at $1 - \alpha$ is greater than the target. Consider the quantile function that gives the sample quantile of any random variable r as follows:

$$q_\alpha(r) := \inf\{v \in \mathbb{R} : \Pr(r \leq v) \geq \alpha\} \tag{9}$$

where v is the value that is chosen as the minimum such that the probability that r is less than v is greater than α. In other words, out of all the samples of r, the proportion of samples of r that fall below the quantile v is no more than α. Essentially, if $\alpha = 0.1$, then $q_\alpha(xr_k)$ is the 0.1 quantile of the distribution of xr_k across all k.

Given this definition, the chance-constrained problem is equivalent to the following representation:

$$q_{1-\alpha}(xr) \geq T \tag{10}$$

Because the $(1 - \alpha)$ quantile is held above the target, the proportion of samples of r that fall below T cannot exceed $1 - \alpha$, that is, the target is met in at least α of the cases.

When x is linear with respect to r, the equivalent constraint can be modelled using integer variables as follows:

$$\begin{aligned} & xr_k + m_k T \geq T && \forall \quad k = 1, ..., K && (11) \\ & \sum_k m_k p_k \leq 1 - \alpha && && (12) \\ & m_k \in \{0, 1\} && \forall \quad k = 1, ..., K && (13) \end{aligned}$$

where m_k is a binary variable that indicates whether the constraint $xr_k \geq T$ has been violated ($m_k = 1$) or not ($m_k = 0$), also known as the "big-M" formulation. The first constraint ensures that xr_k is greater than T if m_k is 0, and the constraint no longer necessarily holds if $m_k = 1$. m_k therefore counts the total number of constraint violations recorded across all data realizations k. In the second constraint, the constraint violation variable m_k is multiplied with the probability of data realization k to obtain the overall probability of violating the constraint, and holds that the total probability is less than $1 - \alpha$.

Although the chance-constrained problem has an intuitive interpretation, it is a non-convex problem that requires the use of integer linear constraints, which could add significant computational difficulty for problems that were originally convex (e.g., problems with continuous decision variables).

5.2.3 Conditional Value-at-Risk formulation

In contrast, the Conditional Value-at-Risk (CVaR) formulation (also known as the Expected Shortfall formulation) harnesses advancements in financial economics to retain the convexity of the original problem while still providing a way to control for the risk of constraint violations. The Conditional Value-at-Risk formulation ensures that the expected value of the constraint in the worst $(1 - \alpha)$ percent of data realizations is still greater than the target T.

Now consider the following expression that measures the average value of all samples of r_k that fall below its $(1 - \alpha)$-quantile:

$$\mathbb{E}_k[xr_k \mid xr_k \leq q_{1-\alpha}(xr)] \geq T \tag{14}$$

where $\mathbb{E}$ is the expectation operator, q is the quantile function that finds the $(1 - \alpha)$ quantile of the distribution of xr_k. To understand this intuitively, the Conditional Value-at-Risk is the average value of xr_k across all k that fall below their $(1 - \alpha)$ quantile, representing the average of the riskiest (lowest) values in the distribution.

Rockafellar and Uryasev (2000) have shown that optimizing for the Conditional Value-at-Risk is equivalent to optimizing the following problem:

$$\begin{aligned} & \min \quad xc && && (15) \\ \text{subject to} \quad & xr_k - \eta + s_k \geq 0 && \forall \quad k = 1, ..., K && (16) \\ & \eta - \frac{1}{(1-\alpha)K} \sum_{k=1}^{K} s_k \geq T && && (17) \\ & s_k \geq 0 && \forall \quad k = 1, ..., K && (18) \\ & \eta \in \mathbb{R} && && (19) \end{aligned}$$

where η is an auxiliary variable that, when optimized, corresponds to the quantile of the distribution of xr_k at $1 - \alpha$, s_k is an auxiliary variable that represents the deviation of xr_k with η if xr_k is smaller than η, and takes the value of 0 otherwise, and K is the total number of realizations of uncertain data variables. This formulation thus simultaneously optimizes the variables η, s and x to find the minimum area x to protect while ensuring that the Conditional Value-at-Risk does not breach the target. This reformulation of the Conditional Value-at-Risk problem into a set of linear inequalities lays the groundwork for formulating robust constraints in the full problem.

5.3 Full mathematical formulation

Here, we present the robust minimum set objective that this study is based on, and the robust minimum shortfall objective that is not illustrated in this study but is available in the package.

5.3.1 Robust minimum set objective

The robust minimum set objective seeks to find the set of planning units at a minimum cost such that the solution meets the targets in a robust manner for each feature group. Each feature in the feature group represents a different realization of uncertainty for the same feature.

The robust minimum set problem is formulated as follows:

$$\text{Minimize} \quad \sum_{i=1}^{I} x_i c_i \tag{20}$$

subject to:

$$\Pr_k \left\{ \sum_{i=1}^{I} x_i R_{ijk} \geq T_j \right\} \geq \alpha \qquad \forall \quad j = 1, ..., J \tag{21}$$

$$x_i = 1 \qquad \forall \quad i \in L \tag{22}$$

$$x_i \in \{0, 1\} \qquad \forall \quad i = 1, ..., I \tag{23}$$

Where:

- I: the total number of planning units (indexed by $i = 1, ..., I$)
- J: the total number of feature groups (indexed by $j = 1, ..., J$)
- K: the total number of features associated with each feature group (indexed by $k = 1, ..., K$).
- L: the set of planning units corresponding to existing protected areas.
- c_i: cost of planning unit i.
- R_{ijk}: amount of feature k associated with planning unit i for feature group j.
- T_j: target for feature group j.
- α: confidence level for uncertainty.
- x_i: binary decision variable for planning unit i.

To formulate this chance constraint, the user can select between the chance-constrained and Conditional Value-at-Risk approaches.

Chance-Constrained approach

The CCP method uses a "big-M" formulation to linearize the probabilistic constraints. Here, T_j serves as the big-M value: when $M_{jk} = 1$, the first constraint reduces to $\sum_{i=1}^{I} x_i R_{ijk} \geq 0$, which is satisfied under the non-negativity assumption $R_{ijk} \geq 0$ which holds for habitat suitability data.

$$\sum_{i=1}^{I} x_i R_{ijk} + T_j M_{jk} \geq T_j \qquad \forall \quad j = 1, ..., J, k = 1, ..., K_j \tag{24}$$

$$\sum_{k=1}^{K_j} \frac{M_{jk}}{K_j} \leq 1 - \alpha \qquad \forall \quad j = 1, ..., J \tag{25}$$

$$M_{jk} \in \{0, 1\} \qquad \forall \quad j = 1, ..., J, k = 1, ..., K_j \tag{26}$$

Where:

- M_{jk}: binary auxiliary variable for each feature k in feature group j
- K_j: pre-computed value describing the number of features associated with each feature group j
- α: minimum proportion of targets that must be met within a feature group

The CVaR method provides a tighter approximation of the probabilistic constraints as follows:

$$\sum_{i=1}^{I} x_i R_{ijk} - \eta_j + S_{jk} \geq 0 \qquad \forall \quad j = 1, ..., J, k = 1, ..., K_j \tag{27}$$

$$\eta_j - \frac{1}{(1-\alpha)K_j} \sum_{k=1}^{K_j} S_{jk} \geq T_j \qquad \forall \quad j = 1, ..., J \tag{28}$$

$$S_{jk} \geq 0 \qquad \forall \quad j = 1, ..., J, k = 1, ..., K_j \tag{29}$$

$$\eta_j \in \mathbb{R} \qquad \forall \quad j = 1, ..., J \tag{30}$$

Where:

- η_j: continuous auxiliary variable for each feature group j
- S_{jk}: continuous auxiliary variable for each feature k associated with each feature group j
- $(1-\alpha)$: the quantile defining the "tail" of the distribution for feature representation

Robust minimum shortfall objective

The robust minimum shortfall objective seeks to minimize the weighted sum of representation shortfalls for each feature group, subject to the total budget constraint. This formulation ensures that the resulting conservation plan remains effective across a range of uncertain scenarios by incorporating a confidence level in the shortfall calculations.

The robust minimum shortfall problem is formulated as follows:

$$\text{Minimize} \quad \sum_{j=1}^{J} y_j \frac{\sum_{k=1}^{K_j} W_{jk}}{K_j} \tag{31}$$

subject to:

$$\sum_{i=1}^{I} x_i c_i \leq B \tag{32}$$

$$\Pr_k \left\{ \sum_{i=1}^{I} x_i R_{ijk} + T_j y_j \geq T_j \right\} \geq \alpha \qquad \forall \quad j = 1, ..., J \tag{33}$$

$$0 \leq y_j \leq 1 \qquad \forall \quad j = 1, ..., J \tag{34}$$

Where:

- I: the total number of planning units (indexed by $i = 1, ..., I$)
- J: the total number of feature groups (indexed by $j = 1, ..., J$)
- K_j: the total number of features associated with each feature group (indexed by $k = 1, ..., K_j$)
- c_i: cost of planning unit i
- R_{ijk}: amount of feature k associated with planning unit i for feature group j
- T_j: target for feature group j
- W_{jk}: weight for feature k in feature group j
- α: confidence level for uncertainty
- B: total budget available for the conservation plan
- x_i: binary decision variable for planning unit i
- y_j: representation shortfall for feature group j

Because the probabilistic constraints are nonlinear, the chance constraint programming method is used to linearize them using a "big-M" formulation. The probabilistic constraints are replaced with the following linear constraints:

$$\sum_{i=1}^{I} x_i R_{ijk} + T_j y_j + T_j M_{jk} \geq T_j \qquad \forall \quad j = 1, ..., J, k = 1, ..., K_j \tag{35}$$

$$\sum_{k=1}^{K_j} \frac{M_{jk}}{K_j} \leq 1 - \alpha \qquad \forall \quad j = 1, ..., J \tag{36}$$

$$M_{jk} \in \{0, 1\} \qquad \forall \quad j = 1, ..., J, k = 1, ..., K_j \tag{37}$$

Where:

- M_{jk}: binary auxiliary variable for each feature k in feature group j
- K_j: pre-computed value describing the number of features associated with each feature group j
- y_j: representation shortfall variable for feature group j, calculated based on the subset of target shortfalls allowed by α
- $1 - \alpha$: the allowable proportion of features within a group that may exceed the calculated representation shortfall y_j

The current package does not yet support a Conditional Value-at-Risk formulation of the shortfall objective, but this can be feasibly implemented in a future version of the package.

5.4 Summary of main prioritization results

Here, we provide a numerical summary of the prioritizations presented in the main results (i.e., 50 species).

For a planning problem comprising 12,988 planning units, 50 species, and 16 data realizations (climate scenarios and time-steps) (Table 3), robust versions of the same problem must be represented by a larger number of decision variables and inequality constraints, thereby increasing the problem size and memory requirements. Whereas the non-robust version of the problem can be represented with only 12,988 decision variables and 50 inequality constraints, 850 constraints are required to represent the fully robust version of the same problem. Partially robust problem formulations increase both the number of decision variables and the number of constraints in the problem, with the number of decision variables increasing to 13,838 (chance constraints) and 13,938 (CVaR constraints), and the number of inequality constraints increasing to 950. Therefore, problems with partially robust constraints require even more memory than those with fully robust constraints. Whereas the partially robust CVaR problem uses a mix of continuous and binary variables, all the other problems exclusively use binary variables.

	Number of decision variables	Number of inequality constraints	Percent of decision variables that are binary
A. Non-robust: Assume historic baseline	12,988	50	100%
B. Fully Robust	12,988	850	100%
C. Partially Robust: Chance Constraints	13,838	950	100%
D. Partially Robust: Conditional Value-at-Risk Constraints	13,938	950	93%

Table 3: Problem size of the four prioritizations for the prioritization problem.

Table 4: Protected area size (sq. km) under each planning approach. Total planning area: 237,117 sq. km.

Planning approach	Current PA	New PA	Total (% of planning area)
A. Non-robust	35,746	38,960	74,706 (31.5%)
B. Fully Robust	35,746	76,185	111,931 (47.2%)
C. Chance Constraints	35,746	48,909	84,656 (35.7%)
D. CVaR Constraints	35,746	66,984	102,730 (43.3%)

Table 5: Cost metric under each planning approach.

Planning approach	Current PA	New PA	Total
A. Non-robust	12,037	18,025	30,062
B. Fully Robust	12,037	43,149	55,186
C. Chance Constraints	12,037	24,854	36,891
D. CVaR Constraints	12,037	35,800	47,836

Table 6: Representation of all species across climate scenarios under each planning approach (sq. km, mean (min–max) over 5 scenarios).

Species	Target (sq. km)	A. Non-robust	B. Fully Robust	C. Chance Constraints	D. CVaR Constraints
Antechinus minimus	43,016	35,541 (17,691– 46,116)	69,692 (44,820– 81,096)	45,018 (24,738– 56,139)	61,470 (37,572– 74,085)
Anthochaera phrygia	57,393	56,518 (53,601– 57,454)	88,105 (84,674– 89,585)	64,678 (61,634– 65,979)	79,976 (76,568– 81,534)
Aprasia striolata	42,458	31,947 (18,184– 42,465)	53,156 (42,465– 64,793)	42,011 (24,975– 50,607)	50,524 (37,499– 60,192)
Bellatorias frerei	8,128	18,104 (12,634– 24,592)	38,649 (24,172– 56,942)	25,486 (17,271– 33,976)	34,938 (22,784– 49,603)
Brachyurophis australis	58,001	63,402 (58,220– 67,659)	89,360 (80,840– 97,782)	71,009 (65,450– 76,221)	82,745 (75,856– 89,859)
Burramys parvus	310	2,976 (237– 7,850)	4,919 (310– 14,404)	3,923 (274– 11,155)	4,883 (292– 14,350)
Butorides striatus	12,044	29,251 (12,049– 54,606)	46,822 (20,685– 86,007)	32,557 (12,798– 63,533)	40,043 (15,719– 78,230)
Callocephalon fimbriatum	49,808	52,349 (42,812– 56,650)	83,920 (74,414– 88,946)	60,787 (51,849– 65,249)	75,906 (66,418– 80,713)
Calyptorhynchus baudinii	4,113	9,184 (6,591– 10,516)	15,755 (11,447– 17,983)	11,915 (8,982– 13,528)	15,300 (11,137– 17,380)
Chalinolobus gouldii	70,752	74,706 (74,706– 74,706)	111,931 (111,931–111,931)	84,656 (84,656– 84,656)	102,730 (102,730–102,730)
Climacteris rufa	23,737	37,997 (22,803– 41,899)	52,820 (36,148– 57,508)	44,127 (28,407– 48,216)	51,170 (34,505– 55,902)
Cophixalus crepitans	201	449 (91– 767)	875 (201– 1,442)	703 (128– 1,187)	854 (183– 1,424)
Coracina tenuirostris	43,767	52,405 (51,885– 52,689)	83,131 (82,082– 83,615)	60,133 (59,608– 60,411)	74,973 (74,067– 75,418)
Crenadactylus ocellatus	16,152	29,302 (26,454– 31,073)	37,441 (31,274– 43,962)	33,447 (28,918– 36,586)	37,495 (31,602– 42,830)
Crinia remota	22	103 (73– 237)	190 (73– 438)	135 (73– 274)	190 (73– 438)
Ctenophorus nuchalis	3,215	21,590 (5,002– 47,431)	25,120 (5,897– 54,240)	21,591 (4,692– 47,504)	23,429 (5,440– 52,305)
Ctenotus calurus	1,851	3,555 (2,738– 5,331)	4,429 (3,469– 6,353)	3,780 (2,958– 5,660)	4,355 (3,396– 6,226)
Ctenotus ingrami	3,308	18,171 (3,323– 55,537)	19,770 (3,323– 77,463)	17,314 (3,323– 59,279)	18,235 (3,323– 69,430)
Egernia saxatilis	62,898	57,490 (44,911– 64,829)	90,647 (74,597– 99,152)	67,195 (52,433– 75,491)	83,192 (67,568– 91,922)
Falcunculus frontatus	70,752	74,641 (73,592– 74,706)	111,852 (110,580–111,931)	84,592 (83,561– 84,656)	102,663 (101,598–102,730)
Grus rubicunda	70,319	74,516 (73,574– 74,706)	111,703 (110,507–111,931)	84,453 (83,396– 84,656)	102,516 (101,416–102,730)
Gymnobelideus leadbeateri	31,858	27,081 (11,137– 44,802)	49,445 (31,858– 73,684)	36,719 (16,358– 53,309)	46,121 (26,363– 67,257)
Hemiergis millewae	19,120	20,269 (15,390– 21,579)	26,770 (20,174– 28,206)	22,521 (17,636– 23,825)	25,793 (19,772– 27,129)
Leipoa ocellata	44,260	52,676 (44,400– 56,650)	70,046 (56,742– 75,363)	56,870 (47,686– 60,904)	65,593 (54,149– 70,142)

Continued on next page

Species	Target (sq. km)	A. Non-robust	B. Fully Robust	C. Chance Constraints	D. CVaR Constraints
Lerista fragilis	1,325	22,050 (1,461– 54,715)	23,981 (1,333– 74,158)	21,443 (1,333– 59,243)	22,842 (1,333– 68,499)
Lichenostomus melanops	59,666	57,536 (54,350– 62,255)	89,819 (85,788– 95,884)	66,278 (62,638– 72,570)	81,907 (77,718– 88,855)
Liopholis guthega	18	1,580 (18– 4,290)	2,355 (18– 8,234)	1,938 (18– 6,280)	2,314 (18– 8,161)
Litoria adelaidensis	12,739	27,268 (19,352– 30,306)	41,537 (28,900– 46,372)	34,168 (24,592– 37,262)	39,979 (28,499– 44,364)
Litoria raniformis	70,752	74,105 (66,819– 74,706)	111,312 (103,679–111,931)	84,165 (78,175– 84,656)	102,218 (95,884–102,730)
Litoria spenceri	11,173	13,428 (5,532– 19,845)	26,479 (11,173– 35,509)	18,852 (8,124– 24,792)	25,626 (11,064– 32,898)
Miniopterus schreibersii	64,508	63,728 (59,590– 65,560)	98,656 (93,784–101,178)	74,187 (70,270– 75,838)	91,025 (86,774– 93,036)
Mixophyes balbus	22,686	27,028 (21,196– 29,065)	43,066 (36,148– 46,901)	30,207 (25,395– 32,515)	38,447 (33,318– 41,461)
Morethia adelaidensis	41,674	41,509 (36,605– 43,122)	58,107 (52,396– 59,882)	44,819 (39,745– 46,682)	54,098 (48,836– 55,810)
Morethia lineoocellata	8,232	17,422 (15,774– 19,023)	31,079 (24,573– 34,834)	23,161 (19,991– 25,322)	29,230 (24,354– 32,205)
Neophema chrysogaster	15,270	12,181 (5,021– 15,336)	26,238 (15,281– 29,813)	16,350 (7,357– 19,608)	21,328 (10,753– 24,811)
Oedura monilis	11,830	35,507 (11,830– 53,583)	46,895 (11,830– 81,826)	37,123 (11,830– 60,776)	42,191 (11,830– 73,921)
Pedionomus torquatus	53,680	59,813 (53,693– 62,328)	82,146 (69,868– 90,133)	62,609 (54,697– 67,020)	74,345 (63,606– 81,589)
Petrogale herberti	170	4,495 (256– 14,624)	8,180 (566– 29,466)	5,774 (383– 19,169)	7,521 (566– 25,997)
Petrogale penicillata	55,909	52,508 (42,282– 57,636)	80,609 (67,641– 87,796)	59,903 (49,293– 65,413)	72,712 (60,302– 79,763)
Philoria frosti	365	2,001 (91– 5,495)	4,596 (365– 13,747)	2,788 (219– 7,960)	4,448 (347– 13,108)
Podargus ocellatus	838	3,283 (1,022– 7,467)	7,894 (2,665– 18,403)	5,139 (1,625– 11,629)	7,193 (2,173– 16,796)
Poliocephalus poliocephalus	70,752	74,706 (74,706– 74,706)	111,931 (111,931–111,931)	84,656 (84,656– 84,656)	102,730 (102,730–102,730)
Pseudomys fumeus	38,547	35,804 (24,719– 43,889)	62,945 (45,003– 75,929)	43,077 (31,237– 52,597)	55,344 (40,584– 67,403)
Pseudophryne corroboree	712	2,411 (621– 5,568)	3,957 (712– 10,662)	3,142 (621– 7,887)	3,903 (675– 10,534)
Pseudophryne pengilleyi	3,527	5,553 (4,400– 7,211)	9,950 (7,796– 12,871)	8,152 (6,426– 10,607)	9,980 (7,741– 13,035)
Sarcophilus harrisii	4,400	14,299 (2,227– 40,183)	33,965 (4,400– 71,675)	19,740 (2,921– 48,654)	28,944 (3,962– 63,880)
Sminthopsis murina	70,752	74,706 (74,706– 74,706)	111,931 (111,931–111,931)	84,656 (84,656– 84,656)	102,730 (102,730–102,730)
Stipiturus mallee	21,985	20,081 (16,522– 23,734)	26,462 (21,999– 30,489)	22,916 (17,691– 26,819)	25,883 (20,046– 30,087)
Trichoglossus haematodus	66,255	71,895 (66,272– 74,615)	108,685 (100,448–111,840)	81,706 (74,962– 84,565)	99,593 (91,740–102,639)
Tympanocryptis lineata	43,230	45,098 (43,232– 46,427)	63,078 (59,973– 64,501)	48,967 (45,988– 50,699)	58,357 (55,409– 59,900)

5.5 Computational speed test

We conducted a speed test to evaluate the performance of the prioritization problem formulated with robust constraints for increasing numbers of species. We solved the problem from 18 to 872 species across the four problem formulations, with 10 replicates each, to characterize the average and worst-case performance of the solution. All runs were completed using `robust.prioritizr` with the CPLEX solver in a Linux high-performance computing cluster environment, provisioned with an 8-core Intel Xeon Computational Processing Unit (CPU) for each run. Runs were allocated sufficient memory: 4 GB for problems with fewer than 100 species, 8 GB for problems with fewer than 400 species, 28 GB for problems with fewer than 800 species, and 48 GB for problems with up to 872 species. Each run had a maximum time limit of 5 h and was terminated if it did not complete within the time limit. All problems were solved within the time limit without encountering any out-of-memory errors.

Table 7: Solve times (minutes, mean (standard deviation) over 10 replicates) under increasing problem sizes. Time limit is set to 300 minutes; values marked with + hit the limit.

Number of species	A. Non-robust: Assume historic baseline	B. Fully Robust	C. Partially Robust: Chance Constraints	D. Partially Robust: Conditional Value-at-Risk Constraints
18	0.02 (0.00)	0.05 (0.01)	0.23 (0.06)	0.06 (0.01)
30	0.02 (0.00)	0.07 (0.02)	0.40 (0.10)	0.09 (0.01)
50	0.03 (0.00)	0.08 (0.02)	0.78 (0.22)	0.16 (0.05)
100	0.03 (0.01)	0.14 (0.04)	1.94 (0.45)	0.42 (0.07)
200	0.04 (0.01)	0.26 (0.09)	4.17 (1.57)	0.81 (0.30)
400	0.08 (0.02)	0.33 (0.07)	9.35 (2.41)	2.50 (0.92)
600	0.12 (0.03)	0.61 (0.11)	15.60 (4.68)	4.17 (0.92)
800	0.21 (0.03)	0.73 (0.19)	20.71 (7.62)	7.14 (1.65)
872	0.20 (0.06)	0.75 (0.25)	32.70 (7.11)	7.01 (1.78)

As we can observe in this computational speed test, the non-robust and fully robust prioritization problems were substantially faster in finding an optimal solution than the partially robust solutions. We also see that the partially robust Conditional Value-at-Risk constraint was able to handle larger problems at a short run time (less than 10 minutes). In contrast, the partially robust chance constraint problem usually took substantially longer for large problem sizes, averaging more than 30 min for the full problem with 872 species in the case study.