Decision-making under uncertainty for natural capital resources

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Abstract

Natural capital resources provide valuable goods and services to humans that help tackle global environmental challenges such as climate change and the loss of biodiversity. However, if actions towards managing these resources neglect the wide range of possible future outcomes under uncertainty, it could fail to provide the benefits to humanity necessary to mitigate these challenges. In this thesis, I discover how different ways of incorporating risk into decisions for natural capital resources will lead to different results. First, I present a systematic comparison of the different methods that can be used to make natural capital decisions under uncertainty and show that methodological choices on how risks are measured in the objective functions used for decision-making have a major effect on the quality of guidance that analysts can recover. Second, I draw on these methods to an exemplar in the United Kingdom of identifying low-risk tree-planting strategies to remove carbon dioxide from the atmosphere and reach "net-zero" carbon emissions by 2050, a problem encountered by every major industrialised nation with a commitment to the Paris Agreement. Using state-of-the-art natural capital valuation models, I quantify the risks associated with selecting a portfolio of tree planting activities that ignore the vast array of climate and economic uncertainties. Subsequently, I illustrate that risk mitigation is possible through the application of portfolio optimisation using methods that explicitly reduce downside risks, but substantial cost risks still exist even when sophisticated approaches are used. Third, I present another study in the context of creating protected areas to conserve the habitats of the threatened koala (*Phascolarctos cinereus*) in New South Wales, Australia. In this study, I extended the problem so that decision-makers can make decisions over time in a dynamic and uncertain environment, where uncertainties in the precise effects of climate change are resolved over time. I show that flexible strategies that adapt based on new information about climate change can deliver significant cost savings to achieve conservation objectives while minimising risks. This illustrates that decision-makers who exploit the temporal nature of their decisions can realise substantial improvements in benefits without increasing risk. Overall, this thesis provides an in-depth discussion of how decision problems used to protect and restore natural capital can be extended to account for risk and uncertainty and illustrates its generality across case studies in terms of minimising risks.

Declaration by author

This thesis is composed of my original work, and contains no material previously published or written by another person except where due reference has been made in the text. I have clearly stated the contribution by others to jointly-authored works that I have included in my thesis.

I have clearly stated the contribution of others to my thesis as a whole, including statistical assistance, survey design, data analysis, significant technical procedures, professional editorial advice, financial support and any other original research work used or reported in my thesis. The content of my thesis is the result of work I have carried out since the commencement of my higher degree by research candidature and does not include a substantial part of work that has been submitted to qualify for the award of any other degree or diploma in any university or other tertiary institution. I have clearly stated which parts of my thesis, if any, have been submitted to qualify for another award.

Publications included in this thesis

No publications included in this thesis

Submitted manuscripts included in this thesis

1. **Cho, F. H. T.**, Aglonucci, P., Bateman, I.J., Lee, C., Lovett, A., Mancini, M., Rapti, C., and Day, B. H., Resilient tree-planting under compounding climate and economic uncertainties, submitted to *Proceedings of the National Academy of Sciences* on 29 November 2023.

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Contributions by others to the thesis

All chapters are written with the candidate as first author.

Table 1: Author contributions for Chapter 2: *Spatially-explicit land-use decision-making with catastrophic risk: a Monte Carlo experiment*

Contributor	**Statement of Contribution**
Frankie H. T. Cho (candidate)	Conceptualisation, Formal Analysis, Methodology, Software, Validation, Visualisation, Writing–original draft, Writing–Review & Editing
Brett H. Day (primary supervisor)	Conceptualisation, Writing–Review & Editing

Table 2: Author contributions for Chapter 3: *Resilient tree-planting under compounding climate and economic uncertainties*

Contributor	**Statement of Contribution**
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Paolo Aglonucci	Data Curation, Formal Analysis, Methodology
Ian J. Bateman	Funding Acquisition, Investigation, Writing – Original Draft Preparation, Writing – Review & Editing
Christopher Lee	Conceptualization, Data Curation
Andrew Lovett	Supervision, Funding Acquisition, Project Administration, Writing – Review & Editing
Mattia C. Mancini	Software, Writing – Review & Editing
Chrysanthi Rapti	Data Curation, Formal Analysis, Methodology
Brett H. Day (primary supervisor)	Conceptualisation, Formal Analysis, Funding Acquisition, Investigation, Methodology, Software, Supervision, Writing – Original Draft Preparation, Writing – Review & Editing

Table 3: Author contributions for Chapter 4: *Flexible climate adaptation can halve conservation costs while mitigating risks*

Contributor	**Statement of Contribution**
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Brooke A. Williams	Conceptualization, Writing – Review and Editing
Carla Archibald	Writing—Review & Editing
James Brazill-Boast	Conceptualization, Writing – Review and Editing
Michael Drielsma	Data Curation, Writing – Review and Editing
Daniel Lunney	Writing—Review & Editing
Jonathan R. Rhodes (co-supervisor)	Conceptualisation, Writing – Review and Editing

Statement of parts of the thesis submitted to qualify for the award of another degree

No works submitted towards another degree have been included in this thesis

Research involving human or animal subjects

No animal or human subjects were involved in this research

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Keywords

Natural capital, Decision-making under uncertainty, Climate Change

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Abbreviations	
AUD	Australian Dollars
BECCS	Bioenergy with Carbon Capture and Storage
CBD	Convention on Biological Diversity
CCC	Climate Change Committee
CDR	Carbon dioxide removal
CE	Certainty Equivalent
CER	Climate-economy Realisation
CRRA	Constant Relative Risk Aversion
CVaR	Conditional Value-at-Risk
DACCS	Direct Air Carbon Capture and Storage
DGP	Data generating process
DPE	Department of Environment and Planning of New South Wales
EU	Expected Utility
EUT	Expected Utility Theory
EV	Expected Value
GPD	Generalised Pareto distribution
HE	High Emissions
HM Treasury	Her Majesty's Treasury
i.i.d.	Identically and independently distributed
IPCC	Intergovernmental Panel on Climate Change
LDP	Land-use Decision Problem
LGA	Local Government Areas
LSS	Local spatial shock
ME	Moderate Emissions

NEV	Natural Environment Valuation
NH	Near-historic
NPV	Net Present Value
NSW	New South Wales
P-EV	Planting for maximising Expected Value
P-HE	Planting for High Emissions
P-ME	Planting for Moderate Emissions
P-NH	Planting for Near Historic
P-RA	Planting with Risk Averse
QLD	Queensland
RA	Risk Averse
REMP	Rapid Evaluation of Metapopulation Persistence
SAR	Spatial autoregressive process
SCP	Systematic Conservation Planning
SD	Standard Deviation
SLATS	Statewide Landcover and Trees Study
UK	United Kingdom
USDA	United States Department of Agriculture

Symbols	
arg	Argument for maxima or minima
β	Risk percentile in the CVaR function, or variables in a regression model
$\Delta\Gamma$	Change in cost of conservation strategy
η	Threshold for exceedance
γ	Cost of CDR by the alternative carbon dioxide removal technology
Γ	Total cost of conservation strategy
∞	Infinity
κ	Indicator variable for whether a parcel is affected by a local spatial shock
λ	Risk aversion parameter in a mean-risk objective function
$\lVert . \rVert_2$	L2 norm of a vector
$\mathbb{R}$	Real numbers

$\mathbf{W}$	Spatial weights matrix
$\mathbf{X}$	Matrix of independent variables
$\mathcal{X}$	Set of feasible decisions
max	Maximisation operator
min	Minimisation operator
$\mu, \boldsymbol{\mu}$	Mean, or mean vector
ϕ	Risk measure
π	Parameter in local spatial shocks data generating process
ρ	Mean-risk objective function (if a function), or the spatial weights parameter (if a scalar), or a discount rate parameter
Σ	Variance-covariance matrix
sup	Supremum
τ	Land clearing indicator
θ	Risk aversion parameter in CRRA, or time variable
ε	Error term
$\varkappa$	Binary indicator for a spatial shock
φ	Degree of distance decay
ζ	Risk factor
c	Annual payment
C	Net present value of a perpetual annuity payment
d	Distance
F	Cumulative density function, or function in the Generalised Pareto Distribution
G	Conservation goal
i	Index for parcel/ cell
j	Index for tree species, or simulation replicate
J	Replicates
k	Land clearing future
m	Average annual carbon storage, or metric for koala habitats
M	Total amount of koala habitat
N	Number of parcels
N	Number of units for decision-making
p	Probability
Q	Carbon sequestration target
q	Quantile

r, $\mathbf{r}$	Net benefits, or vector of net benefits
t	Time index
v	Value function
$x, \mathbf{x}$	Decision (vector for a series of decisions)
y	Second-stage decisions
z	Amount of deployment of the alternative carbon dioxide removal technology
s	Index for state of the world
S	Number of states of the world, or the set of states of the world
U	Utility function

Chapter 1

Introduction

Natural capital resources, the stock of natural assets from which humans derive service flows, provide valuable goods and services to people that are vital to the survival of mankind (Bateman and Mace, 2020; Costanza and Daly, 1992; Daly and Farley, 2004; Guerry et al., 2015; Shepherd et al., 2016). Increasingly, the restoration and conservation of natural capital resources are highlighted as keys to addressing a variety of global sustainability challenges such as climate change, loss of biodiversity, and food security (Strassburg et al., 2020; Bastin et al., 2019; Hanson et al., 2020). Trees, for example, could absorb carbon from the atmosphere and contribute to the mitigation of climate change (Mo et al., 2023), with some projections estimating that it can remove up to 25% of atmospheric carbon worldwide if deployed globally (Bastin et al., 2019). The protection of biodiversity by establishing land for conservation is also vital to support other services that humanity receives, such as the regulation of nutrients and the pollination of food crops (Ghaley et al., 2014; Smith et al., 2015). Of course, the land used to grow or protect forests could alternatively be used to support other human needs, such as the needs for food through agriculture (Kreidenweis et al., 2016), housing and transport (Arman et al., 2009; Nyelele and Kroll, 2021).

The decision of whether to favour the restoration of natural capital over alternative productive uses is made complex by uncertainties about future conditions (Levin and Lubchenco, 2008; Folke et al., 2010; Polasky et al., 2011), which influence several components of the value of natural capital. For example, uncertainty over climate change will affect several components that determine the value of natural capital in land, such as how valuable will the crops that we could grow (Ritchie et al., 2020; Agnolucci et al., 2020), whether the trees that we plant survive in a changing future climate (Yousefpour and Hanewinkel, 2016), and whether threatened species that are the subject of protection will continue to persist in that habitat (Meir et al., 2004; Conradi et al., 2024).

Decision-makers rely on predictions about future conditions and often commit land to decisions to protect or restore natural capital, or commit them to alternative uses (such as agriculture or other developments), before these uncertain future factors are known (Arrow and Fisher, 2013). If the realised future differs from what was predicted, irreversible policy interventions could fail to support these competing human economic and environmental needs; for example, goals to reverse biodiversity loss through global commitments to protect 30% of ecosystems around the world could be undermined by uncertain climate change that makes protected areas no longer suitable for species persistence (Leclère et al., 2020; Dobrowski et al., 2021). When there is uncertainty about the benefits and costs provided by alternative uses, how can land-use be planned to ensure that the needs of mankind are met cost-effectively across a wide range of futures?

This thesis is motivated by the problem of having to make irreversible decisions about natural capital resources when there are substantial uncertainties. Indeed, the topic of decision-making under uncertainty is not new and there are numerous approaches in fields of economics to mathematics. Particularly in economics, the use of the Expected Utility Theory (discussed in detail in Chapter 2) advanced by von Neumann (1928), Savage(1954) and others has been the standard for analysing individuals' decision-making under uncertainty. Similarly, we see that a growing set of models have been created and applied to identify optimal patterns for decision-making under uncertainty in a wide range of academic fields, ranging from finance (Young, 1998; Konno and Yamazaki, 1991; Chopra and Ziemba, 1993; Chopra et al., 1993; Simaan et al., 2018; Levy and Markowitz, 1979), engineering (Soroudi and Amraee, 2013; MacKenzie and Hu, 2019) and, more recently, management of natural capital (Polasky et al., 2011; Yousefpour and Hanewinkel, 2016; Figge, 2004; Ando and Mallory, 2012).

Indeed, methods developed to cope with these uncertainties are limited by the amount of knowledge over the set of possible states of the world that could characterise future conditions. For example, when the set of future conditions in which decisions must be made remains unpredictable or cannot be agreed on, as is the case in "deep uncertainties," methods for guiding decision-making are severely limited (Marchau et al., 2019; Walker et al., 2013). Other forms of uncertainty, generally classified as "Knightian uncertainty" or "ambiguity," create challenges to the methods presented in this thesis, because the set of possible conditions that characterise the future are known, but its probabilities remain hard to predict (Knight et al., 1921; Ellsberg, 1961a). However, the methods for decision-making under uncertainty can be applied effectively to many other decision problems with some uncertainty. In this thesis, we focus on natural capital decision problems where reasonable assumptions about the set of future states of the world and its probabilities can be made, with the decision-maker only being uncertain over which state of the world will be realised.

A series of advances makes the application of decision theory to empirical natural capital decision problems with uncertainty a timely topic of study. First, the field is benefiting from a proliferation of computational tools that make complex, high-dimensional optimisation problems tractable. Problems that involve the optimisation of decisions over a large number of parcels–previously considered intractable or where only heuristic approaches with unknown levels of optimality can be applied–can now be solved to a proven level of optimality through the use of modern mathematical solvers that use Integer Linear Programming or Quadratic Programming (Beyer et al., 2016; Schuster et al., 2020). Several examples of these show these approaches applied at a fine resolution across the world (Strassburg et al., 2020; Jung et al., 2021), consisting of millions of parcels that span a large geographical space. The generalisation of these well-known fine-resolution decision problems to consider uncertainties became a frontier for research (e.g. Runting et al., 2018; Shah et al., 2017; Popov et al., 2022). Second, the topic is aided by the rapidly growing availability of predictive models that relate large-scale changes in climate and economic systems to fine-scale impacts on natural capital resources (van Ruijven et al., 2014; Frame et al., 2018). As aided by work on scenario modelling, such as the Representative Concentration Pathway set of scenarios (Riahi et al., 2007), fine-resolution datasets of projections across multiple emissions pathways have been derived, such as the CHESS-SCAPE projections that provide 2-kilometer resolution projections of climate variables across emissions scenarios in the United Kingdom (Robinson et al., 2022)). These datasets help further characterise the uncertainty of ecological models, such as species distribution models frequently used in biodiversity modelling (Thuiller et al., 2019). Although there has been some work focused on uncertainties in ecological systems (Meir et al., 2004; Wintle et al., 2011), there is new but underused work linking climate change to uncertainty in future socioeconomic variables that can also have a strong influence on natural capital (Bastien-Olvera et al., 2024). These include integrated models that relate emissions pathways to socioeconomic variables (such as the Shared Socioeconomic Pathways (Riahi et al., 2017) methodology). Integrated estimates of the uncertainty of coupled climate and economic variables allow researchers to assess detailed plausible scenarios of future socioeconomic and physical variables that determine the value of natural capital. Examples of those relevant to natural capital are the so-called social cost of carbon (Yang et al., 2018; Russell et al., 2022) and agricultural prices (Kreidenweis et al., 2016). Through the use of these new models, decision-makers are now armed with a data-rich understanding of the interactions between key climate, economic, ecological, and social variables that together drive the value of natural capital resources that are fundamental to decision-making.

This enriched understanding of the interactions between uncertain inputs presents an underused opportunity to inform and reduce risks in natural capital decision-making. Here, I identify three knowledge gaps based on the prevailing literature that highlight significant hurdles for the application of decision-making methods under uncertainty in natural capital problems.

1.1 Methodological choice in decision-making

Before analysts can help decision-makers identify investments that are resilient to uncertainty, they must first choose a methodology that allows them to incorporate their information about uncertainty into decision-making. Indeed, the methodological choice to handle uncertainty can have significant effects on the decisions made (Seppelt et al., 2013; Neuendorf et al., 2021). Several studies found significant changes in the sites selected in scenarios with optimal land use decisions when those are optimised using incomplete or biased information (Freitag and Van Jaarsveld, 1998; Grand et al., 2007; Wilson et al., 2005). Studies also found that decisions that account for uncertainty can increase expected returns and lower management costs, with Janssen et al. (2004) finding that decision-makers that do not account for uncertainty in rainfall events make decisions that lead to 33% less expected returns and Haight and Polasky (2010) finding that the costs of monitoring and managing a landscape are 20- 30% lower if monitoring of uncertain ecological systems is perfect and costless.

The plethora of methods available to solve natural capital decision problems under uncertainty creates an acute problem–which method should the decision-maker select? These problems are typically approached through scenario analysis, which involves imagining a set of possible futures and evaluating how well different policy decisions could play out in these futures (Polasky et al., 2011). The scenario analysis approach supports several high-profile analyses of land-use and natural capital decisions (Bateman et al., 2013; Hatfield-Dodds et al., 2015; Lawler et al., 2014; Bryan et al., 2011; Law et al., 2015). However, as I demonstrate in Chapter 3, a limitation of scenario analysis is that it can only represent a subset of possible futures. Decisions that are viewed as optimal in one future may prove to be wholly suboptimal if another future is played out, which could lead to similar losses in the efficiency of natural capital decisions as reported by the prevailing literature if another scenario plays out.

Several articles use approaches analogous to scenario analysis to mitigate risk in managing natural capital, particularly in the context of mitigating climate change in biodiversity management. For example, these articles explored whether a conservation goal can be met in a single or several climate scenarios using species distribution models (Hannah et al., 2007; Carvalho et al., 2011) or cost-effectiveness analysis (with integration into socioeconomic data) (Wintle et al., 2011).

In a scenario analysis approach, an analyst would create a set of plausible futures that a decision-maker might pursue, as supported by data and models, and the decision-maker would choose from this set which one to pursue. A limitation of such approaches is that they do not identify a set of optimal decisions (across multiple parcels) that ensure that the objective (the total amount of natural capital protected) is robust to uncertainty. Although the choices of policy-makers with respect to land-use decisions affects several sites simultaneously, many of these studies focus on the uncertainty from one site to another site without focussing on the risk associated with the whole "portfolio" or the sum of several sites, at once (Popov et al., 2022). Of course, there are other approaches to making decisions under uncertainty that we do not cover here, particularly the use of information-gap theory that analyses how much uncertainty will start to lead to changes in the optimal set of decisions (Regan et al., 2005; Moilanen et al., 2006). However, information-gap theory focusses on just the sensitivity of decisions to multiple possible uncertain scenarios and identifying solutions that do the best in the worst-case scenario, and are therefore unable to accommodate situations where decision-makers are willing to take certain risks in their decisions in line with their risk preferences (Sniedovich, 2007).

Decision-makers confronted with uncertainty over several scenarios can use a different approach based on maximising Expected Utility, a widely influential decision-theoretic model in mathematical economics. The Expected Utility Theory was first introduced by von Neumann and Morgenstern (von Neumann, 1928). Despite its influence in economics, underpinning widely-used models such as the Merton-Samuelson portfolio problem of lifetime portfolio allocation (Merton, 1969) , there were no empirical applications to date that directly applied the Expected Utility Theory to model natural capital decision problems. For a detailed overview of this theory, the reader is referred to the Appendix A, or for a formal mathematical explanation, the reader is referred to Chapter 2.

As I show formally in Chapter 2, a special case of maximising Expected Utility is the problem of maximising expected value, where the level of utility increases linearly with the value of natural capital (net benefits) of natural capital decisions. Essentially, this approach involves assuming the expected, or most likely, value of natural capital and then choosing the decision, or set of decisions, that maximises the expected value. Although simple in nature, this approach still neglects the variability in the distribution of outcomes, where the actual outcome that is realised could differ from the expected value. This means that there is a potential for expected value-based approaches to lead to "risky" decisions where the actual outcome arrived could be substantially different from what the expected value was.

Recently, the use of Modern Portfolio Theory in natural capital decision-making was proposed as a strategy to reduce risks by Ando and Mallory (2012) and Mallory et al. (2014), where it was demonstrated in the context of conserving biodiversity in the Prairie Pothole region in the United States. In essence, Modern Portfolio Theory departs from just the use of Expected Value by optimising an objective function that comprises not just the Expected Value (or the mean), but also a measure of risk, with the risk measure of variance being used most widely in the field. This idea is drawn from financial economics that was initially popularised by Markowitz (1952). These methods have been widely used in the field to plan for the conservation and restoration of natural capital resources, with applications to minimise the risks to ecosystem services in land-use planning in China (Liang et al., 2017), to reduce the risks in habitat conservation for the Lesser White-fronted Goose in China (Liang et al., 2018), to reduce the risks from sea level rise to ecosystem services in Australia (Runting et al., 2018), to improve the design and social equity of marine protected areas (Halpern et al., 2011) and to improve the zoning of marine protected areas in the context of protecting coral reefs from climate change (Beyer et al., 2018).

Although there are many approaches to guide investments in natural capital, because these methods typically arise from other disciplines such as financial economics and operations research, the quality of guidance these approaches can give to natural capital investment problems remains unclear. In particular, portfolio theory in its traditional format of estimating risk using variance attracted substantial criticism from practitioners in financial economics and land-use decision-making (Chopra and Ziemba, 2016; Chopra et al., 1992). A main criticism of using variance (or standard deviation) as a measure of risk in decision-making about natural capital is that it is insensitive to low-probability catastrophic events in the model (Dunkel and Weber, 2012). Its importance to decision-making was emphasised in the literature on the economics of climate change (Wagner and Weitzman, 2016; Weitzman, 2009; Dietz, 2009).

A core criticism of the mean-variance approach was that it was unable to quantify downside risks, which are realisations of outcomes that are worse than the expected value, in decision-making. To overcome these criticisms, other approaches that explicitly focus on downside risks can be drawn from the financial economics literature. There are many approaches, but the Conditional Value-at-Risk measure (Rockafellar and Uryasev, 2000), also known as the Expected Shortfall measure (Acerbi and Tasche, 2002), received much attention and was established as a standard in the banking industry for measuring risks in portfolios by the Basel Committee on Banking Supervision (Basel Committee, 2013). It is also desirable in terms of (1) being tractable, as it can be optimised, after reformulation, using commercially-available linear programming solvers (Rockafellar and Uryasev, 2000) and (2) satisfies a number of criteria that make it part of a set of "coherent risk measures" (Artzner et al., 1999; Acerbi and Tasche, 2002), which describe a set of characteristics that make a risk measure desirable for use in the financial risk management literature. There are many other possible extensions to the original portfolio theory formulation that I do not explore, but can be further investigated, such as the minimax formulation (Young, 1998), the mean absolute deviation model (Konno, 1990), downside risk measures (Sortino and Satchell, 2001), formulations that measure risk also in terms of the skew and kurtosis of the distribution (Lai et al., 2006; Athayde and Flôres, 2003), or robust optimisation approaches popularised by (Bertsimas and Sim, 2004) and applied in natural capital decision problems by others (Knoke et al., 2015, 2016). The prevailing knowledge gap is that it is unclear whether, and in what situations, these newer measures of risk deliver gains to the solution when compared to approaches based on the mean and variance.

To my knowledge, there are no studies explicitly exploring whether portfolio theory approaches that use mean-variance optimisation are likely to identify investment strategies for natural capital creation that are better or worse than approaches that explicitly quantify downside risks, as suggested by Dunkel and Weber (2012). Even studies comparing approaches in a natural capital investment context (e.g. Shah and Ando, 2015) only compare their performance in a real-world dataset that makes the study findings difficult to generalise to other datasets with different levels of risk and uncertainty.

Focussing only on expected value, mean-variance (or mean-standard deviation) and mean conventional value-at-risk approaches to natural capital decision-making under uncertainty, in Chapter 2 I present the first major contribution in this thesis by revealing when these mean-risk objective functions will lead to better decision-making for a wide range of natural capital decision problems. In this chapter, I found that natural capital decisions that maximise risk-averse objective functions lead to decisions that have substantially higher expected utility compared to decisions that only maximise the expected value. Through a Monte Carlo experiment, I demonstrated that this remains true for a large number of computationally generated datasets that exhibit features typically found in natural capital decision problems. While the use of an objective function that accounts for risk leads to substantial improvements in the expected utility of the solutions as evaluated using Expected Utility Theory, the relative improvements arrived by moving to a sophisticated risk-averse objective function relying on the Conditional Value-at-Risk appears small in comparison. Our work also illuminates the pitfalls of misspecifying risk-aversion parameters in the objective function and underscores the need for decision-makers to calibrate their underlying risk preferences with the parameters of the objective function. Our work identifies clear situations where a more sophisticated risk measure is useful, in situations where there are low-probability, catastrophic risks, and the decision maker is strongly risk-averse.

1.2 Integrated approaches to multiple interacting uncertainties

The use of a natural capital framework to assess possible policy options for decision making involves quantification and assimilation of the multiple effects of various components of environmental and economic systems on natural resources through an integrated approach (Bateman and Mace, 2020). Take the example of land use decision making between forest and agricultural uses. The use of the natural capital framework for decision-making in that context requires that decision makers assess the value of the forest grown, which is a function of tree growth (ecological modelling) and the value humans ascribe to the services provided by the growth of the forest (e.g. carbon sequestration, timber production, recreational services, etc.), all of which could affect decision-making (Bateman et al., 2013; Goldstein et al., 2012). Therefore, the evaluation of the value of tree-planting in natural capital terms is sensitive to several uncertain inputs, ranging from future climate variables, the price of carbon (from carbon sequestration), the price of wood (from timber sales), and the value society attributes to other effects of tree-planting (e.g. changes in flooding, recreational values, and biodiversity enhancement) (Day, 2020). The same can be said for the alternative of pursuing agricultural production, which is strongly sensitive to future climate variables that affect crop growth and the value society places on the crops grown (Agnolucci et al., 2020). Uncertainties over key economic and environmental drivers jointly drive several components of the valuation of natural capital that drive decision-making.

Many studies that make decisions about natural capital under uncertainty focus only on a subset of uncertainties in isolation. Of course, the approach of treating uncertainties in isolation could be justified if only a limited set of key drivers of uncertainty drive decision-making, with previous work focused on identifying drivers of uncertainty that are key sensitivities of natural capital decision. These works are done in the context of decision-making in socioecological systems (Davis et al., 2019; Rounsevell et al., 2021; Haag et al., 2022) and decision-making using biodiversity models (Thuiller et al., 2019; Brodie et al., 2022), but much of this work does not apply the natural capital decision-making framework that considers the wide range of benefits and costs arising from environmental change in decision-making. Johnson et al. (2012) looked at the impact of multiple sources of uncertainty on a problem of natural capital decisions in the Minnesota River Basin, comparing the impact of uncertainties in agricultural returns relative to the value of other ecosystem services (carbon sequestration and air pollution) on the classification of multiple alternatives and concluded that uncertainties in the valuation of ecosystem services drive the results strongly relative to others.

However, the issue still exists even if decision makers use an approach similar to Johnson et al. (2012) to identify key sources of uncertainty and focus only on those to identify natural capital decisions. In the natural capital decision problems we look at in this thesis, decision-makers could be easily misguided if they only consider one source of uncertainty in isolation, even if that source of uncertainty is found to have the most impact on results. This is because the interacting nature of multiple sources of uncertainty could mean that analyses that focus only on one source of uncertainty that is identified as more important than others could belie the full range of uncertainty. For example, the evaluation of decisions to restore ecosystems through tree-planting through the natural capital approach depends on two interlinked inputs: future climate patterns and its impact on the physical growth of restored ecosystems, and the value society ascribes to carbon sequestration services, commonly expressed through the so-called Social Cost of Carbon. These two inputs are hardly independent to one another; research illustrates that the global society would be willing to place a higher value on carbon sequestration services on a high-emission pathway to avoid the worst outcomes of climate change (Yang et al., 2018; Russell et al., 2022). Yet, the effect of climate change extends far beyond that; climate acts to further affect other uncertain inputs to the decision problem, such as the prices of several agricultural and timber commodities, for example. Research that looks at these variables in isolation risks omitting key interactions between uncertain variables that jointly drive the decision-making process.

In contrast to the integrated nature of multiple sources of uncertainty, most analyses that use portfolio theory or similar approaches to reduce uncertainty seem to focus only on one source of uncertainty in isolation. Almost overwhelmingly, these articles focus only on the direct physical impacts of climate change on ecosystems (e.g. Hua et al., 2015; Liang et al., 2017; Ando and Mallory, 2012; Anderson et al., 2015; Shah and Ando, 2015; Eaton et al., 2019; Runting et al., 2018; Beyer et al., 2018), while neglecting the secondary impacts of climate change on socioeconomic variables that jointly drive the decision-making of natural capital. A minor set of articles examines how socioeconomic uncertainty will drive natural capital decisions (McBride et al., 2007), but this was also only done in isolation of other interlinked uncertainties. Indeed, climate change could have a major effect on natural capital decisions, but its effects do not stay within the limits of physical and ecological systems; it will have strong interactions with several other socioeconomic variables that jointly drive natural capital decision-making (Fezzi and Bateman, 2015; Kreidenweis et al., 2016; Yang et al., 2018).

There is a lack of analyses that can integrate several sources of uncertainty and comprehensively identify optimal decisions under compounding interacting uncertainties. Historically, a challenge in characterising multiple sources of uncertainty at the same time lies in the fact that the relationship between these interacting uncertain inputs needs to be quantitatively modelled and simulated in order for decision-makers to recover the joint distribution of these variables (see, for example, the work in Appendix B).

In the work leading up to the paper presented in Chapter 3, I present a novel framework to characterise the joint uncertainty arising from the combination of climate and economic uncertainties with natural capital decision-making and applied these methods to an empirical case study of the identification of spatial strategies for tree-planting in the United Kingdom. This study addresses a fundamental hurdle in achieving the scale of climate change mitigation through large-scale tree planting necessary to meet the Paris Climate Agreement signed by almost every major industrialised nation across the world; that irreversible decisions for land-use carbon dioxide removal must be made, over how much, where, and what trees to plant, before uncertainties over future climate conditions and marcoeconomic variables are resolved. Bringing together a state-of-the-art suite of integrated environment-economy models (the Natural Environment Valuation (NEV) suite of models), with statistical models that capture the variability in future climate and economic variables, I simulated the net benefits of tree planting across a wide range of futures and found that a decision-maker that adopts a scenario analysis approach typical in the field–one that assumes a certain predicted future to be true and then plans accordingly–risks ending up with a planting strategy that incurs significant costs to society. With a risk-averse optimisation algorithm informed by the latest advances in mathematical finance, I found that the tree planting strategies identified through this approach substantially outperform strategies identified through the scenario analysis approach and, therefore, have major impacts on where and which trees are planted. But another primary conclusion reached by this study is that it was not possible to completely eliminate risks even with risk-averse objective functions, as demonstrated by the substantial risks still remaining in the most risk-averse planting strategy. Bringing these conclusions together, I demonstrate how risk-averse optimisation techniques can be used to advance decision-making and support decisions over the optimal mix of carbon dioxide removal technologies that are likely to incur the least costs to society at the lowest risks possible.

1.3 Reducing risk through optimal timing

Beyond just looking at how the spatial configuration of land-use can help natural capital decision-makers reduce risks, my thesis also explores how decision-makers can optimise the timing of decisions to further reduce risks. Decision-makers who exploit the temporal dimension to reduce risks recognise the fact that decisions made in the future could progressively benefit from improved information that reduces uncertainties that allow future decision-makers to make much better decisions. To fully exploit these opportunities to reduce uncertainties, however, decision-makers will have to work out not just where, but also when, to protect and restore natural capital.

In economics, the value of being able to improve decisions by delaying decision-making has long been recognised through the ideas of the quasi-option value (Arrow and Fisher, 2013; Fisher and Hanemann, 1987) that argue that irreversible developments in the environment remove the option for future generations to enjoy environmental benefits. Thus, when the environmental costs of irreversible developments are not well known, there exists a value in preserving the environment until uncertainties of the environmental benefits are ascertained. These ideas share strong parallels with the ideas of real options (Dixit and Pindyck, 1994) that recognise the real value of an option to delay investments until uncertainties are resolved. Importantly, economic theory predicts that resolving these uncertainties is only valuable if current decisions preserve options for future decision-makers, as future decision-makers cannot act on new information if suboptimal, irreversible decisions were already made before the information is available (Conrad, 1980).

The intuitions in options theory in economics have trickled down to empirical applications in the planning of natural capital resources, such as the optimal scheduling of conservation activities or restoration of forests. Costello and Polasky (2004) presented a stochastic dynamic integer linear programme that showed that in a conservation setting, a decision-maker facing uncertainty over where land could be developed will realise the highest rewards if the conservation budget is available upfront rather than over regular cycles, as these conservation spending prevent irreversible losses to biodiversity. However, that piece of work does not consider the possibility that decision-makers are averse to risks and are willing to pursue strategies that do not maximise expected benefits if it can help reduce risks. Other work focusses on the importance of saving, or the regular and predictable availability of conservation funding, in terms of hedging against fluctuations in conservation budgets and achieving optimal outcomes in biodiversity conservation (Drechsler and Wätzold, 2007, 2020; McBride et al., 2007; Iacona et al., 2017). However, these works did not consider opportunities for the decision maker to implement actions during the interim to resolve general uncertainties around species distribution as affected by climate change.

The role of learning and resolving uncertainties in dynamic conservation planning problems has been emphasised in studies looking at "adaptive management," where decision-makers simultaneously plan actions (to protect biodiversity or improve environmental outcomes) as well as activities to reduce uncertainty. Previous work shows that this can be achieved by monitoring activities in the ecosystem or evaluating the effectiveness of management actions, or even strategically planning these actions to learn about the system more effectively (Westgate et al., 2013; Wilhere, 2002; van Wilgen and Biggs, 2011). In many cases, adaptive management solutions are identified with the use of stochastic dynamic programming (McCarthy and Possingham, 2007; Marescot et al., 2013). Although a large number of studies on adaptive management focus on learning to resolve the site-specific uncertainty of ecological data in managed landscapes (van Wilgen and Biggs, 2011; Martin et al., 2009; Chadès et al., 2008), some other studies have applied it to general and broad uncertainties related to ecological management, such as climate change (McDonald-Madden et al., 2011; Martin et al., 2011; Perry et al., 2020).

Although adaptive management strategies typically assume complete flexibility to modify actions and activities to reduce uncertainty, the set of feasible actions in real-world actions to manage natural capital may not always be altered, especially if it consists of irreversible commitments. For example, decisions to create protected areas often commit land to permanent protections that are not commonly reversed (Fuller et al., 2010; Golden Kroner et al., 2019), and habitats protected on private land also often involve permanent and fixed-in-time management actions (Rissman et al., 2015). Conservation organisations typically face severe challenges in terms of being able to flexibly allocate funding and activities over time, although their management actions have been found to be more effective if made flexible (Lennox et al., 2017; Lennox and Armsworth, 2011). The permanent and locked-in nature of actions to protect and restore natural capital requires decision-makers to think carefully about present-day actions because actions undertaken today could be hard to reverse in the future, especially if those actions restrict the amount of options available in the future to adapt to newly-acquired information as predicted by options theory.

How present-day activities can be configured to explicitly consider these future learning opportunities to keep options open, and the value of doing so remains an open research question. In Chapter 4 I showed that optimal decisions for conservation in the present-day could be radically changed if decision makers consider opportunities to adapt flexibly under climate change. Using stochastic dynamic optimisation informed by climate-ecological and economic modelling of koala persistence and modelled protection costs in New South Wales, Australia, I show that a median of 50% of the conservation budget can be saved by strategically-delaying investments for koala (*Phascolarctos cinereus*) conservation into the future, taking advantage of the learning opportunities available in the future, while mitigating risks in undershooting biodiversity protection targets in some climate change trajectories. More importantly, my study reveals that the cost-saving and risk-mitigating potential of delays to conservation investments can only be realised if decision-makers strategically configure conservation priorities in the present-day to keep options for future adaptation open.

Throughout this thesis, I demonstrate that the careful spatial configuration of policy actions to mitigate environmental degradation can have important effects on the level of risk in land-use policy interventions. The risk reduction potential of spatial resource targeting can be further enhanced if decision makers have the option to delay investments. The body of work presented in this thesis identifies a major toolkit available to decision-makers to mitigate risks and achieve environmental protection goals cost-effectively. This renewed toolkit for handling risk and uncertainty in natural capital decision-making brings new approaches and understanding that helps decision-makers make better decisions that enable society to achieve the range of goals and commitments essential for addressing mankind's biggest challenges, such as climate change mitigation and rapid biodiversity loss, across a wide range of possible futures.

Chapter 2

Natural capital decision-making under catastrophic risk: a Monte Carlo experiment

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Abstract

The returns to natural capital investments are frequently characterised by uncertainty in future returns on land use and the possibility of spatially-correlated shocks such as bushfires, pest diseases, and flooding. Recently, analysts have sought to guide decision-making over where to invest in natural capital by solving Land-use Decision Problems (LDP), often through optimising objective functions that are comprised of the Expected Value and a chosen risk measure, such as the standard deviation of returns. However, the quality of natural capital investment guidance recovered by optimising these mean-risk objectives remains unclear, particularly when downside risks are not explicitly quantified in the risk measure. Here, we apply methods of Monte Carlo experiments to systematically compare the objective functions of (a) Expected Value, (b) Mean-Standard Deviation (M-SD), and (c) Mean-Conditional Value-at-Risk (M-CVaR) that explicitly quantifies downside risks. We compare these objective functions across a range of LDPs arising from a data generating process similar to those encountered in real-world natural capital decision problems. Our analyses reveal that when a decision-maker is moderately risk-averse, both the M-SD

and M-CVaR objective functions offer only marginal improvements over the much simpler EV objective function. However, an extremely risk-averse decision-maker can recover substantial improvements in expected utility by adopting a mean-risk objective function rather than EV, with M-CVaR offering further improvements compared to M-SD. Nevertheless, these improvements are only likely to materialise when the analyst carefully calibrates these objective functions to the decision-maker's underlying risk preferences.

2.1 Introduction

The efficiency of investments in natural capital is threatened by uncertain future changes in environmental and socioeconomic systems. To reduce the effects of uncertainty on natural capital investment strategies, analysts increasingly turn to identifying these investment strategies by using optimisation techniques that account for risk in the objective function. This paper contrasts several approaches to incorporate risks into the objective when identifying optimal natural capital investment strategies. In contrast to previous work that examines the performance of these approaches in the context of the financial market, in this study, we explore these in the context of making decisions about natural capital that occur in space and present characteristics of spatial autocorrelation and local catastrophic risks. The evidence in this paper shows that the use of objective functions that explicitly accommodate risks can improve the quality of investment guidance delivered by optimisation approaches. It also illustrates the pitfalls of these tools if analysts misrepresent the risk preferences of the decision-maker when identifying these natural capital investment strategies. Our results uncover insights that show that the use of objective functions that incorporate risk measures to identify natural capital delivers marked improvements in the quality of natural capital investment guidance compared to objective functions that only maximise expected value.

The values of natural capital resources are driven by uncertain future changes in a myriad of social, environmental, and economic variables. These changes stem from at least two sources. First, the dynamic evolution of complex environmental and socioeconomic systems can affect the future productivity and value of these assets (Bastien-Olvera et al., 2024; Conradi et al., 2024; Fuchs et al., 2024). Second, the significant potential that future extreme events will severely degrade the value of these assets (Smith et al., 2021; Fairchild et al., 2021). For example, the scale of the carbon sequestration services provided by planting new forests depends on how well these trees grow under an uncertain future climate, how much future societies value the services they provide and whether they are affected by catastrophic failures driven by extreme events such as wildfires and outbreaks of pest diseases (Kreidenweis et al., 2016), factors which remain unknown. Similar uncertainties challenge efforts to conserve biodiversity through the creation of protected areas (Thuiller et al., 2019; Wintle et al., 2011). The presence of uncertainties means that the returns that will be realised from any particular decision over how and where to invest in the creation of natural capital, which we refer to as a natural capital investment strategy, are characterised by a distribution of possible values. Whereas one particular choice of strategy may generate good returns in one set of future conditions, the same investments may turn out to do poorly in a plausible alternative set of future conditions.

In recent years, analysts have sought to identify strategies for investing in natural capital by developing data-driven mathematical representations of these problems, often termed Landscape Decision Problems (LDPs) (Bryan, 2010; Wilson et al., 2007; Hajkowicz et al., 2009; Ferraro, 2003; Crossman and Bryan, 2009; Wu and Boggess, 1999). In a LDP, the problem of comparing alternative natural capital investment strategies is framed as a problem of maximising an objective function subject to constraints (Margules and Pressey, 2000; Beyer et al., 2016), using methods drawn from financial economics and operations research. Although this problem has been extensively studied in the field of financial economics in the context of investment portfolio allocation under uncertainty, the objective of this paper is to examine the quality of the guidance recovered by analysts when those methods are applied to data resembling a typical LDP. The particular LDP we examine here is one that describes decisions for forest planting, where a policy maker must make irreversible decisions in the current period over where to plant trees. That problem equivalently describes the "reserve site selection problem" where the decision is on where to create or enhance habitats to support conservation goals (Costello and Polasky, 2004; Polasky and Solow, 2001; Church et al., 2000).

The evaluation of the quality of natural capital investment strategies depends on the decision-maker's preferences to risky outcomes. We begin by assuming that the preferences of a natural capital decision-maker are best described by Expected Utility Theory (EUT), a model developed in economics to describe rational decision-making under uncertainty (von Neumann, 1928). We further assume that the decision-maker's attitudes to risk can be adequately represented by a Constant Relative Risk Aversion (CRRA) utility function. The literature shows empirical support for risk preferences to be in line with a CRRA specification with a risk preference coefficient ranging between 0 and 10, with 2 being taken as appropriate for substantive risk aversion (Azar and Karaguezian-Haddad, 2014; Gandelman and Hernandez-Murillo, 2015; Schechter, 2007; Groom and Maddison Pr., 2019). In contrast, analyses published in the LDP literature have so far adopted specifications of the decision-maker's objective function that are best described as approximations to the utility-theoretic specification. One such approach is to express decision-maker preferences on the distribution of possible returns to a particular natural capital investment strategy by its expected value (EV). Decision guidance then consists of choosing the strategy that has the largest EV. Such an approximation implies that the decision-maker is neutral to risks.

An extension of EV optimisation that accommodates risk aversion is the application of objective functions of mean variance (M-V) or mean standard deviation (M-SD) informed by the Modern Portfolio Theory in financial economics (Markowitz, 1952). Here, the risk inherent in any natural capital investment strategy is quantified by the variance or standard deviation of the distribution of possible returns. Therefore, an optimal strategy for investing in natural capital would be one that has high EV and low risk, with risk quantified as variance or standard deviation. In this specification, the weight that is put on risk reduction relative to EV maximisation is governed by a risk weighting parameter. Where direct maximisation of the expected utility of a decision-maker with a nonlinear utility function will require the use of complex, non-linear optimisation routines (Lambert and McCarl, 1985; Kaylen et al., 1987), the EV and M-V/M-SD problems can typically be recast into linear programming or quadratic programming problems that can be solved using standard methods (Corazza and Favaretto, 2007; Markowitz, 2014), enabling LDPs of much larger scales to be solved efficiently.

These specifications of the objective function have attracted criticism within the financial economics literature. One such criticism arises from the fact that optimising M-V is equivalent to maximising expected utility while assuming a decision maker with a quadratic utility function (Levy and Markowitz, 1979; Johnstone and Lindley, 2011). Since most reasonable specifications of risk-averse utility functions (including the CRRA utility function assumed in this paper) are strictly-increasing in the returns to investments, there exist significant doubts regarding how well M-V optimisation can approximate optimal decision-making for a risk-averse decision-maker. Another criticism lies in the insensitivity of M-V/M-SD optimisation to skewed and fat-tailed distributions, for example, where investments exhibit extreme downside risks (Dunkel and Weber, 2012). This may be particularly relevant in the natural capital problem, where extreme events such as wildfires, pest diseases, and flooding introduce small but significant chances of a catastrophic loss of value to some natural capital assets. In response to that criticism, alternative specifications for the objective function have been proposed. In this paper, we consider an alternative, the Mean-Conditional Value-at-Risk (M-CVaR) objective function (Rockafellar and Uryasev, 2000). In this specification, rather than summarising the risk inherent in some investment by the variance or standard deviation of its possible returns, that risk is summarised by the distributions' Conditional Value-at-Risk (CVaR). This measure of risk is given by the expected value of the downside tail of the distribution of possible returns. Again, with the addition of a suitable risk weighting parameter, the objective function of M-CVaR represents a trade-off between increasing EV and reducing downside risk. In addition to being adopted as a standard risk measure by the Basel Committee on Banking Supervision (Basel Committee, 2013), the CVaR also satisfies a number of properties deemed desirable by financial economists such that it qualifies as a "coherent" risk measure (Rockafellar and Uryasev, 2002; Artzner et al., 1999), while M-V or M-SD do not.

How well EV, M-SD and M-CVaR optimisation fare in providing effective guidance to a risk-averse investor has been studied previously in the financial economics literature. For example, in the context of portfolio theory, Dexter et al. (1980) conducted a computational study that compared the expected utility (in certainty-equivalent) terms of an investor with a power utility function investing in assets that have returns from a simulated log-normal distribution. The researchers concluded that the M-V approach identifies financial portfolios that are almost identical, in terms of certainty-equivalent units, to a portfolio that directly maximises expected utility. These results may, however, not be directly applicable to natural capital problems, because uncertainty in natural capital investment problems may exhibit patterns very different to those characterising financial investment decisions. In particular, uncertainty in the LDP tends to exhibit high levels of spatial autocorrelation with nearby locations displaying similar patterns of deviation in returns. Moreover, the possibility of events such as fires and disease that can devastate natural capital investments introduces the rare possibility of extremes on the downside of the uncertain distribution of returns. The core objective of this paper is to examine EV, M-SD and M-CVaR optimisation in the context of the LDP and assess which approach, if any, should be preferred by analysts in supporting decision-makers in the design of natural capital investments.

Little work exists in this area, although Shah and Ando (2015) examined a similar question in the context of natural capital decision-making under climate change uncertainty that is close to our contribution. They found that using an objective function with a downside risk measure similar to M-CVaR provided better investment guidance to risk-averse decision-makers compared to the M-V approach. However, their analysis focused only on the uncertainty induced by a small sample of possible climate scenarios. Our study goes further in additionally examining uncertainty from stochastic environmental disturbances, such as wildfires, pests, flooding, or drought, as modelled in other studies (e.g. Albers et al., 2016).

Another contribution of this paper is to explore the impact of the choice of the risk weighting parameter in the application of M-SD or M-CVaR approaches. Recall that this parameter determines the relative weight placed on the mean and the risk measure in those two objective function specifications. Currently, clear guidance to its selection remains absent. Previous studies suggest that the risk weighting parameter that leads to maximisation of the expected utility (in line with the CRRA utility specification) depends on the stochastic model and data generating process (Bodnar et al., 2018). However, many applications in decision-making of natural capital do not seek to align the risk weighting parameter in M-SD or M-CVaR with the risk preferences of decision-makers. Instead, an efficiency frontier approach is used (Liang et al., 2018; Ando and Mallory, 2012; Ando et al., 2018), where an array of investment decisions are identified, each maximising the objective function for a different possible value of the weighting parameter. The selection of natural capital investment strategies based on this approach implies that the decision-maker can be guided by the data to decide their risk aversion levels, an assumption that lies in stark contrast to economic theory that assumes that decision-makers' attitudes to risk are inherent and stable (Riddel, 2012; Weber et al., 2002; Wakker and Deneffe, 1996). This raises questions as to which approach should analysts use to guide decision-makers when they are uncertain about the decision-maker's risk preferences. Even if the analyst can elicit the decision-maker's risk preferences using techniques standard in the literature and use that to guide their choice amongst a set of investment strategies that lie on the mean-risk efficiency frontier, elicitation exercises could indeed be inaccurate and misrepresent the decision-maker's true risk preferences (Charness et al., 2013; Andersen et al., 2008). In this regard, a desirable property that an objective function could have is that it delivers relatively high expected utility according to the decision-maker's true preferences even when specifications that inaccurately represent the decision-maker's true preferences are made over the weighting parameter used in the objective function.

In this paper we apply methods of Monte Carlo analysis to systematically compare EV, M-SD and M-CVaR methods across a range of LDPs arising from a data generating process that simulates the uncertainties likely to be observed in real-world natural capital investment problems. We first assume that we know the decision-maker's true risk preferences and that those are defined by a CRRA utility function. With that assumption, we can rank the natural capital investment recommendations made by EV, M-SD and M-CVaR optimisation for a particular LDP by comparing the certainty equivalent (CE) value of the distribution of possible returns from each investment recommendation. Our Monte Carlo environment allows us to carry out this comparison across solution methods for a wide variety of different possible LDPs and for decision-makers with differing levels of risk aversion.

Our analyses reveal that when decision-makers are moderately risk-averse, both M-SD and M-CVaR offer only marginal improvements over the much simpler EV objective function. However, when the decision-maker has preferences for high-risk aversion, the strategies identified through M-SD and M-CVaR significantly outperform the strategies identified by maximising EV. It is also only at these high levels of risk aversion do we observe a marked superiority in the strategies identified by maximising M-CVaR relative to M-SD. Our conclusions are valid in several different simulated LDPs with differing data-generating processes. However, our study also shows that these findings are only robust if the analyst carefully selects the weighting parameter for M-SD and M-CVaR to ensure its alignment with the decision-maker's risk preferences. If an inappropriate risk weighting parameter is chosen, then M-SD and M-CVaR can actually identify natural capital investment strategies that are worse than simply maximising EV. Relative to M-CVaR, M-SD is particularly sensitive to such misspecification. These results highlight that while the EV objective function remains a solid choice for many natural capital decision problems, the M-CVaR objective function is also a defensible choice as it offers clear advantages in situations where the decision-maker exhibits high risk aversion. While M-SD performs reasonably well across a range of settings, it appears that the M-CVaR objective resolves a number of challenges linked to its use in the LDP.

2.2 The Landscape Decision Problem

2.2.1 Comparing investment strategies with random net benefits

Identifying the natural capital investment strategy that solves a LDP requires tackling several interrelated complexities. The first complexity lies in identifying the scale of the multiple changes in ecosystem services that are produced by a change in natural capital assets and summarising those into a single measure of net benefits. For this purpose, the framework of natural capital for decision-making is increasingly advocated in academic and government communities (Bateman and Mace, 2020; HM Treasury, 2020), with numerous examples that illustrate how economic and environmental data can be assimilated to inform the design of land-use policies (Bateman et al., 2013; Hatfield-Dodds et al., 2015; Lawler et al., 2014; Polasky et al., 2001). In essence, the natural capital framework for decision-making advocates that the myriad of ecosystem services arising from land-use investment strategies be aggregated in a unified measure of the change in social welfare, typically quantified in monetary terms.

The valuation framework for evaluating investment strategies can be represented with a value function that relates changes in natural capital assets and the ecosystem services they provide to the total net benefits of that investment strategy. This is described in Equation 2.1:

$$w_{\mathbf{x}} = v(\mathbf{x}), \quad \mathbf{x} \in \mathcal{X} \tag{2.1}$$

where $\mathbf{x}$ is a vector of decision variables of elements N and is found in the set $\mathcal{X}$. In the LDP this vector of strategies $\mathbf{x}$ is taken to comprise land use decisions in discrete parcels in the landscape. In our case, an element in $\mathbf{x}$ takes the value 1 if a parcel is selected for a natural capital investment (e.g. planting of a woodland, protection for biodiversity conservation) and 0 otherwise. Each particular spatial configuration of investments, representing a natural capital investment strategy, can be identified by a different realisation of $\mathbf{x}$. Any such strategy delivers a potential change in social welfare, which we describe as aggregate net benefits of that strategy w, and that quantity can be identified by applying the natural capital approach represented by the value function

$v : \mathbb{R}_N \to \mathbb{R}$. Therefore, a decision-maker can compare alternative investment strategies to identify the strategy that maximises social benefits.

The second complexity of solving the LDP lies in the fact that the predicted flows of ecosystem services from a set of natural capital investments are sensitive to future conditions not knowable at the time of decision-making and, therefore, uncertain. Because the impacts of a strategy on the value of natural capital depend on the state of the world, any natural capital investment strategy will lead to a random distribution of possible net benefits, with the exact state of the world unknowable at the time of decision-making.

A fuller characterisation of the LDP, therefore, extends the problem to consider outcomes across the range of possible future states of the world.

$$w_{\mathbf{x}}^{s} = v(\mathbf{x}, s) \quad \forall \quad s \in S \tag{2.2}$$

In Equation 2.2, we extend the value function to consider $s \in S$ possible states of the world that lead to different possible net benefits, with $w_{\mathbf{x}}^{s}$ being aggregate net benefits in the s state of the world if investment strategy $\mathbf{x}$ is followed.

Our research focusses on how exactly this value function under uncertainty should be specified in analyses seeking to solve the LDP for optimal land use decision making. Throughout this paper, we assume that the decision-maker's true underlying preferences follow Expected Utility Theory (EUT). EUT is a formal decision-theoretic criterion in mathematical economics that is used to compare possible choices that lead to random net benefits (von Neumann and Morgenstern, 1944). The theory posits that, in each state of the world, the net benefits arising from an investment strategy can be quantified through a utility function that maps net benefits to utility. The utility produced by a natural capital investment strategy with random net benefits is therefore the expected value of the utilities generated in each state of the world weighted by their probabilities, and the decision-maker's goal is to choose the investment strategy that maximises expected utility.

The EUT posits that the decision-maker's choice of strategy can be identified by maximising their expected utility as follows.

$$\mathrm{EU}_{\theta}(\mathbf{x}) = \sum_{s \in S} p_s U_{\theta}(w_0 + w_{\mathbf{x}}^{s}) \tag{2.3}$$

where in Equation 2.3, the expected utility is calculated as the weighted sum of the probability of each state of the world p_s, multiplied by the utility generated by v in each state of the world, using a utility function $U_\theta : \mathbb{R} \to \mathbb{R}$ defined with a risk aversion parameter θ.

Importantly, the utility function embeds the risk preferences of the decision-maker. In the risk-neutral case ($\theta = 0$), the decision-makers' marginal increase in utility towards every unit of increase in aggregate welfare W is the same. However, in the risk-averse case ($\theta > 0$), the marginal increase in utility per unit of increase in W is larger when W is small and the marginal increases in utility per unit of increase in W are much smaller when W is large.

Our choice of the Constant Relative Risk Aversion (CRRA) family of utility functions (Arrow and Others, 1965; Pratt, 1964) is motivated by analytical tractability (Wakker, 2008). The functions in this family are defined by the coefficient of relative risk aversion θ.

$$U_\theta(w) = \begin{cases} \frac{w^{1-\theta}}{1-\theta} & \theta \neq 1 \\ \log(w) & \theta = 1 \end{cases} \tag{2.4}$$

The CRRA family of utility functions are strictly-increasing and concave for $\theta > 0$, and linear for $\theta = 0$. Although this framework also accommodates risk-loving preferences (where $\theta < 0$), we do not consider such cases here.

In the case where U_θ is a concave function, Jensen's inequality shows that the expected utility of a random distribution of net benefits cannot be larger than the utility derived from that same level of net benefits enjoyed with certainty, as follows:

$$U_\theta(\mathrm{EV}(\mathbf{x})) \geq \mathrm{EU}_\theta(\mathbf{x}) \tag{2.5}$$

A concept that we will use extensively in our analyses is that of certainty-equivalent values. The certainty-equivalent value is the net benefits enjoyed with certainty that a decision-maker with utility function U_θ regards as giving the same value as a random outcome w. For a strictly-increasing utility function U_θ, the certainty-equivalent is defined as follows:

$$\mathrm{CE}_\theta(\mathbf{x}) = U_\theta^{-1}(\mathrm{EU}_\theta(\mathbf{x})) \tag{2.6}$$

where U_θ^{-1} is the functional inverse of the utility function U_θ. Under the standard assumption that the function U is strictly-increasing and concave (as is true for the CRRA

θ	Certainty equivalent
0	1.193
2	1.183
10	0.83

Table 2.1: Certainty equivalent of a investment strategy with random outcomes (99% chance of a 20% increase in welfare and 1% chance of a 50% decrease in welfare)

utility function), a natural capital investment strategy with higher expected utility must also have a higher certainty equivalent, making the problem of maximising expected utility equivalent to the problem of maximising certainty equivalents.

The parameter θ exerts considerable influence on the investment strategy that maximises the expected utility. Empirical evidence finds strong support for values for this parameter between 1 and 2 (Groom and Maddison Pr., 2019; Evans, 2005; Bergstrom and Dodds, 2023), although values up to 10 have been reported in some cases (Gandelman and Hernandez-Murillo, 2015). To see how this parameter translates into alternative choices in decision analysis, consider the case where $w_0 = 1$ and a decision-maker face a strategy $w^{\mathbf{x}'}$ that has a 99% chance of being $0.2w_0$ (20% increase in welfare) and a 1% chance of being $-0.5w_0$ (50% decrease in welfare). The decision whether to pursue this strategy or remain in the status quo (in this case, $W = w_0$ for certain and, therefore, equivalent certainty equals 1) depends on the decision-makers' risk preferences, as depicted in Table 2.1. A risk neutral ($\theta = 0$), or a mildly risk-averse ($\theta = 2$) decision-maker, would still consider this strategy worth pursuing, because it generates more than 1 unit of welfare. This is no longer true if the decision-maker is highly risk-averse ($\theta = 10$); in this case, the decision-maker would prefer the status quo, since the certainty-equivalent welfare of the strategy is less than that of the status quo.

The application of EUT for decision analysis underscores the issue that, under uncertainty, the optimal natural capital investment strategy is sensitive to the risk attitudes held by the decision-maker. Therefore, even with an objective measurement of the probabilities of each state of the world, the investment strategy that maximises expected utility differs across decision-makers with contrasting degrees of risk aversion.

Through EUT, we recover the Expected Value (EV) objective function, which is a special case for EU for a linear increase in utility function, such as CRRA utility with $\theta = 0$. This is equivalent to comparing investment strategies based on their average net benefits across states of the world. The EV function simply quantifies the value of the investment strategy as the sum of the net benefits from each state of the world weighted by the probability of occurrence of that state. The EV of the net benefits of a given investment strategy is thus calculated as follows.

$$\mathrm{EV}(\mathbf{x}) = \sum_{s \in S} p_s (w_0 + w_{\mathbf{x}}^s) \tag{2.7}$$

In equation 2.7, the function EV maps the investment strategy $\mathbf{x}$ to its expected value as the weighted sum of the probability of the state of the world and the net benefits of the investment strategy in that state of the world. Although simple to apply in practice, EV maximisation ignores the variability in net benefits from a particular natural capital investment strategy in different states of the world. When evaluated in terms of EV, an investment strategy with highly variable returns is seen as equally good as an alternative investment strategy with certain returns if those two strategies have the same EV. As such, EV optimisation does not accommodate the fact that a decision maker may be averse to taking on risk.

When developing investment guidance for natural capital decision makers, the obvious way for an analyst to proceed would be to identify the decision maker's risk preferences and with that measure of θ define and maximise an LDP using the decision maker's true utility-theoretic preferences as an objective function. In general, analysts have eschewed that approach as that LDP requires application of nonlinear solvers and quickly becomes intractable as the size of the problem increases to high dimensions (problems where N is large) (Lambert and McCarl, 1985). Indeed, in financial settings, a different set of tools are typically used to inform decision-making problems, such as identifying optimal portfolios of stocks and bonds for investment, that attempt to approximate the EU maximisation problem in some way.

2.2.2 Approximating expected utility with a mean-risk objective function

In the context of financial investment decision-making, the use of risk measures, which quantify the level of risk inherent in a random variable (such as the random net benefits of investment strategies), is commonplace (Pedersen and Satchell, 1998). However, it is possible to see that these risk measures, when combined with the EV objective function into what is known as a mean-risk objective function, are approximations of the EU function.

Consider the following mean-risk objective function as follows:

$$\rho(\mathbf{x},\lambda;\phi) = (1-\lambda)\mathrm{EV}(\mathbf{x}) - \lambda\phi(\mathbf{x}) \tag{2.8}$$

Where $\rho(\mathbf{x},\lambda;\phi)$ is the mean-risk function given a risk measure that quantifies the level of risk in the investment strategy $\mathbf{x}$ and is parameterised by a risk measure function ϕ. The risk measure ϕ is typically such that with higher values of $\phi(\mathbf{x})$ corresponding to strategies that are higher in risk.

Therefore, the investment guidance that an analyst can provide using a mean risk objective function is sensitive to (1) the choice of the risk measure ϕ and the risk weighting parameter λ in the function. If a decision-maker has underlying risk preferences described, for example, by equation 2.3, their underlying utility function can guide the analyst's choice of λ. We refer to λ that best aligns a mean-risk objective function with a decision maker's true risk-sensitive preferences as λ^*. As such, the challenge for the analyst is to choose both the risk measure ϕ and the weighting parameter λ that leads to the investment strategy $\mathbf{x}$ that maximises the expected utility of the decision maker. For a given utility function with parameter θ and risk measure ϕ, the analyst solves the following problem to identify λ, where we call this optimised lambda λ^*:

$$\lambda^*(\theta;\phi) = \arg\max_{\lambda\in[0,1]} \mathrm{CE}_\theta(\arg\max_{\mathbf{x}\in\mathcal{X}} \rho(\mathbf{x},\lambda;\phi)) \tag{2.9}$$

In other words, the analyst chooses λ within its range that leads to the investment strategy that delivers the highest expected utility to the decision maker within the set of investment strategies that maximise ρ for some value of λ.

However, what is common in the literature is that analysts choose λ based on estimates of risk preferences θ and identify the investment strategy that maximises this mean-risk objective function for the chosen λ. The use of an "efficiency frontier" approach, where an analyst identifies several land-use investment strategies that optimise a mean-risk objective function (e.g. (Ando and Mallory, 2012; Alvarez et al., 2017a; Matthies et al., 2015)) and guides the decision-maker to selecting the strategy that best aligns to their risk preferences. Even if the choice of the weighting parameter λ is guided by risk preference elicitation exercises that provide some information about θ, there is often a chance that these exercises will lead to inaccurate estimates of θ. We explore the implications of a choice of λ that fails to represent the true underlying θ in the subsequent analysis.

2.2.3 Examples of risk measures

The risk measures that have seen the most widespread application are those originally proposed by Markowitz's Modern Portfolio Theory (Markowitz, 1952), based on the variance or standard deviation of returns to an investment strategy. In our subsequent Monte Carlo analyses of the LDP, we focus on the standard deviation measure, where natural capital investment strategies whose returns exhibit a higher standard deviation are deemed more risky and less preferable for risk-averse decision-makers. The closely-related variance measure of risk has been widely applied in environmental decision-making problems. Some examples include protection of wetland habitat (Ando and Mallory, 2012), ecosystem services of land-use change (Liang et al., 2017), conservation planning to protect against coastal sea-level rise under climate change (Runting et al., 2018), marine protected areas (Halpern et al., 2011) and coral reef protection (Beyer et al., 2018).

The variance and standard deviation of the net benefits from a natural capital investment strategy can be formally expressed as a risk measure function ϕ:

$$\phi_{\text{Variance}}(\mathbf{x}) = \sum_{s \in S} p_s(v(\mathbf{x}, s) - \text{EV}(\mathbf{x}))^2 \tag{2.10}$$

$$\phi_{\text{SD}}(\mathbf{x}) = \sqrt{\text{Variance}(\mathbf{x})} \tag{2.11}$$

where ϕ_{Variance} and ϕ_{SD} are, respectively, functions that quantify the variance and standard deviation of the net benefits from the investment strategy $\mathbf{x}$.

Despite the popularity of the mean-variance (M-V) and mean-standard deviation (M-SD) objective functions in empirical work, whether they accurately approximate expected utility as defined in Equation 2.3 has been the subject of substantial debate (Best and Grauer, 1991, 1992; Chopra et al., 1992, for example). A common critique of variance/standard deviation as risk measures is that they fail to accurately quantify risks for distributions of net benefits that are not symmetrically-distributed (Owen and Rabinovitch, 1983; Chamberlain, 1983). To see this potential issue, consider an investment strategy that leads to a distribution of net benefits with a very small chance of an extremely high level of net benefits, far higher than its expected value. Although this investment strategy would be desirable to a risk-averse decision-maker (according to equation 2.3, it would have a high variance/standard deviation and therefore be erroneously considered ”high-risk.” Another critique is that variance/standard deviation, as a risk measure, fails to adequately quantify risks when there are small possibilities of ”catastrophic” states of the world. Evaluating that prospect using 2.3, a risk averse decision maker may attribute extremely-low levels of utility to policies vulnerable to such catastrophic risks. Of course, when the possibility of these catastrophic states is very small, the distribution of net benefits from such policies will likely exhibit low variance/ standard deviation and potentially high expected value.

In the literature, a series of more sophisticated risk measures have been proposed to overcome these potential problems. In particular, the Conditional Value-at-Risk (CVaR) risk measure has received much attention, being designated as the recommended risk measure by the Basel Committee on Banking Supervision (Basel Committee on Banking Supervision, 2019). In this paper, we compare the investment guidance for the LDP from approaches that use a standard deviation-based risk measure to those using this more sophisticated risk measure.

Formally, the CVaR measure considers the realisations of net benefits from an investment strategy that fall below a certain quantile in its distribution. It evaluates the level of risk associated with that strategy in terms of the expected value of realisations falling in this downside tail. An investment strategy is more risky the lower this measure. The CVaR risk measure is defined as follows:

$$\phi_{\text{CVaR}-\beta}(\mathbf{x}) = \min_{\alpha \in \mathbb{R}} \alpha + \frac{1}{1-\beta} \sum_{s \in S'(\mathbf{x},\alpha)} p_s(-v(\mathbf{x},s) - \alpha) \tag{2.12}$$

$$S'(\mathbf{x},\alpha) = \{s : s \in S, v(\mathbf{x},s) \leq \alpha\} \tag{2.13}$$

where the function $\phi_{\text{CVaR}-\beta}$ is a function of the investment strategy $\mathbf{x}$ and β, where β is the quantile of the distribution of results selected to delineate the downside tail of possible returns. Specifically, with CVaR, only the states of the world that lead to net benefits lower than a specific threshold $v(\mathbf{x},s) \leq \alpha$, thus lying in the set $S'(\mathbf{x},\alpha)$, are considered. The net benefits v are converted to negative quantities such that states of the world with small v are considered ”undesirable.”

It is possible that the use of a more sophisticated risk measure like CVaR can address some of the criticisms present in the use of a M-SD objective function. Indeed, Shah and

Ando (2015) offered initial insights on this problem in the context of decision-making for wetland protection in the United States under climate change risk and found that allocation decisions for limited conservation areas change substantially when moving from the variance-minimisation model (that is, the standard Markowitz variance model) to the downside risk-minimisation (Mean Second-degree Lower Partial Moments) model. These differences were most apparent when the decision maker had high levels of risk aversion. However, examining the differences between contrasting methodologies for optimising land-use decisions under risk with empirical data is challenging because the underlying distribution of uncertainty is unknown. Shah and Ando (2015) focusses on a small sample of predictions from the climate change model that cannot fully characterise the full probability distribution of uncertainty for a wider range of problems. Problems lying outside of the scope examined in (Shah and Ando, 2015) could include a small probability of catastrophic, spatially-correlated risk, such as those modelled in Albers et al. (2016), arising from stochastic ecological disturbances such as wildfires, pests, flooding, or drought events. The use of a M-CVaR objective function is itself open to criticism, for example, because it does not use information on the full distribution of the outcomes and is difficult to interpret (Grootveld and Hallerbach, 1999). Thus, a larger amount of data is needed to characterise the full distribution of outcomes.

2.2.4 Optimisation under uncertainty

An additional complexity in solving the LDP is how investment strategies that maximise these objective functions can be tractably identified by taking advantage of advances in the field of operations research. Although in the case where the set of possible values $\mathcal{X}$ is relatively small, it could be possible to enumerate all values in the set, calculate its objective value, and select the investment strategy that maximises the objective value. Alternatives include the use of nonlinear numeric solvers. But nonlinear optimisation is intractable when N is large and the set $\mathcal{X}$ is a full combinatorial set that could comprise thousands or even millions of parcels, thus requiring tractable approximations through the use of mean-risk optimisation.

In the operations research literature, a common class of algorithms is available to solve the LDP where the value function v is linear in $\mathbf{x}$ and independent (that is, the net benefits in one parcel do not depend on whether an investment strategy occurs in another parcel).

In this paper, we exclusively consider the special case where v is a linear function and demonstrate the broad applicability of this formulation even though it cannot represent a more general class of value functions, which could be nonlinear or dependent. In this paper, we focus specifically on LDPs in this form that can be tractably solved with linear programming algorithms.

$$v(\mathbf{x},s) = \sum_{i=1}^{N} r_i^s x_i \quad \mathbf{x} \in \mathcal{X}, s \in S \tag{2.14}$$

$$\mathcal{X} = \left\{ [0,1]^N : \sum_{i=1}^{N} a_i x_i \leq B \right\} \tag{2.15}$$

In equation 2.14, the value function is the total sum of net benefits r_i in parcel i, multiplied by a binary indicator x_i that takes the value 1 if a parcel is selected for the investment strategy and 0 otherwise. We further define the feasible set $\mathcal{X}$ by constraining that the sum of all parcels selected for the investment strategy, multiplied by a_i, the cost of the investment strategy on the parcel i, cannot exceed B, a budget constraint.

Since the value function cannot be directly optimised with s as a random variable, the distribution of values of this value function needs to be mapped to a scalar with a function. For example, the EV function can be represented as follows:

$$\mathrm{EV}^*(\mathbf{x}) = \max_{\mathbf{x} \in \mathcal{X}} \sum_{s \in S} p_s v(\mathbf{x},s) \tag{2.16}$$

Where the investment strategy that maximises expected value is one that maximises the EV function (EV^*).

Conic equivalent of a mean-standard deviation problem

Similarly, mean-risk optimisation problems can be formulated as tractable linear or conic optimisation problems. In this paper, we examine two risk measures: standard deviation and conditional value-at-risk, with corresponding mean-risk optimisation problems known as mean-standard deviation (M-SD) and mean-conditional value-at-risk (M-CVaR) respectively.

We first consider the variance of the net benefits r_i^s in the value function, writing this as a random vector $\mathbf{r_s} = \{r_1^s, ..., r_N^s\}$, where $\mathbf{r} \in \{\mathbf{r}_s : s \in S\}$, and the probability of the states of the world is $\mathbf{p} = \{p_s : s \in S\}$.

Let the expected value of $\mathbf{r}$ be a vector $\mu_{\mathbf{r}}$:

$$\mu_{\mathbf{r}} = \sum_{s \in S} p_s \mathbf{r}_s \tag{2.17}$$

And let the variance of the random vector be $\Sigma_{\mathbf{r}}$:

$$\Sigma_{\mathbf{r}} = \sum_{s \in S} p_s (\mathbf{r}_s - \mu)(\mathbf{r}_s - \mu)^{\intercal} \tag{2.18}$$

The standard deviation of $v(\mathbf{x}, s)$ can be written as follows:

$$\phi_{SD}(v(\mathbf{x}, s)) = \sqrt{\mathbf{x}^{\intercal} \Sigma_{\mathbf{r}} x} \tag{2.19}$$

The mean-standard deviation optimisation problem can be modelled efficiently as a second-order conic programming problem based on a Cholesky decomposition of the variance-covariance matrix. We first introduce the notation for representing the L^2 norm of any vector, $t \in \mathbb{R}^n$.

$$||\mathbf{t}||_2 = \sqrt{t_1^2 + t_2^2 + ... + t_n^2} \tag{2.20}$$

The n-dimensional second-order cone for the vector t is defined as follows:

$$\mathcal{Q}^n = \{\mathbf{t} \in \mathbb{R}^n \mid t_1 \geq ||[t_2, t_3, ..., t_n]||_2\} \tag{2.21}$$

For the lower triangular matrix where $\Sigma = \mathbf{G}\mathbf{G}^{\intercal}$, the standard deviation of v can be expressed as follows:

$$\sqrt{\mathbf{x}^{\intercal} \Sigma_{\mathbf{r}} x} = \sqrt{\mathbf{x}^{\intercal} \mathbf{G}\mathbf{G}^{\intercal} \mathbf{x}} = \sqrt{||\mathbf{G}^{\intercal}\mathbf{x}||_2^2} = ||\mathbf{G}^{\intercal}\mathbf{x}||_2 \tag{2.22}$$

Therefore, it is possible to model the standard deviation of the values v as a second-order conic constraint. Given an auxiliary variable $\xi \in \mathbb{R}$ used to model the upper bound of the standard deviation of the optimisation problem, the M-SD optimisation problem can be modelled as a second-order conic programming problem that maximises the mean-risk objective function ρ.

$$\rho^*(\mathbf{x}, \lambda; \phi_{\text{M-SD}}) = \max_{\mathbf{x} \in \mathcal{X}} (1 - \lambda) \mu_{\mathbf{r}}^{\intercal} \mathbf{x} - \lambda \xi \tag{2.23}$$

$$s.t. \quad (\xi, \mathbf{G}^{\intercal}\mathbf{x}) \in \mathcal{Q}^{N+1} \tag{2.24}$$

Linear equivalent of the Mean-CVaR optimisation problem

The M-CVaR problem can also be modelled as a linear programme as described in Rockafellar and Uryasev.

$$\rho^*(\mathbf{x},\lambda;\phi_{\text{M-CVaR}-\beta}) = \max_{\mathbf{x}\in\mathcal{X},\alpha\in\mathbb{R},\mathbf{u}\in\mathcal{U}} (1-\lambda)\mu_{\mathbf{r}}^{\intercal}\mathbf{x} - \lambda\left(\alpha + \frac{1}{1-\beta}\sum_{s\in S} p_s u_s\right) \tag{2.25}$$

$$s.t. \quad u_s \geq \sum_{i=1}^{N} r_i^s x_i - \alpha \quad \forall s \in S \tag{2.26}$$

$$\mathcal{U} = \{u_s : u_s \geq 0, s \in S\} \tag{2.27}$$

Here an auxiliary variable $\mathbf{u}$ is introduced to model the quantities in the set $S'(\mathbf{x},\alpha)$, which takes a positive value if the value in the state of the world s falls outside of the quantile in β, and zero otherwise.

2.3 Uncertainty in the Landscape Decision Problem

The methods of mean-risk optimisation have been relatively well-tested in the financial economics literature using both real-world and simulated financial data. Several articles, for example, have used stock market data to examine how successfully these methods can guide investment decisions (Rockafellar and Uryasev, 2000; Bertsimas et al., 2004; Angelelli et al., 2008, for example). However, few studies have explored the application of these methods in land-use decision-making. These problems seek configurations of land use change that maximise ecosystem service benefit flows from the landscape. Whether our understanding of the properties of mean-risk optimisation derived from conventional financial stock market data carry over to the context of data generated in this very different way is an open research question.

There are many reasons why findings in financial economics may not adequately transfer to the context of natural capital decision-making. On the one hand, the benefits of restoring ecosystem services often show patterns of spatial organisation; parcels that are close to each other tend to exhibit more similar values from natural capital investments than parcels that are more greatly separated in space. The presence of spatial autocorrelation in ecosystem services is repeatedly illustrated in empirical models (Li et al., 2022; Shaikh et al., 2021). For this reason, a decision-maker aiming to maximise aggregate net benefits will likely find that high net-benefit parcels are located close to one another and an optimal investment strategy will be to concentrate investments in a group of neighbouring parcels. On the other hand, the effect of exogenous shocks to ecosystem services, as might be caused by extreme weather events, wildfires, pest diseases, and flooding, are also strongly spatially focused and run the risk of the catastrophic loss of natural capital in an impacted location. The risk of that downside loss introduces a counteracting incentive for investment strategies that provide protection against extreme events by dispersing those investments across the landscape. These two spatially determined considerations in natural capital investment problems motivate the choice of data generating processes we use for simulating the LDP.

In our subsequent Monte Carlo experiments, we examine data-generating processes that capture key patterns of spatial autocorrelation that might arise in LDPs. Specifically, we posit that the net benefits of natural capital investment in parcel i under state of world s, r_i^s, follows the following distribution:

$$r_i^s = \begin{cases} \tilde{r}_i^s & \text{if} \quad \kappa_{is} \neq 0 \\ -\upsilon & \text{otherwise} \end{cases} \tag{2.28}$$

$$\tilde{r}_i^s \sim \mathrm{SAR}(\rho, \sigma, \mathbf{W}, \mathbf{X}) \tag{2.29}$$

$$\kappa_{is} \sim \mathrm{LSS}(\pi) \tag{2.30}$$

Where $\tilde{r}_i^s$ is a random variable with a distribution following the spatial autoregressive process (SAR) defined by parameters ρ and σ, a spatial weights matrix $\mathbf{W}$ and a vector of independent variables $\mathbf{X}$, and κ_{is} is an indicator variable of whether a parcel is affected by a local spatial shock. This framework combines two sources of spatially-correlated risks: risks arising from spatial dependence through the SAR data generating process, and κ_{is}, an indicator of whether a location is affected by a local spatial shock. When a parcel does not experience a spatial shock, it generates net benefits comprising a certain component υ and a random component $\tilde{r}_i^s$. On the other hand, a parcel that is shocked does not receive benefits in that state of the world. The random variable of whether a parcel is affected in a particular state of the world is determined by LSS, a distribution for Local Spatial Shocks (LSS) that is controlled by a parameter π, the probability of a shock event in any given year. If a parcel is affected by the local spatial shock, the net benefits of the investment strategy in the parcel will be υ, which denotes the net loss incurred by selecting a parcel that is then affected by an LSS.

2.3.1 Spatial autoregressive process

In geography, the hypothesis of Tobler's first law of geography argues that locations that are closer to each other are more likely to share stronger interactions and relationships (Tobler, 1970). In the LDP one can envisage such interactions as spatial spillovers, where the environmental outcomes realised in one land parcel are dependent on those that arise in nearby parcels. When these spatial lags are present, parcels that are nearby not only share expected outcomes but are also spatially correlated, meaning that for a particular realisation, the outcome experienced in a parcel is more likely to be higher than its expected outcomes if the outcomes in nearby parcels exceed their expectations.

We simulate these spatial lags using a widely applied specification in spatial econometric modelling (LeSage, 2009). Such models rely on a spatial weight matrix $\mathbf{W}$ that specifies the strength of the spatial dependence across units, with w_{ij} being the element in the i^{th} column and j^{th} row of the spatial weights matrix that quantifies the strength of spatial dependence between i and j.

Let $\tilde{\mathbf{r}}$, the net benefits of the investment of natural capital in the absence of local spatial shocks follow a spatial autoregressive (SAR) data-generating process (DGP). Then given $\mathbf{X}$, a matrix of independent variables, a vector of coefficients β, a scalar ρ controlling the degree of spatial lag across variables, and a normally-distributed error term ε with mean zero, the $SAR(\rho, \mathbf{W}, \mathbf{X})$ is defined as follows:

$$\tilde{\mathbf{r}} = \mathbf{X}\beta + \rho\mathbf{W}\tilde{\mathbf{r}} + \varepsilon \tag{2.31}$$

$$\tilde{\mathbf{r}} = (\mathbf{I}_N - \rho\mathbf{W})^{-1}(\mathbf{X}\beta + \varepsilon) \tag{2.32}$$

$$\varepsilon \sim N(0_N, \sigma^2 I_N) \tag{2.33}$$

A standard approach to construct a row-normalised spatial weights matrix $\mathbf{W}$–the approach used in this paper–is to specify spatial dependencies based on the inverse of the distance between i and j, d_{ij}. Given two parameters φ and bandwidth, the inverse spatial weights matrix $\bar{\mathbf{W}}$ can be specified as follows:

$$\bar{w}_{ij} = \begin{cases} d_{ij}^{-\varphi} & \text{if} \quad 0 < d_{ij} \leq \text{bandwidth} \\ 0 & \text{otherwise} \end{cases} \tag{2.34}$$

The parameter φ controls the degree of distance decay of spatial dependencies, and the bandwidth controls the distance at which spatial effects become insignificant. Parcel pairs with non-zero entries are considered as "neighbours". Because $\bar{w}_{ij}$ can only be nonzero if d_{ij} is strictly greater than zero, a parcel cannot be defined as a neighbour to itself, which implies $w_{ii} = 0$.

A common practice in specifying the spatial weights matrix is to row normalise, in which case parcels that have fewer neighbours are similarly affected by neighbouring units as those with more neighbours. Elements of the row-normalised spatial weights matrix $\mathbf{W}$ is defined as follows:

$$w_{ij} = \frac{\bar{w_{ij}}}{\sum_j \bar{w_{ij}}} \tag{2.35}$$

It can be inferred from equation 2.38 that the realisations of SAR follow a multivariate normal distribution with the correlation of net benefits between parcels dependent on the parameter ρ. By linear transformation of a multivariate variable, the distribution of $\tilde{\mathbf{r}}$ can be written as follows:

$$\tilde{\mathbf{r}} \sim N\left(\tilde{\mu}, \hat{\Sigma}\right) \tag{2.36}$$

$$\tilde{\mu} = (\mathbf{I}_N - \rho\mathbf{W})^{-1}\mathbf{X}\beta \tag{2.37}$$

$$\tilde{\Sigma} = (\mathbf{I}_N - \rho\mathbf{W})^{-1}\sigma^2((\mathbf{I}_N - \rho\mathbf{W})^{-1})^{\intercal} \tag{2.38}$$

Where $\tilde{\mu}$ and $\tilde{\Sigma}$ are the expected values of the spatial autoregressive process. Note that $\tilde{\mu}$ and $\tilde{\Sigma}$ are different from μ and Σ in a M-V and M-SD objective function, with $\tilde{\mu}$ and $\tilde{\Sigma}$ the mean and variance of $\mathbf{r}_s$ before considering local spatial shocks.

Figure 2.1 shows the effect of spatial autocorrelation on net benefits in a simulated landscape where the land parcels consist of cells on a 20×20 grid. In Figure 2.1a, we show the spatial weight of each cell, indicating how strongly the net benefit at each cell is related to the value realised in cell (10,10). Clearly, these weights are largest for cells immediately contiguous to cell (10,10) but decay as distance from that locality increases. Such a distance decay in the spatial weights applies analogously for all other cells. Figure 2.1b

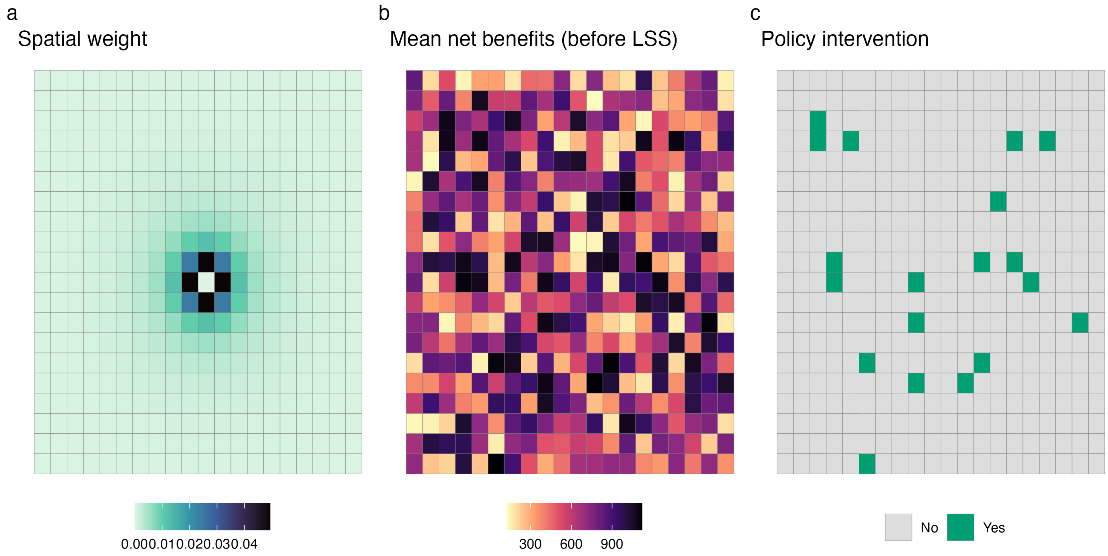

Figure 2.1: Visualisation of a 20 × 20 landscape. a. shows the spatial weights at parcel (10,10) with other parcels, b. average spatially-autocorrelated net benefits from the landscape, and c. investment strategy that maximises EV

illustrates the expected net benefits in the stylised landscape before accounting for local spatial shocks ($\tilde{\mu}$) and shows that the expected benefits are spatially-autocorrelated; cells in closer proximity are more likely to share similar net benefits due to spatial dependencies.

2.3.2 Local spatial shocks

Rare and extreme events such as bushfires, pest disease, flooding and similar ecological disturbances across the landscape threaten part or the entire landscape under management and lead to asymmetric left-tailed distributions in the net benefits of landscape management across parcels. We term these "local spatial shocks" (LSS). The distribution arising from a SAR DGP can simulate the property of spatial autocorrelation but falls short of being able to represent a variety of nonnormal, asymmetric uncertainty distributions found in empirical applications. To that end, we introduce the idea of spatial shocks that extends the previous work by (Albers et al., 2016). The presence of a shock introduces a low chance of a significant environmental disturbance that leads to a net loss if investments in natural capital were directed to it.

In this paper, we motivate local spatial shocks as representing stochastic wildfire disturbances, but these could just as easily be imagined as representing disturbances such as pest diseases, droughts and flooding events. Local spatial shocks originate from an origin parcel but are rarely confined to that parcel. Rather, shocks can spillover to nearby parcels and in so doing negatively impact gains from natural capital investments in those parcels as well. Recent work on understanding the role of extreme weather events in diversified tree planting strategies also highlights that the impacts of these events on natural capital assets exhibit patterns of strong spatial autocorrelation (Fuchs et al., 2024).

We imagine a local spatial shock as a disturbance that, if realised, starts at one parcel (the shock origin) and spreads to affect a number of parcels that are neighbouring it. There are three factors that determine the characteristics of spatial shocks. First, the quantity of spatial shocks: in a single state of the world, there could be anywhere from 0 to a finite number of shocks. Second, the location of the spatial shock; this affects the probability that each parcel is at the origin of the shock. The third is the magnitude, or the number of parcels, that a shock will affect outside of the shock origin.

Number of spatial shocks

Here we describe our model of the number of spatial shocks in each state of the world. Imagine that under each unknown state of the future world s, we progress through $t = 1,...,T$ periods where the vector of net benefits $\mathbf{r}^s$ is subject to risk in each period. To motivate this, consider a landscape where every year for the next 100 years ($T = 100$), the landscape will be susceptible to the local spatial shock at a given probability level. In each period, an underlying stochastic risk factor $\zeta_1,...,\zeta_T$ is drawn independently from an underlying statistical distribution. Local spatial shock occurs only if the stochastic risk factor, over any period, exceeds a threshold η. This can be imagined as wildfires that do not manifest unless a certain set of environmental conditions are met, or, for flooding, the peak flow of a river that does not flood unless the peak flow exceeds a certain threshold.

Suppose that if the local spatial shock is realised, it will affect a certain set of parcels in the landscape. If a parcel is affected by a spatial shock, then this eliminates all net benefits accrued from investments in that parcel throughout all periods, and the total net benefits r_i^s will be set to υ, where there is a net loss if investments were made in that parcel. For example, following a wildfire event, trees in parcels that are affected by wildfires will have carbon released back into the atmosphere that offsets the carbon stored prior to the spatial shock, not to mention loss of initial investments into acquiring land or damages that are a result of it.

In the case where ζ is identically and independently distributed (i.i.d.), the total number of shocks in the T number of periods experienced in the landscape follows the binomial distribution given by;

$$\Pr(\text{NumShocks} = k) = \binom{T}{k} \pi^k (1-\pi)^{T-k} \tag{2.39}$$

$$\text{where} \quad \pi = \Pr(\zeta \geq \eta) \tag{2.40}$$

Where π is the probability that ζ exceeds η in a given period. π can be interpreted as the probability of a shock such that $\pi = 1/100$ represents a 1-in-100 year shock event.

Size of the shock

We design these experiments such that the size of the shock is (a) positively related to the amount of exceedance of ζ relative to η, where the size of the shock is greater if the difference between ζ and η is greater, and (b) negatively related to the probability of a shock π, such that shocks with lower probability will produce a greater amount of impact across the landscape.

We model ζ with a Student's t distribution with 3 degrees of freedom, which has the characteristics of being heavy-tailed. The size of the shock, conditional on a shock, is given with the following formula.

$$\text{SizeShock}_{st} \mid \zeta_{st} \geq \eta, \pi > 0 = -\log(\pi)(\zeta_{st} - \eta) \tag{2.41}$$

Here, the Size of the Shock in state of the world s and epoch t, conditional on ζ_{st} exceeding η, is the difference between ζ and η, multiplied by the log of the probability of exceedance π. As we can observe in Figure 2.3.2, the mean of the size of the shock increases as π decreases, with catastrophic events with more than 50% of parcels affected, for example, extremely unlikely for $\pi = 0.1$ but somewhat possible for $\pi = 0.001$, conditional on the shock. This means that, while spatial shocks itself are unlikely for $\pi = 0.001$, the effects of those shocks are much more likely to be severe.

Location of the origin of the shock

For each shock, we draw a random parcel in $i = 1,...,N$ that is the origin of the shock in t, which is indicated by the binary indicator $\varkappa^*_{ist}$, with the probability of being selected

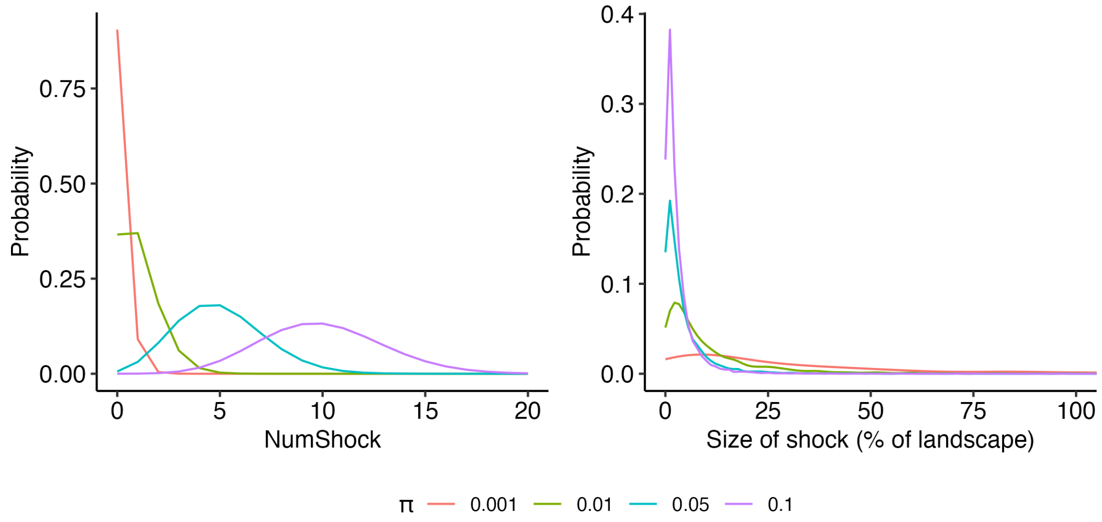

Figure 2.2: a. shows the distribution of number of shocks for a number of possible values of π, and b. shows the distribution of the size of shocks (number of parcels affected) conditional on a shock, for given values of π

as the origin being a function of $\tilde{\mu}_i$. This implies that parcels with a higher level of net benefits will also have a higher chance of being an origin and affected by the spatial shock. Specifically, we draw the index of the parcel that becomes the origin of a spatial shock based on the following equation.

$$P(\varkappa^*_{ist} = 1) \propto \tilde{\mu}_i \tag{2.42}$$

Where $\tilde{\mu}_i$ is the mean of the net benefits before accounting for the spatial shock. This assumption implies that the parcels that are more likely to deliver higher net benefits (through the SAR DGP) are more likely to be affected by the spatial shock, as it is more likely for those to be in the origin location of a spatial shock.

Spread of the shock to neighbouring parcels

We then simulate the spread of the shock from its origin location to its neighbouring parcels. The probability that parcel i is affected, conditional on parcel j being the origin of a shock, is defined by this equation:

$$\Pr(\varkappa_{ist} = 1 \mid \varkappa^*_{jst} = 1) \propto d_{ij}^{-\varphi} \tag{2.43}$$

where $\varkappa_{ist}$ is the binary indicator of whether the parcel i in state of the world s is shocked by the shock in t, and $d_{ij}^{-\varphi}$ is the inverse distance between the parcel i and parcel j,

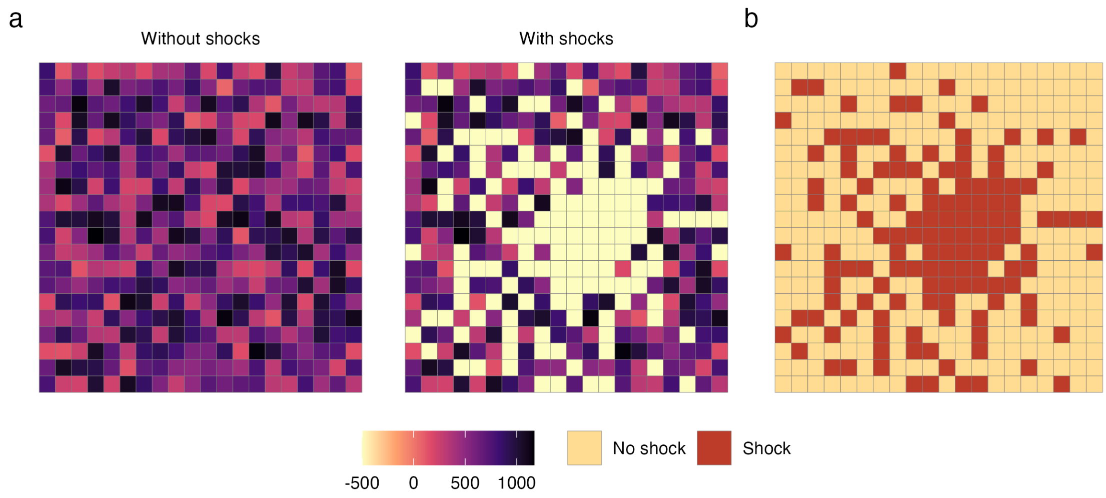

Figure 2.3: Spatial shocks affect the final net benefits realised in land-use change. a, the net benefits before (left) and after (right) spatial shocks, b, the location of spatial shocks. Notice that parcels affected by spatial shocks have strongly negative net benefits.

The binary indicator of whether a parcel is affected in the state of the world s is a binary indicator of whether it has been affected by any of the shocks across all T.

$$\kappa_{is} = \begin{cases} 1 & \text{if} \quad \sum_{t=1}^{\mathrm{T}} \varkappa_{ist} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{2.44}$$

Figure 2.3 illustrates how spatial shocks affect the net benefits realised in the landscape. When the threshold η is exceeded, a parcel becomes a shock origin location, and the amount of spillovers that shock has on neighbouring parcels is dependent on by how much of that threshold is exceeded. If a parcel is affected by the spatial shock, all the net benefits of that location becomes zero.

2.4 Monte Carlo experiment

We designed a Monte Carlo experiment to examine how well Expected Value (EV), M-SD, and M-CVaR objective functions are able to identify investment strategies that maximise the expected utility of decision-makers with different levels of risk-aversion. The goal of the Monte Carlo experiment is to solve the LDPs generated from the distribution of $\mathbf{r}$ to maximise the objective functions and evaluate how well these solutions deliver when compared with regards to the expected utility they would bring to the decision maker evaluated with that decision maker's true preference function.

The algorithm 1 describes the approach used to generate the LDPs that are used to compare the relative performance of M-SD and M-CVaR in terms of the expected utility of the decision-maker. Each LDP is characterised by a set of LDP parameters and objective function parameters. Table 2.2 gives a description of the values chosen for these parameters.

For each replicate ($m = 1, \ldots, M$), the algorithm generates a new LDP characterised by $\mathbf{r}$, simulated through the SAR and LSS data-generating processes. This results in M sets of LDPs ($\mathbf{R}$), each LDP with a set S of the states of the world.

Algorithm 1 LDP simulation

Require: $(\rho, \sigma, \eta, \upsilon, N)$

for m = 1,...,M **do**
    $\mathbf{X} \leftarrow \text{Random}(0,1)$
    for $s \in S$ **do** $\qquad \triangleright$ Simulate net benefits in each state of the world
        $\tilde{\mathbf{r}}_i^s \leftarrow \text{SAR}(\rho, \sigma, \mathbf{W}, \mathbf{X})$
        $\kappa_{is} \leftarrow \text{LSS}(\pi)$
        for i = 1,...,N **do**
            if $\kappa_{is} \geq 0$ **then**
                $r_i^s \leftarrow 0$
            else
                $r_i^s \leftarrow \upsilon + \tilde{r}_i^s$
            end if
        end for
    end for
    $\mathbf{R}_m \leftarrow \{\mathbf{r}_s : s \in S\}$
end for

Each LDP is then solved in the Algorithm 2, where the objective functions EV, $\rho_{\text{M-SD}}$ and $\rho_{\text{M-CVaR}}$ are created based on the set $\mathbf{R}_m$. The LDP was solved using values of λ from the range of values, and each solution was evaluated based on its CE for a given θ. The quantity of interest Γ is the percentage difference in CE reached by the different solutions. Here;

- $\Gamma^{\theta}_{\text{M-SD/EV}}$ is the percentage difference between the CE of the best solution in the M-SD objective function versus the CE arrived by the EV function

- $\Gamma^{\theta}_{\text{M-CVaR/EV}}$ is the percentage difference between the CE of the best solution in the M-CVaR objective function versus the CE arrived by the EV function

- $\Gamma^{\theta}_{\text{M-CVaR/M-SD}}$ is the percentage difference between the CE in the best performing solution of the M-CVaR and M-SD objective functions.

Investigating the distribution of percentage differences Γ between multiple risk aversion values θ between different LDPs (in M) reveals the relative performance of these objective functions to maximise expected utility.

Algorithm 2 Monte Carlo experiment

Require: $\mathbf{R}_m \quad \forall m = 1,...,M$
  for m = 1,...,M **do**
    $\mathbf{r}_s \leftarrow \mathbf{r}_s^m$ for all of s = 1,...,S
    $\mathbf{x}^*_{\text{EV}} \leftarrow \arg\max \text{EV}(\mathbf{x})$
    Construct objective functions EV, $\rho_{\text{M-SD}}$ and $\rho_{\text{M-CVaR}}$ based on $\mathbf{r}_s$
    for $\lambda = [0, 0.05, ..., 1]$ **do**
      $\mathbf{x}^{\lambda}_{\text{M-SD}} \leftarrow \arg\max \rho_{\text{M-SD}}(\mathbf{x}, \lambda)$
      $\mathbf{x}^{\lambda}_{\text{M-CVaR}} \leftarrow \arg\max \rho_{\text{M-CVaR}}(\mathbf{x}, \lambda)$
    end for
    for $\theta = [0, 0.01, ..., 50]$ **do**
      $\text{CE}^*_{\text{EV}} \leftarrow \text{CE}_{\theta}(\mathbf{x}^*_{\text{EV}})$
      $\text{CE}^*_{\text{M-SD}} \leftarrow \max_{\lambda} \text{CE}_{\theta}(\mathbf{x}^{\lambda}_{\text{M-SD}})$
      $\text{CE}^*_{\text{M-CVaR}} \leftarrow \max_{\lambda} \text{CE}_{\theta}(\mathbf{x}^{\lambda}_{\text{M-CVaR}})$
      $\Gamma^{\theta}_{\text{M-SD}} \leftarrow (\frac{1}{\text{CE}^*_{\text{EV}}})(\text{CE}^*_{\text{M-SD}} - \text{CE}^*_{\text{EV}})$
      $\Gamma^{\theta}_{\text{M-CVaR}} \leftarrow (\frac{1}{\text{CE}^*_{\text{EV}}})(\text{CE}^*_{\text{M-CVaR}} - \text{CE}^*_{\text{EV}})$
      $\Gamma^{\theta}_{\text{M-CVaR/M-SD}} \leftarrow (\frac{1}{\text{CE}^*_{\text{M-SD}}})(\text{CE}^*_{\text{M-CVaR}} - \text{CE}^*_{\text{M-SD}})$
    end for
  end for

We ran this Monte Carlo experiment with a set of Central parameter specifications (see Table 2.2), each for $M = 100$ replicates. We then evaluated the distribution of Γ across all replicates of M. We then characterised the distribution of Γ by evaluating the mean, 5th and 95th percentile of Γ. The distribution of Γ thus reveals which of the objective functions are able to deliver higher CEs consistently across several LDPs.

2.5 Results

2.5.1 The impact of optimising for mean-risk on expected utility

We find strong support that maximising the M-SD or M-CVaR objective with λ^* can identify investment strategies that substantially improve results compared to maximisation of EV in situations of high risk-aversion. Figure 2.4 illustrates the change in certainty-

Parameter	Description	Central specification	Alternative specifications
	LDP parameter		
ρ	Spatial correlation coefficient in SAR	0.8	0, 0.2, 0.4, 0.6
σ	Variance in SAR	6	2, 4, 8, 10
π	Probability of a shock in each epoch (over 100 epochs)	0.01	0, 0.00001, 0.0001, 0.001, 0.05, 0.1
υ	Net loss when a parcel is affected by the spatial shock	1000	-
N	Number of parcels in the LDP	400	-
w_0	Initial level of wealth	$(\upsilon \times B)+1$	-
	Objective function parameter		
B	Budget constraint for the investment strategy	20	40, 60, 80, 100
β	Quantile in the M-CVaR objective function	99%	50%, 75%, 90%, 95%

Table 2.2: Parameter specifications

equivalent values for decision-makers with different levels of risk aversion in 100 replicates of the Monte Carlo experiment, using the central parameter specification (Table 2.2). Focussing first on the left-hand side of Figure 2.4, the certainty-equivalent values of the optimal solution in M-SD and M-CVaR are compared with the certainty equivalent value of the optimal solution in EV. Each value on the x-axis represents a class of decision makers, classified by increasing degrees of risk-aversion defined by the coefficient of relative risk aversion θ. Focussing first on 2.4a, the shaded areas show the net change in certainty-equivalent by moving from the EV objective to the mean-risk objective, with higher values being better in terms of maximising expected utility. For example, decision-makers with risk-neutral preferences ($\theta = 0$) assess the random outcomes of the LDP produced by all approaches the same, because when $\theta = 0$ the solution that maximises either of the mean-risk objective functions is the same as the solution that maximises EV.

Recall that when maximising either of the mean-risk objective functions we simultaneously identify the risk weighting parameter λ that best aligns that objective function with the decision-maker's true preference function as determined by their risk aversion parameter θ. Figure 2.4c shows the mapping between θ and the best-fitting risk weighting parameter, λ^*, as identified across our Monte Carlo experiments. Unsurprisingly, increasing risk aversion is associated with a higher value of the risk weighting parameter in a mean-risk objective function. In other words, in a mean-risk objective function, increasing risk aversion is represented by attributing increasing weight on the risk element of that objective function. Notice also that the shape of the relationship differs between the M-SD and M-CVar objective functions, although, as expected, for a risk-neutral decision maker where $\theta = 0$, we observe that λ^* is also zero for both mean-risk objective functions. In other words, in a mean-risk objective function, a risk-neutral decision maker is represented by an objective function that places no weight on the risk element.

For a decision-maker with risk-aversion broadly consistent with the literature ($\theta = 2$, for example), we find that a mean-risk objective function is not substantially better than the EV. For M-SD and M-CVaR, the gain in certainty-equivalent units over EV maximisation are 0.03% and 0.05% respectively. In such cases, it appears that it does not matter which mean-risk objective function is used to solve the LDP; the solutions delivered by using the more complex mean-risk specifications offer only marginal gains over those which can be achieved by EV optimisation. Indeed, for coefficients of risk aversion, θ, between 0 and 5, the percentage differences between EV and mean-risk objectives lie very close to 0. Furthermore, as shown in Figure 2.4 b, at low levels of risk aversion, choosing the relatively more sophisticated M-CVaR mean-risk objective does not offer any advantages over the M-SD objective.

The benefits of using a mean-risk objective function, relative to the EV objective function, only become apparent as we move to higher levels of risk aversion. Whereas under risk neutrality, maximising mean-risk objectives does not lead to any improvement in certainty-equivalent values compared to maximising EV, moderately risk-averse decision-makers ($\theta = 5$) can achieve a median increase of 1.7% gains in certainty-equivalent values when optimising a M-SD objective and 1.8% gains when optimising an M-CVaR objective. At higher levels of risk-averse a decision-maker becomes increasingly unwilling to expose themselves to downside risk. Compared to the EV maximisation approach, once tuned to the appropriate risk weighting parameter (λ^*), M-SD and M-CVaR favour patterns of land use change that lower the chance of downsides and, as such, can better reflect the true preferences of risk-averse decision makers. These improvements are amplified as we move towards an extreme level of risk aversion ($\theta > 10$). At $\theta = 10$, we observe that M-SD and M-CVaR outperform EV by 17% and 18%, respectively, the gap between the mean-risk objective functions and the EV solution further widening as the level of risk aversion increases.

It is also at these high levels of risk aversion ($\theta > 10$) where the improvement of using an M-CVaR objective compared to the M-SD objective begins to result in significant improvements in the certainty-equivalent, as depicted in Figure 2.4b. At this level of risk aversion, more than 95% of the runs showing that M-CVaR leads to higher certainty-equivalents than M-SD. At $\theta = 10$, M-CVaR results in a 1% improvement in CE compared to M-SD, and this difference increases to 9% for $\theta = 30$. These results reveal that the choice of which mean-risk objective function to employ in solving the LDP only significantly improves investment guidance in situations where that guidance is being generated for decision-makers who are extremely averse to risk. At these levels of risk aversion, the decision-maker is strongly averse to the small probability that several parcels selected for the investment strategy are simultaneously impacted by the correlated spatial shock and is very much indifferent to the level of net benefits achieved in other states of the world.

Another striking conclusion revealed in Figure 2.4c is that the optimal choice for the weighting parameter λ^* for the two mean-risk objective functions increases as θ increases, but does not reach its maximum value of 1 even as θ is at the maximum in the range of our evaluation (that is, extremely risk-averse). This suggests that the use of an objective function composed only of the risk measure (as a result of $\lambda = 1$) does not appear to be justified even at extreme levels of risk aversion; the incorporation of the mean in the objective function can improve the expected utility even at an extremely high level of risk-aversion. In the following section, we explore the implications of setting λ to 1, a specification that could be guided by inaccurate estimates of the decision-maker's θ.

Our central conclusion is that, conditional on the weighting parameter λ being selected to closely approximate an underlying expected utility function, the decision-maker cannot be left worse-off if they move from EV maximisation to use a mean-risk objective function. The use of a mean-risk objective can further elevate the certainty-equivalent value of investment strategies for decision-makers adopting extreme levels of risk aversion. Yet, for the range of risk-aversion levels reported in the literature, EV, M-SD, and M-CVaR approaches appear to deliver investment guidance that would be considered equally good by a decision maker.

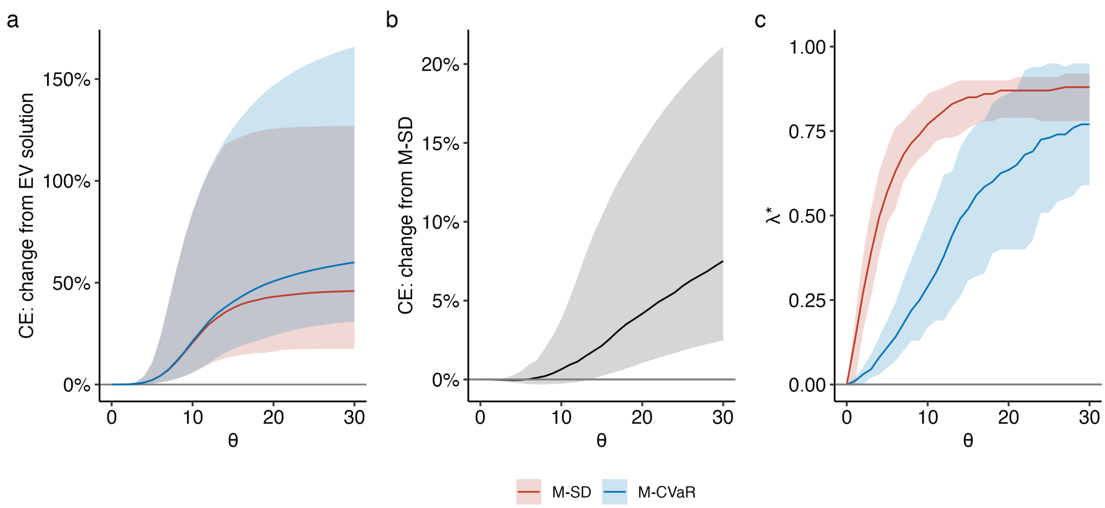

Figure 2.4: Change in certainty-equivalent values of mean-risk objective functions with optimised weighting parameter λ^* relative to a EV-optimal solution across a range of risk preferences defined by the coefficient of risk aversion θ. a. shows the percentage change of certainty-equivalent values for EV, M-CVaR and M-SD compared to the certainty-equivalent from the EV solution. b., depicts the percentage difference in certainty-equivalents between M-CVaR compared to M-SD, and c, the optimal weighting parameter λ^* chosen for each level of θ. Lines show median run iteration and shaded areas show 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles of iterations.

2.5.2 Incorrect choice of the weighting parameter

The results presented in Figure 2.4 assume that the weighting parameter in the mean-risk objective functions, λ, has been chosen specifically to best reflect the true risk preferences of the decision maker (that is, $\lambda = \lambda^*$). We can imagine situations where the analyst chooses λ while holding incorrect estimates of the decision-maker's risk preferences. In these situations, as implied by the creation of "risk-return" frontiers in the literature, decision-makers can end up with investment guidance that is far from optimal.

To illustrate the impact of an incorrect choice of λ, rather than optimally choosing that parameter, we fix its value at $\lambda = 1$ (the results for other inappropriately chosen values for λ can be found in the fifth column of Figure 2.6). Under that restriction, EV no longer carries any weight in the objective function, and the problem becomes one of risk minimisation. We then compare the certainty-equivalent value of the M-CVaR and M-SD solution with that fixed weighting parameter with the EV solution across a range of different values for the true risk aversion of the decision maker. The findings are plotted in Figure 2.5. Our analysis reveals that across the full range of decision-maker risk preferences, policy guidance based on only minimising standard deviation leads to certainty-equivalents that are far worse than that provided by maximising EV. We observe that in Figure 2.5a that arbitrarily choosing $\lambda = 1$ in a M-SD objective function can result in a 50% decrease in certainty-equivalent value compared to the EV solution when the decision maker is actually risk neutral (that is, $\theta = 0$) . Looking at just the M-SD objective function, we find that the investment strategy that minimises the standard deviation is still inferior to the expected value solution even for an extremely risk-averse decision-maker lying at the bounds of the range of our evaluation ($\theta = 30$). In this case, the investment guidance arising from the purely minimisation of the standard deviation is still set to lose 20% of the certainty-equivalent that would be achieved by following the investment guidance arising from the maximisation of EV.

We also find that M-CVaR is less vulnerable to the inefficiency that arises from assuming incorrectly that $\lambda = 1$. Although an objective function that maximises M-CVaR (with $\lambda = 1$) still results in a 6% decrease in certainty-equivalent values compared to the EV, this is considerably better than the potential losses that result from maximising M-SD (with $\lambda = 1$). Furthermore, M-CVaR with $\lambda = 1$ outperforms EV at higher levels of risk aversion (specifically if $\theta > 6$), potentially increasing the levels of certainty-equivalents by 20% compared to EV optimisation if $\theta = 10$. Furthermore, M-CVaR outperforms M-SD in all levels of risk-aversion for $\lambda = 1$, achieving certainty equivalents nearly double in a wide range of risk preferences.

The core message of this analysis is that while an arbitrary choice of the weighting parameter can lead to inferior results, the analyst is able to avoid giving investment guidance that are far worse than the EV across a wide range of decision-maker risk preferences if he/ she uses an M-CVaR rather than a M-SD objective. The adverse impact of selecting $\lambda = 1$ on expected utility motivates the need to incorporate the expected value as part of the objective function of the decision maker.

2.5.3 When does the mean-risk objective function matter?

Repeated Monte Carlo experiments that use different values of the LDP and objective function parameters reveal the specific conditions where the M-CVaR is likely to deliver better natural capital investment guidance than the M-SD. Our main conclusion is that provided the risk weighing parameter is chosen accurately (that is, $\lambda = \lambda^*$), there is never

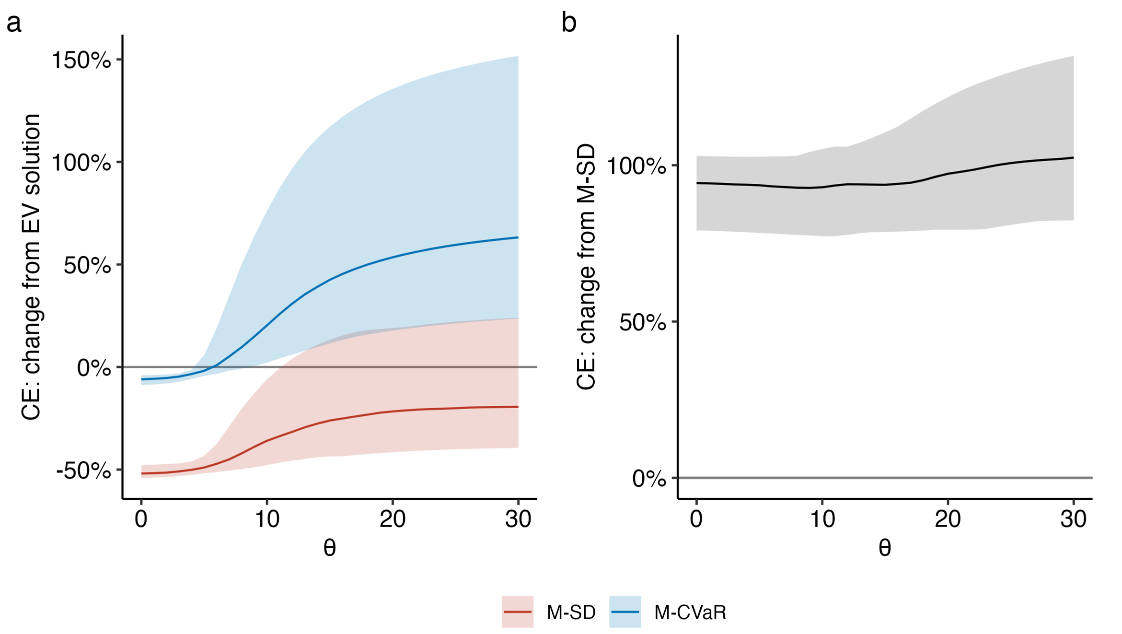

Figure 2.5: Change in certainty-equivalent values of mean-risk objective functions with $\lambda = 1$. a, change in CE compared to the EV solution, and b, change in CE of the M-CVaR compared to the M-SD solution.

a disadvantage in choosing a mean risk objective function to identify the best investment strategies compared to maximising EV, regardless of which mean risk objective function is used.

Figure 2.6 illustrates the percentage changes in CE by moving from M-SD to M-CVaR across a wide range of parameters, where each column represents a parameter in the LDP and each row represents a different level of risk aversion. As expected, in the first row where $\theta = 0$ implies risk neutrality, we observe no changes in CE when moving from M-SD to M-CVaR because both objective functions maximise expected utility. However, moving to decision makers with moderate risk aversion ($\theta = 5$) and extreme risk-aversion ($\theta = 20$), we begin to observe substantial differences in the expected utility of the identified investment guidance.

We focus first on how the parameters driving the net benefits of natural capital investment will affect the relative performance of M-CVaR and M-SD. In particular, we consider the relative performance for different values of the spatial dependence parameter (ρ) that governs how much net benefits in one parcel affect the net benefits in neighbouring parcel and of the variance parameter (σ) that drives the amount of uncertainty in net benefits (excluding spatial shocks). Focussing first on instance of risk-neutrality ($\theta = 0$) and moderate ($\theta = 5$) risk aversion, we find that M-SD and M-CVaR produce around the same improvements in certainty-equivalents compared to EV optimisation. Only at high levels of risk aversion ($\theta = 20$) does M-CVaR optimisation deliver marginally higher certainty equivalent values than M-SD. These gains are amplified when there is more spatial autocorrelation (ρ is larger).

Turning our focus to the third column of Figure 2.6, our analysis also identifies when M-CVaR will likely deliver better investment guidance compared to M-SD as we change the probability of the occurrence of severe downside shocks (π) . We observe that M-CVaR and M-SD do not deliver any improvement over the EV objective function when there is no chance of such spatial shocks ($\pi = 0$) but as the probability of such shocks increases, both mean risk objectives deliver superior investment guidance where those gains are increasing in the risk aversion of the decision maker. At the same time, there is relatively little difference between the two solutions of the mean-risk objectives, although M-CVaR tends to outperform M-SD in situations where the probability of spatial shocks is not too low ($\pi = 0.01$) and at high risk-aversion ($\theta = 20$). Thus, it appears that the M-CVaR objective is not sensitive to these local catastrophic shocks, unless their probability is high enough to affect the distribution of net benefits at its tail. Furthermore, we observe a decrease in CE improvements for M-SD and M-CVaR relative to EV as the probability of these spatial shocks increases further and becomes relatively likely ($\pi = 0.05$ and $\pi = 0.1$). This is because as these spatial shocks become likely, the presence of these spatial shocks will begin to have a major effect on the expected value of an investment choice, which makes parcels prone to receiving spatial shocks undesirable even to the EV objective function. For that reason, parcels that frequently receive spatial shocks are not selected by maximising EV either, which lowers the risk profile of the EV solution and therefore closes the gap between it and M-SD and M-CVaR in terms of expected utility.

In the fourth column of Figure 2.6, we observe the effects of misspecifying the parameters of the objective function. We focus on β, the quantile parameter in the M-CVaR objective that defines that part of the distribution of possible outcomes that will be taken to represent downside risk. Our analysis reveals that the choice of the quantile parameter can have an impact on the quality of guidance provided by the M-CVaR objective. Some choices for β cause the M-CVaR objective to recommend natural capital investment strategies that are worse than those identified from M-SD optimisation. Defining the CVaR risk measure using $\beta = 0.5$, which means that the decision maker is averse to outcomes that are worse than the median of the distribution of outcomes, results in a proposed investment strategy from the M-CVaR optimisation that is worse in terms of certainty-equivalent value than the strategy identified by the M-SD optimisation under both moderate ($\theta = 5$) and high ($\theta = 20$) risk-aversion. Although in risk-neutral situations ($\theta = 0$), the parameter β does not have an effect on the resulting expected utility on M-SD or M-CVaR, we generally find lower levels of expected utility when using a M-CVaR objective with quantiles other than 0.99. These results suggest that M-CVaR may lead to adverse results compared to M-SD if the β parameter is not chosen to reflect the underlying utility function of the decision-maker.

In the fifth column of Figure 2.6, we observe the effects of not choosing λ to maximise the decision-makers' underlying expected utility. As seen previously in Figure 2.5, misguided selection of $\lambda = 1$ in cases of risk neutrality can lead to results that have 50% lower expected utility (for M-SD) and 6% decrease (for the M-CVaR). In general, we find that the analyst is much more susceptible to providing investment guidance that result in dramatically less value to the decision maker in certainty-equivalent terms (-50%) if they use a M-SD objective. In fact, the use of an M-CVaR objective prevents the analyst from giving investment guidance that is substantially worse than the EV solution.

2.6 Concluding remarks

Risks and uncertainty are major challenges to designing programmes of natural capital investment that deliver robust outcomes across a wide range of futures. Risk-averse decision-making could reduce downside risks, but the methods chosen to identify patterns of land-use change will also have an effect on the investment guidance provided by analysts to decision makers. Our computational results show that accounting for uncertainty delivers first-order improvements in the quality of guidance provided to a risk-averse decision maker. More precisely, using methods that maximise a mean-risk objective function improves the expected utility that a decision maker would realise by following the investment guidance relative to what they would experience if they followed the guidance arising from the conventional approach of maximising EV. These gains are sometimes greater than 150% in certainty-equivalent value. The adoption of a more sophisticated objective function to capture downside risks leads to consistently higher-quality solutions across plausible

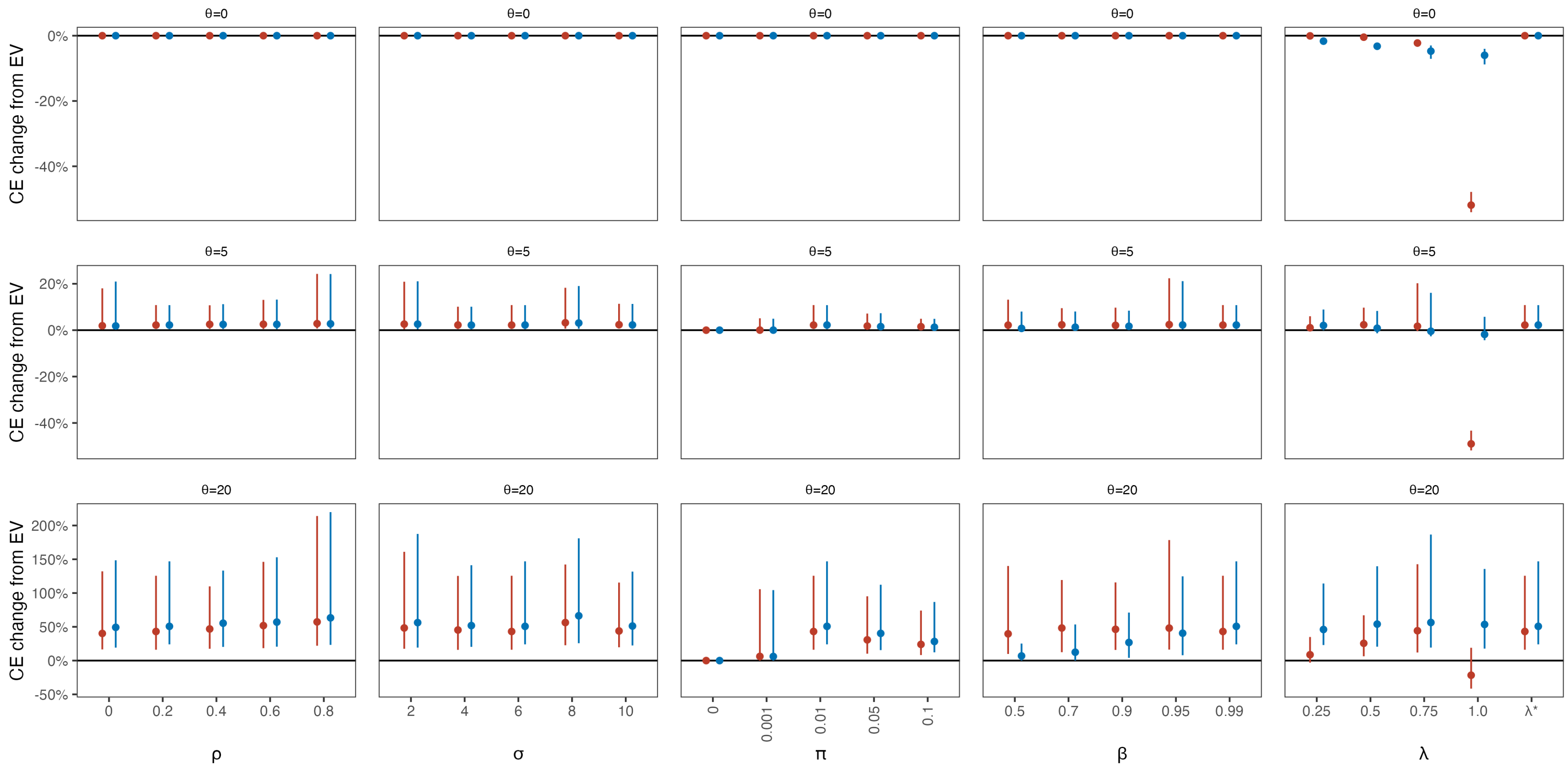

Figure 2.6: Percentage difference in CE when moving from an EV objective function (set at 0%) to a M-SD or M-CVaR objective function, across runs with different parameter settings for the LDP. Runs where 90% or more replicates show a positive change in CE are highlighted in blue.

parameter choices that define the LDP. These improvements are nevertheless marginal compared to the improvements brought about by moving from simply maximising expected value to maximising mean-risk objectives. This study gives a strong motivation for analysts to adopt mean-risk objective functions when devising natural capital investment guidance for risk averse decision makers.

Our study contributes to a literature that shows that optimal investment strategies in space identified through natural capital and ecosystem services models could change depending on a decision-maker's aversion to risk (Runting et al., 2018; Knoke et al., 2015; Ando and Mallory, 2012). Although portfolio analysis methods common in the literature are not capable of entirely eliminating risks arising from natural capital investments, our results illustrate that explicit consideration of risks in decision-making, even with simple variance or standard deviation mean-risk objective functions, can elevate the quality of natural capital investment guidance. This is especially true when the decision-maker is risk-averse, with average improvements in certainty-equivalent values reaching 17% or more in the case of extreme risk-aversion. These findings motivate the use of mean-risk objective functions as an approach to tractably solve LDPs and identify optimal patterns of natural capital investments.

Our computational results further resolve a debate regarding the use of mean-variance and mean-standard deviation approaches to identify risk-averse investment strategies in land-use settings. This is a long-standing tension in the financial economics literature (Markowitz, 2014; Best and Grauer, 1991; Chopra and Ziemba, 2016), and was introduced into the context of land-use decision-making as a critique to the application of mean-variance approaches in land-use decision-making by Dunkel and Weber in 2012. The results of our study show that the use of the original mean-variance portfolio and a similar M-SD objective function is already producing substantial improvements in expected utility, although the more sophisticated M-CVaR can provide further, but marginal, improvements in expected utility delivered by the recommended investment strategy. In this sense, the M-SD objective function is already capable of approximating a risk-averse expected utility function in a wide array of land-use decision problems, with the M-CVaR offering an even closer approximation to EU that leads to marginal improvements. These conclusions are only apparent if low-probability shocks to the landscape are modelled; otherwise, the M-SD objective functions perform nearly the same as the M-CVaR.

This model analysis also highlights a set of fundamental conditions where decision-makers are likely to realise benefits by transitioning from maximising Expected Value to maximising a mean-risk objective. First, the benefits of using mean-risk objectives will only materialise if the weighting parameter λ that controls the trade-off between mean and risk is chosen to reflect the underlying risk preferences of the decision maker. We illustrated the "best-case" outcome with the use of λ^*, where decision makers can realise substantial gains when λ is chosen specifically to reflect the underlying utility function. The assumption of a careful choice of λ readily breaks down if an analyst has to rely on risk preference elicitation approaches to uncover the decision-maker's risk preferences that could deliver inaccurate results. The consequences of an inaccurate calibration of λ are significant, in some conditions precipitating a 50% loss in the certainty-equivalent value compared to the EV solution. In fact, analysts must carefully consider the risk preferences of decision makers and align their choice of λ accordingly if they want to achieve the gains in the quality of investment guidance promised by the use of mean-risk objectives. If an analyst needs to align λ with the decision-maker's risk preferences using potentially inaccurate estimates of the latter, our research shows that they are better off using an M-CVaR objective because it has a much smaller chance of proffering investment guidance that is substantially worse (more than half) than that suggested by EV maximisation in certainty-equivalent value.

Second, we find that the M-CVaR objective function needs to be calibrated properly if it is to deliver improvements, albeit marginal, over the M-SD objective function in a certain set of situations. Sensitivity analyses reveal that if the β parameter is not chosen correctly to reflect the nature of risk in the simulations, analysts can identify investment strategies that, although not worse than EV, are worse than the less sophisticated M-SD objective function. But even if the parameters of the M-CVaR objective are calibrated well, its relative improvement over M-SD appears marginal at best, with the M-SD realising most of the benefits of the mean-risk objective. Therefore, it appears advisable for analysts to use a M-SD objective rather than the M-CVaR, particularly if they have the capacity to calibrate the weighting parameter in the mean-risk objective to the decision-maker's risk preferences. Only in situations where the analyst is unable to calibrate the weighting parameter does it appear suitable for analysts to use M-CVaR, in order to avoid the possible errors that arise with M-SD when λ is incorrectly specified.

Although tractability and modelling convenience demanded the adoption of a number of assumptions, the modelling framework presented in this paper could be further expanded to investigate the sensitivity of our results to these assumptions. One such assumption is that the decision-maker has knowledge of all the possible states of the world and their associated probabilities of occurrence. The only uncertainty concerns the state of the world to be realised. Future work can extend current results using this framework to evaluate the impact of "deep uncertainties," where some possible states of the world are not present in the decision-maker's information set (Walker et al., 2013), or situations of ambiguity, where uncertainties exist in the probabilities of states of the world (Knight et al., 1921). The presence of ambiguity and deep uncertainties can have major effects on the relative performance of investment strategies identified by maximising an objective function that does of those phenomena. For instance, the predicted mean and variance of a natural capital strategy can be wrongly estimated if the information set about the states of the world is incorrect, reducing the quality of solutions identified by the incorrectly specified LDP. An incomplete information set about uncertainties could impact investment guidance arising from the EV and mean-risk objective functions. As such, it will be important to evaluate how such sources of uncertainty change the results reported in this paper.

Another assumption imposed in our analyses is that there is no spatial feedback in net benefits across parcels chosen or not chosen for natural capital investment. In our modelling setup, it is assumed that the net benefits accrued from investing in natural capital in a parcel do not depend on whether or not another parcel is chosen. This independence assumption results in a value function that is linear and therefore tractable for mathematical solvers, but may be an assumption that is too strong for real world applications. Several examples in economics and ecology demonstrate that the actions undertaken at one location could have an effect on the net benefits in another location, for example, through "leakage" of deforestation that causes conservation in one location to increase deforestation or create land market feedback in another area (Armsworth et al., 2006; Wunder, 2008; Murray et al., 2004), or co-benefits through improving ecological connectivity that arises from protecting and restoring a combination of parcels that are spatially-contiguous to one another (Polasky, 2006; Hodgson et al., 2009). A model that incorporates these feedbacks will likely have a nonlinear value function, or enforce relationships across parcels chosen for land-use change through a series of constraints in the decision space $\mathcal{X}$ (Beyer et al., 2016), which are generally intractable in larger decision spaces.

Despite the assumptions in this analysis, our work provides compelling evidence that mean-risk objective functions can significantly improve the quality of land-use decision-making by explicitly incorporating data on risks into natural capital investment guidance. Our results establish that the question of which objective function is more suitable is of relatively minor concern to mildly risk-averse decision-makers and is only substantive if a decision-maker adopts a position of extreme risk aversion. This chart a clear path forward for adopting tools for risk-averse decision-making in identifying optimal and robust land-use investment strategies that are likely to deliver social welfare over sustained uncertainties in our current understanding of future conditions.

Chapter 3

Resilient tree-planting under compounding climate and economic uncertainties

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Abstract

To meet decarbonisation targets, nations around the globe have made ambitious commitments to expand forested land. Operationalising these commitments requires choosing a planting strategy: how many trees should be planted, of which species and where? Given those choices must be made now but have long term consequences, such decisions are plagued by uncertainty. For example, species that are well suited to present conditions may perform poorly under future climates, yet those future climates are themselves highly uncertain. Using the exemplar of the UK, a nation committed to achieving net zero emissions by mid-century, we quantify key uncertainties pertaining to co-evolving climate and economic conditions and examine how modern methods of decision-making under uncertainty can advise on planting choices. Our analysis reveals that the best planting strategy assuming a 'high-emissions' future is radically different to that for a future that remains on a 'near-historic' path. Planting for the former while experiencing the latter results in substantial net costs to UK society. Assimilating uncertainty into decision-making identifies planting strategies that diversify risk and significantly reduce the probability of high-cost outcomes. Importantly, our research reveals that the scope for mitigating risk through choice of planting strategy is relatively limited. Despite this persistent risk, we find that tree planting remains a highly cost-effective carbon removal solution when compared to alternative technologies, even when those alternatives are assumed to be riskless.

3.1 Introduction

To honour commitments made under the Paris Agreement and in support of initiatives such as the Bonn Challenge, nations across the world are developing plans to plant trees as a means of removing atmospheric greenhouse gases. The scale of promised planting is very substantial. The European Commission has pledged to plant 3 billion trees across member states by 2030 (European Commission, 2021) by which time the United States will plant a further one billion trees (USDA, 2022), with Australia planning to match the US commitment by 2050 (Australian Government, 2018) while China is expected to plant some 35 million ha of new forest by that date (Welz, no date). Tree planting on this scale has the potential to play a central role in efforts to curb climate change (Bastin et al., 2019; Roe et al., 2021).

To move from policy pledges to growing trees, however, demands that a number of urgent decisions be made concerning how many trees to plant of what species, and where, decisions that create trade-offs across carbon, agricultural and timber production outcomes. The use of the Natural Capital approach for decision-making has been increasingly advocated in the academic and policymaking circles to resolve these trade-offs (Bateman and Mace, 2020; HM Treasury, 2020). In essence, it imagines natural resources like trees as assets that provide services to mankind that can be captured and compared in monetary terms. Applying the framework for tree planting decision-making thus means policymakers select the configuration of tree planting that delivers the best net benefits for society in the long run.

Unfortunately, those pressing choices must be made under conditions of significant uncertainty. As we show in this paper, the degree to which a programme of afforestation and reforestation delivers carbon dioxide removal (CDR) services and how cost-effective those services are compared to other CDR technologies (IPCC, 2022) depends critically on future environmental and economic conditions that are currently unknowable. Whether a particular tree species thrives or struggles when planted in a given location and the level of CDR services it can deliver depends on uncertain future environmental conditions (Luyssaert et al., 2018). Moreover, the value society ascribes to those CDR services, the so-called Social Cost of Carbon (SCC), depends on uncertain future conditions (Yang et al., 2018; Russell et al., 2022). In a high-emissions future, CDR services are highly valuable, but along a low-emissions trajectory the benefits to society of drawing down atmospheric carbon are less significant (Yang et al., 2018). Likewise, the financial costs of planting trees in a location are determined by the difference in the value of the products generated by the forest (often principally timber) (Kirilenko and Sedjo, 2007) and the products that could have been generated by that land in its alternative use (often principally agricultural outputs) (Fezzi and Bateman, 2015; Bateman et al., 2016; Ritchie et al., 2020). Again, the path those values will follow over time is highly uncertain being determined by yields and prices that reflect uncertain future environmental and economic conditions. In this paper, we consider how decision-makers should respond to this pervasive uncertainty and examine whether the risks associated with tree planting challenge the assumption that tree planting represents the most cost-effective CDR technology.

Scenario analysis provides one tool through which decision-makers might begin to engage with uncertainty. In essence, the approach involves imagining a set of possible futures (scenarios) and considering how different policy decisions might play out under those futures (Polasky et al., 2011). The latter information is usually derived with the help of models that relate land-use change to economic and environmental outcomes under each alternative assumption of future conditions (Fezzi et al., 2014; Bateman et al., 2016; Day et al., 2020). Scenario analysis, however, has certain limitations. For one, those scenarios selected for analysis only represent some subset of possible futures. Decisions founded on that limited information space may prove wholly unsuitable under other possible future conditions. Likewise, as our research demonstrates, the best planting strategy under one scenario may prove to be amongst the worst under another. Scenario analysis fails to provide a coherent structure through which policy-makers can resolve the inherent uncertainties that confound planting decisions.

In this paper we pursue an alternative approach, reframing the problem as a portfolio investment decision and drawing on state-of-the-art, risk-averse optimisation methods to identify planting strategies which are optimal given the range of potential futures. The portfolio analysis framework has been broadly shown to be applicable for mitigating climate risks associated with environmental decision-making (Ando and Mallory, 2012; Mallory and Ando, 2014; Knoke et al., 2016; Beyer et al., 2018; Runting et al., 2018). In this paper we go further and extend that approach to the consideration of economic risks that we show to co-evolve with previously-explored climate uncertainties. Unlike scenario analysis, the portfolio approach selects a planting strategy based on an assessment of the returns to that investment across the full range of uncertain future conditions (Ando and Mallory, 2012). From this perspective, a desirable planting strategy might be one whose distribution of future returns does well on average and limits exposure to the possibility of very bad outcomes. Selecting such a planting strategy often involves seeking out what are termed 'hedging' opportunities. Here trees of one species are planted in one location because they tend to give good returns under future conditions in which trees planted in another location give poor returns, and vice versa. The planting strategy is a portfolio in the sense that it includes planting of both these varieties and thereby limits exposure to downside risk.

This framework of analysis is globally applicable, though to illustrate its application we present a case study focused on UK tree planting in support of commitments to achieve Net Zero commitments by 2050. Here we characterise decision-makers' uncertainty using the best current understanding of the joint distribution of future climatic and economic conditions and show that the returns to tree planting vary widely across those conditions. We show how planting strategies based on portfolio optimisation differ markedly from those that would deliver the best outcomes under the assumption of some single future scenario and explore the hedging possibilities afforded to policymakers through the selection of tree-species and planting locations. Finally, we compare the costs of meeting decarbonisation targets from an optimal portfolio of tree planting to those of an alternative CDR technology. Even when we adopt the extreme assumption that this alternative technology can deliver carbon capture without cost risk, we find that it is outperformed by tree planting except in extreme cases of highly risk-averse decision makers or unrealistically low assumptions regarding the cost of the alternative technology.

3.2 Methods

3.2.1 Study area

As part of its commitment to attaining net zero emissions of greenhouse gases by 2050, the UK Climate Change Committee has proposed a UK-wide target to establish 30,000 hectares of trees a year by 2025. Delivering on those targets would increase the country's total woodland area from 13% to 17%, an expansion expected to offset emissions equivalent to 12MtCO_2e per year by mid-century (Climate Change Committee, 2020). A critical decision remains over which planting strategy to pursue, a decision which will define the set of locations where trees will be grown and hence the land that will be taken out of agricultural production.

At present, woodland in the United Kingdom comprises 49% broadleaf and 51% conifer species (The Woodland Trust, 2021). Fast-growing conifers thrive in the cooler, wetter climates typical of the north, west and southwest, delivering both carbon storage and commercial timber revenues. In contrast, slower-growing broadleaf species prefer warmer, drier areas as found in the southeast region of the UK. Climate change projections show that many parts of the country will experience warmer and drier summers (Lowe et al., 2018). Under moderate emission projections of future climate, the higher growth rates of conifers yield higher rates of carbon storage. However, under higher emission climates modelling shows that UK tree planting strategies with a higher proportion of broadleaf trees sequester substantially more carbon by 2100 than conifer-dominated planting strategies (Bradfer-Lawrence et al., 2021).

The major consequences of alternative climate futures upon optimal tree-planting strategies sets up a challenge for decision-makers seeking to maximise the net benefits to society of tree planting. Within the UK (HM Treasury, 2020) and increasingly globally (European Commission, 2015; Environmental Protection Agency, 2000), official guidelines have adopted a natural capital approach (Bateman and Mace, 2020) to decision appraisal. This requires that all major benefits and costs, including those arising outside markets (such as the benefits of CDR), must be included within spending appraisals, typically by monetising those values using an array of valuation tools (ibid.). This permits the use of standard economic assessment methods of investment appraisal such as the calculation of the net present value (NPV) of a project. Here we adopt such standard methods, seeking to maximise NPV over a typical 30-year time horizon (2020-2050) with the assumption that trees are planted in 2020, with net benefits discounted at a rate of 3.5% consistent with British policy-making recommendations (HM Treasury, 2020).

While there are myriad costs and benefits associated with the planting decision (Bateman et al., 2022), for the purposes of this paper we focus on three components that capture the focal changes to natural capital value flows: the monetary value of carbon sequestration; revenues from timber harvesting and; the costs of foregone agricultural profits from land on which trees are planted, all of which are sensitive to future climate and economic variables (described in detail in Appendix B). These values are assessed using the Natural Environment Valuation (NEV) suite of models (Day et al., 2020), a spatially-explicit integrated environment-economy model of land use in Great Britain that have already been extensively used to inform national land-use decision-making (Bateman et al., 2013). NEV operates on a 2km grid defining 57,230 gridded locations across Great Britain. Accordingly, we model the planting decision as selecting a set of cells across that grid and the species to be planted on the agricultural land in each chosen cell.

3.2.2 Climate-economy realisations (CER)

The costs and benefits of a particular planting strategy are determined by a set of variables describing both future climate conditions and co-evolving economic values including prices for timber and agricultural outputs as well as the social cost of carbon (SCC) (Tol, 2011). When making the planting decision, however, the future pathway of those co-evolving variables is not known with certainty. Our modelling framework captures that uncertainty by generating 4,000 different climate-economy realisations (CERs), where each CER describes one internally-consistent spatial and temporal pathway for those uncertain variables drawn from current empirical understanding of their possible distributions.

A key component of each CER is the assumed path of global emissions. Following standard practices in the climate sciences (van Vuuren et al., 2011) we use realisations of climate conditions that conform with a set of four Representative Concentration Pathways (RCPs) covering the broad range of predicted climate outcomes. We use the CHESS-SCAPE projections produced by the Centre for Ecology and Hydrology, which contains climate projections for four emissions pathways, and 4 members of the Regional Climate Model (RCM) ensemble for each emissions pathway. Each CER has an emissions pathway

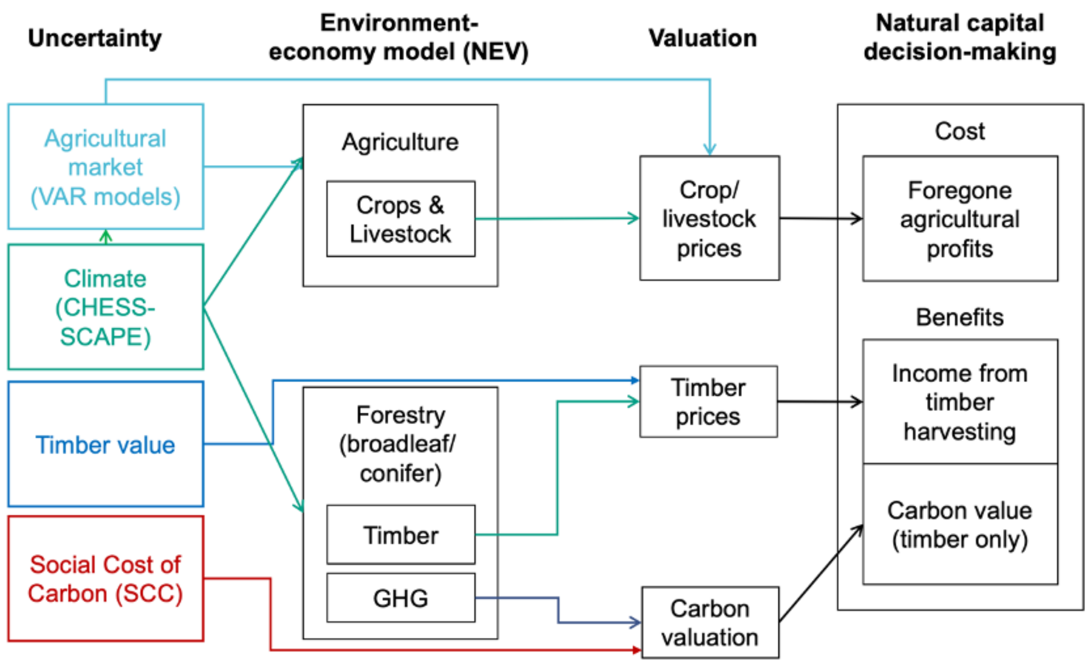

Figure 3.1: A flowchart representing the methodology used to quantify uncertainties in natural capital values produced by tree-planting activities.

and climate model member drawn independently with equal probability. Another key component of a CER is the assumed relationship between global temperature increases and loss in global economic productivity (also known as the "temperature-damage relationship") which directly influences the SCC. We draw the temperature-damage relationship from a probability distribution modelled in Howard and Sterner 2017. A CER also contain other variables that depend on climate and the temperature-damage relationship, primarily the SCC, agricultural commodity prices (wheat, potatoes, rapeseed oil, sugarbeet, cattle, sheep, and milk), and timber prices. A full description of how these variables were modelled from the climate and the temperature-damage relationship is given in the Supplementary Information.

Therefore, CERs differ widely in their predictions and outcomes even if they follow the same emissions pathway. For the purposes of illustrating key insights from our research, we selected three 'focus' CERs: a "Near Historic" (NH) realisation selected to typify the general features of the set of CERs drawn from RCP2.6; a "Moderate Emissions" (ME) realisation selected to typify the general features of the set of CERs drawn from RCP6.0; and "High Emissions" (HE) realisation selected to typify general features of CERs drawn from RCP8.5 (IIASA, 2010) (Figure 3.1).

Quantifying uncertainties in net benefits from tree planting activities. We modelled changes in natural capital from the planting of a representative conifer (Sitka spruce) and broadleaf (Pedunculate oak), in the arable land available in each grid cell. Cells where tree-planting activities lead to net emissions, for example through disturbance of soil organic carbon, were excluded.

Our analyses seek to identify which trees to plant and where to plant them in order to achieve the carbon sequestration target Q (12MtCO_2e per year). Since the rate at which trees sequester carbon differs from year to year as they grow over time, we take the yearly average carbon storage achieved over a single rotation period (where the rotation period is chosen to maximise timber revenues) to represent the annual sequestration services provided by growing trees. That quantity is calculated according to;

$$m_{ijs} = \frac{1}{T_{ijs}} \sum_{t=1}^{T_{ijs}} g_{ijst} \quad \forall\, i,\ j,\ s \tag{3.1}$$

where, m_{ijs} is the average annual carbon storage delivered by planting species j in cell i under the climate pathway described by CER s. T_{ijs} is the rotation period for that tree species in that cell and g_{ijst} is the marginal net storage of carbon in harvested wood products, deadwood and soil in each year t.

In achieving the sequestration target, choices on planting locations and tree species are made to maximise a monetary measure of social benefits. This measure encompasses net revenues from the planting and growing of trees for timber production (calculated using CER-specific timber prices), and the value of the carbon sequestered in trees (monetised using the CER-specific SCC). Additionally, it considers costs that comprise foregone profits from agricultural production on the land used to grow trees (calculated using CER-specific food prices).

In calculating the benefit flows that trees provide in timber and carbon sequestration, we again encounter the problem that their magnitudes differ markedly over time. The major cost of timber production, for example, is in the initial planting of trees while the primary revenues arise only once those trees are harvested at the end of the rotation. As such, we choose to represent those uneven flows in the form of an equivalent annual benefit flow using the annualisation of net present value (NPV) approach calculated over a full rotation. The annualised benefit flows from timber are calculated as;

$$r_{ijs}^{Timber} = \left(\sum_{t=1}^{T_{ijs}} \frac{b_{ijst} - c_{ijst}}{(1+\rho)^t} \right) \frac{\rho}{1-(1+\rho)^{-T_{ijs}}} \quad \forall\, i,\ j,\ s \tag{3.2}$$

where ρ is the discount rate and b_ijst and c_ijst are respectively the revenues and costs from timber production in year t. Similarly, the annualised benefit flows carbon sequestration this is calculated as

$$r_{ijs}^{CO_2} = \sum_{t=1}^{T_{ijs}} \frac{g_{ijst}\mathrm{SCC}_{st}}{(1+\rho)^t} \frac{\rho}{1-(1+\rho)^{-T_{ijs}}} \quad \forall\, i,\ j,\ s \tag{3.3}$$

where SCC_{st} is the social cost of carbon in year t along the SCC pathway dictated by CER s. To simplify, we analyse the problem as if all planting occurs in the current period and that the decision-maker adopts a 30-year planning horizon. The value of planting trees of species j in cell i under CER s, therefore, is given by the NPV;

$$R_{ijs} = \sum_{t=1}^{30} \frac{r_{ijs}^{Timber} + r_{ijs}^{CO_2} - r_{ijst}^{Farm}}{(1+\rho)^t} \quad \forall\, i,\ j,\ s \tag{3.4}$$

where r_{ijst}^{Farm} are the farm profits from cell i in year t that are foregone on account of using that agricultural land to plant trees. Optimisation problem. The policy-maker in the UK is confronted with the task of maximising the value function, V, that quantifies the NPV of their CDR strategy:

$$V(\mathbf{x}, z|s) := \sum_{i=1}^{N} \sum_{j=1}^{J} R_{ijs}x_{ij} + z \sum_{t=1}^{30} \frac{\mathrm{SCC}_{st} - \gamma}{(1+\rho)^t} \quad \forall\, s \tag{3.5}$$

This function has two elements; (a) the value of tree planting for CDR and (b) the value of CDR from an alternative riskless technology. The tree planting strategy is identified by the vector x, comprising elements, x_{ij}, which are binary decision variables identifying whether tree species j (from the J species in the analysis) is planted in cell i (from the N cells where planting could occur). Choices over deployment of the alternative CDR technology are given by z, a continuous variable identifying the quantity of that alternative technology (in units of $MtCO_2e$/yr) to include in the solution. Deploying the alternative technology delivers CDR services valued using the SCC at a cost of γ per $MtCO_2e$/yr which, because this technology is riskless, is constant across different CERs.

Choices over tree planting strategy and deployment of the alternative CDR technology must satisfy a series of constraints as follows:

$$\sum_{j=1}^{J} x_{ij} \leq 1 \quad \forall\, i \tag{3.6}$$

$$\frac{1}{S}\sum_{i=1}^{N}\sum_{j=1}^{J}\sum_{s=1}^{S} m_{ijs}x_{ij} + z \geq\; Q \tag{3.7}$$

$$x_{ij} \in [0,1] \qquad \forall\;\, i,\; j \tag{3.8}$$

These constraints ensure that;

- a cell can only be used as a location to grow trees once and, in our analysis, those trees can only be of one species (equation 3.6);
- the annual carbon sequestration target, Q, is met through the combination of the sequestration in planted trees, $m_i js$ (averaged across all CERs), and by the alternative CDR technology, z (equation 3.7);
- the planting strategy variables are binary (equation 3.8).

Since, the optimisation is constrained to deliver the target level of annual sequestration Q (equation 3.7), no matter how that delivery is apportioned between sequestration in trees and sequestration by the alternative technology, the value of CDR services remains approximately constant across all solutions of x and z.

Therefore, the least-cost strategy to meet the target level of annual sequestration can be found by maximising V':

$$V'\left(\mathbf{x}, z \middle|\; s\right) = \sum_{i=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{30}\left[\left(r_{ijs}^{Timber} - r_{ijst}^{Farm}\right)x_{ij} - z\gamma\right] \tag{3.9}$$

The principal difficulty in defining the least cost CDR strategy, however, is that s is not known; that is to say, that the environmental and economic conditions that will be faced in reality are unknown. As such, V is stochastic from the perspective of the decision-maker.

3.2.3 Scenario analyses

Our examination of a standard scenario analysis assumes that the carbon sequestration target is met by tree planting alone ($z = 0$). The problem is solved by assuming that some particular CER, s', is "true", and integer programming methods are used to find the tree planting strategy that maximises V:

$$x' = \arg\max_{x} V(\mathbf{x}, z = 0 | s = s') \tag{3.10}$$

Of course, the actual value delivered by a planting strategy depends not on the CER that is assumed by the decision-maker in choosing that strategy, but by the CER that is experienced in reality. To identify what that realised value might be, we take the tree-planting strategy x' that is optimal under CER s', and then evaluate V under an alternative CER, s":

$$V(\mathbf{x} = \mathbf{x}', z = 0 | s = s\prime\prime) \tag{3.11}$$

Figure 3.2j is constructed using this approach. Indeed, by repeating this calculation across the full range of possible CERs we are able to evaluate the full distribution of V for any given tree planting strategy.

Optimal tree-planting strategies under uncertainty. We use linear programming to identify optimal planting strategies under any particular CER to meet the UK target of sequestering 12MtCO_2e per year by 2050. In contrast to heuristic-based optimisation approaches that identify several solutions of unknown optimality, linear programming can identify a single solution to the optimisation problem with known optimality (Beyer et al., 2016). Our initial analyses consider the decision problem where the 12MtCO_2e p.a. target must be achieved through tree planting alone, subsequently we explore how decisions might change if that carbon sequestration target can be met with a mix of tree planting and deployment of a hypothetical riskless CDR technology.

Given the function V that estimates the NPV of tree planting strategy x under CER s, the problem of maximising the value of tree planting to society under an assumed climate-economy realisation s' can be written as:

$$\max_{\mathbf{x},z} V(\mathbf{x}, z \mid s = s') \tag{3.12}$$

Of course, the 'true' future climate-economy pathway is not known, such that from the point of view of a decision maker, a tree planting strategy is not characterised by one NPV but a distribution of NPVs defined across the range of possible CERs. Given that reality, a decision-maker might be better advised to choose a planting strategy whose distribution of outcomes under future possible realities has desirable properties. One possible objective is to identify a planting strategy that maximises the Expected Value (EV) of the distribution of outcomes. In that case, identifying the planting strategy that maximises Expected Value (P-EV) amounts to solving the following problem:

$$\max_{\mathbf{x},z} \ \mathrm{EV}(\mathbf{x},z) = \sum_{s=1}^{S} p(s)V(\mathbf{x},z|s) \tag{3.13}$$

Where p(s) is the probability CER s, which were constructed in such a way that we can assume each is equally likely to be a correct prediction of future conditions (i. e., $p(s) = 1/S \quad \forall s \in \{1,\ldots,S\}$).

Figures 3.2 and 3.3 report findings where no alternative CDR technology is available, therefore $z = 0$. In Figure 3, we allow the alternative CDR technology to form part of the portfolio of CDR technology, and solutions in Figure 3.4 are identified by iteratively solving for x and z for a range of values of γ.

Another possible objective is to choose a planting strategy that minimises the chances of undesirable outcomes, which we refer to as risk averse (RA) decision-making. In this work, we quantify this downside risk using Conditional Value-at-Risk (CVaR), also known as Expected Shortfall, a measure widely used in financial economics to quantify the risks associated with investment portfolios. The CVaR has been widely used as the standard for banks internationally as the recommended measure by the Basel Committee on Banking Supervision for quantifying risks and stress-testing in bank asset portfolios (Basel Committee, 2013). The CVaR measure quantifies the average value of "poor outcomes" given that "poor outcomes" are defined as those that are smaller than a specified quantile of the distribution of outcomes. In contrast to typical land-use optimisation applications that use variance as a measure of risk in land use (Ando and Mallory, 2012; Mallory and Ando, 2014; Beyer et al., 2018; Runting et al., 2018), CVaR satisfies the properties of "coherent" risk measures found to be desirable in financial economics (Artzner et al., 1999; Pflug, 2000; Acerbi and Tasche, 2002; Rockafellar and Uryasev, 2002). CVaR thus remains a robust measure of downside risk even when the distribution of outcomes is non-symmetrical (Sarykalin et al., 2008; Dunkel and Weber, 2012).

In this problem, we view realisations in V that are lower than a specified quantile in the distribution of V as "risky." The objective is to maximise the value of the realisations that are deemed as "poor outcomes" so that the value of tree-planting will still be relatively high in realisations that are worse than expected.

$$CVaR_\beta = -\mathbb{E}_{s\in S}\left[V(\mathbf{x},z \mid s) \mid V(\mathbf{x},z \mid s) \leq q_\beta\right] \tag{3.14}$$

$$q_\beta = \sup_{\alpha\in\mathbb{R}}\{\alpha \mid \Pr(V(\mathbf{x},z| s) \geq \alpha) \geq \beta\} \tag{3.15}$$

CVaR is the negative of the expected value of realisations in V that are lower than a quantile q_β, taken at the negative such that higher values of CVaR correspond to "riskier" outcomes. Here β is a parameter taking a value between 0 and 1 that indicates the probability of the value V being larger than q_β. For this analysis, the parameter β is specified as 90%, implying that q_β is the 0.1-quantile of the distribution of V and the undesirable outcomes are defined as the worst 10% of outcomes in the distribution.

As shown in Rockafellar and Uryasev 2000, the solution that minimises CVaR can be identified by minimising the choice variable α, allowing us to express the CVaR of V in terms of x and z:

$$CVaR_\beta(\mathbf{x},z) \;= \min_{\alpha} \alpha + \frac{1}{1-\beta}\sum_{s=1}^{S} p(s)\max(-V(\mathbf{x},z|s)-\alpha,0) \tag{3.16}$$

The optimal risk averse planting strategies, P-RA, is identified by minimising this CVaR metric, or in other words, maximising the negative of the CVaR.

$$\max_{\mathbf{x},z} \mathrm{RA}(\mathbf{x},z) = -\mathrm{CVaR}_\beta(\mathbf{x},z) \tag{3.17}$$

Like P-EV, P-RA is identified by setting z to 0 for Figures 1 and 2 and solved for different values of γ to optimise the objective function in Figure 3.

3.3 Results

Using a spatially-explicit integrated environment-economy model of the UK (Day et al., 2020) (more details in Appendix B), we estimated the net present value (NPV) of different tree planting strategies under 4,000 internally-consistent realisations of future climate and economic variables – each referred to as a climate-economy realisation (CER). Our NPV calculations capture three decision-critical components of the planting decision: the monetary value of the CDR services from planted trees; revenues from timber harvesting and the costs of foregone agricultural profits from land on which trees are planted. The generation of CERs from an integrated model is critical in establishing coherent pathways for that set of variables. We find, for example, that the climate arising under different emissions futures not only drives particular patterns in the uncertain returns to woodland and agriculture but also shapes the SCC, that is to say, the value society attributes to carbon-removal services.

Following a classic scenario analysis approach, we initially focus on three CERs selected from across the range of possible futures confronted by policymakers in Great Britain. Those three scenarios comprise a near-historic emissions (NH) CER, a medium-emissions (ME) CER and a high-emissions (HE) CER and are defined by the timepaths of climate and economic variables illustrated in Figure 3.2a-f. As per UK policy aspirations, we assume that decision makers wish to select a tree planting strategy that delivers carbon sequestration totalling 12MtCO_2e per year by 2050 (Climate Change Committee, 2020). A planting strategy consists of choosing where to plant trees and choosing which species to plant in each location where our analysis allows for a choice between broadleaf and coniferous trees. We use optimisation tools to identify the planting strategy that delivers the maximum value under each scenario. Those optimal planting strategies, labelled P-NH for the NH realisation, P-ME for the ME realisation and P-HE for the HE realisation, are plotted in the maps in Figure 3.2g-i.

Figure 3.2g-i clearly illustrates the fact that different future climate and economic conditions suggest drastically different optimal planting strategies to meet Net Zero commitments. Under NH conditions the value delivered by coniferous planting in less agriculturally-intensive northern and southwestern parts of the UK consistently outweigh the possible benefits produced by broadleaves (Fig. B.2c-d). As a result, the best planting strategy (P-NH) consists almost entirely of conifers (1% broadleaf). The policy recommendation is modestly changed under the ME realisation (70% broadleaf) and almost entirely reversed in the HE realisation (99% broadleaf). Under HE conditions, the natural capital benefits provided by broadleaf planting in agriculturally-productive southern parts of the country dominate the benefits offered by coniferous planting in most parts of the country. Our analysis underscores the central problem that policy makers face when presented with information from a scenario analysis: which tree planting strategy should they adopt when the best strategy differs markedly from scenario to scenario?

The potential deficiencies of choosing to pursue the planting strategy recommended under the assumption of some particular scenario for future conditions are illustrated in Figure 3.2j. We used our optimisation tools to identify the NPV-maximising planting

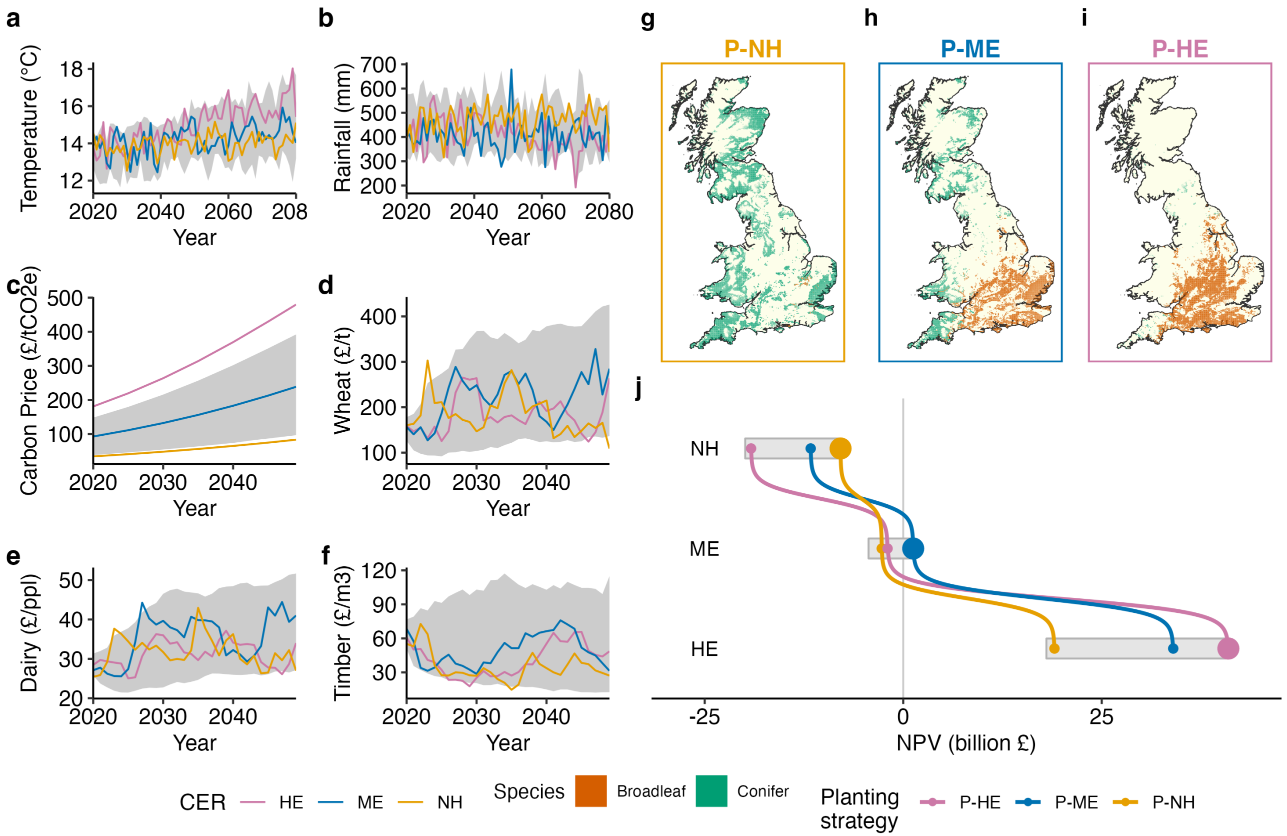

Figure 3.2: Natural capital outcomes of woodland planting and optimal planting strategy changes under alternative climate-economy realisations (CER). a-f describes the three focus CERs in terms of the changes of six key climate and economic variables: Carbon Price (Social Cost of Carbon, in tons of CO2-equivalent units), Dairy Prices (£/ppl), Wheat Prices (£/t), Timber Prices (£/m3), average Temperature (°C) and total Rainfall (mm) over the growing season (April to September), of the Near-Historic (NH), Moderate-Emissions (ME) and High-Emissions (HE) realisation. Shaded areas show 90% confidence intervals for each probability distribution. g-i, shows the planting maps of three illustrative planting strategies with corresponding species mix (percentages show percentage of broadleaves): Planting under Near-Historic (P-NH); Planting under Moderate Emissions (P-ME); and Planting under High Emissions (P-HE). j shows the range of natural capital values obtained by 4,000 planting strategies (shaded rectangles), each delivering the required 12MtCO_2e annual sequestration target, under (from top) the NH, ME and HE CER.

strategy to meet carbon sequestration targets under each of our 4,000 CERs. We then evaluated the NPV delivered by each of those 4,000 planting strategies under the NH, ME and HE realisations. The range of resulting NPV values are shown by the shaded grey bars in the Figure. Observe that the net benefits of all planting strategies tend to increase as we move from the NH to the ME to the HE realisation, a phenomenon primarily reflecting the greater value society attaches to carbon sequestration under higher-emissions futures.

By definition, the strategies P-NH, P-ME and P-HE are optimal under their respective CERs (e.g., the P-NH planting strategy is optimal under the NH realisation). Of course, if we were to pursue some planting strategy alternative to P-NH when conditions turn out to be NH, then UK society would realise a substantial opportunity cost. Pursuing the P-ME planting strategy under NH conditions results in a cost of £3.6 billion, whereas pursuing the P-HE planting strategy under NH conditions results in a cost of £13.0 billion. Of course, while P-NH is optimal under NH conditions it is sub-optimal under ME; indeed, the optimal P-ME satisfies the Net Zero carbon removal target while delivering £4.2 billion more in net benefits than does P-NH. Such differences are amplified when we move to the HE realisation where society places much greater value on carbon sequestration and a drying climate reduces farming profits in southern England, making broadleaf tree planting the preferred use of land in those locations (Fezzi et al., 2014; Ritchie et al., 2020). Under this HE CER, pursuing P-HE instead of P-NH can lead to planting that delivers £24.5 billion more value to UK society.

The central message of this analysis is that a planting strategy designed to deliver optimally for one CER does not necessarily deliver well if the future follows a different pathway. For instance, while the P-HE strategy delivers significant net benefits under the HE realisation, it is amongst the worst possible planting strategies under the NH realisation. Likewise, while the P-NH strategy is optimal under low (NH) emissions, it misses valuable opportunities to deliver cost-effective carbon sequestration under high emissions (e.g., HE).

Fig.3.3 develops an alternative way of visualising the outcomes associated with any given planting strategy, one that better aligns with the characterisation of uncertainty used in portfolio analysis. For each of our 4,000 CERs we can evaluate the costs and benefits associated with a particular planting strategy and describe our uncertainty over the returns that will be realised by that strategy as a probability distribution of NPVs.

Fig.3.3a provides box and whisker presentations of the NPV distributions for planting

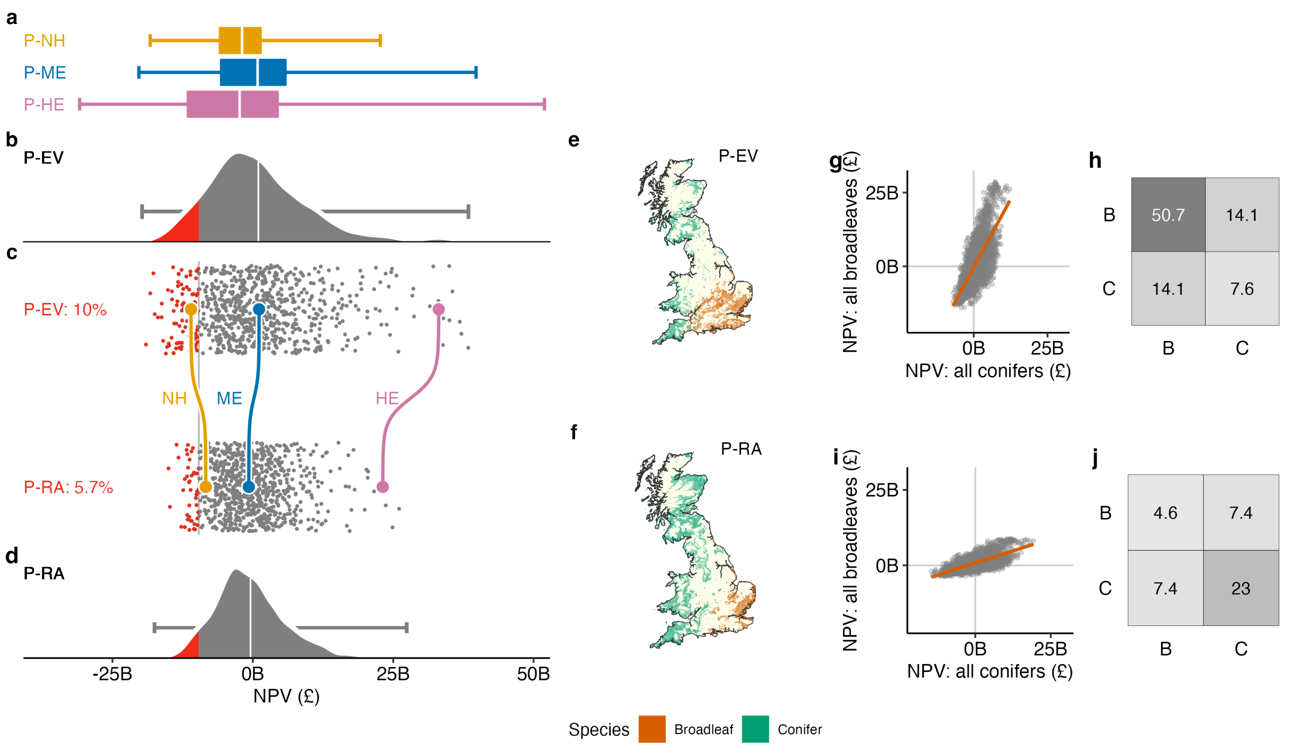

Figure 3.3: Risk-averse planting of diverse species reduces the chance of extreme losses. a, distribution of net present value (NPV) from 4,000 CERs under P-NH, P-ME and P-HE, showing minimum, 25th percentile, mean, 75th percentile and maximum value. b, distribution of monetised net benefits for 4,000 CERs under the P-EV strategy with the horizontal line denoting the minimum and maximum of the distribution and the red shading denoting a user-defined risk threshold (losses exceeding £10 billion) which is replicated in the lower panels of the Figure. c, shows a random subset of CERs and the corresponding net benefits achieved by the P-EV planting strategy (upper) and P-RA planting strategy (lower). CERs below the risk threshold (losses exceeding £10 billion) are again highlighted, and the probability of exceeding £10 billion losses shown. Outcomes of the P-EV and P-RA strategies under NH, ME and HE are highlighted by the coloured dots and lines joining the data points. d, distribution of monetised net benefits for 4,000 CERs under the P-RA strategy with the horizontal line denoting the minimum and maximum of the distribution, e-f, spatial distribution of conifer and broadleaf planting across Great Britain under strategies P-EV and P-RA, g. bivariate plot of the sum of NPV from all coniferous and all broadleaf planting in the P-EV strategy, h. the variance-covariance matrix of the bivariate plot in g, i, bivariate plot of the sum of NPV from all coniferous and all broadleaf planting in the P-RA strategy, and j, the variance-covariance matrix of the bivariate plot in i.

strategies P-NH, P-ME and P-HE. The wide distribution of NPV reveals the extent of risk underlying possible tree planting strategies. None of these three tree planting strategies can strictly deliver positive net benefits – all three have some chance of generating negative net benefits. Furthermore, no single planting strategy results in a distribution of outcomes that is consistently superior to others across all CERs. The P-NH strategy is the least variable of the three (-£18.3B to +£22.7B), the P-ME planting strategy results in the highest overall expected value (+£0.8B), while the P-HE strategy has the highest best-case outcome (+£51.9B).

To progress we must first understand the decision-makers' preferences for risk. Here we focus on two canonical risk preference positions: risk neutrality and risk aversion. A risk-neutral decision maker would wish to pursue the planting strategy with a NPV distribution that has the greatest expected value (see Equation 3.13). Following our labelling convention, we denote this the P-EV planting strategy. In contrast, a risk-averse decision maker might wish to minimise downside risk exposure, a goal which in this study is identified as selecting the planting strategy with a NPV distribution that has the minimum conditional value-at-risk (CVaR) (see Equation 3.16). We label this the P-RA planting strategy. We employ methods of optimisation under uncertainty originally developed for portfolio investment problems in financial applications to identify the planting strategies that best deliver to those two differing objectives.

Fig.3.3b details the NPV distribution arising from the P-EV planting strategy. By definition, this planting strategy produces a NPV distribution with the highest possible expected value, +£0.99B, a value which exceeds those resulting from the three planting strategies explored previously (P-NH: -£1.91B, P-ME: +£0.85B and P-HE: -£2.35B), or any other tree planting strategy within feasibility constraints. In focusing on expected value maximisation, however, the P-EV planting strategy ignores other characteristics of the NPV distribution, including the range of possible outcomes. All the same, Fig.3.3b reveals that the range of outcomes under P-EV is considerably more condensed than that associated with P-HE (Fig.3.3a), reducing worst-case NPV losses from -£30.8B to -£19.7B.

In contrast, the P-RA planting strategy is chosen to minimise downside risk. It achieves this by exploiting opportunities for risk diversification, choosing a portfolio of planting that ensures that under conditions where one species of tree planted in one set of locations delivers poor returns to society, some alternative set of trees is planted elsewhere which perform strongly. More technically, it chooses a planting strategy with a combination of planting sites that have jointly low covariance. If, for illustrative purposes, we define "poor outcomes" as losses exceeding £10B (red-shaded areas in Fig.3.3b-d), the P-RA planting strategy almost halves the incidence of poor outcomes, reducing the probability of getting such an event from 9% to 5%.

Yet, reducing risks comes with trade-offs. Choosing a portfolio of planting that minimises downside risk is achieved in part by forsaking the opportunity to plant trees in locations that, under some possible futures, deliver very significant social benefits. Indeed, best-case outcomes under P-RA are significantly lower than those achievable under P-EV.

Fig.3.3e and 3.3f present maps of planting locations chosen by the P-EV and P-RA planting strategies. From those, it is evident that both strategies comprise a mix of broadleaves planted in the south and east with conifers planted in the north, west and southwest, though P-EV locates substantially more broadleaves in southern regions than P-RA, which instead places more emphasis on conifer planting in northern regions. This change in planting strategy suggest that the emphasis placed on conifers over broadleaves in the P-RA strategy is important in delivering risk reduction. Further light is shed on that supposition in Fig.3.3g and 3.3i which summarise how the returns to broadleaf and conifer planting under the two strategies vary across the range of future conditions. Notice how under P-EV, widespread planting of broadleaves in the south leads to a very high dispersion of NPV outcomes for the broadleaf planting element of the planting strategy. The P-RA strategy achieves risk reduction by swapping some of the broadleaf planting locations most prone to delivering a high downside outcome, with coniferous planting. Dispersion in outcomes for broadleaf planting reduces substantially, though of course there is an offsetting but relatively less substantial increase in the dispersion of NPV outcomes across potential futures for coniferous planting (Fig.3.3i).

The P-RA planting strategy illustrates that the careful choice of species and location can reduce downside risk, but even with P-RA, variability in the returns to tree planting remains high. One of the central difficulties in reducing risk in this context lies in the high degree of covariance in returns across candidate planting sites and species. That covariance arises through the existence of key uncertainties such as climate and agricultural prices that tend to have the same directional impact on returns for all tree species in all locations. In other words, when conditions result in planting being relatively costly for one tree species in one location, they also tend to be relatively costly for other species in other locations, limiting the possibilities for hedging risks. The importance of 'global risk factors' in determining uncertainty over the benefits of portfolios of environmental interventions has been noted before in the context of risks to biodiversity conservation (Dunkel and Weber, 2012). In our tree planting problem, the phenomenon is illustrated in the covariance matrices in Fig 3.3h and 3.3j. These compare the returns arising from the broadleaf element of a planting strategy with that from the coniferous element across the range of possible future conditions. With the P-EV planting strategy (Fig 3.3h), the returns from broadleaves exhibits very high variance (50.1) and there is relatively high covariance between returns to broadleaf and conifers (14.1). Risk-reducing planting choices under the P-RA strategy results in a reduced variance for broadleaf planting (4.6) coupled with an offsetting but less substantial increase in the variance of returns for coniferous planting (23.0). Moreover, P-RA exploits hedging possibilities, the success of which is reflected in the halving of the covariance in returns between the broadleaf and conifer elements of the planting strategy (covariance is 14.1 under P-EV and 7.4 under P-RA). Even so, covariance remains high, suggesting that hedging only serves to diversify some of the risk associated with adopting tree planting as a CDR technology.

Given the limits to risk reduction possible within a CDR strategy that relies exclusively on tree planting, consideration should be given to the possibility of incorporating other CDR technologies in the portfolio of assets delivering CDR services. If the returns to an alternative technology are uncorrelated with the global factors that drive returns to tree planting, then that alternative may have an important role to play in defraying risks in the cost of achieving the decarbonisation target.

Fig. 3.4 explores this mixed-technology portfolio strategy. In this analysis we introduce the possibility of deploying an alternative CDR technology making the strongly-optimistic assumptions that this technology can deliver up to the target sequestration rates of 12MtCO_2e per year and that its cost risks are uncorrelated with the cost of tree planting. Now, our portfolio optimisation algorithms not only select the locations and species for tree planting but also the optimal mix of tree planting and deployment of the alternative CDR technology. As illustrated in Fig.3.4, the relative mix of the tree and riskless CDR technologies depends on two factors: how expensive the riskless CDR is, and whether the decision-maker is risk-averse.

Consider first a risk-neutral decision-maker. Their objective is to select the mix of tree planting and the alternative CDR technology to achieve the target sequestration rate

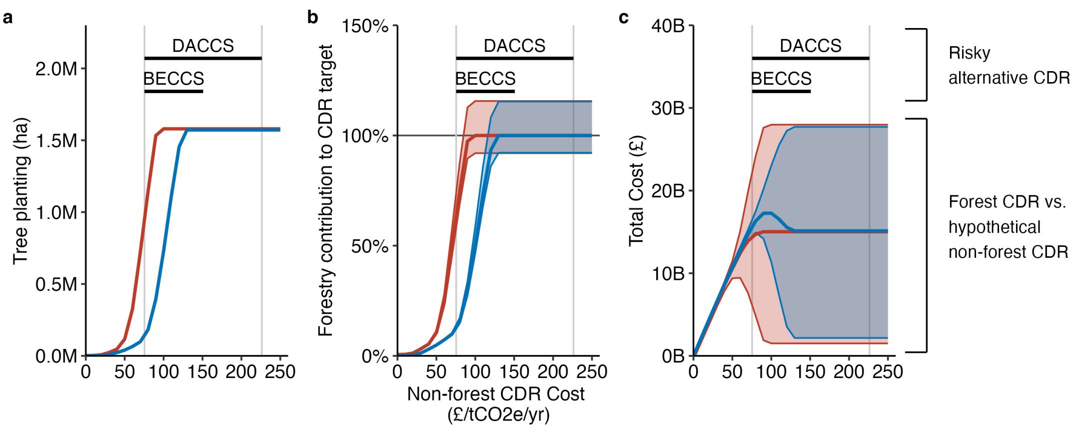

Figure 3.4: Tree planting remains a highly cost-effective approach to CDR compared to hypothetical risk-free alternatives. a, The number of hectares of trees planted by a risk-neutral (red line) or risk-averse (blue line) decision maker to meet the 12MtCO_2e/year sequestration target as the per tonne cost CO2 removal (in £2020/tCO_2e/year) of a hypothetical, risk-free, alternative CDR technology increases. b, The contribution of that tree planting to the carbon sequestration target of 12MtCO_2e/year. c, total costs of tree planting and the riskless CDR technology. Shaded areas show the full range of estimated carbon sequestration and costs from 4,000 modelled CERs, All plots also depict IPCC "medium confidence" cost estimates (in £2020/tCO_2e) for CDR using Bioenergy with Carbon Capture and Storage (BECCS) and Direct Air Carbon Capture and Storage (DACCS) technologies.

(12MtCO_2e/year) so as to maximise expected value. Fig.3.4 charts the outcome of such decisions across the range of possible costs associated with the riskless CDR technology, plotting the decisions of the risk-neutral decision maker in red. Fig.3.4a shows that if the riskless CDR technology is available at a cost of less than £50/tCO_2e, then the decision-maker would elect to pursue that in favour of tree planting. At higher costs for the alternative CDR technology, trees begin entering the optimal portfolio of a risk-neutral decision-maker. At a cost of £75/tCO_2e, that decision maker would be best served planting 0.1M hectares of trees, which deliver about 10% of the sequestration target as shown in Fig.3.4b. The advantage of the riskless CDR technology over risky tree planting quickly diminishes as it becomes more costly. At £100/tCO_2e, the optimal quantity of tree planting for the risk-neutral decision-maker increases to 1.5M hectares where 92%-115% (11.0 - 13.9 MtCO_2e/year) of the sequestration target will be met with tree planting (Fig.3.4c).

A risk-averse decision-maker (blue lines) chooses the risk-free CDR technology over tree planting until the former reaches a cost of around £75/tCO_2e after which they too add tree planting to their CDR portfolio. However, by the time the alternative technology costs

£130/tCO_2e or more, even a risk-averse decision-maker relies fully on tree planting to meet the 12MtCO_2e decarbonisation target.

Comparison with real world (i.e., risky) alternative CDR technologies is provided below Fig.3.4a-c which provides “medium confidence” cost estimates for Bioenergy Carbon Capture and Storage (BECCS) and Direct Air Carbon Capture and Storage (DACCS) as reported by the IPCC (5,46). Even at the lowest levels of these costs both the risk-neutral and risk-averse decision-maker would be advised to include tree planting within their CDR portfolios.

3.4 Discussion

Around the world substantial and time-critical CDR investments must be made so as to avoid the worst impacts of climate change. For many countries, tree planting is mooted as a critical component of that investment. But tree planting is not a riskless CDR technology. Record-breaking heatwaves in Europe in 2003 and 2018 saw widespread tree deaths with stem dehydration disproportionately impacting conifer species (Ciais et al., 2005; Salomón et al., 2022). In Sri Lanka a substantial portion of newly planted trees do not survive and are affected by inappropriate planting sites (Kodikara et al., 2017). In California (United States) the future possibility of wildfires or sudden oak death have been cited as key risks to investments in trees as carbon offsets (Badgley et al., 2022). Managing these risks through the careful development of risk-reducing planting strategies will determine the success with which tree planting contributes to decarbonisation.

As illustrated by our research, such planting strategies can be identified through the application of investment portfolio approaches. The portfolio approach has been shown to effectively reduce risk in a number of other land-use investment settings (Crowe and Parker, 2008; Ando and Mallory, 2012; Anderson et al., 2015; Knoke et al., 2015; Alvarez et al., 2017b; Liang et al., 2018; Runting et al., 2018; Eaton et al., 2019). Our work extends its application in two ways; first in applying it to the tree planting for decarbonisation problem and second by examining uncertainties relating to economic conditions as well as those relating to climatic conditions. We show that the cost risks of carbon removal through tree planting can be mitigated through selecting combinations of planting sites and species that limit downside risk. Adopting this risk-averse approach to planting in the UK would limit the risk of experiencing extreme losses (defined here as greater than

£10B) to just 5%.

Even with the adoption of risk-reducing planting portfolios, we find that the cost variability of tree planting in the UK remains relatively high. It proves difficult to hedge away the risks associated with tree planting because key drivers of uncertainty, particularly climate effects and the SCC, tend to impact the costs of planting similarly, irrespective of where planting takes place and which species is chosen in each location. Of course, our analysis only allows for choice between two species, selected on account of being the dominant coniferous (sitka spruce) and broadleaf (pedunculate oak) species in the UK's national forests (The Woodland Trust, 2021; Forest Research, 2022). It is possible, that expanding the planting portfolio to include a range of species (perhaps even those not in the current UK forest estate), each potentially better adapted to some particular future conditions, may open up new hedging opportunities increasing the resilience of delivery of CDR services from new forests under uncertain climatic and economic futures (Knoke et al., 2016; Mina et al., 2022). The portfolio approach demonstrated in our analysis provides the framework through which a decision-maker could be guided in choosing which, if any, of those tree species should be incorporated in that resilient planting portfolio.

The alternative risk-diversifying strategy examined in this paper is to expand the portfolio of CDR technologies beyond tree planting. As we show, even given the limited options for risk hedging through species and location choice, tree planting emerges as a low-regret option for CDR primarily on account of its relatively low costs. Indeed, tree planting forms part of the optimal CDR portfolio across the range of projected costs of alternative technologies such as BECCS and DACCS. Of course, the reason why those technologies exhibit such a wide potential cost range (see Fig.3.4) is because their implementation at the scales required has yet been demonstrated (Nemet et al., 2018; Fuss and Johnsson, 2021). As such, decision-makers face real uncertainty over the potential costs of these CDR technologies. Indeed, if one were to extend our work with an accurate characterisation of the cost uncertainty in those alternative CDR technologies, it is undoubtedly the case that tree planting would dominate the CDR portfolio for a risk-averse decision maker.

In such an analysis, a further reason to believe that tree planting will remain central to a resilient CDR investment strategy arises from possible correlation in the uncertain costs of tree planting and the uncertain costs of BECCS and DACCS. That correlation arises through land-use change. Like tree planting, BECCS makes large demands on land for the purposes of growing feedstock plants such as short rotation coppice willow or Miscanthus (Smith et al., 2016). DACCS, on the other hand, has a comparatively small land footprint but likely will require energy produced through expansion of renewable energy supply that need to be produced on land (National Research Council, 2015). Common demands on land-use resources suggest that when conditions lead to high (low) land costs all technologies are relatively more (less) costly driving correlated costs risks across CDR technologies. As such, the additional deployment of these alternative technologies may not necessarily deliver very significant risk reductions, lessening the value of their contribution to a low-risk CDR portfolio.

One further reason to favour tree planting over other CDR technologies is that forests provide a wide array of ecosystem services in addition to CDR services. Such benefit flows include those from flood mitigation (Nadal-Romero et al., 2016; Takata and Hanasaki, 2020), water quality enhancements (Duffy et al., 2020) and improvements to noise and air pollution (Ge et al., 2023). Indeed, a wider analysis might incorporate these effects into economic decision-making would likely change the optimal locations for tree planting but in a way that delivers overall increases in social value (Bateman et al., 2013; Burke et al., 2023). Following the lessons of this paper, such analyses should acknowledge that the flows and values of these additional ecosystem services are also subject to uncertainties (Polasky et al., 2011; Bateman and Mace, 2020).

While our analysis does much to support the strong presence of tree planting in CDR strategies, the prospect of technological change makes investment in alternative emerging CDR technologies worthy of consideration. Perhaps most importantly, early investments in those technologies could help resolve feasibility concerns and cost uncertainties (Rueda et al., 2021). Decision-makers are effectively buying uncertainty-reducing information and providing themselves with the option to expand investment if those trials establish that alternative technologies are capable of delivering CDR at scale and at reasonable cost (Way et al., 2019).

Even though our study characterises many of the central uncertainties in the tree planting decision, numerous further uncertainties exist. Our analysis, for example, does not consider the potential for technological change in agriculture that might alter the opportunity costs of land used for tree planting. Likewise, uncertainties exist over other side effects of national tree planting through its endogenous macroeconomic price effects (Kreidenweis et al., 2016). “Leakage” effects also attenuate the CDR potential of national afforestation initiatives if planting displaces agricultural activities and increases emissions overseas (Murray et al., 2004; Styles et al., 2018). Further, our study only models climate effects not those arising from weather. Indeed, weather-related extreme events such as wildfires, heatwaves and windfall have potentially severe impacts on forest CDR service flows (Albers et al., 2016; Cunniffe et al., 2016; Hasegawa et al., 2021; Badgley et al., 2022), and their frequency and scale are highly uncertain in a changing climate (Stott, 2016; Kirchmeier-Young et al., 2019).

Notwithstanding the numerous potential avenues for expanding our analysis, our study demonstrates the effective integration of cutting-edge environment-economy modelling with modern methods of risk-averse optimization. This integration is able to provide detailed guidance to policy-makers when faced with complex environmental decisions confounded by pervasive climatic and economic uncertainties. In our UK case study, for example, we are able to identify tree-planting strategies that diversify risks and limit exposure to downside cost outcomes. Moreover, we are able to establish that, despite uncertainties over the net benefits arising from new forests, a carefully constructed portfolio of tree planting remains an indispensable component of a robust decarbonisation strategy.

Chapter 4

Flexible climate adaptation can halve conservation costs while mitigating risks

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Abstract

Climate change is expected to have profound and unexpected impacts on biodiversity in the future. These impacts could potentially be mitigated through adaptive and responsive conservation planning, but it remains unclear how adaptation opportunities can be harnessed through careful planning of present-day activities. Here, we show that the use of flexible conservation strategies that exploit opportunities for climate adaptation can mitigate climate risks without increasing total conservation costs. We estimate the value of allowing flexible delays of conservation investments for protecting habitats of the iconic and threatened koala (*Phascolarctos cinereus*) in eastern Australia. We find conservation strategies that have no option to strategically delay investments face significant trade-offs between minimising conservation costs and reducing risks in conservation outcomes. These trade-offs are substantially mitigated by flexible strategies that strategically delay investments into the future when the effects of climate change are likely to be better understood. In fact, we show that these delays could mitigate climate risks in inflexible conservation strategies without even increasing conservation costs. These results show that conservation planning that strategically allocates present-day conservation resources while also allowing

the flexibility to shift these resources in the future is much more likely to achieve cost-effective conservation outcomes in the face of uncertain climate change impacts.

4.1 Introduction

Climate change is profoundly restructuring ecological dynamics and ecosystems (Hanson et al., 2020; Pinsky et al., 2018; Scheffers and Pecl, 2019). Targets to secure biodiversity, such as the United Nations Convention on Biological Diversity's Global Biodiversity Framework's target to protect 30% of the Earth's ecosystems by 2030, must account for climate change if reaching these targets are to effectively secure biodiversity in the long term (CBD, 2018, 2022). Achieving these goals requires strategic targeting of conservation investments across space (CBD, 2022), often informed by systematic conservation planning, a structured decision-support process to identify cost-effective conservation investments (Margules and Pressey, 2000). Yet, uncertainties over how climate change will impact conservation outcomes compromises this task (Ando and Mallory, 2012; Drechsler, 2020a; Scheffers and Pecl, 2019). Conservation planning strategies that are fixed in time (e.g. Beyer et al., 2018; Jung et al., 2021; Strassburg et al., 2020) could fail to achieve their objectives if those plans cannot continually adapt to ongoing climate change. We therefore urgently need conservation planning strategies that deal explicitly with climate risks to ensure positive outcomes for biodiversity (Dobrowski et al., 2021).

Climate risks to conservation success could be mitigated through strategic flexibility, the act of planning present-day activities that keep future options open for responding to uncertain events (Rhodes et al., 2022). One way strategic flexibility can help reduce climate risks in conservation outcomes is through strategically-delaying investments into the future. In economics, the theory of option value allows decision-makers to make better decisions by helping them decide whether to invest now or delay decision-making and only commit to irreversible decisions when uncertainties are resolved (Dixit and Pindyck, 1994). Because biodiversity projections used to inform planning are highly sensitive to the uncertain trajectory of future climate change (Buisson et al., 2010; Reside et al., 2018; Thuiller et al., 2019), strategic delays could be one approach to keeping conservation agencies' options open, enabling them to adapt actions as new information about climate and ecological systems emerges (Drechsler, 2020b; Drechsler et al., 2021; Rhodes et al., 2022).

Private land conservation presents an opportunity to plan conservation flexibly in response to climate risks. A common way to conserve biodiversity on private land is through voluntary conservation covenants or easements (Adams and Moon, 2013; Rissman et al., 2007). These are usually legal agreements between a conservation agency and private landholders that restrict land clearing or promote other conservation actions (Fitzsimons, 2015). In many cases, these agreements are incentivised through payments to landholders to offset opportunity costs or support management actions that incur costs (Iftekhar et al., 2014; Selinske et al., 2022). Although a majority of conservation organisations view climate change as a risk to conservation, few conservation agreements include provisions for flexible adaptation under climate change (Rissman et al., 2015), underscoring a critical gap in the existing practice of private land conservation. Because conservation covenants enable organisations to flexibly choose when to create conservation covenants, it represents an opportunity for conservation organisations to implement conservation actions that are flexible under climate change.

Here, we develop a strategically-flexible planning framework and apply it to a case study in New South Wales (NSW), Australia to identify private properties for the conservation of the endemic koala (*Phascolarctos cinereus*). The koala is a charismatic species that has experienced dramatic population declines in eastern Australia and where its conservation on private land is critical, with 77% of the population occurring on private land (DAWE, 2022a,b; Kearney et al., 2022; Williams et al., 2023b). Habitat loss and human-caused mortality continues to be the biggest existing threats to koalas (McAlpine et al., 2015). However, climate change is an emerging threat to koalas (Lunney et al., 2012; Phillips et al., 2021; Ward et al., 2020), emphasising the need for effective climate adaptation measures.

We examine four hypothetical conservation planning strategies that do not represent official policy, to quantify the potential outcomes of strategically-flexible conservation. We assume that a decision-maker plans investments in covenants on private land to meet a conservation target for koala habitat protection for all years up to 2070 (Figure 1). Two of our strategies are inflexible over time, where decision-makers can only make investments in a first time-period (2020-2049): (i) "Inflexible - Ignore Risk," in which the decision-maker assumes koala habitat conditions (to 2070) will follow average predictions under climate change (thus ignoring the risk that climate outcomes may differ from the average prediction), and (ii) "Inflexible - Robust," in which the decision-maker again accounts for the effect of climate change (to 2070), but the target is met in all projected climate scenarios. Two of our strategies are flexible over time, where the decision-maker in the first time-period is also presented with an option to delay funding to the start of a second time-period (2050-2070). We assume that while the decision-maker can only act while knowing several possible outcomes in the first time-period, in the future the decision-maker can act based on observations of these outcomes. The two flexible strategies we considered are: (i) "Flexible," where the decision-maker in the second time-period still faces uncertainty over the true climate scenarios between 2050-2070, and (ii) "Flexible & Learning," where the decision-maker in the second time-period has resolved climate uncertainty and knows the true climate scenario between 2050-2070. By comparing between inflexible and flexible strategies, we provide important insights on how flexible strategies can help conservation agencies achieve more cost-effective plans and illustrate how this can be achieved.

4.2 Methods

4.2.1 Case study

Koala populations in the eastern Australian states of New South Wales (NSW) and Queensland (QLD) have experienced considerable declines leading to the koala being listed as Vulnerable under NSW and Queensland and uplisted to Endangered in 2022 (DAWE, 2022a,b). As part of the 2022 NSW Koala Strategy, the government pledged to double koala populations by 2050 through an investment of more than AUD $190 million through concerted conservation actions with an ambition of protecting a total of 100,000 hectares of koala habitat by 2050 (DPE, 2022). However, a large proportion of the destruction of koala habitat occurs on private land (land outside protected areas) meaning that the protection of koala habitat on private land is of utmost importance to reversing koala population declines (Williams et al., 2023b). We developed a systematic conservation planning approach to address this conservation problem while accounting for risk of future climate change.

The study area (depicted in Figure 4.1) covers an area of 323241km^2 across 106 Local Government Areas (LGA) in the state of New South Wales in Australia. These regions cover a large majority of the range of the koala in the state and contains areas that have been studied extensively through habitat mapping and formal planning instruments (Lunney

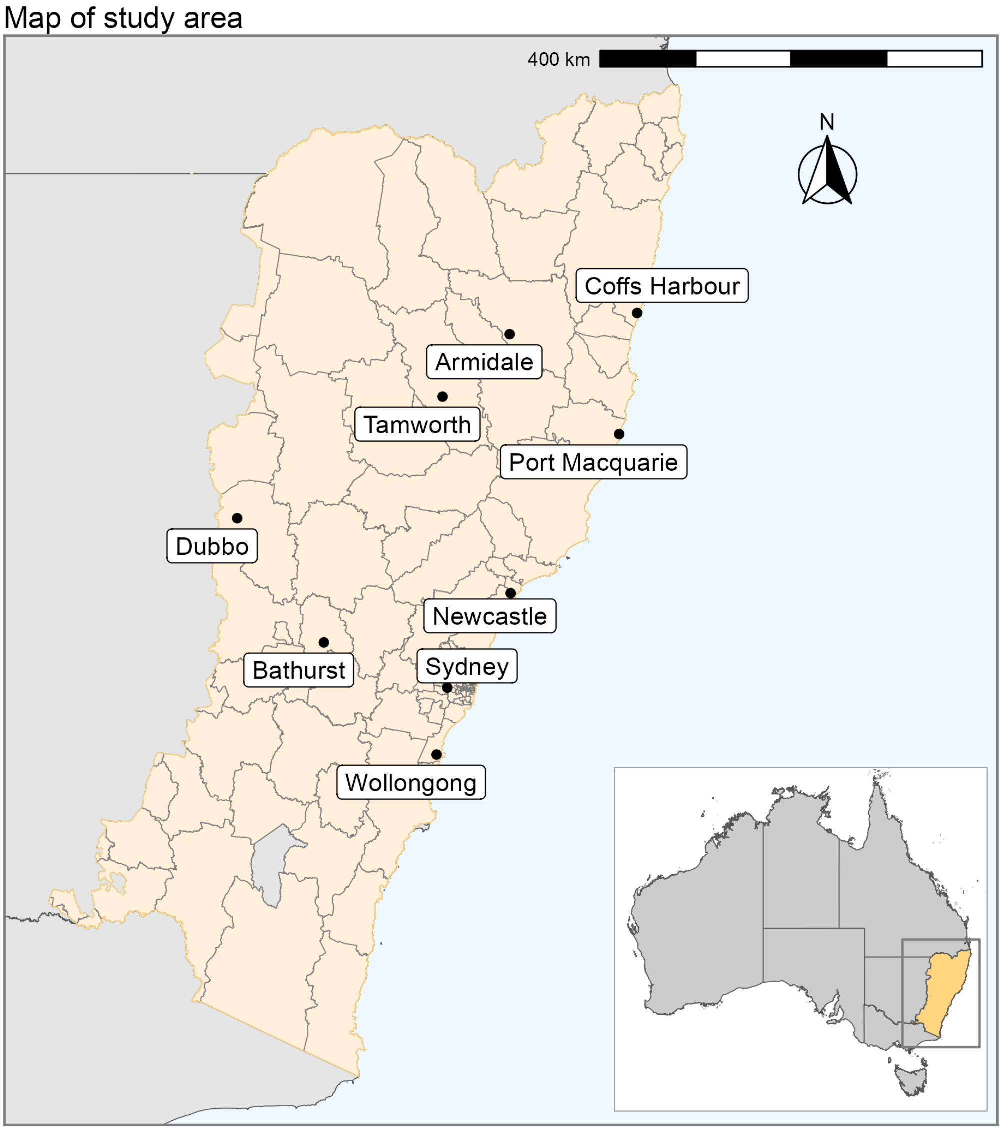

Figure 4.1: Map of the study area (orange) in New South Wales, Australia

et al., 2000, 2016). The NSW Koala Strategy outlines that outside of newly-created protected areas acquired through property purchases, 7,000 hectares of koala habitat will be protected on private land through a combination of compensated covenants offered to private landholders and unfunded voluntary conservation covenants (DPE, 2022).

We describe the planning problem in detail in the section 4.2.2, describing strategies to solve this problem that are inflexible and flexible over time. Strategies that solve the conservation planning problem depends on whether landholders voluntarily bid to participate in conservation covenants. Here we simulate landholders' hypothetical participation in bidding for conservation covenants in section 4.2.3, where their participation is simulated from a statistical model of landholder preferences (Williams et al., 2023a). Solutions to the conservation planning problem then chooses, from within the group of bids received, which bid are awarded contracts for conservation covenants. The conservation planning problem is thus confounded by uncertainty over the quality of koala habitats in candidate sites, which are affected by climate change. To address this problem, we use a species distribution model based on the Rapid Evaluation of Metapopulation Persistence (REMP) approach for modelling koala metapopulation persistence that quantifies the landscape capacity of habitats used as a proxy for the quality of koala habitats (Taylor et al., 2016; Drielsma and Love, 2021), described in further detail in section 4.2.4. The last section 4.2.5 illustrates how land clearing risks are modelled and incorporated into the model that reflects the possibility of conservation opportunities that could be missed if not acted upon immediately.

4.2.2 Systematic conservation planning problem

We consider a conservation problem in NSW where a hypothetical public conservation agency (subsequently referred to as a "decision-maker") solicits bids from private landholders across the state requesting them to submit bids for conservation covenants. When a landholder places a bid, they specify the annual amount of compensation and the proportion of the property they are willing to place under the covenant (see section (c) for a description of the models used to estimate these quantities). The decision-maker then needs to decide which bids are awarded contracts for conservation covenants in perpetuity. The decision-makers aim to meet a predefined policy target to protect a specified amount of koala habitat by the end of the time-period (2070). We used the policy target of protecting 7,000 hectares of koala habitat in the main results presented but find consistent support for the findings of this paper across a range of policy targets (Figure 4.6). The objective of the decision-maker is to meet the target while minimising the total expected cost.

We characterise the problem faced by the decision-maker by being explicit that decisions need to be made without complete certainty of the full extent of climate change impacts. Primarily, the decision-maker is uncertain about whether the land placed under protection will continue to meet the criterion needed for the protected koala habitat to be counted towards the policy objective or cease to meet this criterion. Whether or not land placed under protection will meet this criterion depends on climate change. The decision-maker's information set consists of a set of different plausible climate projections and the decision-maker is uncertain over which one will prove to be true. For the purposes of this study, we assume one of the projections will prove to be correct by 2070.

The objective of these covenants are to minimise the total cost of offering in-perpetuity covenants to landholders to protect koala habitat without perfect information about future koala habitat quality under climate change. Two of these strategies ("Inflexible - Ignore Risks" and "Inflexible - Robust") are inflexible in time, where in-perpetuity covenants cannot be added after the first time-period. The other two strategies ("Flexible" and "Flexible & Learning") are flexible in time and allow new in-perpetuity covenants to be added in 2050. Here, we do not consider reversible protection mechanisms, such as fixed-term covenant agreements.

We model the decision problem to achieve the conservation goal by using the following steps:

1. Invitations – The decision-maker selects a subset of properties to invite tenders for covenants. We assume that the decision-maker selects 10% of the available properties in the study area through a stratified sampling approach from the full list of properties and invites them to bid for an in-perpetuity covenant.

2. Bidding - Landholders are invited to submit a bid for a covenant (as would be the case in tender or reverse-auction mechanisms). The decision-maker notes the payment required (annual payment per hectare) and the proportion of the property that the landholder is willing to put on the in-perpetuity covenant. The bids and proportion of the property are simulated using a landholder preference model for the study area (Williams et al., 2023a)

3. Determine winning bids (first time-period – 2020) – the decision-maker has two options for each property.

    - Conserve now – sign an in-perpetuity covenant contract immediately. In this case we assume land clearing is prevented but koala habitat quality is still susceptible to climate change. Aside from prevention of land clearing, it is assumed that no activities are undertaken to counteract the effects of climate change on koala habitat after the signing of the covenant. The landholder is assumed to accept the covenant at the payment and proportion of the property defined in the bid.

- No conservation – no cost is incurred. The land could potentially be cleared in the future, but even if it remains uncleared, the koala habitat within the property with a declined tender bid does not count towards the conservation objective.

4. Determine winning bids (second time-period – 2050) – in the case of flexible strategies, budget deferred to the second time-period can be spent by future decision-makers in 2050. These future decision-makers decides whether to sign a contract with properties starting at 2050 without a conservation covenant in the first time-period. Some properties that put in a bid in the first time-period could clear the land making it no longer suitable for conservation in the second time-period. An assumption we make for model tractability is that landholders' willingness to accept a covenant and its cost stays the same across the two time-periods. Therefore, the properties without a conservation contract in the first time-period will be in one of three states:

    - No conservation pursued – either that conservation no longer possible in the second time-period due to land clearing, or conservation is not pursued in the second time-period by the future decision-makers' choice.
    - Conserve in the second time-period – sign an in-perpetuity covenant, preventing any land clearing from the start of the second time-period.

We considered four conservation strategies that employ increasingly sophisticated approaches for dealing with uncertainty in climate change and future land clearing. Specifically, the decision-maker is confronted with three sources of uncertainties which we refer to as "replicates", "scenarios" and "futures" to indicate different sources of uncertainty, as follows:

- Landholder bid *replicate*: whether the landholder puts in a bid, the minimum financial compensation for the landholder to accept a covenant contract, and the proportion of the property on the contract bid. The bid replicate is assumed known to the decision-maker before making a decision in the first time-period (2020), so the decision-maker can plan according to these bids.

- Climate *scenario*: the decision-maker knows a range of possible scenarios (uncertain) but does not know which exact scenario will transpire. The prediction of future

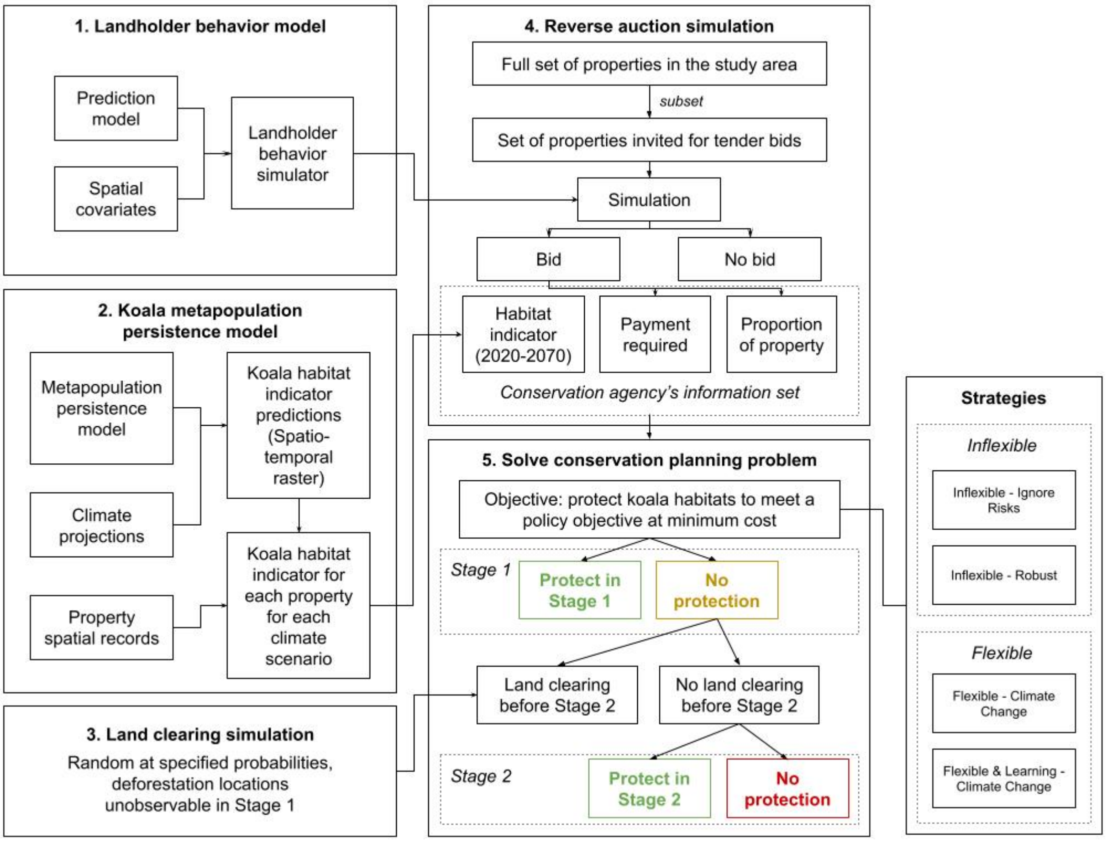

Figure 4.2: Conceptual diagram of the planning framework

climate is always uncertain in the first time-period. In the second time-period, the decision-maker may still be uncertain over the range of scenarios ("Inflexible" and "Flexible" case), or may observe which scenario is "true" in the second time-period so that all uncertainty is resolved by 2050 ("Flexible & Learning" case). This may enable the decision-maker to be more precise when spatially-targeting covenant contracts awarded.

- Land clearing *future*: the extent of land clearing by the start of the second time-period for land not protected by a covenant contract in the first time-period. The land clearing future (which properties will be cleared) is unobservable in the first time-period but always known with certainty in the second time-period.

Below we describe the conservation planning problem in mathematical detail. The cost incurred to support payments towards an in-perpetuity covenant starting at year θ is as follows:

$$C_{ij}(\theta) = \sum_{t=\theta}^{\infty} c_{ij}\Big(\frac{1}{1+r}\Big)^{t-1} = \Big(\frac{c_{ij}}{r}\Big)\Big(\frac{1}{1+r}\Big)^{\theta-1} \tag{4.1}$$

Where C is the present value of a perpetual annuity payment to property $i \in \mathcal{N}$ in the population N for bid replicate $j \in J$ starting at the year , c being the amount of annual payment, t being an indicator for the year and r being the discount rate. Payments are assumed to be made in the beginning of each time-period, therefore those payments in year t is discounted by $t-1$. The discount rate r discounts the value of payments made in the future relative to that in the present. Assuming that the annual payments stay constant across time-periods, the earlier the perpetual payment is started, the more it costs the decision-maker viewed at present.

The set of landholders putting forward bids in such an exercise is stochastic and simulated from the bid probability estimates modelled for the study region (Williams et al., 2023a). For the $j = 1,...,J$ replicates of the simulations from the bid probability estimates, we obtain $N_j \in \mathcal{N} \quad \forall j = 1,...,J$, where N_j is a subset of properties from the full set N.

For each iteration, the decision-maker then solves for the optimal choice of properties to choose from within the set of properties that put forward a bid in the iteration j. The optimal choice of properties were identified using a linear programming approach. The inflexible strategies are formulated as linear programmes, whereas the flexible strategies are solved as Two-stage Linear Programme with Fixed Recourse, originating from Dantzig and Beale (Beale, 1955; Dantzig, 1955). The optimal strategies are identified using stochastic programming written in Julia and the JuMP algebraic modelling language (Lubin et al., 2023) and solved using Gurobi 10.0.

"Inflexible - Ignore Risk" strategy

The "Inflexible - Ignore Risk" strategy is identified by minimising the following objective function subject to constraints, for each of $j = 1,...,J$:

$$\min_{x_{ij}} \sum_{i \in N_j} C_{ij}(\theta = 1)x_{ij} \tag{4.2}$$

$$\text{s.t.} \quad \mathbb{E}_{s\in\{1,...,S\}}\Big[\sum_{i \in N_j} m_{ijs}(\theta = t)x_{ij}\Big] \geq G, \qquad t = 1,...,T, \tag{4.3}$$

$$x_{ij} \in [0,1], \qquad i \in N_j. \tag{4.4}$$

Where x_{ij} is a binary decision variable of whether the bid from property i in replicate j is awarded a contract in the first year, which is the only time when the decision-maker can put new covenant contracts in, m_{ijs} is the area of the koala habitat in property i in replicate j (see Methods section c for details), climate scenario $s \in 1,...,S$ and year θ, and G is the policy target. The equation 4.2 models the total cost of initiating perpetual conservation covenants in the first year across all properties, and the second constraint equation 4.3 ensures that the total amount of koala habitat under protection (summed across all properties, averaged across climate scenarios) in all years up to 2070 reaches the policy target G.

"Inflexible - Robust" strategy

The "Inflexible - Robust" strategy is identified by minimising the same objective function as for "Inflexible - Ignore Risk" but under tighter constraints, for each of $j = 1,...,J$, as follows:

$$\min_{x_{ij}} \sum_{i \in N_j} C_{ij}(\theta = 1)x_{ij} \tag{4.5}$$

$$\text{s.t.} \quad \sum_{i \in N_j} m_{ijs}(\theta = t)x_{ij} \geq G, \qquad t = 1,...,T, \quad s = 1,...,S, \tag{4.6}$$

$$x_{ij} \in [0,1], \qquad i \in N_j \tag{4.7}$$

Where the constraint enforces that the policy target G must be met across all years $t = 1,...,T$ and all climate scenarios $s = 1,...,S$ in the analysis. This constraint ensures that the policy target is met irrespective of which climate scenario turns out to be "true."

"Flexible" strategy

The "Flexible" strategy is identified by solving the following optimisation problem for each of $j = 1,...,J$:

$$\min_{x_{ij}} \sum_{i \in N_j} C_{ij}(\theta = 1)x_{ij} + \mathbb{E}_k\Big[\min_{y_{ijk}} \sum_{i \in N_j} C_{ij}(\theta = t')y_{ijk}\Big] \tag{4.8}$$

$$\text{s.t.} \quad \sum_{i \in N_j} m_{ijs}(\theta = t)x_{ij} \geq G, \qquad t = 1, ..., (t'-1), \quad s = 1, ..., S, \tag{4.9}$$

$$\sum_{i \in N_j} m_{ijs}(\theta = t)(x_{ij} + y_{ijk}) \geq G, \qquad t = t', ..., T, \quad s = 1, ..., S, \quad k = 1, ..., K, \tag{4.10}$$

$$x_{ij} + y_{ijk} \leq 1, \qquad i \in N_j, \quad k = 1, ..., K, \tag{4.11}$$

$$y_{ijk} \leq \tau_{ik}, \qquad i \in N_j, \quad k = 1, ..., K, \tag{4.12}$$

$$x_{ij}, y_{ijk} \in [0, 1], \qquad i \in N_j, \quad k = 1, ..., K. \tag{4.13}$$

Here, we introduce another decision variable y_{ijk} that denotes the set of properties that are offered a covenant at time t' (the second time-period) subject to the land clearing future $k = 1, ..., K$. The objective function is now the sum of the cost incurred for properties protected in the first time-period and the cost incurred for properties protected in the second time-period for each land clearing future, with the decision-maker solving a cost minimisation problem after observing land clearing patterns. The constraint equation 4.9 ensures that the set of properties protected before the second time-period reaches the policy target across all climate scenarios for the time-steps before the start of the second time-period. The constraint 4.10 ensures that the combined set of properties protected by the second time-period (x and y) reaches the policy target, across all climate scenarios and land clearing futures, for all the time-steps in the second time-period. The constraint 4.11 ensures that a property that was selected in the first time-period for a covenant cannot be selected again in the second time-period. The constraint 4.12 ensures that covenant protection in the second time-period is no longer possible if τ_{ik}, a binary variable of indicating whether property i has been cleared in the absence of protection, is zero, ensuring that properties that are cleared during the first time-period ($\tau_{ik} = 0$) cannot participate in a covenant in the second time-period. The constraint equation 4.13 enforces the decision variables x and y to be binary variables.

“Flexible & Learning” strategy

The “Flexible & Learning” strategy is identified by solving the following problem, solved for j=1,...,J:

$$\min_{x_{ij}} \sum_{i \in N_j} C_{ij}(\theta = 1)x_{ij} + \mathbb{E}_{k,s}\left[\min_{y_{ijks}} \sum_{i \in N_j} C_{ij}(\theta = t')y_{ijks}\right] \tag{4.14}$$

$$\text{s.t.} \quad \sum_{i \in N_j} m_{ijs}(\theta = t)x_{ij} \geq G, \qquad t = 1, ..., (t'-1), \quad s = 1, ..., S, \tag{4.15}$$

$$\sum_{i \in N_j} m_{ijs}(\theta = t)(x_{ij} + y_{ijks}) \geq G, \qquad t = t', ..., T, \quad s = 1, ..., S, \quad k = 1, ..., K, \tag{4.16}$$

$$x_{ij} + y_{ijks} \leq 1, \qquad i \in N_j, \quad k = 1, ..., K, \quad s = 1, ..., S, \tag{4.17}$$

$$y_{ijks} \leq \tau_{ik}, \qquad i \in N_j, \quad k = 1, ..., K, \quad s = 1, ..., S, \tag{4.18}$$

$$x_{ij}, y_{ijks} \in [0, 1], \qquad i \in N_j, \quad k = 1, ..., K, \quad s = 1, ..., S. \tag{4.19}$$

The constraints in this strategy is largely similar to the “Flexible” strategy other than one key exception that parameterises the “Learning” component in this strategy. The key difference is that in this strategy, the climate scenario is known by the second time-period, therefore covenants to protect land in the second time-period are formulated with that knowledge. Learning of climate scenarios is parameterised with the inclusion of the index s in the decision variable y_{ijks} in the “Flexible & Learning” strategy. In the “Flexible” strategy, learning is absent, thus the climate scenario is still not known by the second time-period, meaning that y has to be chosen to meet the policy goal across all climate scenarios $s = 1, ..., S$ to ensure that the policy goal is still met irrespective of which climate scenario are eventually realised. In contrast, the inclusion of the index s in the decision variable y in the “Flexible & Learning” strategy implies that by the start of the second time-period, the decision-maker knows which climate scenario is realised and therefore can select y using such knowledge. This ensures that covenants in the second time-period are only given if the decision-maker knows the climate scenario makes the habitat for that property suitable for conservation, thus less budget is spent on properties that turns out to not contain habitat of sufficient quality for conservation.

Quantifying the value of flexible planning strategies

We found the optimal strategies for different bid replicates for $J = 100$ times to propagate the uncertainty across different sets of bids. The total cost of the strategies can be calculated for bid replicate j, land clearing future k and climate scenario s, as follows:

$$\Gamma(\mathbf{x}_j, \mathbf{y}_{jks} \mid j,k,s) = \sum_{i \in N_j} C_{ij}(\theta = 1)x_{ij} + \sum_{i \in N_j} C_{ij}(\theta = t')y_{ijks}, \quad j = 1,...,J, \quad k = 1,...,K, \quad s = 1,...,S. \tag{4.20}$$

Where $\mathbf{x}$ and $\mathbf{y}$ are vectors of binary variables of whether properties $i = 1,...,N_j \quad \forall j = 1,...,J$ are protected by covenants. The values of Γ were propagated across j,k and s to get a distribution of conservation costs depicted in Figure 4.3.

Likewise, the ecological outcomes can be calculated as a habitat quality metric as follows:

$$M(\mathbf{x}_j, \mathbf{y}_{jks}|t,j,k,s) = \begin{cases} \sum_{i \in N_j} m_{ijs}(\theta = t)x_{ij}, & \text{if } t < t' \\ \sum_{i \in N_j} m_{ijs}(\theta = t)(x_{ij} + y_{ijks}), & \text{otherwise} \end{cases} \tag{4.21}$$

This habitat quality metric was used to quantify the amount of quality koala habitat protected by the covenant programme depicted in Figure 4.3a. This habitat quality metric calculates the total area of properties that are considered high-quality koala habitat (see Methods Section 4.2.4) and protected through a conservation covenant, and is the metric that is used to evaluate whether a conservation strategy meets the policy goal.

The metric of cost reduction of “Flexible” and “Flexible & Learning” strategies we used is the percentage difference in conservation cost between the strategy and the “Inflexible - Robust” strategy. The conservation cost of the “Inflexible - Robust” strategy was chosen as a reference point as opposed to that of the “Inflexible - Ignore Risk” because it does not meet the same conservation goals (robustly across time and climate scenarios) as all the other strategies.

This percentage difference is computed as as follows:

$$\Delta\Gamma(\mathbf{x}_j^*, \mathbf{y}_{jks}^* \mid j,k,s) = \frac{\Gamma(\mathbf{x}_j^*, \mathbf{y}_{jks}^* \mid j,k,s) - \Gamma(\mathbf{x}_j^{'}, \mathbf{0}_{N_j} \mid j,k,s)}{\Gamma(\mathbf{x}_j^{'}, \mathbf{0}_{N_j} \mid j,k,s)} \quad j = 1,...,J, \quad k = 1,...,K, \quad s = 1,...,S \tag{4.22}$$

Where $\mathbf{x}^*$ and $\mathbf{y}^*$are the optimal strategies identified in the "Flexible" and "Flexible & Learning" strategies, and $\mathbf{x}$‘ is the optimal strategy identified in the "Inflexible - Robust" strategy.

We propagated the uncertainty in across all values of j,k and s and then extracted the median, 5th and 95th percentile values of the distribution.

In the subsequent sections, we describe how the inputs of the systematic conservation planning problem: c_{ijs} (annual conservation cost) and m_{ijts} (koala habitat area) are modelled.

4.2.3 Landholder preference modelling

We used landholder preference models described by Williams et al. (2023a). These models were derived from a survey of landholders and used to predict three dependent variables as a function of geographic and demographic covariates for a set of properties in the study area, as follows: Probability a landholder would be willing to consider a conservation covenant (Adopt): modelled as a Bernoulli-distributed dependent variable (equivalent to logistic regression) Minimum payment required as compensation (WTA, in terms of annual payment per hectare): modelled as a normally-distributed variable (linear regression), with censoring applied to account for the range of financial compensation specified in the set of options in the survey Proportion of their property a landholder would be willing to put under a covenant (Prop): modelled as a Bernoulli-distributed dependent variable (equivalent to logistic regression)

The final model outputs consist of 10,000 draws of the parameter values from the MCMC iterations, for each one of 10 missing data imputation iterations, which result in 100,000 (10,000 $\times$ 10) values that describe the probability distribution of the parameters for each of the models fitted. To propagate the model uncertainty, we randomly sample J replicates from the full probability distribution (100,000 values) and made predictions for each property based on X_{ij}, a model matrix of the property characteristics (with j^{th} replicate sampled with replacement from missing data imputations) and the parameter drawn from the probability distributions β.

The predicted probability of adoption of property i in replicate j is given as follows:

$$\text{Prob}\hat{\text{Adopt}}_{ij} = \frac{\exp(\hat{X_{ij}} \times \beta_{\text{Adopt},j})}{1 + \exp(\hat{X_{ij}} \times \beta_{\text{Adopt},j})} \tag{4.23}$$

The predicted willingness-to-accept (WTA) of property i in replicate j is given as follows, and set to zero if the predicted value is less than zero:

$$\text{W}\hat{\text{T}}\text{A}_{ij} = \hat{X_{ij}}\beta_{\text{WTA},j} \tag{4.24}$$

And the proportion of area property i in replicate j is willing to put under a covenant is given as follows:

$$\text{Pr}\hat{\text{o}}\text{p}_{ij} = \frac{\exp(\hat{X_{ij}} \times \beta_{\text{Prop},j})}{1 + \exp(\hat{X_{ij}} \times \beta_{\text{Prop},j})} \tag{4.25}$$

We assume that 10% of the total population of properties are invited to bid. The population invited to bid is a stratified sample of landholders from the full population, sampled based on the strata of land use type and unimproved land value to cover properties of both low and high unimproved value.

We assume, for model tractability reasons, that the properties' willingness to adopt and the financial compensation bid (willingness-to-accept) is assumed to remain the same across both the first time-period and the second time-period in each problem, but is different across replicates j. In reality, it is possible that the availability of properties for conservation could change in the intervening period due to changes in landholders' preferences, with some properties no longer willing to accept a covenant at the bidded compensation level or with new properties entering the set of properties that can be considered for a covenant. While it is possible that the set of properties change in the intervening period, the expected costs of a Flexible strategy will still be lower than the "Inflexible - Robust" strategy, because if conservation costs are predicted to rise overall in the future, the decision-maker can still choose to invest all the budget in securing covenants in the first time-period under the "Flexible" strategy. On the other hand, if conservation costs are expected to decrease, the decision-maker can realise even more gains by flexibly delaying conservation investments.

Once the subset of landholders were selected we assume the landholder decides whether to bid and the terms of the contract (payment required and proportion of property). The decision of whether to bid $\text{Bid}_i j$ is a binary random variable with the following probability of success:

$$P(\text{Bid}_{ij} = 1) = \text{Prob}\hat{\text{A}}\text{dopt}_{ij} \tag{4.26}$$

The random variable Bid_{ij} is the same across the first time-period and the second time-period, meaning that a landholder who put in a bid in the first time-period is assumed to put in a bid again in the second time-period.

The population present in the bidding population Nj only consists of those where Bidij=1. If a bid is placed by the landholder in property i in replicate j, the decision-maker can observe cij, the annual payment required to put the property in a covenant (for the proportion of the property on the covenant specified in the bid):

$$c_{ij} = \text{WTA}_{ij} \times \text{Prop}_{ij} \times \text{Area}_i \tag{4.27}$$

Where WTA_{ij} is the cost per hectare the landholder is willing to consider for an in-perpetuity covenant, Prop_{ij} is the proportion of the property willing to be under a covenant between 0 and 1, and Area_i is the land area of the property.

4.2.4 Koala landscape capacity modelling

The Koala Landscape Capacity Model (KLCM), is based on a rapid evaluation of metapopulation persistence (REMP) methodology building on previous published studies (Taylor et al., 2016). The model combines environmental niche modelling with landscape capacity modelling. We used two environmental niche models based on Maximum Entropy (MaxEnt): (a) a niche model of koala tree species suitability, and (b) a niche model of koalas that synthesises predicted outputs from the koala tree species suitability niche model and other inputs such as ground water and surface water availability, and soil fertility. The REMP model has been applied to koalas in NSW across 12 climate projections based on a high-emissions A2 scenario that represent a credible range of future outcomes under climate change. Specifically the koala bioclimatic and tree species suitability models were projected using 12 climate scenarios based on NARCliM 1.0, described by four separate Global Circulation Models (GCM) (MIROC-medres 3.2, ECHAM5, CGCM 3.1 and CSIRO mk3.0) and three runs of Regional Circulation Models (RCMs) Weather Research and Forecasting (WRF) modelling system used to downscale global climate representations to high-resolution local projections (Evans et al., 2014; Olson et al., 2016). These modelled environmental niches are subsequently fed into a REMP model (Drielsma and Ferrier, 2009; Drielsma and Love, 2021). Elicitation amongst experts were used to elicit parameters in the REMP model, such as the Minimum Viable Habitat Area (3000 hectares), Home Range Movement Ability (1 meter to 1,000 meters), Dispersal Movement Ability (1 meter to 50,000 meters). The KLCM produces indices representing landscape capacities for koala metapopulations (ranging from 0 to 1) across 12 climate scenarios and decadal timesteps between 2000 and 2070, representing the range of prediction uncertainty in future koala landscape capacities across different plausible climate scenarios.

The koala landscape capacity model produces raster layers of predicted koala landscape capacity under climate change. We extracted the average landscape capacity index for each property for each prediction epoch (decadal timesteps from 2000 - 2070) and each climate scenario. The climate-suitable koala habitat in the property is as follows:

$$m_{ijs}(\theta) = (\text{Area}_i \times \hat{\text{Prop}}_{ij}) \times \text{QualityHabitat}_{is}(\theta) \tag{4.28}$$

Where the climate-suitable koala habitat in property i, replicate j, climate scenario s and year θ is a function of the area of the property Area, the proportion of the property in the covenant Prop, and a binary indicator QualityHabitat of whether the habitat meets the quality threshold γ. Specifically, it is defined as follows:

$$\text{QualityHabitat}_{is}(\theta) = \begin{cases} 1 & \text{if} \quad \text{LandscapeCapacity}_{is}(\theta) > \gamma \\ 0 & \text{otherwise} \end{cases} \tag{4.29}$$

4.2.5 Land clearing simulation

We use a simple probabilistic deforestation simulation approach to test the sensitivity of our results to a wide range of possible future deforestation rates. While noting that more sophisticated, data-driven models trained on historical deforestation data to forecast land clearing exists in the literature (e.g. Ball et al., 2022; Linkie et al., 2004; Mas et al., 2004; Silva et al., 2020), there exists deep uncertainty over future deforestation patterns that are not incorporated in data-driven models. Our approach was not intended to assess real deforestation patterns, but rather, to evaluate whether flexible approaches could still yield improved outcomes at different levels of deforestation risks. While this modelling framework assumes that deforestation risk is homogeneous across properties it could be easily extended to incorporate detailed deforestation models that model the spatial heterogeneity of deforestation risk across properties i.

Here the variable of interest is the binomial random variable τ, which represents whether vegetation will remain uncleared during the 30-year period in the first time-period if no conservation covenants were put on the property. Because is random, we draw $k = 1, \ldots, K$ realisations of this variable, with each of k being a land clearing future, which are realisations of this random variable , for $i = 1, \ldots, N_j$ properties.

τ_{ik} is drawn from a probability distribution as follows:

$$\Pr(\tau_{ik} = 0) = \begin{cases} \alpha & x_i = 0 \\ 0 & \text{otherwise} \end{cases} \qquad \forall \quad k = 1, \ldots, K$$

Deforestation risk can be specified as α, which is the probability that vegetated land will be deforested in the absence of covenant protection. We model the case where τ is identically and independently distributed (i.i.d.) across land clearing futures and properties for the deforestation rate $\alpha \in [0, 1]$. If the probability is already protected in the first time-period, τ_{ik} must be equal to 1 (no deforestation).

We iteratively solved the same conservation planning problem with different levels of to obtain estimates of the value of flexibility ($\Delta\Gamma$) under different levels of deforestation risk.

4.3 Results

We find that conservation strategies that are inflexible in the face of climate change face a substantial risk of failing to meet its objectives. Focusing first on comparing between the inflexible strategies, we find that although the “Inflexible - Ignore Risk” strategy meets the conservation target in 2070 if conservation outcomes are assumed to follow the average prediction under climate change (meeting 105% of the target based on the median), it is projected to fail to reach the conservation target in 28% of the climate scenarios (Figure 4.3b). The consequences of ignoring variabilities across climate scenarios are severe; in 2050, the “Inflexible - Ignore Risk” strategy has the risk (at the 5th percentile of outcomes) of a massive shortfall in conservation outcomes at 88% less than the conservation target in 2050 (Figure 4.3a). This could undermine the effectiveness of the new protected areas if proven true. It is feasible to mitigate these risks while still being inflexible, as illustrated by the “Inflexible - Robust” strategy that meets at least 100% of the conservation target across all climate scenarios and all time-steps. But mitigating these risks while being inflexible inevitably elevates conservation costs. Indeed, comparing the “Inflexible - Ignore Risk” strategy to the “Inflexible - Robust” strategy shows that the latter almost doubles conservation costs (94%), from AUD $72 million to AUD $143 million (Figure 4.3c).

On the other hand, flexible strategies can mitigate risks from climate change while keeping costs low. Focusing first on comparing the “Inflexible - Robust” with the “Flexible” strategies, we show that the flexible strategy to delay some conservation investments to 2050 is still able to meet the conservation target across all climate scenarios (Figure 4.3b) while reducing the median costs of meeting conservation targets across all climate scenarios by 32% (90% range: 25%-52%) (Figure 4.3a, i). These cost reductions are amplified if opportunities to learn and resolve uncertainties at the later date are available to future decision-makers. Contrasting the “Flexible & Learning” strategy with the “Inflexible - Robust” strategy shows that flexibility to climate change and learning of its impacts jointly contributes to a median 53% (90% range: 37%-83%) reduction in total conservation costs (Figure 4.3a, ii). This makes the “Flexible & Learning” strategy (median: AUD $70 million) cost even less than the “Inflexible - Ignore Risk” strategy (median: AUD $72 million strategy), if the costs of learning about climate change are not counted towards conservation costs. These results suggest that flexible approaches to conservation planning can mitigate risks inherent in inflexible strategies without even increasing conservation costs.

These flexible strategies consistently deliver robust cost savings relative to inflexible ones repeated across plausible parameter choices, policy targets and conservation settings. Compared to robust inflexible strategies, strategies that exploit flexibility and combine opportunities for flexibility and learning respectively reduce expected conservation costs by at least 10% and 30% across model runs while still maintaining robustness towards the policy target (Figure 4.6).

The spatial prioritisations of the strategies depicted in Figure 4.4a suggest that efforts to mitigate climate risks can strongly shape present-day conservation decisions. The “Inflexible - Ignore Risk” strategy directs conservation resources towards protecting the northern parts of the study area, while the “Inflexible - Robust” strategy directs conservation resources to protect the southern and coastal parts of the study area as well. More importantly, only 31% of priorities overlap across these two inflexible strategies (Figure

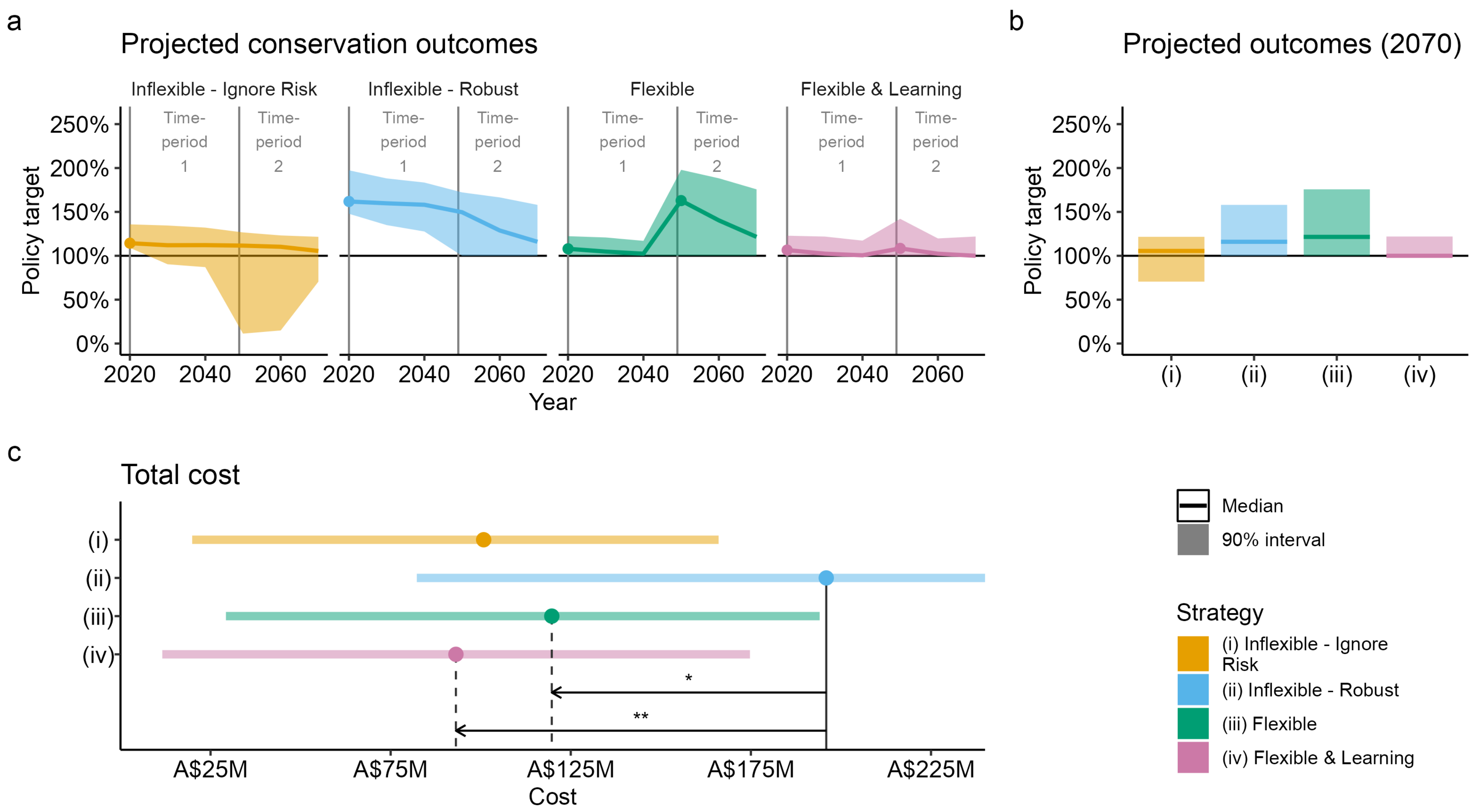

Figure 4.3: **Flexible conservation planning that exploits learning opportunities meets the same conservation objective across climate scenarios at half of the cost**. a, Projected conservation outcomes (solid line and 90% intervals in shaded areas) in terms of percent of the policy target reached by the conservation strategies: "Inflexible - Ignore Risk," "Inflexible - Robust," "Flexible" and "Flexible & Learning" planning strategies. b, median and 90% intervals of conservation outcomes (relative to the policy target) in 2070, and c, conservation cost of the four strategies with arrows depicting (*) the value of flexibility, and (**) the value of flexibility and learning.

4.4c). While the northern part of the study area is expected to be valuable koala habitat under climate change, there is a risk for it to experience severe declines in habitat quality as predicted in some climate models (Figure 4.7). The "Inflexible - Robust" strategy therefore spends more resources to also protect habitats in the south to protect against possible declines in the north.

We find that the benefits of flexible planning can only be effectively harnessed if present-day conservation decisions factors in future adaptation opportunities. Under flexible strategies, conservation decisions made in the first time step are radically different from priorities under the inflexible strategies (Figure 4.4c). Only 45% of the area protected in the first time step under the "Flexible" strategy overlaps with the "Inflexible - Robust" strategy. The differences amongst flexible and inflexible strategies are further amplified when learning opportunities are allowed, where only 35% of the area protected in the first time step under the "Flexible & Learning" strategy overlaps with that in the "Inflexible - Robust" strategy. Properties in the southern parts of the study area are not chosen for covenants in the majority of climate scenarios; however, in a minor subset of climate scenarios, these properties could provide high-quality koala habitat. If uncertainty over climate scenarios is resolved in second time-period through learning, investments into the southern parts of the study area do not have to be made unless the climate turns out to be favourable to koalas in the south, which has not been the case over recent decades (Lunney et al., 2014). Flexibility can therefore help avoid ineffective spending of conservation resources and improve cost-effectiveness.

Human-driven habitat loss could however potentially undermine flexible strategies that wait before committing investments, because sites potentially suitable for cost-effective conservation could be cleared in the intervening period and reduce the set of options available for future decision-makers. Therefore, if there is a high chance suitable properties could be cleared while agencies wait to resolve uncertainties, agencies could better achieve their goals if those sites are protected upfront instead. Consequently, conservation agencies will have to navigate this trade-off by weighing the benefits of waiting versus the risk of direct habitat loss when determining whether to delay conservation investments or act immediately (Iacona et al., 2017).

Our results show that delaying the creation of new protected areas to second time-period through flexible strategies is still optimal even when the risk of land clearing is doubled compared to long-term averages (Figure 4). Extrapolation from long-term

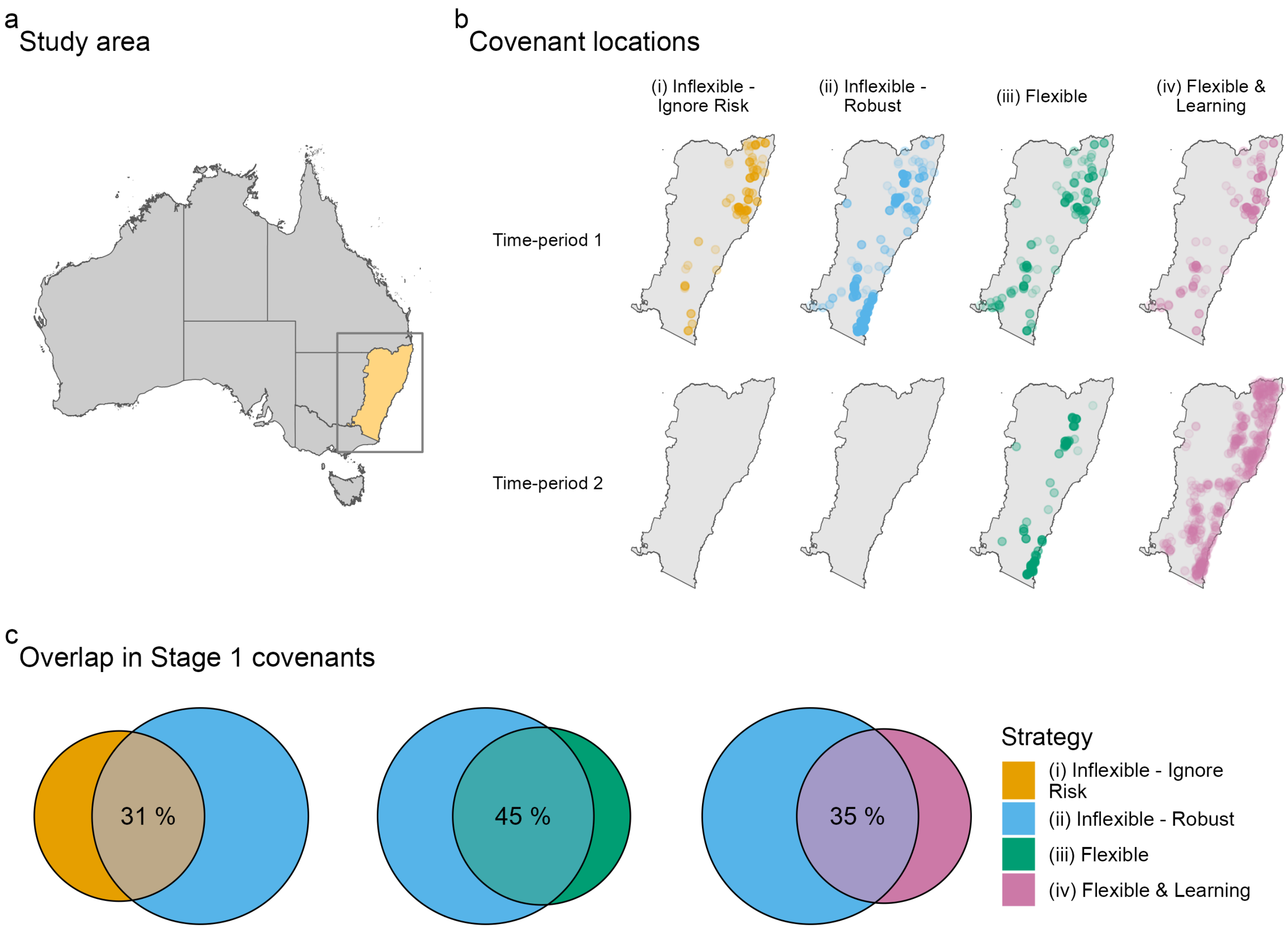

Figure 4.4: **Strategic flexibility alters present-day conservation investment decisions**. a, Map of Australia depicting the study region, b, Maps showing properties with an accepted covenant agreement larger than 20 hectares in 2020 (first time-period) and 2050 (second time-period) under the different planning strategies: (i) “Inflexible - Ignore Risk”, (ii) “Inflexible - Robust”, (iii) “Flexible”, and (iv) “Flexible and Learning”, shaded by the probability it was awarded the covenant agreement, and c, size of the protected area under covenants in the first time-period overlapping.

Variable	Source	Value
NSW Woody Vegetation Extent (2011) total area	NSW DPIE	21958266.47 hectares
Sum of vegetation lost between 2012-2020	NSW DPIE SLATS report	425200 hectares
Vegetation Extent in 2020	Calculated	21533066.47 hectares
Long-term annual vegetation loss (2009-2020)	NSW DPIE SLATS report	43025 hectares
Percent of vegetation loss in a 30-year period	Annual vegetation loss (multiplied by 30) divided by vegetation extent in 2020	5.99%

Table 4.1: NSW historical deforestation rate calculation assumptions

historical trends suggest that around 6% vegetation will be lost to clearing in a 30-year period in the study area (Table 4.3); in this case, the optimal strategy would be to only allocate 47% and 45% of the budget (total spending under the “Inflexible - Robust” strategy) in the first time-period (taken at the median) in the “Flexible” and “Flexible & Learning” strategies respectively. Assuming historical trends, this approach of delaying funding is able to achieve reductions in cost, relative to the “Inflexible - Robust” strategy, of 30% (“Flexible”) and 50% (“Flexible & Learning”). Even in the highly-pessimistic assumption where 50% of unprotected land is cleared in the intervening 30-year period (2020-2050), flexible approaches still only spend around half of the total budget (53% and 47% for “Flexible” and “Flexible & Learning” respectively), resulting in reductions in conservation cost by 52% (21%-84%) and 26% (21%-40%) for the “Flexible” and “Flexible & Learning” strategies respectively. This suggests that uncleared sites that offer cost-effective conservation opportunities are still available even if many other sites could be potentially lost to land clearing. Only in the extreme case where all lands unprotected in the first time-period will be lost in the intervening period does the optimal strategy become one where all funding is spent upfront.

4.4 Discussion

Climate change is threatening efforts to reverse global biodiversity loss, making the question of how to make conservation efforts adaptive to climate change key to conservation decision-making. Our work shows that conservation that is strategic about flexible adap-

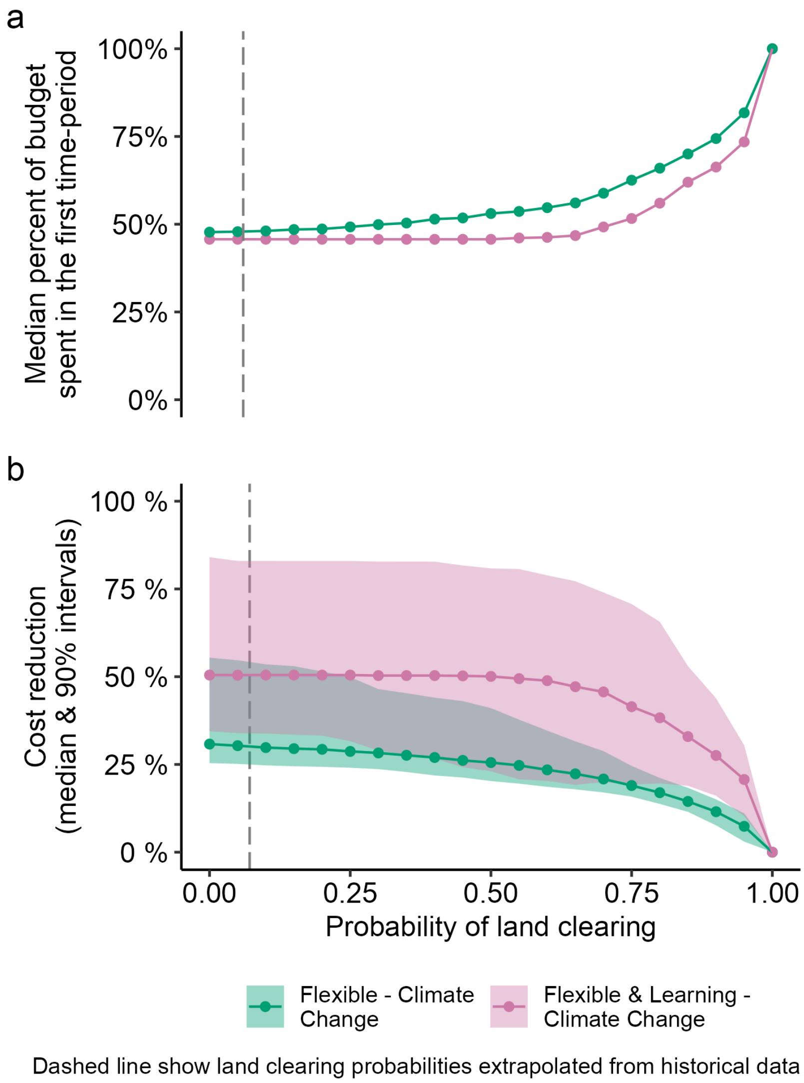

Figure 4.5: **Strategic delays still yield substantial cost reductions even under high future land clearing rates.** a, the median percent of funding allocated in the first time-period (relative to the amount of spending in the first time-period in the "Inflexible - Robust" strategy) under different land clearing risk assumptions. b, Lines and shaded areas show median and 90% intervals of cost reductions (conservation cost of strategy relative to the "Inflexible - Robust" strategy) under alternative assumptions over future land clearing patterns of properties not protected by covenants in the first time-period, for "Flexible" and "Flexible & Learning" approaches. Dashed line show 30-year deforestation risk extrapolated from long-term annual average rates of land clearing in the study area (Figure 4.3)

tation can mitigate climate change risks without sacrificing cost-effectiveness. However, to reap the full benefits of flexible climate adaptation, conservation agencies will have to account for potential decisions made in the future when making decisions today. Conservation investments are likely to be most successful when agencies strategically embed flexibility at the beginning of the planning process, allowing future flexibility at different points in time, and being sensitive to risk when spatially-targeting investments (Rhodes et al., 2022). Although strategic delays in conservation investments have been shown to be beneficial when they allow conservation agencies to generate more capital through financial interest and alternative investments (Iacona et al., 2017), we now show that delays can also be beneficial to keep options open to facilitate climate adaptation (Golub et al., 2021).

While it is well-established that planning that overlooks the risk to conservation success due to climate change is a high-risk strategy (Runting et al., 2018), a wide range of planning approaches can be used to tackle climate risks. Modern Portfolio Theory and robust optimization approaches commonly used to tackle conservation planning problems under climate risks find explicit trade-offs between maximising expected returns and minimising risks (Ando et al., 2018; Ando and Mallory, 2012; Beyer et al., 2018; Runting et al., 2018). This trade-off exists because conservation agencies have to invest in several conservation activities to spread risk and in anticipation that some will fail under climate change. But by delaying some conservation investments, conservation agencies can use new information accumulated over time to spatially-target conservation resources more precisely and limit conservation investments that could fail. Strategic flexibility can therefore partially mitigate the trade-off between risk and return.

We show specifically that trade-offs can be mitigated when present-day decision-making actively accounts for future adaptation options, informed by the principles of real options (Chadès et al., 2015; Golub et al., 2021; Hildebrandt and Knoke, 2011; Regan et al., 2015; Shah and Ando, 2016). A real options approach quantifies the value of the option, but not an obligation, to undertake further action (for example, conservation investments) in the future when uncertainties may be resolved (Dixit and Pindyck, 1998). The stochastic dynamic programming approach we adopted, analogous to the real options framework, also allows a decision-maker to quantify the value of flexibility as the cost difference between strategies to achieve conservation outcomes with up-front investments versus a strategy with the option to wait before investing. Our approach not only captures the value of these adaptation opportunities, but also uses knowledge of possible future adaptations to ensure that present-day decisions minimise future adaptation costs. Our approach is novel in its application in terms of applying the principles of real options to a spatial conservation planning problem, illustrating the importance of considering future adaptation options in present-day conservation activities.

Our work further finds explicit differences in strategies that rely on future learning opportunities to resolve climate uncertainty from those that do not, both in terms of cost-effectiveness and its spatial prioritisation in the first time-period. Whilst learning to resolve climate uncertainty leads to cost reductions compared to strategies without learning, these cost reductions may need to rely on investments in learning that improves climate predictions, which may or may not rely on investments directly from conservation decision-makers. We do not explicitly consider these costs in our analysis. In some cases, if learning costs are high enough, a flexible strategy could be less cost-effective than a fixed strategy (Drechsler et al., 2006). In our case, however, the costs of learning would need to be more than 50% of the cost of the fixed strategy to make the flexible strategy less cost-effective, assuming that climate uncertainties can be fully resolved through learning. These gains could indeed be attenuated if uncertainties are only partially resolved, and depend on which uncertainties are resolved. Here, such a cost-benefit analysis could benefit from a value of information perspective that determines whether it would be worth investing in resolving these uncertainties, and if so, resolving which aspects of uncertain socio-ecological systems are likely to yield the most benefit (Davis et al., 2019; Maxwell et al., 2015; Polasky and Solow, 2001; Runting et al., 2013). A decision-maker could therefore use value of information analysis to weigh relative cost savings achieved through learning that leads to improved spatial targeting of resources versus the cost incurred when resolving uncertainties.

Our analysis also only considered flexible adaptation through strategically-delayed creation of new covenants and did not consider many other actions that can further reduce species' vulnerability to climate change, such as the active improvement to the climate resilience of habitats already in the protected area network (Simonson et al., 2021). Conservation plans are likely to achieve higher cost-effectiveness if it combines both conservation and restoration (Possingham et al., 2015). Specifically for koala conservation, actions like planting trees that preserve the richness of tree species that koalas feed on can improve the koalas' climate resilience (Cristescu et al., 2013; Reckless et al., 2018;

Rhind et al., 2014). Another way conservation planning can adapt to climate change, but not considered here, is through temporary conservation agreements, which could be used to complement static protected areas to provide dynamic protection to species tracking evolving niches under climate change (Alagador et al., 2014; D'Aloia et al., 2019; Gerling et al., 2022). This would give agencies the flexibility to modify or reverse conservation actions that become unsuitable under climate change (Drechsler, 2020a; Drechsler and Wätzold, 2020; Owley et al., 2018; Rhodes et al., 2022; Rissman et al., 2015). In the case where securing long-term conservation contracts leads to a cost premium due to restrictions on landholders' options, short-term contracts could prove to be a more cost-effective option (Lennox and Armsworth, 2011). However, these short-term contracts could also incur transaction costs when renewed and this could render short-term contracts less attractive (Juutinen et al., 2014). While implementing short-term contracts or modifying perpetual contracts may not always be feasible under legal settings (Rissman et al., 2013, 2015), having at least some conservation investments strategically in short-term agreements may lead to better biodiversity outcomes than only having perpetual agreements across all privately protected areas (Juutinen et al., 2014; Lennox and Armsworth, 2011).

Flexible strategies that delay conservation investments also need to confront the reality of accelerating global deforestation that continues to contribute to irreversible habitat loss (Bradshaw, 2012; Evans, 2016). In the absence of concerted efforts to halt deforestation, habitats that are not protected immediately are exposed to the risk of habitat loss in the intervening period. We demonstrated how decision-makers can use a clear and transparent framework to account for the risk of land clearing when considering whether to delay conservation to mitigate climate risks. In our case, the value of strategic delays outweighs the risk of deforestation in the meantime. But the opposite could be true in other cases, particularly in cases where the habitat that is at risk of loss is irreplaceable and face a higher risk of deforestation than other habitats (Baisero et al., 2022; Ferrier et al., 2000; Meir et al., 2004; Pressey, 1999). We only considered a simple assumption where the risk of habitat loss is homogeneous across properties. A more sophisticated approach could recognise the heterogeneity in land clearing risks across properties recognising the physical, socioeconomic and contextual factors that drive deforestation decisions in each property (Alix-Garcia, 2007; Armenteras et al., 2017; Cushman et al., 2017; Mena et al., 2006; Negret et al., 2019). The relative probabilities of habitat loss modelled by its deforestation drivers could have a major effect on which properties are prioritised for investments in the first time-period and the value of strategic delays (Moilanen et al., 2009).

The flexible strategies described in this paper however may sometimes be difficult to achieve in practice due to governance arrangements that constrain the shifting of budgets across years. These constraints can include provisions to spend budgets within a given timeframe or inability to release funding from previously-committed investments (Lennox et al., 2017) , and can lead to massive inefficiencies (Barnett et al., 2015; Drechsler and Wätzold, 2020; Meir et al., 2004). In practice, conservation decision-making is made difficult because funding available for conservation can radically vary year-by-year (Wintle et al., 2019) and decision-makers are unable to guarantee that funding is still present in the future. There are growing calls for international conservation policy to be adaptive and flexible as a vital strategy reducing climate change risks and our study re-emphasises this need (Gross et al., 2015; IPBES and IPCC, 2021). These calls suggest that institutional arrangements that could facilitate flexible conservation and preserve options to adapt could be needed in an era where climate change is already under way. Strategies such as budget borrowing and carry-overs across years employed by conservation organisations in practice could serve as a useful model for organisations aiming to improve flexibility to cope with climate uncertainties (Lennox et al., 2017). With the effects of climate change already impacting ecosystems worldwide, global area-based targets for conserving 30% of Earth's ecosystems by 2030 could still fail to reverse biodiversity loss if conservation planning does not adapt to climate change (Arneth et al., 2020; Jaureguiberry et al., 2022). The careful reflection and re-design of conservation governance to enable flexible and adaptive planning in the coming years could be the first step towards ensuring that these conservation measures effectively contribute to biodiversity targets under climate change.

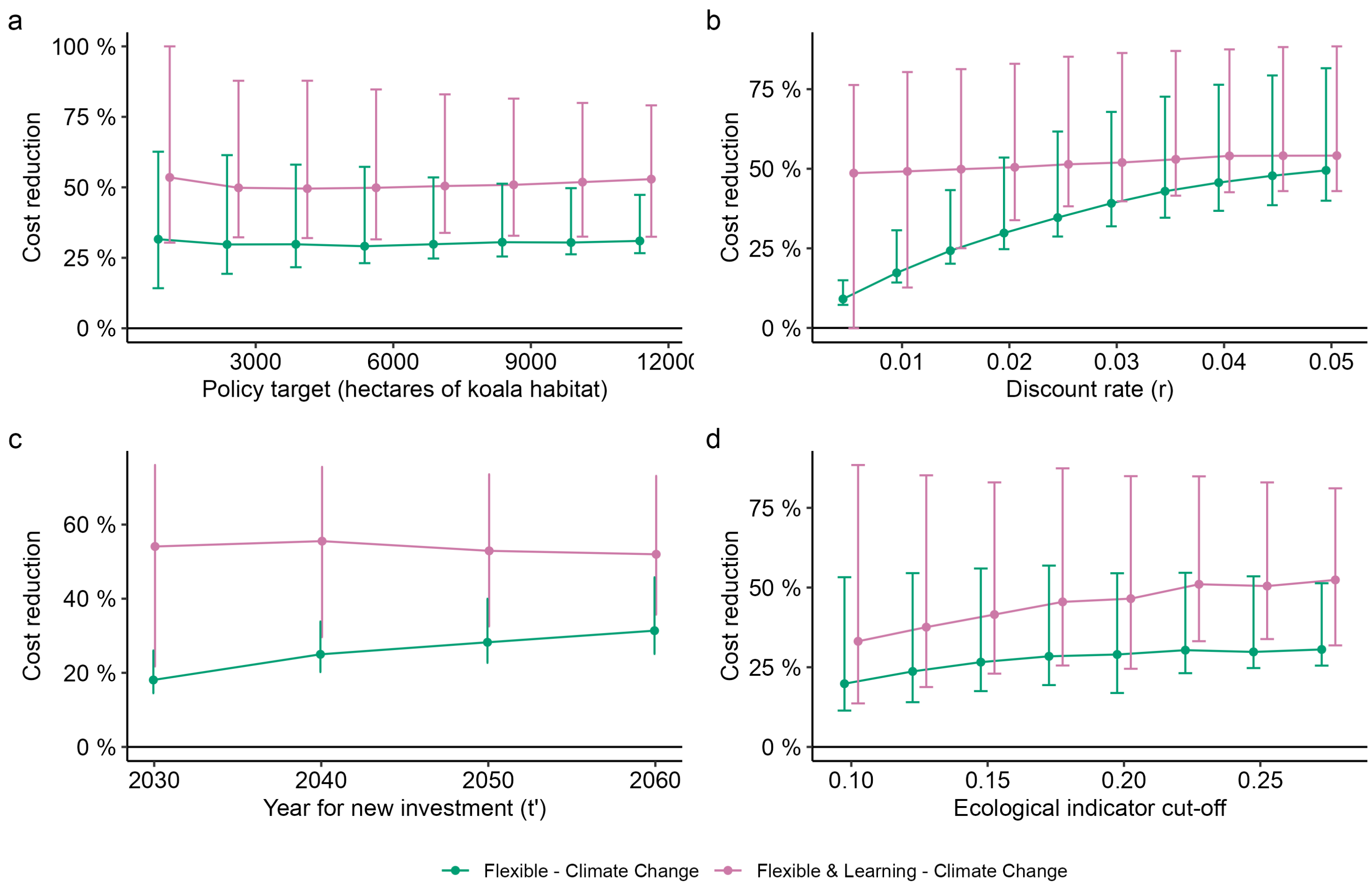

Figure 4.6: Cost reductions ($\Delta\Gamma$ in Equation 4.22) of "Flexible" and "Flexible & Learning" strategies compared to the Inflexible strategy for different choices of parameters: a, policy target (number of hectares of koala habitat in protected areas), b. Discount rate, c. year for new investment (t'), and d, ecological indicator cut-off used to determine whether protected areas can qualify as koala habitat or not.

Figure 4.7: Maps showing the sites where the koala landscape capacity index reaches a threshold (0.25 or higher) in green, predicted for the year 2060 for all climate models included in this study. Notice that most models predict these sites will exist near the northern coast of the study area, except for ECHAM_R1. Under ECHAM_R1, these sites only exist near the central and southern coast of the study area. A strategy that only protects habitats near the north coast is therefore likely to fail under the predictions of ECHAM_R1. Strategies robust to climate change therefore must invest in the central and south coast to reach the policy objective.

Chapter 5

Conclusion

5.1 Summary

Policy-makers across the world need to make urgent decisions about where and when to protect and restore natural capital to address numerous pressing sustainability challenges. Global policy objectives, such as the United Nations Decade on Ecosystem Restoration (2021-2030), the New York Declaration on Forests pledge to plant 350 million hectares of trees globally, and the commitments of the Global Biodiversity Framework to protect 30% ecosystems by 2030, are prime examples of how nations are planning to create new natural capital assets to generate ecosystem services that combat global challenges such as climate change and loss of biodiversity (Fischer et al., 2021; Farrell et al., 2022; CBD, 2022). Decisions affecting natural capital implemented under these global policy commitments not only have far-reaching consequences not only for ecosystem services and well-being, but also play a major role in the sustainability and equity of societies around the world (Johnson et al., 2023).

Uncertainty in the outcomes that may arise from these actions can result in decision-making that fails to adequately address these challenges. Climate change continues to affect biodiversity and ecosystems (Game et al., 2011; Pearson and Dawson, 2003), threatening to thwart efforts to reverse biodiversity loss through global protected area targets (Dobrowski et al., 2021). Extreme weather events, such as wildfires, heat waves, and tree disease, seriously impact the ability of past ecosystem restoration programmes to sequester carbon for the mitigation of climate change (Ciais et al., 2005; Kodikara et al., 2017; Badgley et al., 2022). These reports about action to protect natural capital that fails to deliver promised benefits to mankind illustrate the importance of accounting for these uncertain future events in the natural capital decisions we make today.

The papers in this thesis demonstrate that for decisions ranging from planting trees to sequester carbon to those that wish to devise a strategy for protecting land to conserve iconic fauna, policy-makers can gain much from the application of methods deriving from decision theory for making decisions under uncertainty. By design, natural capital strategies informed by these methods will ensure resilient delivery of decision maker objectives under a wide range of possible future conditions including those relating to changing climate and economic variability.

A recurring theme demonstrated in both the computational and empirical case studies presented in this thesis is that if uncertainties are ignored in decision-making, assumptions about uncertain future conditions can significantly impact on the natural capital strategies that are identified as delivering best to policy-makers' needs. In Chapter 2 I demonstrated that accounting for uncertainty in risk-averse decision-making can lead to natural capital strategies that are worth 20% more in certainty-equivalent units under extreme risk-aversion compared to maximising expected outcomes. In Chapter 3, I demonstrated this in the context of a real-world decision problem regarding tree planting in the UK. Differing but equally valid assumptions over future conditions can lead to recommendations over which tree species to plant and where to plant them that are diametrically opposed. This theme is revisited in Chapter 4, where ignoring risks in climate change can expose decision-makers to the risk of not meeting their objectives in at least 28% of the outcomes. In each case, we see that accounting for risk and uncertainty in environmental decision-making results in markedly different policy recommendations and significantly alters the space of possible outcomes that might arise from those recommendations.

Bringing uncertainty into decision-making requires decision-makers to make explicit trade-offs between maximising expected benefits and minimising exposure to risks. In the static problem, where policymakers face an irreversible decision in the current period, my analyses suggest that land-use decisions that minimise risk exposure are very unlikely to be the same decision as one that maximises expected benefits. Therefore, decision makers will often have to forego sets of decisions that maximise expected benefits in order to minimise risks. Such trade-offs often need to be made quantitatively, but how these trade-offs are characterised differs depending on which method the decision-maker uses to make optimal decisions under uncertainty. In Chapter 2 I motivated the idea of using economic risk preferences as expressed in the decision-makers' utility function as a way of making this trade-off, to reconcile between the differences across the risk preferences implied by maximising expected utility and the weighting parameter used when maximising mean-risk objective functions. These findings bridge the gap between comparable methods for decision-making under uncertainty and make it easier for decision-makers to express these trade-offs quantitatively. In Chapter 3 we see this trade-off explicitly in the context of choosing optimal portfolios for planting trees in the United Kingdom. First, we saw that a planting strategy that minimises risks produces lower expected benefits in terms of natural capital benefits compared to a planting strategy that maximises expected benefits. The bulk of these uncertainties, nonetheless, proves difficult to diversify away due to the high correlation amongst risk factors affecting natural capital outcomes of tree-planting. Second, the analysis also places decision theory at the heart of an application of a wider analysis of optimal portfolios to achieve decarbonisation and account for the risk profile of alternative carbon removal technologies. Both analyses show an explicit trade-off between minimising risk and maximising expected returns. These explicit trade-offs are attenuated as we move to Chapter 4 where we explore a dynamic problem with avenues to resolve uncertainty. Going in parallel with the previous two chapters, we see the tension between reducing risks and maximising expected benefits in the static decision-making case, where a static robust conservation plan can cost more than half as much as a conservation plan that ignores risk. The chapter goes further to illustrating that a decision-maker that strategically exploits the temporal nature of the decision problem–by considering the fact that these decisions do not need to be committed immediately–strongly attenuates the risk-return trade-off. Delays in making decisions after uncertainties about climate variables are realised can contribute to better spatial targeting of financial resources that can boost the cost-effectiveness of conservation programmes. The expansion of the problem to consider the temporal dimension furthers our understanding of how continued learning about these uncertainties can improve decision-making.

In this thesis, I identified where challenges associated with bringing in computational decision sciences to environmental decision-making lie, explored how they affect decision-making and overcame those challenges. I started by articulating three acute challenges and presented three original pieces of work that addresses these challenges. In summary, the first challenge is related to the choice of methodology. Given that different methods could lead to different results, it is unclear how the prevailing approaches in the field are likely to be suitable under which circumstances. The second challenge relates to the integrated nature of uncertainty. While the existing studies I found mostly focus on sources of uncertainty in isolation, the wide range of uncertainties plaguing inputs to natural capital decision-making necessitates an integrated model of uncertainty that accounts for interactions between uncertain inputs. The third challenge relates to optimal timing and options present in decision-making; how can decision-makers make decisions for natural capital that are not just optimal in the present, but also keep options open such that decisions can adapt when better information is available?

The first contribution of this thesis is a systematic analysis of how different methods for measuring and optimising natural capital decisions under risk can lead to different results, starting from the foundational economic decision theory based on Expected Utility Theory and expanding to consider comparable methods based on risk measures and stochastic programming. This contribution solves the difficulties for decision-makers in terms of selecting which method to use. Focussing first on static problems, where policymakers must commit to decisions in the first period before uncertainties are resolved over future periods, I showed in Chapter 2 that risk-aversion can dramatically alter the natural capital strategy that is deemed optimal for a decision maker. In this chapter, I established that methods used in portfolio theory that optimise a mean-risk objective function can identify land-use decisions that are consistent with those that would be identified as optimal by a decision-maker with utility-theoretic risk-averse preferences if the weighting parameter in these mean-risk objective functions is consistent with the decision-makers' underlying risk preferences. Indeed, the use of a more sophisticated mean-risk objective function based on the Conditional Value-at-Risk measure lends itself to decisions that are more closely aligned to Expected Utility Theory, yielding decisions with higher certainty-equivalents compared to those with a simpler measure of risk based on the standard deviation of outcomes. I re-examined the question of how the choice of method through which to identify the 'best' natural capital strategy under uncertainty can change outcomes in Chapter 3, with the aid of predictions from a set of empirically-estimated models based on a question under intense policy debate in the United Kingdom. In Chapter 3, I made the discovery that applying widely-used methods of conventional scenario analysis in order to identify optimal strategies under uncertainty can be highly misleading and support decisions that are dangerously exposed to risk. A portfolio analysis approach can address these concerns by considering all modelled futures at once and identify the strategy that minimises the probability of undesirable outcomes. I expanded the set of tools considered in Chapter 4 when examining dynamic decision-making problems. In this case, the context is koala conservation in New South Wales, Australia. Allowing for decision-making across different stages admits the possibility for strategy adaptation in light of uncertainty-resolving learning and benefits from earning interest on capital by delaying investments so as to take advantage of learning opportunities. At the same time, the dynamic setting introduces a new set of challenges arising from the unpredictability of changes to the environment in which decisions need to be made during the intervening period. Here, I found that accounting for the opportunity to make decisions in the future can drastically alter what decisions are made today, with such decisions contingent on how much uncertainty could be resolved in the future. Throughout this thesis, my work has shown that optimal decisions under uncertainty depend strongly on the methods chosen to identify it.

The second contribution of this thesis is the synthesis and application of an integrated framework to handle and make risk-averse decisions under multiple sources of uncertainty in natural capital decision problems in Chapter 3. In contrast to previous applications of portfolio theory to natural capital decision-making problems that find that, when accounting for just one source of uncertainty, portfolio theory approaches allow decision-makers to substantially reduce risk (Ando and Mallory, 2012; Runting et al., 2018; Liang et al., 2018), we illustrate that decision-makers could face more difficulties in reducing risk when the integrated nature of uncertainties are taken into account. In the context of Chapter 3, the strongly-positive correlation between the magnitude of future climate change, the value of carbon sequestration (the Social Cost of Carbon), and the value of agricultural commodities that ubiquitously affect natural capital values of tree-planting across space render it extremely challenging to reduce a large amount of risks through planting location and species choice. These findings echo those of Runting et al. (2018), where spatial autocorrelation also reduced the effectiveness of the Modern Portfolio Theory in reducing risks. Ando et al. (2018) offers some insight that can help explain this potential issue, showing that portfolio theory approaches are only the most effective when there are a large number of negative correlations between natural capital sites. This is because if the natural capital values of sites in the dataset are almost all positively-correlated, the variability of the sum of the natural capital values of all sites combined must be high, but if negative correlations exist, outcomes poorer than expected in one site can be offset by outcomes better than expected in another site. My work shows that the integrated and correlated nature of risk factors could make these combinations of negative correlations much harder to find. Indeed, the relative magnitude of risk-reduction possible through these methods for decision-making under uncertainty increases as we introduce an outside option for decarbonisation with values unaffected by the integrated sources of uncertainty and spatial autocorrelation between sites, therefore unaffected by correlated risk factors that are hard to diversify away solely through careful spatial targeting of ecosystem restoration. Our findings add to a critical part of the literature that illustrates the importance of integrated uncertainty modelling to decision making.

The third main contribution of this thesis is a renewed understanding of how explicit consideration of future adaptation opportunities in present-day decision-making uncertainty through a flexible, dynamic approach to decision-making could alter present-day actions and mitigate risks associated with uncertainty in natural capital decisions. In Chapter 4 I uncovered general insights by extending the typical static problem of natural capital decision-making (analogous to the problem presented in Chapter 3) to a dynamic, sequential decision-making problem to reveal the added benefit of allowing for delays to committing to irreversible decisions in reducing risks. This enables me to develop a general framework to quantify the value of flexibility (ability to delay decision-making) in an approach informed by options theory when dealing with natural capital investment problems plagued with uncertainty. The empirical application of this framework reveals that the value of flexible delays is enormous (achieving the same goals robustly with a cost reduction of up to 50%) and adds to the growing literature on the importance of flexibility in conservation and natural capital investments in the face of uncertainty (Lennox et al., 2017; Rhodes et al., 2022).

5.2 Future Directions

Risk factors such as climate change are expected to affect every aspect of the natural environment and pose major threats to the viability of natural capital assets. Measures to protect natural capital assets will inevitably have to consider the varied uncertain impacts of climate change and other economic and scientific uncertainties to remain viable. The analysis presented in this thesis presents a critical first step for decision-makers to identify optimal responses to climate change uncertainty through the application of decision science informed by economic theory.

5.2.1 Treatment of uncertainty

An assumption made repeatedly in all the analyses presented in this thesis relies on assumptions about the probability distribution of possible future scenarios that may not always be possible or valid. Ambiguity, also known as Knightian uncertainty, describes situations in which decision makers do not know the probabilities of different states of the world (Ellsberg, 1961b; Knight et al., 1921). One particular area of ambiguity faced by decision-makers confronting climate change relates to the use of climate scenarios that only describe "storylines" of future outcomes and are not associated with probabilities, such as the "Representative Concentration Pathway" (RCP) or "Shared Socioeconomic Pathway" (SSP) scenario modelling frameworks (Riahi et al., 2007, 2017; IIASA, 2010). In many cases, decision-makers are presented with multiple models, where it is impossible to assess the probability for which these models will turn out to be "true." Although the analysis presented in this thesis generally assumes that all the modelled future emissions scenarios share the same probability, violations of this assumption in reality could alter the results presented in this analysis. Of course, the use of probabilities associated with these uncertain future scenarios could greatly aid decision-making (e.g. Huard et al., 2022). The development of decision-theoretic approaches to assess natural capital policies with random outcomes without using the probabilities of random outcomes could be useful for future decision-making. Although information-gap theory does not use probabilities of states of the world, its utility in decision-making may be limited, since it focusses only on the worst case outcomes and not other states of the world (Sniedovich, 2007). To recover more information from the different states of the world without using probabilities, the use of preference functions like the Atkinson-based preference function proposed by Mittelstaedt & Baumgartner (2023) that evaluate the utility of random outcomes without using probabilities or beliefs of uncertain states of the world could open up new possibilities to overcome these challenges.

In connection to this, the papers I presented in this thesis also do not consider "deep uncertainty", a closely related concept to ambiguity. "Deep uncertainty" refers to situations where, in addition to not knowing the probability distribution of different scenarios of future events, decision-makers also cannot agree on the appropriate model to use or the full set of plausible scenarios that might occur (Walker et al., 2013). The literature on planning under deep uncertainty recognises that the future scenario that is realised could be very different from the scenarios that are initially within the set of possible scenarios predicted at the time of decision-making (Marchau et al., 2019). Because deep uncertainty suggests that scenarios are inherently unpredictable at the time of decision-making, adaptive and responsive strategies are deemed valuable because they can quickly react after events that are affected by deep uncertainty are realised (Walker et al., 2010; Hamarat et al., 2013). The possible presence of deep uncertainties in the presented works further illustrates the importance of accounting for learning and adaptation in environmental decision-making.

Given that accounting for learning and adaptation of actions can lead to pronounced improvements in the quality of solutions (as illustrated in Chapter 4), it is important to develop decision problems that account for their temporal nature, for example, through problems explored in the literature on adaptive management (Chadès et al., 2015; Yousefpour et al., 2012; Tanner-McAllister et al., 2017). For example, the decision problem in the UK-based case study in Chapter 3 can potentially benefit from accounting for the fact that policy pledges for tree-planting in the UK commit to annual planting over several years, where there is a potential to improve future planting activities through information learnt by observing the success and failure of planting committed early on. Specifying these multi-temporal decision problems also requires a detailed model of how uncertainties are likely to be resolved across many time-steps, itself subject to the amount of future investments into technological improvements in learning.

Indeed, incorporating the dynamic nature of the decision problem opens up brand new ways of reducing risks that lie beyond the core problem of choosing where investments in natural capital should be placed in, but also introduces new challenges to the computational approaches necessary for solving complex high-dimensional decision problems across space and time within a reasonable amount of time.

5.2.2 Applying computational approaches to decision-making

From a methodological perspective, this thesis also improves our understanding of how optimisation algorithms in operations research can be adapted and applied to solve a wide variety of problems and highlights the need for more tools to solve these problems. My research shows that it is possible for many decision problems relating to managing natural capital from land-use to be expressed as stochastic optimisation problems. In Chapter 2 I illustrated how common measures of risks used in the financial economics literature, such as standard deviation and Conditional Value-at-Risk, can be rewritten as stochastic optimisation problems that can be efficiently solved using linear programming techniques, even for a large number of parcels, a feature common for datasets that informs decision-making at the global or national level. Chapter 3 presents a compelling case for these techniques where I applied the algorithm for identifying land-use decisions with an optimal Conditional Value-at-Risk measure for a decision problem with more than 50,000 parcels and 4,000 uncertain scenarios. Similarly, Chapter 4 demonstrates how adapting the formulation of the two-stage stochastic optimisation problem can yield problems that are tractable for nearly 20,000 parcels and 12 uncertain climate scenarios. Examples in this thesis illustrate that it is possible for decision-makers to account for the uncertainty in their data and still identify optimal decisions with limited computing power through advanced and efficient linear programming solvers.

Likewise, the papers that I present make the limitations of computational approaches to solving natural capital decision problems explicit. For instance, in data-rich problems presented in this paper, the size of the decision problems increases exponentially as the number of uncertain scenarios and number of time-steps increases, rendering these problems intractable to those without access to large amounts of computing power. For example, the size of sequential spatial decision problems like that presented in Chapter 4 grows exponentially in size for problems covering more time-steps and could be intractable or too large for standard computer memory resources. Of course, advances in raw computing power available for everyday use could help, but the size and tractability of these problems could be aided by the use of more efficient simulation and approximate methods, such as Sample Average Approximation methods that are specialised in solving multistage stochastic optimisation programmes (Birge and Louveaux, 2011; Kim et al., 2015; Kleywegt et al., 2002). Heuristic or approximate solution methods to solving larger problems could also be of utility, particularly if specialised algorithms cannot be applied to obtain exact solutions to the problem (Nicol and Chadès, 2011; Harris and Holness, 2023). Artificial intelligence approaches using reinforcement and deep learning (e.g. Memarzadeh et al., 2019; Silvestro et al., 2022) could also be the next step towards finding plausible solutions in a finite amount of time. In contrast to the data-rich problems presented here, however, many other problems in the field are only informed by a small number of scenarios that contain insufficient or limited information to characterise the probability distribution of uncertainties necessary to apply the methods used in this thesis (Popov et al., 2022; Shah et al., 2017). Although there are some decision methods that require minimal information on uncertainties, such as robust optimisation (Bertsimas and Sim, 2004; Knoke et al., 2015, 2016), these methods may not lead to the most efficient solutions, especially when a small but insufficient amount of data is available to characterise these uncertainties. In these cases, recent advances in the field of "Data-Driven Robust Optimisation" could address these challenges (Bertsimas et al., 2018), enabling practitioners to apply techniques similar to those presented in this thesis to a wider range of problems facing insufficient information.

5.2.3 Development of policy decision support tools

Operationalising the analytical frameworks advanced in this thesis into decision support tools will require additional work to encourage its uptake in policy design. In contrast to the emphasis on risk and uncertainty in this thesis, surveys of policy makers shows that in many cases, risk and uncertainty often play only a minor role in policy-making (Knaggård, 2014; Arentsen et al., 2000). In particular, the acceptance of these tools in natural capital decision-making requires decision-makers to start to think explicitly about risk and uncertainty in their decision problems and treat the problem of natural capital decision-making as a risk management problem (Wagner and Weitzman, 2016). As I demonstrated in Chapter 3, even the best strategies for natural capital identified using advanced mathematical algorithms could lead to a wide range of uncertain outcomes. In many cases, a first step to improving policy decisions is to ensure that uncertainties are clearly communicated to decision-makers (Manski, 2019), where a range of tools to quantify and visualise uncertainties in complex socio-ecological systems could help (Rounsevell et al., 2021). But even if uncertainties are identified and clearly communicated to decision makers, decision support tools need to help policy-makers process data associated with quantified uncertainties and develop decisions that actively manage the risks associated with plausible policy decisions (van Beest et al., 2021; de Kort and Booij, 2007).

The sharp trade-off lying between the policy that will deliver the best outcomes on average (maximum expected value) and the one that minimises risks means that policy-makers need to be explicit about their preferences towards risk and uncertainty when using these decision support tools. As we saw in Chapters 2 and Chapter 3, the optimal solution to uncertain natural capital problems is highly sensitive to the level of risk aversion specified in the model. Incorporating risk aversion into decision support tools brings about a further set of questions. Whose risk preferences will the optimal natural capital investment strategies represent? The elucidation of risk preferences itself is the subject of sustained academic debate, with practitioners confronted with the engima of having to choose among several methods and models to describe risk preferences (Charness et al., 2013). To some extent, whether economic models for decision-making (like Expected Utility Theory) can accurately represent how people think about risk is also an open question (Cubitt et al., 2001; Barseghyan et al., 2018). Further difficulties arise when we consider the case for multiple decision-makers, or as implied in decision-making in a democratic government, the need to account for heterogeneous risk preferences across a broad general population. Although experts in the field have starkly different views on the critical parameters that represent risk preferences (Nesje et al., 2023), the development of decision support tools that can identify natural capital decisions that are consistent with risk preferences of a broad range of stakeholders is an important future direction. Future work can fuse experimental data from risk-based decision problems to calibrate risk aversion parameters used when identifying optimal decisions to manage natural capital (Schechter, 2007; Bocquého et al., 2014).

Similarly, an increasing range of evidence shows that the efficiency of programmes designed to encourage the creation and protection of natural capital assets will depend on how public agencies design mechanisms to encourage the participation of private landowners (Balmford et al., 2023; Cramton et al., 2021). In the studies presented in this thesis, I assume that public agencies have a policy instrument that enables them to incentivise only the set of landholders whose participation can maximise the cost-effectiveness of the programme and successfully deter those who cannot. In practice, public agencies could rely on other policy instruments to allocate incentives that cannot target natural capital at locations as precisely as implied in the case studies. The use of imprecise spatial targeting instruments will inevitably fail to attract certain landholders that deliver highly cost-effective natural capital improvements and draw in others who can provide only relatively mediocre gains. Examples of these real-life policy instruments include fixed price offers in the Environmental Land Management programme in the UK (Collas and Balmford, 2023; Collas et al., 2023; Defra, 2023) and fixed-price offers for conservation covenants at the Biodiversity Conservation Trust (BCT) in New South Wales, Australia (BCT, 2024). Future work can further incorporate the details of the programmes in question into problem formulation and enable policy-makers to identify optimal areas to invest that are in line with the set of feasible policy instruments (e.g. Day et al., 2023; Williams et al., 2023a) and employ the techniques in this thesis to uncover how the choice of policy instrument can interact with risks in decision-making.

5.2.4 Feedback and interactions at global and local scales

Indeed, the protection and restoration of natural capital to address global sustainability challenges requires the careful consideration of social, political, and economic factors in the context that jointly shape outcomes. The role played by uncertainties becomes even more important as we begin to examine feedback and interactions on the global scale caused by policies that protect and restore natural capital (Lambin and Meyfroidt, 2011). For example, tree-planting and forest conservation can potentially displace agricultural activities elsewhere and contribute to deforestation elsewhere, often with poorer environmental protection and lower crop yields (West et al., 2010). Displacement of these activities could reduce the net effect of the benefits of natural capital derived from tree planting. Quantitative evidence of these leakage and feedback effects of natural capital decisions exists (Gan and McCarl, 2007; Sohngen et al., 1999), but these estimates are also context-dependent and sensitive to uncertainty. The explicit consideration of these negative effects, and its associated uncertainty, in decision-making is set to become a critical challenge for forming policy that are sustainable over the long run.

Although policies to manage natural capital could inevitably lead to positive or negative effects elsewhere, natural capital resources remain a critical part in mitigating global sustainability challenges such as climate change, loss of biodiversity, and food production behind global policy commitments such as the Global Biodiversity Framework and the Paris Agreement (Shepherd et al., 2016; Guerry et al., 2015). The presence of strong competition for the use of natural, renewable and non-renewable resources requires decision makers to formulate strategies and policies that effectively achieve multiple objectives (Lambin and Meyfroidt, 2011). In fact, translating the theoretical strategies for managing natural capital identified in this thesis into real-world policies requires decision-makers to grapple with further complexities associated with managing natural capital not explored here, such as the need to use complex models that evaluate the feedback of proposed policies, for example, through the use of methods in Villoria et al. (2022) in the context of evaluating leakage effects of a policy in Brazil aimed at reducing deforestation.

5.3 Concluding remarks

This thesis presented a systematic approach to incorporate our predictions of economic, ecological, and social uncertainties to make better decisions about the management of natural capital resources. Through the three main studies presented in this thesis, I illustrated that the framework for incorporating uncertainty into decision-making can be applied to a range of different contexts, generating new knowledge of how using these methods will affect both the decisions we make and the outcomes of these natural capital decisions. My contributions pave the way for a framework for evaluating the multiple risks associated with natural capital decision-making and identifying strategies for coping with sustainability challenges at the global and local scale that ensure robust and resilient delivery of the needs of mankind. These contributions to the literature will guide policymakers tasked with making long-term decisions about the environment in a highly uncertain environment, thus contributing to better actions towards mitigating global environmental challenges facing society today and in the future for the benefit of mankind.

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Appendix A

Overview of decision theory in economics

The simplest problem of decision-making under uncertainty is one in which choices must be made over a small discrete set of possible policy interventions. I begin with an exploration of that problem before later extending to the analysis of problems with a near-continuous space of possible policy interventions. For simplicity, I characterise these policy interventions according to a metric that measures its value to decision-maker, denoted v. Say, for example, net economic gains or frequently in the case of this thesis, the net natural capital values. Consider the set $x \in \mathcal{X}$ that contains the array of feasible policy interventions. A simple example might consist of Policy A, Policy B, Policy C, and Policy D giving $\mathcal{X} = \{A, B, C, D\}$ and their associated real-numbered values given by $v(x)$. Of course, in the case where these values are deterministic, the decision-maker can select the policy intervention that has the highest v. It is easy to see that this simple decision criterion can become complicated when $v(x)$ is a risky prospects described by probability distributions $p(v(x))$, characterised by $s = 1, ..., S$ number of states of the world, with $v(x,s)$ being the value of policy intervention x in the s state of the world, and for notation convenience, $v(x)$ (without the state of the world superscript) being a random variable of the value of policy intervention x across all states of the world.

Our point of departure for comparing these risky prospects is the theory of stochastic dominance used widely in mathematical economics to establish general principles for identifying optimal decisions (Hadar and Russell, 1971). For the probability distributions of $v(x)$, the cumulative density function F of its probability distribution can be defined as follows:

$$F_{v(x)}(y) = p(v(x) : v(x) \leq y) \tag{A.1}$$

Where v is a random variable describing the probability distribution of the outcome of a policy intervention, and $y \in \mathbb{R}$ is a real number. To establish general principles for decision-making, I say that the policy intervention A is first-order stochastically-dominant over the policy intervention B under the following condition:

$$F_{v(A)}(y) \leq F_{v(B)}(y) \qquad \forall y \in \mathbb{R}, \text{ and} \tag{A.2}$$

$$F_{v(A)}(y) \neq F_{v(B)}(y) \qquad \text{for some } y \tag{A.3}$$

The equation A.2 establishes that the value of the cumulative density function of $v(A)$ must be less than or equal than $v(B)$ at all points on the number line. Equation A.3 establishes that the value of the cumulative density function must be less for some value of y, thus ensuring that the conditions for first-order stochastic dominance cannot be met if $v(A)$ and $v(B)$ are identical distributions, which in that case, the decision-maker should be indifferent between the two.

The left panel of Figure A.1 depicts the cumulative density functions of $v(A)$ and $v(B)$ where $v(A)$ fulfils conditions for first-order stochastic dominance over $v(B)$. In this particular case, these are two normally-distributed variables with mean 3 and 1 respectively, and the same variance. In the figure, I show that the cumulative density functions of $v(A)$ is less than or equal to $v(B)$ for any value of x. Not only does this suggest that the expected value (the mean of the distribution) of $v(A)$ is higher than $v(B)$, but it also suggest that for any given level of x, the decision-maker has a higher probability of achieving a value that is higher than x by selecting A over B. For this reason, policy intervention A is always more preferable than B for any decision-maker, irrespective of their risk aversion.

In the case where first-order stochastic dominance over value distributions cannot be established, the decision-maker can also potentially establish second-order stochastic dominance as a decision criterion for establishing a relative ordering between the two policy interventions. Here on the right panel of Figure A.1 illustrates the conditions where second-order stochastic dominance can be established. Formally, second-order stochastic dominance can be established for C over B if the following condition is met:

$$\int_{-\infty}^{c} F_{v(C)}(y)dy \leq \int_{-\infty}^{c} F_{v(B)}(y)dy \quad \forall c \in R \tag{A.4}$$

$$F_{v(C)}(y) \neq F_{v(B)}(y) \qquad \text{for some } y \tag{A.5}$$

The equation A.4 measures the probability mass of the cumulative density function on the left, which are specifically less-desirable outcomes than those on the left. If a policy intervention has more probability mass on the left, it is more likely to have extremely low values of v compared to one with less probability mass on the left. The equation A.5 again ensures that the two distributions are not identical. Note that any distribution that satisfies the conditions for first-order stochastic dominance also satisfies those of second-order stochastic dominance.

The right panel of Figure A.1 illustrates these two distributions that satisfy conditions for second-order stochastic dominance, with both distributions being normal distributions with same mean, but $v(B)$ has a higher variance than $v(C)$. It is easy to see that first-order stochastic dominance cannot be established in this case, with $F_{v(C)}$ having lower values than $F_{v(B)}$ for $v < 2$ but higher values for $v > 2$. Here, we see that second-order stochastic dominance can be established by virtue of the smaller probability mass of $F_{v(C)}$ compared to $F_{v(B)}$ on the left hand side. In this example, it means that a policy-maker selecting $F_{v(C)}$, compared to $F_{v(B)}$, has a much smaller chance of getting outcomes that are significantly lower than its mean, such as $v = 0$, but also, has a much lower chance of realising outcomes much higher than its mean, such as $v = 4$.

Second-order stochastic dominance introduces the concept of risk-aversion in the context of decision-making under uncertainty. Because policy intervention C produces much less dispersed outcomes, decision-makers selecting it are much more likely to realise outcomes close to the expected outcomes (mean) compared to selecting policy intervention B. However, selection of C foregoes the possibility of achieving outcomes that are much better than the expected. In this case, and many other cases explored in this thesis, preferences for which policy intervention is the best depends on the risk attitudes of the decision-maker. If C is only second-order stochastic dominant over B and not first-order stochastic dominant, a risk-neutral decision-maker will be indifferent between C and B but a risk-averse decision-maker will prefer C over B.

Whilst a decision-maker who ignores risk would find a distribution that maximises expected outcomes the best, a decision-maker who is risk-averse could find alternatives

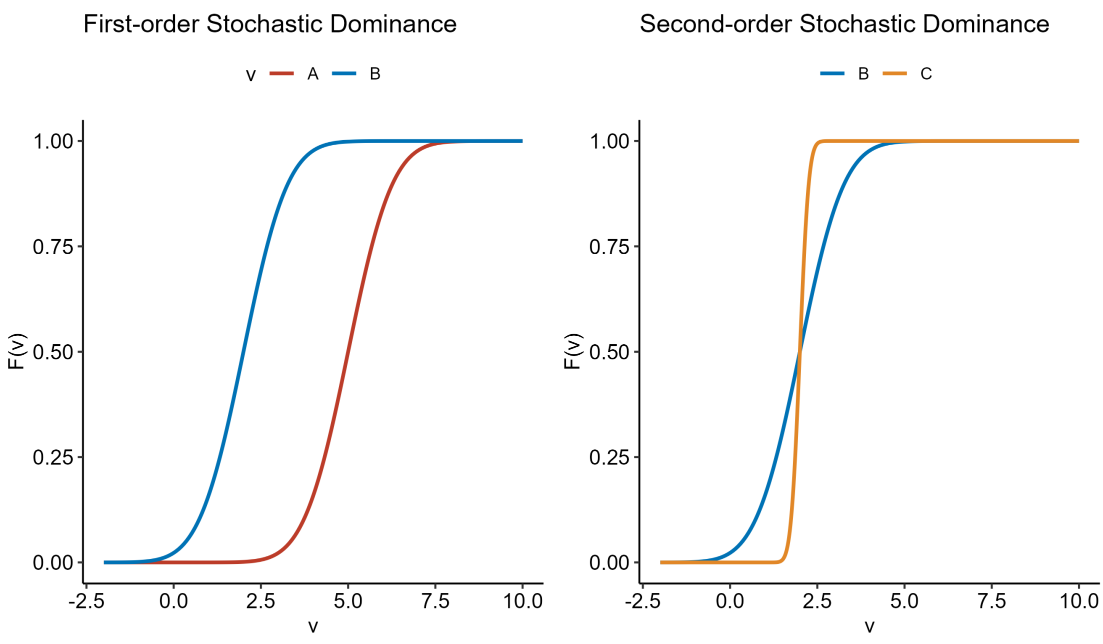

Figure A.1: Cumulative density functions of policy interventions that produce random outcomes that fulfil conditions for first-order and second-order stochastic dominance respectively

that have lower downside risks—outcomes that are far worse than expected on average—as desirable.

Using the principles of stochastic dominance, economic theory allows us to move on to a more general description of preferences using the Expected Utility Theory proposed by von Neumann and Morgenstern (von Neumann and Morgenstern, 1944). The Expected Utility Theory posits that in the face of uncertainty, decision-makers maximise their expected utility that relates outcomes they receive in different states of the world to the utility they derive. These theories outline principles to how decision-makers can develop preference ordering for policy interventions that produces random distributions of outcomes.

Consider a strictly-increasing utility function $U_\theta : \mathbb{R}^S \to \mathbb{R}$ that maps the distribution of outcomes across the number of states of the world S to a real number that expresses the "utility" received by the decision-maker, with the properties of U being controlled by $\theta \in \mathbb{R}$, a risk-aversion parameter. The expected utility theory argues that the decision-maker will choose the policy intervention that maximises the following function:

$$\max_{x \in \mathcal{X}} \mathbb{E}_{s \in \{1,\dots,S\}} \left[U_\theta(v(x,s)) \right] \tag{A.6}$$

Here, the decision-makers' optimal choice for x, the policy intervention, is one that maximises the expected value of the utilities produced in each state of the world. To see how the expected utility theory is connected to stochastic dominance, we revisit the two policy interventions introduced earlier, policies A and B, with a Constant Relative Risk Aversion (CRRA) utility function specification, the same specification I use in Chapter 2.

$$U_\theta(w) = \begin{cases} \frac{w^{1-\theta}}{1-\theta} & \theta \neq 1 \\ \log(w) & \theta = 1 \end{cases} \tag{A.7}$$

I only focus here on two special cases: $\theta = 0$ (risk-neutral) and $\theta = 1$ (risk-averse log utility function).

We examine first the distributions of outcomes of first-order stochastic dominance, depicted in Figure A.2. Mapping the distribution of values in Figure A.2a to the utility functions in Figure A.2b reveals that in the case of comparing just A and B where A fulfils condition for first-order stochastic dominance over B, the expected utility of these outcomes (dashed line in Figure A.2c) is higher for A irrespective of which utility function is used, so long as the utility function is strictly-increasing. In other words, the decision-maker will still be better-off selecting A over B if he/ she uses the expected utility theory to choose between the two.

The utility function chosen–and by extension, the decision-makers' risk preferences–start to influence decision-making in the case where C is only second-order stochastically-dominant over B. This is illustrated in Figure A.3 where again, here C is only meets conditions for second-order stochastic dominance over B, and not first-order stochastic dominance. Mapping C and B to the same utility functions reveals that in the risk-neutral case, C obtains a higher expected utility than B only in the case of risk-aversion where $\theta = 1$ and not in the risk-neutral case where $\theta = 0$. In the risk-neutral case, the decision-maker is said to be indifferent to C and B.

While stochastic dominance is a crucial concept to establish for optimal decision-making under uncertainty, it does not extend well to cases where stochastic dominance cannot be clearly established. To see when expected utility theory can be uniquely useful for identifying optimal decisions, consider the comparison between B and a new policy

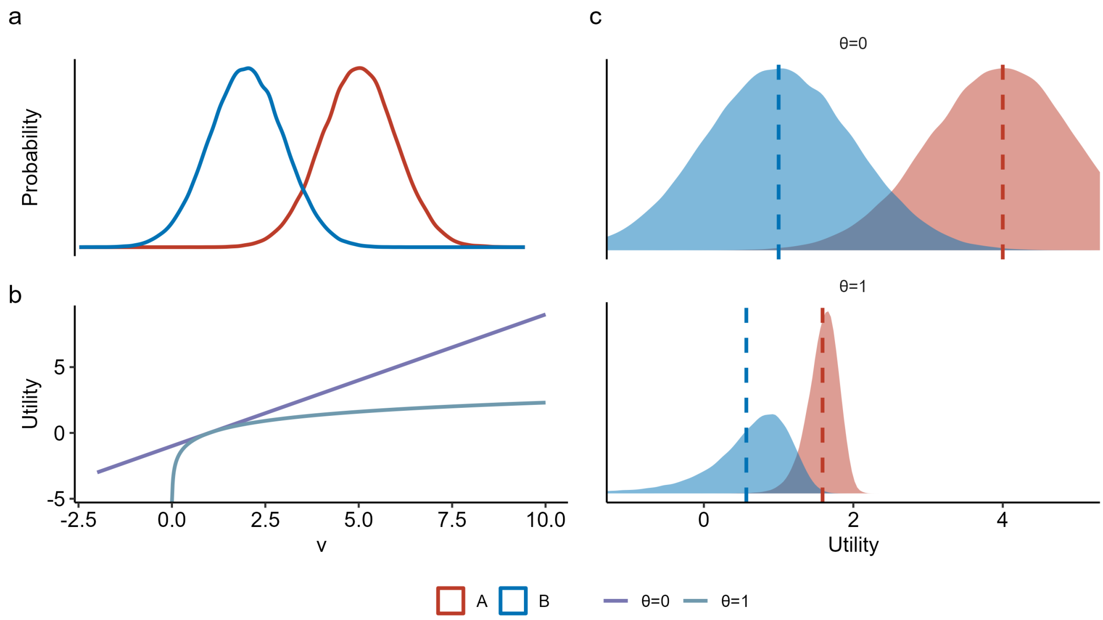

Figure A.2: Expected utility of two random variables A and B where A is first-order stochastically-dominant over B. a, the probability density function of the value of A and B, b, the utility functions where $\theta = 0$ and $\theta = 1$, and c, the distribution of utility values of the distributions respectively, with the dashed line indicating its expected value

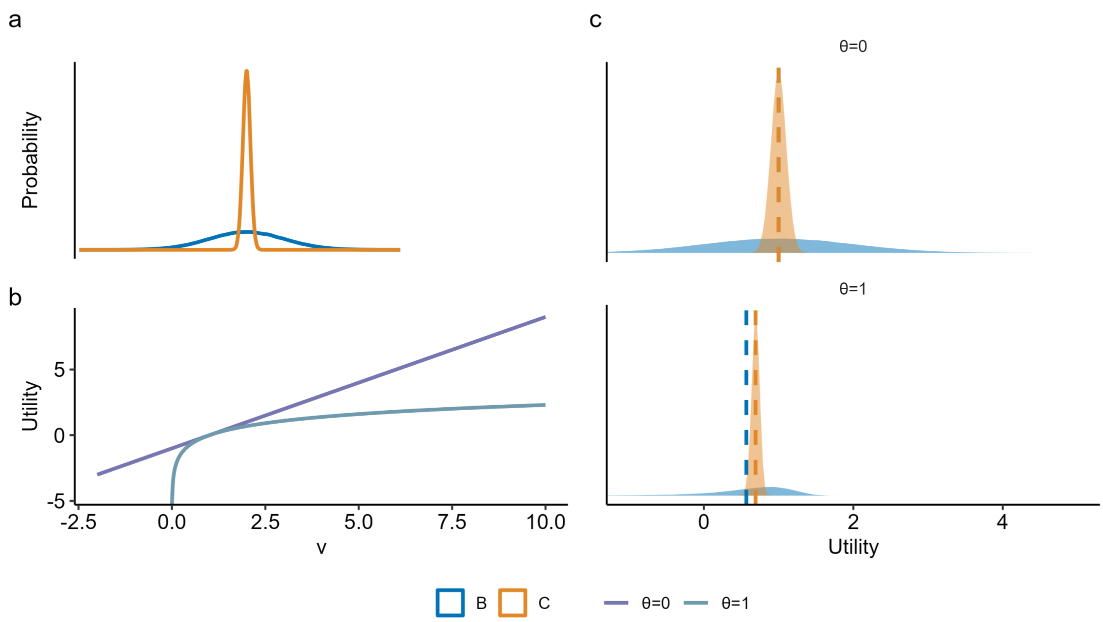

Figure A.3: Expected utility of two random variables C and B where C is second-order stochastically-dominant over B. a, the probability density function of the value of C and B, b, the utility functions where $\theta = 0$ and $\theta = 1$, and c, the distribution of utility values of the distributions respectively, with the dashed line indicating its expected value

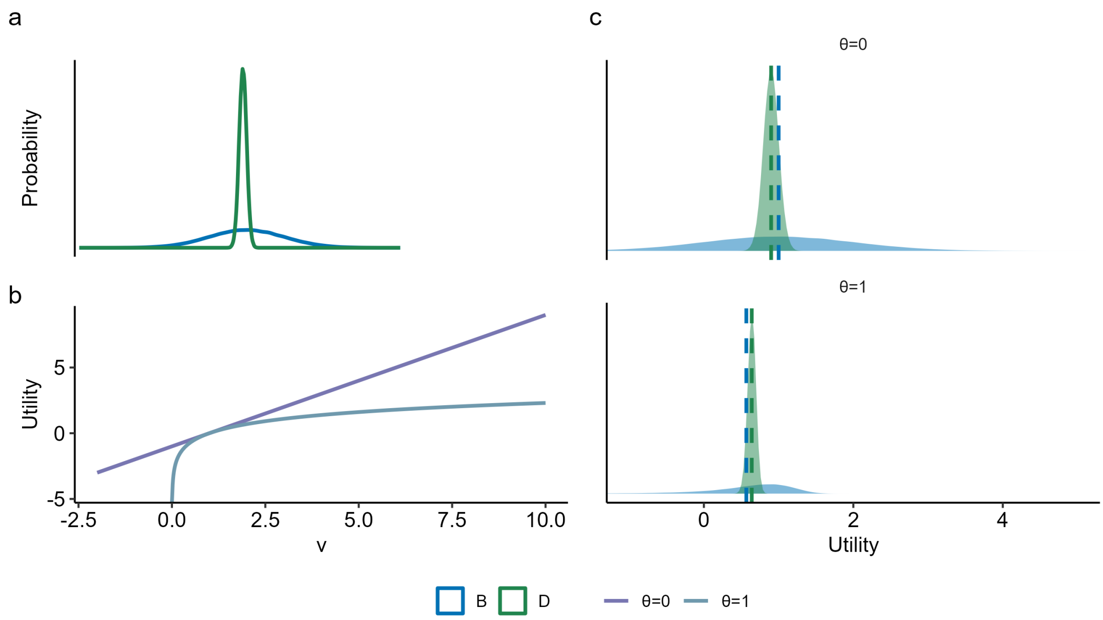

Figure A.4: Expected utility of two random variables B and D where no stochastic dominance conditions are fulfilled. a, the probability density function of the value of C and B, b, the utility functions where $\theta = 0$ and $\theta = 1$, and c, the distribution of utility values of the distributions respectively, with the dashed line indicating its expected value

intervention D where neither first or second-order stochastic dominance can be established between the two. In Figure A.4 observe the two distributions B and D, where $v(B)$ has a higher mean but also higher variance than $v(D)$. We observe that for $\theta = 0$ the decision-maker would be better-off selecting policy B, but in the case of risk-aversion, the opposite is true. Because in this case no stochastic dominance rules are met, the decision-maker will have to rely on expected utility to decide which policy intervention is likely to optimise utility. But here in this case, the expected utility theory leads to a criterion for determining which policy intervention is more desirable to the decision-maker even if stochastic dominance cannot be established.

Appendix B

Supporting information for Chapter 3

B.1 Climate variables

To quantify uncertainties over future climates, we use the latest high-resolution (1 km) climate projections from the CHESS-SCAPE dataset (Robinson et al., 2022). The different projections in this dataset are taken to define the decision-maker's range of uncertainty over the future climate. The uncertainty captured in those projections includes both uncertainty over the possible future pathway for greenhouse gas concentrations in the atmosphere (described by RCP2.6, 4.5, 6.0 and 8.5) and uncertainty emanating from limitations in our ability to project future climates (characterised by variability across perturbed runs of a climate model under different RCPs). The dataset contained bias-corrected projections of climate variables at a 1km gridded resolution across the United Kingdom up to 2080 on a monthly basis. The climate projections are derived from downscaled projections from the UK Hadley Centre Regional Circulation Model (RCM) produced under the UKCP18 at the UK Met Office. The CHESS-SCAPE dataset extends the UKCP18 RCM projections by creating projections for RCPs other than RCP8.5. The dataset also provided projections of four climate model members for each RCP, indexed 01, 04, 06, and 15. These four climate members represent projections of the same RCM under different perturbed physics conditions. We extracted the values of future climate variables to match the 2km grid cell used in NEV. Subsequently, we calculated the growing season (April to September) temperature and precipitation projections of future climate variables on an annual basis up to 2080.

Future climates also drive the prices of goods and services produced by forestry and

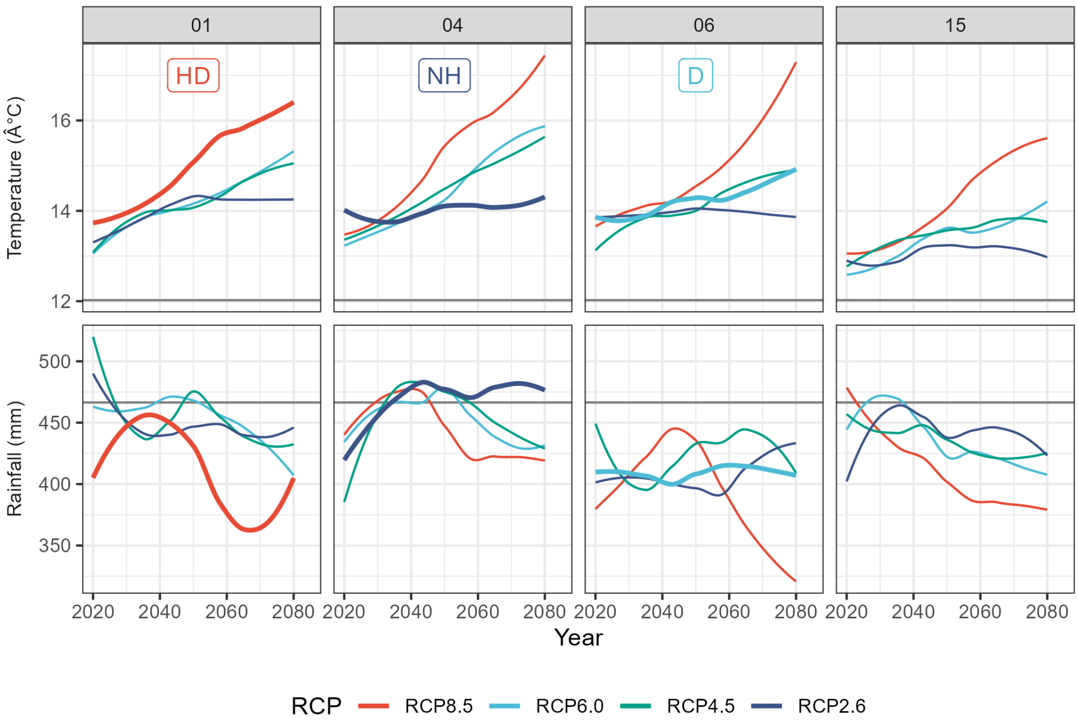

Figure B.1: Time series of growing season temperature and rainfall in under different climate model projections. Each point represents a model member and representative concentration pathway (RCP) pair. 01, 04, 06 and 15 represent model runs with different perturbed-physics conditions for climate projections from the climate model HadREM3-GA705 produced by the Hadley Centre, UK Met Office. Bold lines represent the climate projections used in the selected NH, H, and HD realisations.

agriculture. The values of different agricultural produce are linked to future climates through macroeconomic vector-autoregressive models that capture long-term empirical relationships between climate, macroeconomic variables (e. g. GDP and interest rate) and the prices of agricultural commodities.

B.2 Value of agricultural commodities

Future climates also drive the prices of goods and services produced by forestry and agriculture. The values of different agricultural produce are linked to future climates through macroeconomic vector-autoregressive models that capture long-term empirical relationships between climate, macroeconomic variables (e. g. GDP and interest rate) and the prices of agricultural commodities. The Vector Autoregressive (VAR) models characterise the plausible distribution of prices of 7 major agricultural commodities: wheat, potatoes, rapeseed oil, sugarbeet, cattle, sheep, and milk. This output of VAR model is subsequently used to further characterise the trends of fertiliser and barley prices. To model possible co-movements of prices in agricultural markets, the prices of wheat, cattle sheep and milk are modelled simultaneously, whereas the prices of potatoes, rapeseed oil and sugarbeet are modelled independently. This leads to a set of 4 VAR models that can be used to predict the prices of the 7 agricultural commodities. These VAR models the historical variability and co-variability of prices of agricultural commodities.

Data on the trends in monthly Defra price indices (1990-2018) of these agricultural commodities relative to base year (2015) are modelled as a function of its own lag and other macroeconomic and weather variables. Macroeconomic variables include monthly data on Brent oil price ($/bbl), Real GDP (nominal GDP and GDP deflator) and monthly short-term interest rates. Weather variables include crop specific temperatures (measured in °C) and precipitation (measured in millimetres). Following established practice in the literature (Lobell & Field, 2007; Lobell et al., 2011), weather variables were constructed by averaging monthly weather observations based on a crop growing season (Sacks et al., 2010) and the areas where the crop is cultivated (Monfreda et al., 2008).

All these models take the form of a system of equations, one for each variable, where each variable is modelled as a function of its own and other variables' lagged values.

$$\mathbf{Y}_t = \sum_{i=1}^{p} \mathbf{A}_i \mathbf{Y}_{t-i} + u_{it} \tag{B.1}$$

$\mathbf{A}_i$ is a matrix of coefficients that describe the temporal lag of variables in the multivariate time series. $\mathbf{Y}$ is a k by 1 vector, p is the number of lags, and u_t are errors following this distribution: $\mathbf{u}_t \sim N(0, \Sigma_u)$. k is the number of variables in the multivariate time series.

In addition, responses of fertiliser prices (Defra agricultural price index) are modelled as a function of Brent oil price based on the Engle-Granger ADF Cointegration approach. P_{fert} is the Defra price index of fertilisers and P_{oil} is the price of Brent oil in $/bbl.

$$\ln\left(P_{fert}\right)_t = 2.015 + 0.583 \ln\left(P_{oil}\right)_t \tag{B.2}$$

Winter and summer barley prices in its Defra price indices are predicted with the exact same methodology as a bivariate relationship with wheat prices. P_{barley} is the Defra price index of barley. P_{wheat} is the Defra price index of wheat.

The 4 VAR models contain crop-specific temperatures and rainfall of wheat, potatoes, rapeseed oil and sugarbeet. To produce consistent predictions of future agricultural market predictions, predictions of crop-specific temperature and rainfall based on the percentiles of the spatially explicit climate time series were produced. For a given combination of percentiles of temperature and rainfall, the temperature and rainfall data in the locations where the crops are planted based on predictions of the growing locations of wheat, potatoes rapeseed oil and sugarbeet in the United Kingdom obtained from NEV in 2020 were isolated. This allowed the construction of a time series of crop-specific temperatures specific to each percentile of temperature and rainfall specified within the climate time series. The temperature and rainfall data were subsequently averaged to produce one single time series for simulation in the VAR model.

Following the construction of these VAR models, a Monte Carlo approach was used to simulate random temporal trends from the year 2020 to 2050 conditional on the specified crop-specific temperature and rainfall time series (Lütkepohl, 2005). The VAR model provides a prediction of the most likely price trends of the agricultural commodities going into the future. Confidence intervals can also be estimated through the variance-covariance matrix of the errors: Σ_u. These intervals enable one to estimate the probability of a specific commodity reaching any certain price at any time step. Monte Carlo simulation of a VAR model allows one to simulate several plausible multivariate time series that reflects the temporal relationships between variables expressed in the temporal lag coefficients of the VAR model.

B.3 Social cost of carbon (SCC)

Estimates of the temporal evolution of SCC are sensitive to both the future quantity of emissions and the estimates of the temperature-damage relationship that translate temperature increases to losses in global economic productivity (Russell et al., 2022). We characterise that uncertainty by drawing realisations of the temperature-damage relationship from a meta-regression model of a systematic review of these estimates (Howard & Sterner, 2017). The uncertainty over temperature-damage relationship are propagated through a recently-developed Integrated Assessment Model (IAM) which updates the Dynamic Integrated Model of the Climate and the Economy (DICE) and reflects the latest findings in climate science and economics (Hänsel et al., 2020). Within a CER, therefore, we draw a temperature-damage relationship compatible with that realisation's assumed RCP. The time path for the SCC is then established by solving the IAM using that damage relationship and constraining the model to a pathway of global carbon emissions consistent with the assumed RCP as defined by the IIASA RCP database (IIASA, 2010).

Our analysis considers two inputs that the SCC is sensitive towards: (1) the representative concentration pathway (RCP) and (2) the climate damage parameter, while noting that there are several other sources of uncertainties in the calculation of the SCC such as the equilibrium climate sensitivity to greenhouse gases, social discount rate and intergenerational inequality aversion parameters. We used the "Updated DICE" (Dynamic Integrated Climate-Economy model) with AMPL source code from Hänsel et al. (Hänsel et al., 2020) to estimate the SCC. Hänsel et al. updated Nordhaus' DICE model with modifications in the carbon cycle, energy balance model and updated climate change estimates. We made modifications on top of that to make the code sensitive to uncertainties over future emissions and temperature-damage relationship.

The updated DICE model, analogous to the original DICE model, seeks to find the optimal emission, temperature and carbon tax trajectories to maximise a utilitarian social welfare function discounted over time at a global level. The social welfare function is a function of the utility function U, the per capital consumption c, population L, and the discount factor on welfare $R(t) = (1+\rho)^{-t}$:

$$W = \sum_{t} U\left[c(t)\right] L(t) R(t) \tag{B.3}$$

The utility function has the form $U(c) = \frac{c^{1-\eta}}{1-\eta}$ where η is a parameter for generational inequality aversion. We used the social discount rate of $\rho = 1.5\%$ and an inequality aversion parameter $\eta = 1.45$.

Net output Q is a function of gross output Y, a Cobb-Douglas function of capital, labour and technology, minus damages Ω and mitigation costs Λ, defined as follows:

$$Q(t) = \Omega(t)\left[1 - \Lambda(t)\right] Y(t) \tag{B.4}$$

Of particular interest is the damage function Ω. The damage function is defined as $\Omega(t) = D(t) / [1 + D(t)]$, where $D(t)$ is a function of global average temperature increases relative to historical averages T_{AT} and terms that describes the temperature-damage relationship ϕ_1 and ϕ_2 that translate temperature change to a percentage change in GDP.

$$D(t) = \phi_1 T_{AT}((t)) + \phi_2 [T_{AT}(t)]^2 \tag{B.5}$$

Published estimates of the temperature-damage relationship differ, suggesting vast uncertainties in the functional form of the damage function. While Hänsel et al. 11 set ϕ_2 to be fixed at the value at the "mean" of the preferred estimate reported by Howard and Sterner30, we quantified the sensitivities in the SCC from the parameter ϕ_2 based on the probability distribution of their "preferred estimate", characterised by the mean and standard errors of the estimate, of Howard and Sterner (Howard & Sterner, 2017). Each climate-economy realisation uses a different random draw of the estimate of the temperature-damage relationship. This allows us to characterise a range of possible SCC pathways for a given RCP.

Emissions are the sum of industrial emissions E_{Ind} and land-use emissions E_{Land}.

$$E(t) = E_{Ind}(t) + E_{Land}(t) \tag{B.6}$$

Where land-use emissions E_{Land} is specified exogenously and industrial emissions E_{Ind} is a function of carbon intensity σ and emissions reduction rate μ:

$$E_{Ind}(t) = \sigma(t)[1 - \mu(t)]Y(t) \tag{B.7}$$

We retrieved emissions data corresponding to each RCP from the IIASA RCP Database (IIASA, 2010). We extend Hänsel et al. by using the corresponding land-use emissions scenario data from each RCP, as opposed to assuming exogenous land use emissions in RCP2.6. We further constrain the solution of the solver such that the emissions level match that in the RCP scenario.

The SCC is calculated as the change in economic welfare from an additional unit of CO2-equivalent emissions, defined as a function of global emissions E and aggregate consumption C:

$$SCC = \frac{\partial W}{\partial E(t)} / \frac{\partial W}{\partial C(t)} = \frac{\partial C(t)}{\partial E(t)} \tag{B.8}$$

The SCC is used as the value of each tonne of carbon sequestered in each year.

B.4 Valuation of changes in natural capital

The NEV suite of models is an integrated model of land-use in Great Britain that captures changes of multiple ecosystem services arising from land-use change developed at the Land, Environment Economics and Policy (LEEP) Institute at the University of Exeter. It predicts the change in the value of ecosystem services when land-use is altered through tree-planting. We built on top of the core functionalities of the forestry and agricultural models within NEV to quantify the uncertainties of these predictions under a wide range of climate and economic futures. The reader is referred to Day et al. 2020 for a full technical description of the capabilities of the model inclusive of other ecosystem services, but here we present the description of the model workings relevant to this paper.

The model calculates the benefits and costs of tree planting. For each planted cell, NEV estimates the annualised quantity of timber output and carbon flux from the tree species grown in that cell under the realisation's assumed future climate. Those quantities are translated into monetised benefits using the realisation-specific future timber values and SCC time series. Emissions from agriculture displaced by tree planting activities are not expressly quantified because the carbon sequestration target (12MtCO2e) identified as required to meet UK policy commitments does not account for avoided agricultural emissions. The costs of planting are the value of that stream of foregone outputs from farming, quantities being estimated by the NEV model's predictions of agricultural output choices driven by realisation-specific agricultural yields and prices. Finally, benefit and cost time series are discounted using the UK government social discount rate of 3.5% (HM Treasury, 2020) and NPV is calculated over the standard 30-year time horizon.

B.5 Forestry

For this analysis, we predicted the change in natural capital value of land use of tree planting of representative tree species of conifers (Sitka Spruce) and broadleaf (Pedunculate Oak). Planting is restricted on arable and temporary grassland only and is assumed to completely displace agricultural activities on planted land. The net benefits of woodland planting are quantified as the difference between the natural capital benefits generated by tree planting, including timber revenues and carbon sequestration, minus the costs accrued from profits generated by agricultural production that are foregone because of tree planting.

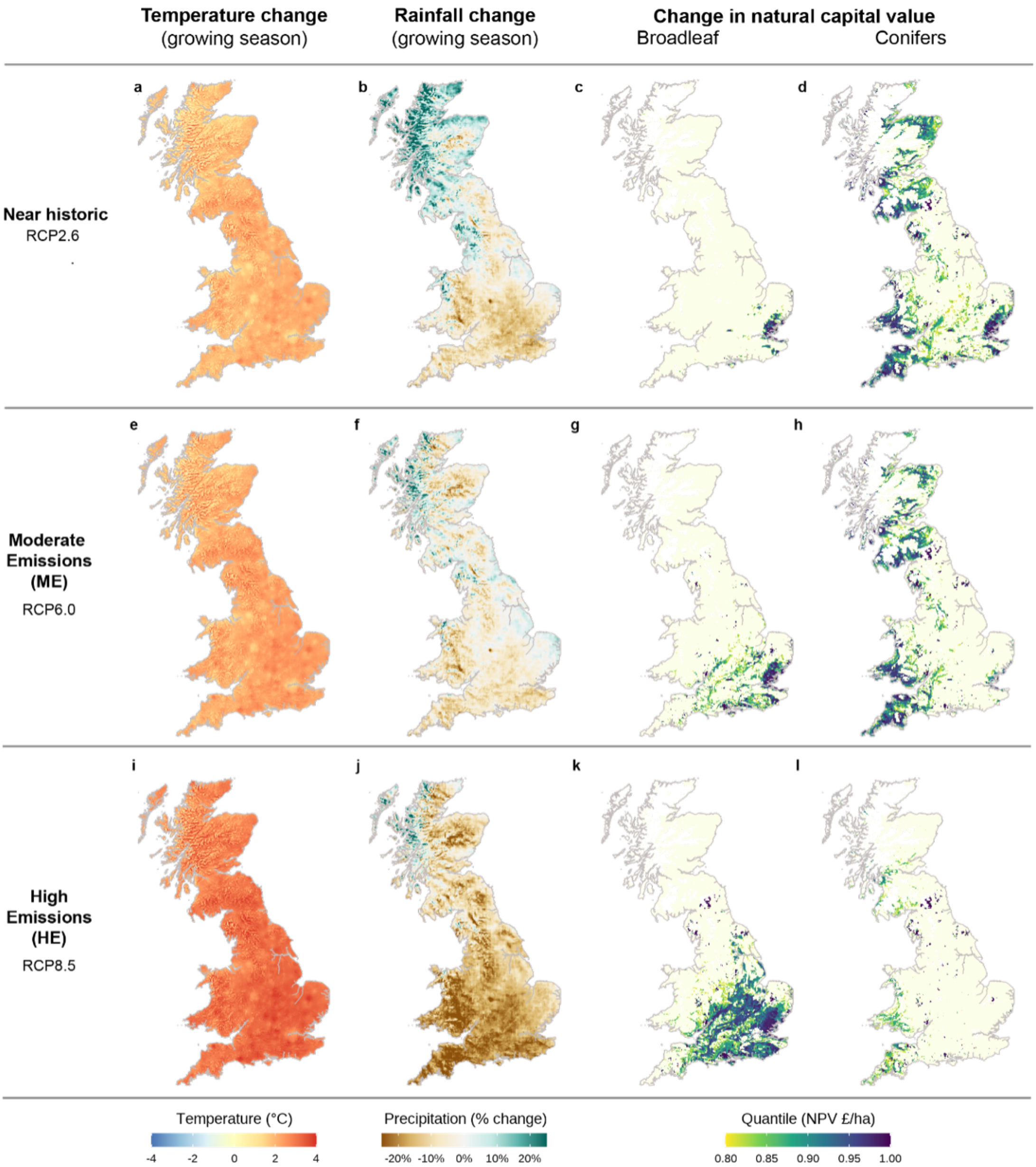

Figure B.2: Optimal locations and species for woodland planting change under different climate-economy realisations. a-d, the spatial distribution of five geographic variables when assuming a Near Historic (NH) climate future (RCP2.6): a, 2020-2080 average growing season (April-September) temperatures (°C), b, 2020-2080 average growing season (April-September) change in precipitation (%), c, change in net present value with broadleaf planting on arable/ temporary grassland, d, change in net present value with conifer planting on arable/ temporary grassland, e-h, shows the same variables under a Moderate Emissions (ME) future (RCP6.0). i-l, the same variables under a High Emissions (HE) future (RCP8.5).

Incomes from timber harvesting are predicted with the aid of the CARBINE model (Thompson D. A and Matthews, 1989) developed by Forest Research embedded within the NEV decision-support integrated environment-economy model. The model predicts forestry planting decisions and resulting timber output and profitability in response to characteristics, climate, and market conditions. It is assumed that a management regime exists over the newly created woodland on an annual basis between 2020 and 2060 for the species of trees planted. The model relies on the concept of yield classes in the framework of the Ecological Site Classification (ESC). The yield classes and site classifications are metrics describing the suitability of the piece of land for the growth of tree species. These metrics are functions of local and climatic factors. In the NEV model, the timber output of land is predicted through a two-stage process. First, timber volumes are predicted on an annual basis over the rotation period of the tree species with the CARBINE model. Second, the impacts of climate change on tree growth were predicted with a semi-parametric model. The semi-parametric model takes as inputs local and climatic factors including growing season temperatures/ precipitation, slope and elevation of the cell, geographical location, and soil characteristics (such as water regime, pH, water capacity and carbon in soil) to make predictions the future yield classes of the site. The growth patterns of timber were adjusted according to predicted future yield classes. The NEV model on timber growth is thus sensitive to future climate projections. The timber volumes predicted through the CARBINE and the semi-parametric models are combined with the FC Forest Investment Appraisal Package to estimate the value of timber production and its associated management costs. By estimating the difference between revenues from timber sales and costs from management, profits are calculated in a Net Present Value terms using the same social discount rate of 3.5%. These Net Present Values are then annualised over one rotation period and constitute the timber revenues component of the tree planting alternatives. Details of this methodology can be found in Binner et al. (Binner et al., 2019). The natural capital value produced by carbon sequestration is estimated by multiplying the change in carbon volume for any given year with the Social Cost of Carbon (SCC) in that year, described in the previous section. The same discount rate (3.5%) was used to convert earnings from one rotation to Net Present Values. These earnings are subsequently annualised by dividing the total NPV with the number of years in the rotation period.

B.6 Foregone agricultural profits

The costs from foregone agriculture were estimated with a farm management model building on several years of spatial econometric modelling of British agriculture (Bateman et al., 2016, 2013; Fezzi et al., 2014). Earlier iterations of the model formed a crucial component of the UK National Ecosystem Assessment (Bateman et al., 2013). The agriculture model predicts farm planting and stocking decisions in response to land characteristics, climate, and market conditions. The model is estimated primarily using data from the June Agricultural Census (1976-present, Defra), and the Farm Business Survey (2007-2015, Defra). Each location is taken as an agricultural decision unit managed by a "farmer." The model assumes that a "farmer" manages the agricultural activity in each location. Crucially the "farmer" decides land use for the current year based on prices of agricultural commodities and weather observed in the previous year. The following process is repeated for each price/ climate scenario, across all locations and in each year:

1. At year t, a biophysical model predicts the share of arable and grazing land in that year based on soil and other site characteristics as well as growing season temperatures and precipitation of that particular year. Details of the biophysical model can be found in Ritchie et al. (Ritchie et al., 2020).

2. Given the allocation of arable and grazing, the "farmer" observes the prices of agricultural commodities, fertiliser, and growing season temperatures/ precipitation of the year. These prices are obtained from the multivariate time series simulated in the climate-economy realisation. The "farmer" decides what crops to plant/ livestock to raise for t+1 based on the observed prices of agricultural commodities and biophysical conditions of the farm.

3. At the year t+1, the "farmer's" profits are calculated based on the land use allocation decided during t and the realisation of prices and climate in that year

4. The opportunity cost of planting in that year is calculated as the agricultural profits in the arable land and temporary grassland portions of the land. If tree planting occurred those pieces of land, it will not be agriculturally productive and therefore these profits will be the opportunity cost of planting

5. The algorithm is repeated for the next year (t = t+1)

After the algorithm estimates the spatial opportunity costs of planting in the years 2020 to 2050, the costs are annualised with a discount rate of 3.5% for all locations.