

1 **Stochastic dominance to account for uncertainty and risk in conservation decisions**

2
3 Stefano Canessa*^{1,2}, John G. Ewen¹, Matt West², Michael A. McCarthy² and Terry V.
4 Walshe³

5 ¹Institute of Zoology, Zoological Society of London, Regents Park, London, United Kingdom

6 ²School of BioSciences, University of Melbourne, Victoria, Australia

7 ³Australian Institute of Marine Science, Townsville, Qld, Australia

8
9 * Corresponding author

10
11 **E-mails:** SC: science@canessas.com; JGE: John.Ewen@ioz.ac.uk; MW:

12 mwest@student.unimelb.edu.au; MAMC: mamcca@unimelb.edu.au; TVW:

13 twalshe@unimelb.edu.au

14
15 **Running title:** Stochastic dominance for conservation decisions

16 **Keywords.** Cumulative distribution function; elicitation; management objectives; risk
17 assessment; threatened species; translocation; triage; uncertainty; utility.

18 **Type of article:** Letter

19 **Word count:** abstract 150; manuscript 2995 (excl. References and figure legends)

20 **Number of references:** 40

This article has been accepted for publication and undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process, which may lead to differences between this version and the [Version of Record](#). Please cite this article as [doi: 10.1111/conl.12218](#).

This article is protected by copyright. All rights reserved.

21 **Number of figures:** 4

22 **Number of tables:** 0

23

24 **Abstract**

25 Practical conservation normally requires making decisions in the face of uncertainty. Our
26 attitude toward that uncertainty, and the risks it entails, shape the way conservation decisions
27 are made. Stochastic dominance (SD), a method more commonly used in economics, can be
28 used to rank alternative conservation actions by comparing the probability distributions of
29 their outcomes, making progressive simplified assumptions about the preferences of decision
30 makers. Here, we illustrate the application of SD to conservation decisions using the recovery
31 plan for an endangered frog species in Australia as a case study. Stochastic dominance is
32 simple and intuitively appealing for conservation decisions; its broader application may
33 encourage conservation decision makers to consider probabilistic uncertainty in light of their
34 preferences, which may otherwise be difficult to recognize and assess transparently. A better
35 treatment of attitudes towards uncertainty and risk may help ensure rational decision making
36 in conservation and remove potential causes of stakeholder conflict.

37

38 **Introduction**

39 Conservation biology aims to develop practical solutions to protect and restore natural
40 systems and their functions (Soulé 1985). However, the predicted outcomes of conservation
41 actions are typically uncertain, reflecting our incomplete knowledge of variable natural
42 systems (Regan et al. 2002). While some actions will be successful in conserving systems,

43 others can end up accelerating the same systems' demise. Consider for example the risk of
44 introducing new diseases during species translocations (Cunningham 1996) or the potential
45 damage from trophic cascades following eradication of invasive species (Bergstrom et al.
46 2009). Conservation decisions are routinely made in the face of such risks.

47 In expected utility theory (EUT: Von Neumann and Morgenstern 1944) decisions under
48 probabilistic uncertainty are represented as *lotteries* which can lead to different outcomes,
49 each with a given probability of occurring. Consider a hypothetical example in which
50 managers need to choose between three conservation actions (Fig. 1a). Action A may
51 preserve either two or six species with equal probability ($p=0.5$); action B may preserve
52 either twenty or zero species with a probability of 0.2 and 0.8 respectively; action C is certain
53 to preserve four species. Although actions with certain outcomes are unlikely in conservation,
54 the use of a "certainty equivalent" assists in understanding risk attitude. Conservation
55 decision makers will generally seek to maximize the number of species preserved; however,
56 the action selected will also depend on their *risk attitude* (Pratt 1964). In this example, a risk-
57 neutral decision maker will rate all actions equally: the expected outcome (the average of the
58 possible outcomes weighted by their probabilities) is the same (four species). A risk-averse
59 decision maker may choose action C to avoid the risk of a poor outcome. A risk-seeking
60 decision maker may choose action B, preferring a chance of achieving the best possible
61 outcome.

62 Within EUT the attitude of a rational decision maker can be represented by a *utility function*,
63 which describes the satisfaction derived from different outcomes (Von Neumann and
64 Morgenstern 1944). Rational decision makers will seek to maximize the utility of their
65 decisions. In the above example, a risk-neutral decision maker has a linear utility function:
66 they obtain the same utility from all actions with the same expected value (Fig. 1b). A risk-

67 averse decision maker will obtain greater utility (satisfaction) by avoiding poor outcomes, so
68 their utility function will be concave. A risk-seeking decision maker will have a convex
69 utility function, reflecting their preference for highly positive outcomes (Fig. 1b).

70 A failure to account for such differences in risk attitude can lead to conflict and undermine
71 conservation efforts, even when stakeholders may share the same broad conservation
72 objective. This problem has been recognized by several authors (Duncan and Wintle 2008;
73 Finnoff et al. 2007; Mace and Hudson 1999). However, risk attitude is rarely openly
74 addressed in real-world conservation decision making (Greiner et al. 2009). Conservation
75 decision makers may find it challenging to address personal values such as risk attitudes,
76 which in turn involve ethical or “protected” values (Gregory et al. 2012), particularly where
77 these are confounded with scientific judgment (Wilhere 2012). Defining utility functions can
78 also be technically challenging (Durbach and Stewart 2009).

79 Here, we illustrate how stochastic dominance (SD; Levy 1998) can facilitate the explicit
80 evaluation of risk in conservation decisions. This method is well known and frequently
81 applied in economics (Levy 1992), but has rarely been applied in conservation, in spite of its
82 potential value (Benítez et al. 2006; Knoke et al. 2008; Yemshanov et al. 2012). We illustrate
83 the concepts and calculations of SD using a case study of threatened species management,
84 and then discuss its advantages and limitations for conservation applications.

85 **Stochastic dominance**

86 *Case study*

87 Stochastic dominance is a decision-analytic tool that allows the preferential ordering of
88 alternative actions with different probabilistic outcomes. To explain the key concepts and

89 calculations of SD we consider the case of the endangered spotted tree frog *Litoria spenceri*
90 in south-eastern Australia. Population declines have been linked to fungal infection (Gillespie
91 2014), habitat degradation (Gillespie 2002) and invasive species (Gillespie 2001). In-situ and
92 ex-situ management actions have been proposed and implemented with the objective of
93 downgrading the species to a less severe threat category (Gillespie and Clemann *in press*).

94 Here, we build on the example described in Canessa et al. (*in press*), focusing on a system of
95 one extant population and one potential reintroduced population, where the objective was to
96 maximize the overall probability of persistence at the end of a 20-year period. We consider
97 five possible management strategies: (1) doing nothing, (2) full in-situ management of the
98 existing population only, including control of weeds and introduced trout, (3)
99 supplementation (*sensu* IUCN/SSC 2013) of the existing population by releasing captive-bred
100 individuals, with full in-situ management, (4) reintroduction of captive-bred individuals to a
101 new site with no further in-situ management and (5) reintroduction of captive-bred
102 individuals to a new site and full in-situ management of all populations. Note this set of
103 actions is not exhaustive and used here only for illustrative purposes.

104 The first step to formally assess risk is to predict the expected outcomes of each action and
105 the relative uncertainty. We consider two scenarios with different levels of risk. The first
106 scenario assumes that an ex-situ population has been successfully established and individuals
107 are available for release (the actual current situation of the *L. spenceri* recovery plan). The
108 second assumes that the ex-situ population has not yet been established; the probability of
109 successful establishment (and production of animals for release) is estimated as 50%. This
110 second scenario represented the decision problem at the beginning of the recovery plan, in the
111 face of greater uncertainty.

112 During a workshop, we used a modified Delphi technique (see McBride et al. 2012 for
113 details) to elicit the expected outcome (probability of persistence) for each of the five
114 management strategies from a panel of experts. The distributions of outcomes for each action
115 under the two scenarios are represented in Figure 2. Particularly in the second scenario (Fig.
116 2b), uncertainty is reflected by the considerable overlap among distributions.

117 *First-order stochastic dominance*

118 We can assess candidate actions in the face of uncertainty by comparing their cumulative
119 distribution functions (CDFs). For any value x over the interval $[a,b]$, the CDF of a function
120 $f(x)$ is the cumulative probability that the value of $f(x)$ is not greater than x . In other words, for
121 a given action the CDF represents the probability that the outcomes of that action will be
122 equal to or worse than a given value. For example, Figure 3a shows the CDFs of the
123 distributions of outcomes for each action, obtained through numerical integration. The CDF
124 for a persistence of 0.2 (x -axis) is 0.6 (y -axis) for Action 1 (doing nothing) and 0.2 (y -axis)
125 for Action 2 (in-situ management only). Therefore, the probability of persistence is more
126 likely to be greater than 0.2 when doing in-situ management than when taking no action.
127 When the objective is to maximize the value of x (in this case species persistence), the
128 rational choice is to select the action with the smallest CDF for a given value of x .

129 Assuming that greater utilities will always be preferred (more is better) implies that the utility
130 function is non-decreasing and its first derivative u' is always positive. Under this
131 assumption, Action A has *first-order stochastic dominance* (FSD) over Action B if:

$$132 F_A(x) \leq F_B(x) \text{ for all } x, \text{ and} \qquad \text{Eq. 1}$$

$$133 F_A(x) < F_B(x) \text{ for at least one value of } x$$

134 where $F_A(x)$ and $F_B(x)$ are the CDFs of the utility functions for actions A and B respectively
135 (Levy 1998). In other words, A dominates B at the first order when it has a smaller or equal
136 CDF for any value of the objective x (in this case persistence): the CDF curve for A is always
137 below or equal to the CDF curve for B, i.e. the two curves do not cross.

138 In the case of *L. spenceri*, the preference assumption is valid, since the recovery objective for
139 the species is to maximize the probability of persistence. In the first scenario (known ex-situ
140 success), the CDFs of the outcomes for all actions do not cross, and Action 5 (reintroduction
141 paired with in-situ management), has first-order dominance over all other actions (Fig. 3a).
142 Therefore, it represents the best action for any rational decision maker, and choosing it over
143 other actions involves no risk.

144 Conversely, when ex-situ success is uncertain, the cumulative distribution functions for the
145 selected actions cross in two cases (Fig. 3b): between Action 2 and Action 3, and between
146 Action 4 and Action 5 (reintroduction without and with in-situ management respectively).

147 The latter pair first-order dominates all other actions, which can therefore be discarded
148 regardless of risk. The choice between Actions 4 and 5, however, involves risk attitude.
149 Action 4 has a small chance of leading to greater persistence (the right-hand tail of the
150 distribution), possibly reflecting less reliance on ongoing management; on the other hand, it
151 also has a greater chance of a less positive outcome (the left-hand tail of the distribution). A
152 risk-neutral decision maker would be indifferent to the level of risk, and would simply select
153 the strategy with the highest mean persistence (0.63 and 0.61 respectively for reintroduction
154 with and without in-situ management). For non-neutral risk attitudes, first-order SD cannot
155 discriminate between these two actions; second-order SD must be explored instead.

156 *Second-order stochastic dominance*

157 Second-order SD requires knowledge of the general risk attitude of the decision maker; that
 158 is, whether they are risk-averse or risk-seeking.

159 For a risk-averse decision maker, the preference for minimizing risk implies a concave utility
 160 function with a second derivative that is always negative (Fig. 1b). Under this assumption of
 161 risk aversion, we can compare actions using the ascending integral of the CDF, $\int_a^x F(y)dy$.

162 Action A has *ascending second-order stochastic dominance* over Action B if

$$163 \int_a^x F_A(y)dy \leq \int_a^x F_B(y)dy \text{ for all } x, \text{ and} \quad \text{Eq. 2}$$

$$164 \int_a^x F_A(y)dy < \int_a^x F_B(y)dy \text{ for at least one value of } x \text{ (Levy 1998).}$$

165 If we consider the *L. spenceri* scenario in which the probability of ex-situ establishment is
 166 0.5, the choice is now restricted to reintroduction with and without in-situ management of
 167 both source and reintroduced population, which dominated all other actions at the first order.
 168 The ascending integrals of the two CDFs do not cross, so again Action 5, reintroduction with
 169 in-situ management of both source and reintroduced populations, is the best action, since it
 170 has second-order dominance (Fig. 4a).

171 Conversely, a risk-seeking decision maker will prefer a higher probability of persistence even
 172 if it involves a greater risk: this attitude implies a convex utility function with a second
 173 derivative that is always positive. Under this condition, we can compare actions using the
 174 descending integral of the complementary CDF, $\int_x^b F'(y)dy$ (Wong & Li, 1999). For any
 175 value of x , this can be interpreted as the area above the CDF to the right of x (as opposed to
 176 the ascending integral in Eq. 2, which corresponds to the area under the CDF to the left of x).
 177 Action A has *descending second-order stochastic dominance* over Action B if

178 $\int_x^b F'_A(y)dy \geq \int_x^b F'_B(y)dy$ for all x , and Eq. 3

179 $\int_x^b F'_A(y)dy > \int_x^b F'_B(y)dy$ for at least one value of x .

180 For the *L. spenceri* example, the descending integrals of the CDFs for Action 4 and Action 5,
181 reintroduction without and with in-situ management respectively, cross (Fig 4b). A risk-
182 seeking decision-maker could not use SSD to discriminate between the two actions: a rational
183 choice could be sought by exploring third-order SD (Whitmore 1970). This would require us
184 to elicit the shape of the marginal utility function of the decision makers (Von Winterfeldt
185 and Edwards 1986), which in turn corresponds to making assumptions about the third
186 derivative of the utility function (Whitmore 1970). Such assumptions, and those for higher-
187 order SD, may be difficult to interpret and apply to conservation decisions. More realistically,
188 since the absolute difference between the two actions is marginal (Fig. 4b), the risk-seeking
189 decision maker might simply be indifferent to the choice, or discriminate based on cost
190 preferences instead.

191 **Discussion**

192 Uncertainty is a key element of conservation decision making (McCarthy 2014), and it can
193 have different implications for decision makers depending on their risk attitude. However,
194 conservation decisions under uncertainty often rely on expected values to choose among
195 actions (mean outcomes; e.g. Canessa et al., in press) which do not immediately convey
196 information about uncertainty or risk attitudes, assuming risk neutrality (Fig. 1a). An
197 alternative approach in economics is to take the variance or standard deviation as a measure
198 of risk, evaluating the mean-variance relationship for a defined degree of risk-aversion
199 (Markowitz 1987; see Leskinen et al. 2006 for a conservation application). However, the

200 variance is an adequate measure of risk only for a normal distribution, which is not likely to
201 represent many conservation outcomes with skewed distributions. Conversely, stochastic
202 dominance uses the full distributions of outcomes instead of one or two moments of the
203 distribution.

204 In addition, a mean-variance analysis still requires a complete formulation of utility functions
205 through indifference curves (Markowitz 1987). In this sense, possibly the greatest benefit of
206 applying a non-parametric method such as SD to conservation decisions is in encouraging an
207 explicit treatment of uncertainty and risk attitudes by reducing the elicitation burden on
208 decision makers. Increasing orders of SD can be tested by progressively eliciting only limited
209 information about the attitudes of decision-makers (Hildebrandt and Knoke 2011). Testing
210 for FSD only requires an assumption of non-decreasing utility, and the calculation of CDFs
211 for predicted outcomes. Full probability distributions can be obtained from quantitative
212 analysis of empirical data or formal methods for the elicitation of expert judgment, as
213 described in our example. For those non-dominated actions that cannot be discriminated at
214 the first order, SSD adds an assumption about the general shape of the utility function
215 (concave or convex).

216 In this sense, SD is advantageous since it does not require the definition of complete utility
217 functions, which can be problematic for complex outcomes and non-monetary values.
218 Moreover, since utilities represent the preferences of individuals, the extent to which they can
219 be compared and aggregated is disputed (Eisenberg 1961). This can present a problem for
220 conservation, where decisions often involve multiple stakeholders. For example, there may be
221 little meaning in comparing the utility functions elicited from a group of stakeholders;
222 however, the same group might reach a consensus about general risk-aversion, and such a
223 simple definition is sufficient for a test of SSD. A general definition of risk aversion may also

224 intuitively represent situations in which the preferences of decision-makers are dictated by
225 mandates (such as institutional commitments to the precautionary principle). The main
226 limitation to the use of SD is the difficulty of interpreting higher orders. Computational
227 intensity may be limiting for large-dimensional problems with hundreds of competing
228 actions; however, in our case numerical integration for SSD required only 2 minutes on a
229 standard desktop computer (see Post 2003 for a more detailed discussion).

230 The specification of risk attitudes might be seen by some as an unnecessary complication.
231 Pannell (2006) found “flat payoffs” to be predominant in agricultural production: the
232 outcomes of different actions are similar enough that deviating from the mathematically
233 optimal action (the one with the best expected outcome for the chosen criterion, such as
234 expected value) will have little effect on utility across a considerable range of candidate
235 actions, and risk attitudes will be essentially irrelevant. When verified for conservation
236 decisions, as exemplified by our case study, the existence of flat payoffs reinforces the appeal
237 of SD as a simple decision-support tool. Rather than discovering the irrelevance of
238 uncertainty after eliciting utility functions, SD can be used to discriminate actions by simply
239 comparing their cumulative distributions. This makes it applicable to any decision problem in
240 which predicted outcomes can be expressed as distributions.

241 In our example, risk-averse and risk-seeking decision-makers would choose different actions;
242 yet both would be rational under their respective attitudes. Unless the uncertainty surrounding
243 outcomes is expressed and risk attitudes are approached transparently, such conflicts may not
244 be resolved. Consider for example the debate concerning conservation triage (Joseph et al.
245 2008). Proponents of triage apply rational decision making to find the set of management
246 actions that maximize the number of species conserved: this might imply that species with
247 little chance of recovery may be less likely to be allocated resources (Bottrill et al. 2009).

248 Critics of triage argue that allocation of resources should allow for currently unforeseen
249 breakthroughs that may eventually allow recovery (Jachowski and Kesler 2009), even if this
250 means a greater chance of poorer overall returns by spreading resources over a larger set of
251 species. It is possible that the two sides cannot agree because of fundamentally different risk
252 attitudes. Tulloch et al. (2015) found that lower risk tolerance by managers would in fact
253 reduce the total number of species protected, since efforts would concentrate on species in
254 more imminent danger of extinction, which would however require greater concentration of
255 resources. Future research could investigate risk attitudes in other areas of conservation (such
256 as assisted colonization; Seddon et al. 2009), and explore violations of the assumption of
257 rational decision making that is fundamental to expected utility theory and stochastic
258 dominance (e.g. Tversky and Kahneman 1981).

259 Recognizing that decisions reflect utility, rather than expected outcomes alone, reveals that
260 the definition of risk depends on preferences, and does not simply coincide with predicted
261 outcomes. Importantly, the preferences that influence conservation decisions may go beyond
262 those of conservation scientists or managers, also reflecting the values of the public or other
263 stakeholders, adding to the challenge of explicitly defining subjective values. However, if
264 such explicit definitions can be established, managers can then take full advantage of
265 quantitative predictive tools that incorporate the full range of probabilistic uncertainty.

266 Stochastic dominance provides a relatively simple tool to assist conservation decisions in the
267 face of uncertainty and risk. Its adoption could provide benefits to conservation managers at
268 two levels. First, it requires definitions of uncertainty and risk that are transparent both
269 quantitatively and semantically. Second, it allows a rigorous comparison of the predicted
270 outcomes of possible actions with open recognition of risk.

271

272 **Acknowledgments**

273 Manuscript preparation was supported by The University of Melbourne and the ARC Centre
274 of Excellence for Environmental Decisions. We gratefully acknowledge workshop
275 participants for providing estimates of persistence.

276
277 **References**

- 278 Benítez P.C., Kuosmanen T., Olschewski R., Van Kooten G.C. (2006) Conservation
279 payments under risk: a stochastic dominance approach. *American Journal of Agricultural*
280 *Economics* **88**, 1-15.
- 281 Bergstrom D.M., Lucieer A., Kiefer K. *et al.* (2009) Indirect effects of invasive species
282 removal devastate World Heritage Island. *Journal of Applied Ecology* **46**, 73-81.
- 283 Bottrill M.C., Joseph L.N., Carwardine J. *et al.* (2009) Finite conservation funds mean triage
284 is unavoidable. *Trends in Ecology & Evolution* **24**, 183-184.
- 285 Canessa S., Converse S.J., West M. *et al.* (in press) Planning for ex-situ conservation in the
286 face of uncertainty. *Conservation Biology*.
- 287 Cunningham A.A. (1996) Disease risks of wildlife translocations. *Conservation Biology* **10**,
288 349-353.
- 289 Duncan D.H., Wintle B.A. (2008) Towards adaptive management of native vegetation in
290 regional landscapes. pp. 159-182 in C. Pettit, W. Cartwright, I. Bishop, K. Lowell, D. Pullar,
291 D.H. Duncan editors. *Landscape analysis and visualisation SE - 9, Lecture Notes in*
292 *Geoinformation and Cartography* Springer Verlag, Berlin, Germany.
- 293 Durbach I.N., Stewart T.J. (2009) Using expected values to simplify decision making under
294 uncertainty. *Omega* **37**, 312-330.

- 295 Eisenberg E. (1961) Aggregation of utility functions. *Management Science* **7**, 337-350.
- 296 Finnoff D., Shogren J.F., Leung B., Lodge D. (2007) Take a risk: preferring prevention over
297 control of biological invaders. *Ecological Economics* **62**, 216-222.
- 298 Gillespie G.R. (2001) The role of introduced trout in the decline of the spotted tree frog
299 (*Litoria spenceri*) in south-eastern Australia. *Biological Conservation* **100**, 187-198.
- 300 Gillespie G.R. (2002) Impacts of sediment loads, tadpole density, and food type on the
301 growth and development of tadpoles of the spotted tree frog *Litoria spenceri*: an in-stream
302 experiment. *Biological Conservation* **106**, 141-150.
- 303 Gillespie G.R., Clemann N. (*in press*) National Recovery Plan for the Spotted Tree Frog
304 *Litoria spenceri*. Department of Environment and Primary Industries, East Melbourne,
305 Victoria, Australia.
- 306 Gregory R., Failing L., Harstone M., Long G., McDaniels T., Ohlson D. (2012) *Structured*
307 *decision making: a practical guide to environmental management choices*. John Wiley &
308 Sons, Hoboken, NJ.
- 309 Greiner R., Patterson L., Miller O. (2009) Motivations, risk perceptions and adoption of
310 conservation practices by farmers. *Agricultural systems* **99**, 86-104.
- 311 Hildebrandt P., Knoke T. (2011) Investment decisions under uncertainty—a methodological
312 review on forest science studies. *Forest Policy and Economics* **13**, 1-15.
- 313 IUCN/SSC. (2013) *Guidelines for reintroductions and other conservation translocations*.
314 *Version 1.0*. IUCN Species Survival Commission, Gland, Switzerland.
- 315 Jachowski D.S., Kesler D.C. (2009) Allowing extinction: should we let species go? *Trends in*
316 *Ecology & Evolution* **24**, 180.
- 317 Joseph L.N., Maloney R.F., Possingham H.P. (2008) Optimal allocation of resources among
318 threatened species: a project prioritization protocol. *Conservation Biology* **23**, 328-338.

- 319 Knoke T., Hildebrandt P., Klein D., Mujica R., Moog M., Mosandl R. (2008) Financial
320 compensation and uncertainty: using mean-variance rule and stochastic dominance to derive
321 conservation payments for secondary forests. *Canadian Journal of Forest Research* **38**, 3033-
322 3046.
- 323 Leskinen P., Viitanen J., Kangas A., Kangas J. (2006) Alternatives to incorporate uncertainty
324 and risk attitude in multicriteria evaluation of forest plans. *Forest Science* **52**, 304-312.
- 325 Levy H. (1992) Stochastic dominance and expected utility: survey and analysis. *Management*
326 *Science* **38**, 555-593.
- 327 Levy H. (1998) *Stochastic dominance: investment decision making under uncertainty*.
328 Kluwer Academic Publishers, the Netherlands.
- 329 Mace G.M., Hudson E.J. (1999) Attitudes toward sustainability and extinction. *Conservation*
330 *Biology* **13**, 242-246.
- 331 Markowitz H.M. (1987) *Mean-variance analysis in portfolio choice and capital markets*.
332 Blackwell, New York, USA.
- 333 McBride M.F., Garnett S.T., Szabo J.K. *et al.* (2012) Structured elicitation of expert
334 judgments for threatened species assessment: a case study on a continental scale using email.
335 *Methods in Ecology and Evolution* **3**, 906-920.
- 336 McCarthy M.A. (2014) Contending with uncertainty in conservation management decisions.
337 *Annals of the New York Academy of Sciences* **1322**, 77-91.
- 338 Pannell D.J. (2006) Flat Earth Economics: the far-reaching consequences of flat payoff
339 functions in economic decision making. *Review of Agricultural Economics* **28**, 553-566.
- 340 Post T. (2003) Empirical tests for stochastic dominance efficiency. *Journal of Finance*, 1905-
341 1931.
- 342 Pratt J. (1964) Risk aversion in the small and in the large. *Econometrica: Journal of the*
343 *Econometric Society* **30**, 122-136.

- 344 Regan H.M., Colyvan M., Burgman M.A. (2002) A taxonomy and treatment of uncertainty
345 for ecology and conservation biology. *Ecological Applications* **12**, 618-628.
- 346 Seddon P.J., Armstrong D.P., Soorae P. *et al.* (2009) The risks of assisted colonization.
347 *Conservation Biology* **23**, 788-789.
- 348 Soulé M.E. (1985) What is conservation biology? *BioScience* **35**, 727-734.
- 349 Tulloch A.I.T., Maloney R.F., Joseph L.N. *et al.* (2015) Effect of risk aversion on prioritizing
350 conservation projects. *Conservation Biology* **29**, 513-524.
- 351 Tversky A., Kahneman D. (1981) The framing of decisions and the psychology of choice.
352 *Science* **211**, 453-458.
- 353 Von Neumann J., Morgenstern O. (1944) *Theory of games and economic behavior*. Princeton
354 University Press.
- 355 Von Winterfeldt D., Edwards W. (1986) *Decision analysis and behavioral research*.
356 Cambridge University Press, Cambridge, UK.
- 357 Whitmore G.A. (1970) Third-degree stochastic dominance. *The American Economic Review*,
358 457-459.
- 359 Wilhere G.F. (2012) Inadvertent advocacy. *Conservation Biology* **26**, 39-46.
- 360 Yemshanov D., Koch F.H., Barry Lyons D., Ducey M., Koehler K. (2012) A dominance-
361 based approach to map risks of ecological invasions in the presence of severe uncertainty.
362 *Diversity and Distributions* **18**, 33-46.

363

364

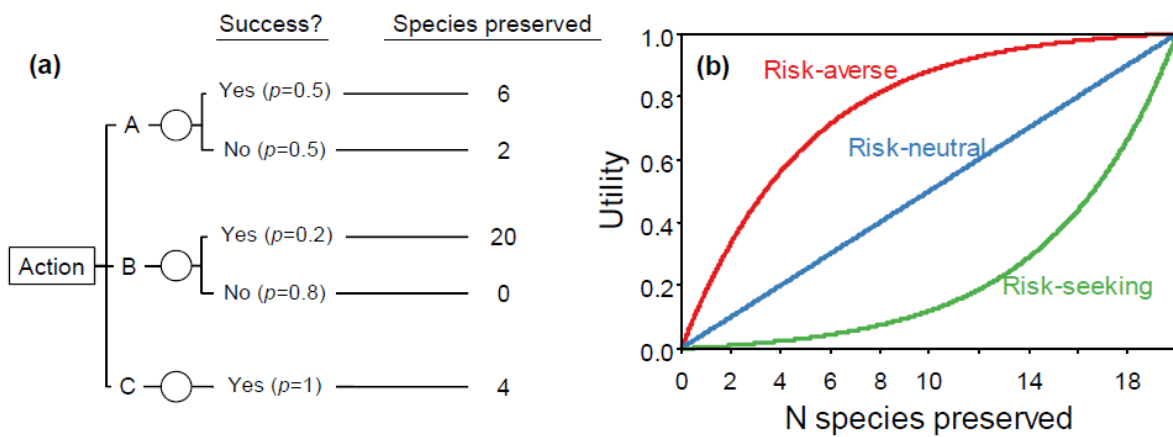
365

366

367

368 **Figure legends**

369 **Figure 1.** Panel (a) represents a hypothetical lottery with a decision between three alternative
 370 actions with different outcomes (numbers of species preserved) depending on success (with
 371 probabilities indicated by branch labels). Expected outcomes are calculated as the mean of
 372 possible outcomes weighted by their respective probabilities (e.g., for action A
 373 $6 \times 0.5 + 2 \times 0.5 = 4$). Panel (b) represents the utility functions of risk-averse, risk-neutral and
 374 risk-seeking decision makers as indicated by labels.



375

376

377

378

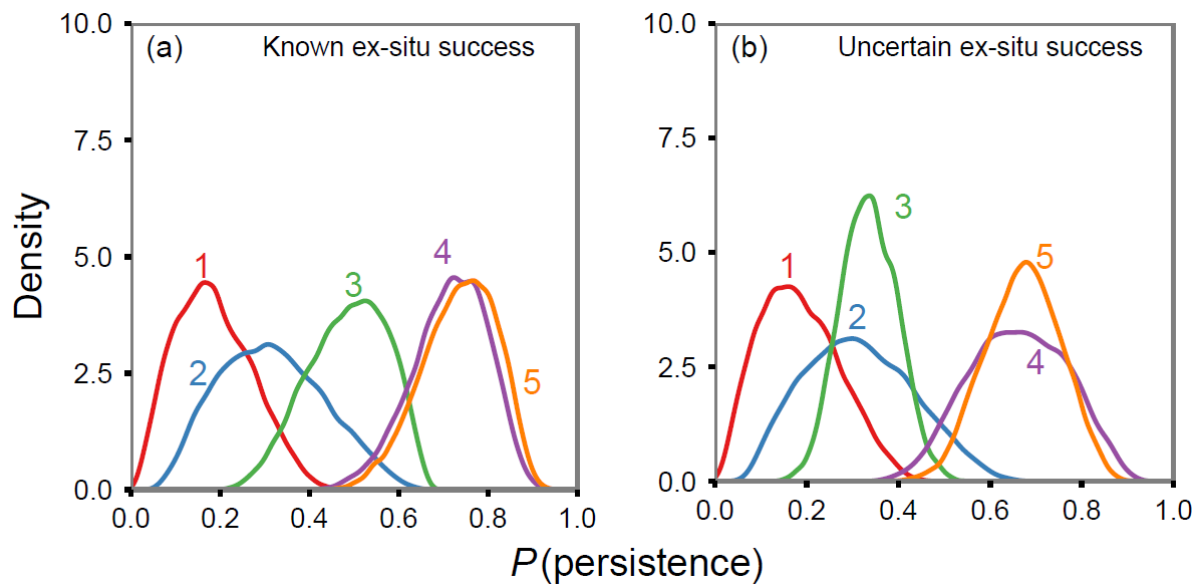
379

380

381

382

383 **Figure 2.** Elicited distributions of expected outcomes for the *Litoria spenceri* example,
384 expressed as the probability of persistence of the species. The two panels correspond to the
385 two uncertainty scenarios considered, respectively (a) known and (b) uncertain success of the
386 ex-situ establishment phase. Actions indicate doing nothing (1), full in-situ management of
387 the existing population only (2), supplementation of the existing population with full in-situ
388 management (3), reintroduction to a new site with no further management (4) and
389 reintroduction to a new site and full in-situ management of all populations (5).
390



391

392

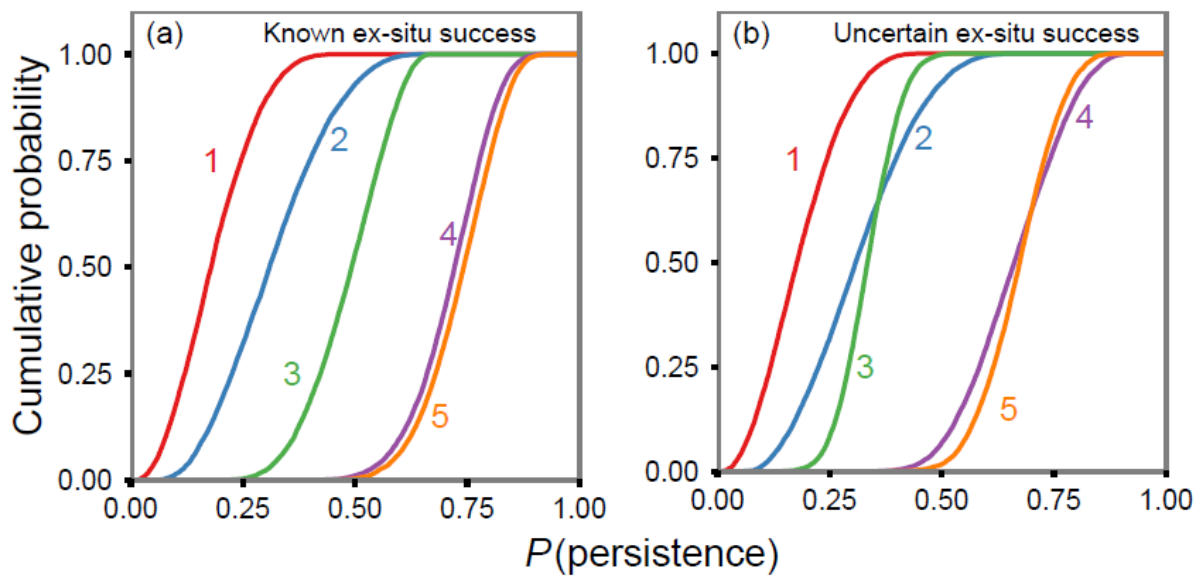
393

394

395

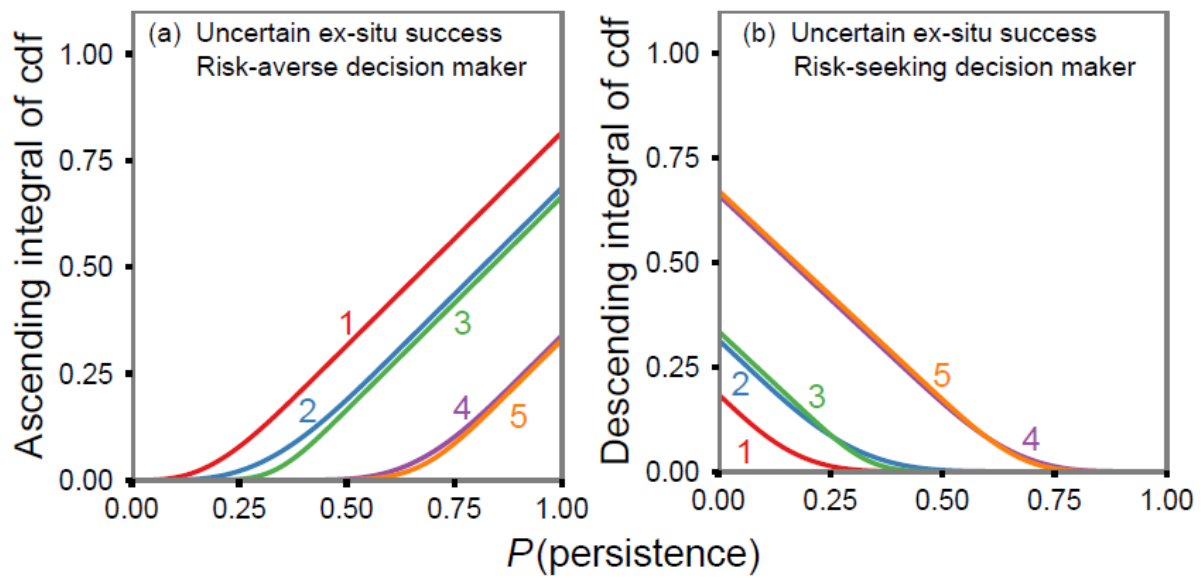
396

397 **Figure 3.** Cumulative density functions of the distributions of expected outcomes for L .
398 *spenceri*, calculated by numerical integration of the distributions in Fig. 2. Where CDFs do
399 not cross first-order stochastic dominance exists: for example, in panel (a) Action 5
400 dominates all other actions at the first order of SD.



401
402
403
404
405
406
407
408
409

410 **Figure 4.** Second-order stochastic dominance for the outcomes for *L. spenceri*, in the
411 scenario of uncertain success of the ex-situ establishment phase. Curves represent the
412 integrals of the CDFs depicted in Figure 3b. Panel (a) and (b) show, respectively, ascending
413 SSD for a risk-averse decision-maker and descending SSD for a risk-seeking decision-maker.



414

415

416

417

418