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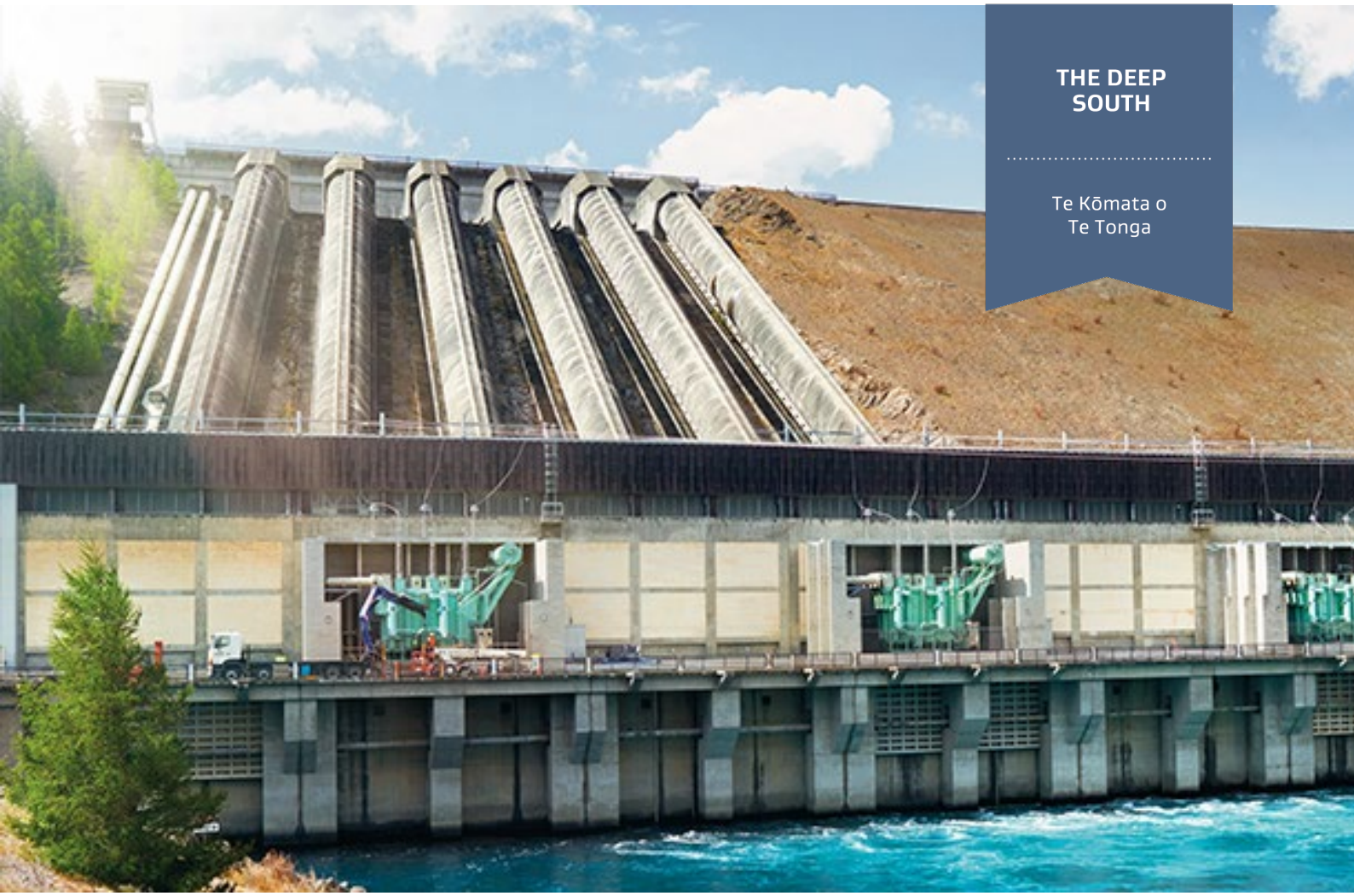

Robust Adaptation Decision-Making Under Uncertainty: Real Options Analysis for water storage

Anita Wreford *Lincoln University*

Ruth Dittrich *University of Portland*

Christian Zammit *NIWA*

Channa Rajanayaka *NIWA*

Alan Renwick *Lincoln University*

Daniel Collins *NIWA*

National Science Challenges

THE DEEP SOUTH

Te Kōmata o Te Tonga

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Author(s)	Anita Wreford Ruth Dittrich Christian Zammit Channa Rajanayaka Alan Renwick Daniel Collins

Author Contact Details

Anita Wreford

Lincoln University

Anita.wreford@lincoln.ac.nz

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Executive Summary

Planning for climate change adaptation is challenging due to the inherent uncertainty associated with future climate changes. Although we have a range of climate projections, even these cannot provide a definitive picture of the future, with little certainty regarding the timing, magnitude and location of change. As a result there is increasing interest in approaches that can accommodate uncertainty better. A range of approaches exist and are being developed across several disciplines. Each has advantages and disadvantages and is suited for different types of decisions.

In this study we focus on one of these approaches, Real Options Analysis (ROA), and chose water storage for irrigation as an example to demonstrate its use in uncertain futures.

ROA is most suited to large, one-off investment decisions, such as water storage. Reservoirs are a significant investment, and without fully considering the range of future water availability, may turn out to be either too large, or not economically viable. Conversely, without their existence to smooth out water variability, significant production losses may be experienced in the future.

While we use a case study location in Canterbury, the intention with this analysis is to demonstrate the process of ROA, the type of information developed, and how it can be used to support decision-making under uncertainty. The approach can be applied to any type of large irreversible investment decision.

Using the full range of climate model and warming scenario combinations available in New Zealand (24), we develop estimates of water requirements out to 2090 for the chosen location. We specify two decision points: 2018 and 2050, and construct a decision tree with 256 potential paths. We develop a method to use the range of 26 GCM/RCP combinations available in New Zealand to generate estimates of likelihood. Using a backward induction technique, we identify the most cost-effective storage size. In this particular example, the most cost-effective option was to construct a reservoir for the most conservative climate change outcome in 2018, and in 2050. The decision to build for the smallest climate change is sensitive to a number of factors however, particularly the discount rate and the milk price, both of which result in larger reservoirs being more cost-effective in the first time period. The decision is also sensitive to assumptions regarding the likelihood of future climate changes – when the higher and lower climate scenarios are assigned a lower likelihood, this changes the decision to a larger storage size in 2018. This analysis illustrates the benefits of ROA when the future is uncertain – by enabling decision-makers to adjust their decisions over time rather than locking themselves into a decision made now that has long-term consequences.

We used an example of water storage on a dairy farm to illustrate how ROA can be used, using the climate data available in New Zealand. This method is suitable for application across a range of investment decisions in New Zealand, where the initial cost is large and the investment is at least partially irreversible. We believe that using ROA for these types of decisions will enable more cost-effective investment than cost-benefit analysis or other methods that use only a single climate scenario.

1. Introduction

Planning for climate change adaptation is challenging due to the inherent uncertainty associated with future climate changes. Although we have a range of climate projections, even these cannot provide a definitive picture of the future, with little certainty regarding the timing, magnitude, and locations of change. Within climate models and their projections, a wide range of futures exist, creating uncertainty for decision-makers. This uncertainty stems from four main sources:

- Scenario uncertainty due to different concentrations of greenhouse gases (GHGs) in the atmosphere. This depends on how successful the global community is at reducing emissions;
- Response uncertainty due to limitations in understanding of climate processes and how they are represented in climate models;
- Uncertainty in natural climate variability;
- Uncertainty in downscaling emissions (CSIRO and BOM 2015)

Despite this uncertainty, many adaptation decisions need to be made now, in advance of climate change, to effectively reduce future vulnerability to climate change. Nonetheless, it is clear that uncertainty creates challenges. Decisions with long-term implications, such as investment in capital, risk locking decision-makers into a certain path with little flexibility to change if other conditions, such as the climate, change.

Because of the challenge of uncertainty, there is increasing interest in approaches that can accommodate uncertainty better. We present further background and briefly review these approaches in the next section. In this project, we focus on one of these approaches, Real Options Analysis (ROA), and chose water storage for irrigation as an example to demonstrate its use in uncertain futures.

ROA is most suited to large, one-off investment decisions. Constructing a water storage reservoir, or dam, is an appropriate example, and particularly pertinent in New Zealand where there is increasing interest in, and construction of these. These reservoirs are a significant investment however, and without fully considering the range of future water availability, may turn out to be either too large, or not economically viable. Conversely, without their existence to smooth out water variability, significant production losses may be experienced in the future.

We use a case study location in Canterbury, but the intention with this analysis is to demonstrate the process of ROA, the type of information developed, and how it can be used to support decision-making under uncertainty. The report is structured as follows: In the following section (section 2) we provide a background to decision-making under uncertainty, and a literature review of the approach taken for this study, ROA. Section 3 provides a summary of climate projections for New Zealand and an overview of uncertainty in this context. Section 4 outlines the case study used to demonstrate the ROA method in this study, and section 5 presents the data and methods used. Section 6 presents the results, while section 7 discusses their implications and limitations, and section 8 concludes.

2. Background and literature review

There is increasing interest in decision-making under uncertainty, as it becomes apparent that planning for future climate changes needs to begin now, despite the inherent uncertainty in understanding the details of the timing, magnitude and location of the climate impacts.

Decision-making under uncertainty (DMUU) is emerging as a body of approaches, using both economic and other techniques, to handle uncertainty. DMUU uses principles such as robustness, flexibility, learning and diversification, to address the challenge of uncertainty in the design of practical adaptation plans and projects. In the area of adaptation economics, support methods and tools for the economic appraisal of adaptation are increasing (Dittrich et al. 2016, Watkiss et al. 2015). Complementary approaches outside of economics include adaptive management, iterative risk management (IPCC, 2014), adaptation pathways (Downing, 2012), and dynamic adaptation pathways (Haasnoot et al. 2013).

Alternative decision-making approaches to appraise and select adaptation options are being explored, both in the academic and policy literature (Dessai & van der Sluijs, 2007; Hallegattee al. 2012; Ranger et al., 2010). The aim is to better incorporate uncertainty while still delivering adaptation goals, by selecting projects that meet their purpose across a variety of plausible futures (Hallegatte et al., 2012); so-called 'robust' decision-making approaches. These are designed to be less sensitive to uncertainty about the future and are thus particularly suited for deep uncertainty (Lempert & Schlesinger, 2000). Instead of optimising for one specific scenario, optimisation is obtained across scenarios: robust approaches do not assume a single climate change projection, but integrate a wide range of climate scenarios through different mechanisms to capture as much of the uncertainty on future climates as possible. This is achieved in different ways: Portfolio Analysis (PA), for example, reduces the risk of choosing a single adaptation option that may prove inappropriate by combining several adaptation options in a portfolio. It is thus akin to combining different stock market shares in a portfolio to reduce risk by diversification (Markowitz, 1952). Real Options Analysis (ROA) develops strategies that can be adjusted (e.g. up-scaled or extended) when additional climate information becomes available. It handles uncertainty by allowing for learning about climate change over time and originates from option trading in financial economics (Merton, 1973, Cox et al., 2002, Wreford et al. 2020). Finally, Robust Decision Making (RDM) identifies how different strategies trade-off in order to identify options which might not be optimal under a specific climate outcome but rather less vulnerable under many climate outcomes. These techniques are particularly suited for adaptation options with long lead and/or life-times as they integrate uncertainty in the decision-making process. For a more detailed overview of robust approaches, see Dittrich et al. (2016) and Watkiss et al. (2015).

Real Options Analysis is the extension of the option pricing theory for managing real assets. The financial option valuation tool was systematically developed by Merton in his article "The theory of rational option pricing" (Merton, 1973) building on Black and Scholes's (1972) theory of valuation of contingency claims. Following from there, the model evolved in several branches, summarised below. Designers of military equipment also use a similar concept, where equipment may be fitted "for but not with" the capability of being equipped in future with missiles (Dobes, 2010). ROA is

different from traditional financial tools, which generally provide a fixed path for future investment decisions. In ROA, options are left open in the future, assuming a gradual resolution of uncertainty, making it ideal for assessing large-scale investments in the context of climate change. The solution of real options models is based on different techniques, such as the Black-Scholes formula, Monte-Carlo path dependent simulations and binomial or multinomial trees (Kontogianni et al. 2014).

The learning in ROA is based on an uncertain underlying parameter. The uncertain parameters in the context of this project will be rainfall and river and aquifer flows. Due to climate change (and changes in land use and river basins), hydrological variables will no longer be reliably constant and past hydrologic data do not necessarily provide a good indicator of future conditions, i.e. non-stationarity applies (Milly et al., 2008). In ROA, the uncertainty of the hydrological variable - at least with respect to climate change - is assumed to resolve with the passage of time due to increasing knowledge. For instance, the confidence in changes of rainfall, extremes and related drought risk under climate change will likely increase over time as time series grow longer, as 'low-data' methods are developed and as model uncertainties in climate and hydrological models are reduced (van der Pol et al. 2014). ROA takes advantage of the assumption that the uncertainty is dynamic rather than deep and provides strategies that can be adapted in a changing context.

The ROA method selected depends on the available data, the type of option and the desired simplicity (Kontogianni et al., 2014). In this study we choose the multinomial tree method.

The majority of ROA studies in the adaptation context apply ROA to an aspect of flood risk management, including coastal sea-level rise. The dominance of studies around flooding reflects the usually high irreversible fixed cost that makes waiting attractive, and the coastal application lends itself to ROA because it involves a uni-directional, bounded and gradual change. Many studies (e.g. Abadie et al., 2017, Rosbjerg, 2016) use the approach to determine whether it is optimal to invest now or to delay the investment, while others (Woodward et al., 2014, 2011, Gersonius et al. 2013) use ROA to determine the value of flexibility within the system, as well as the difference in value between waiting and investing now. These two approaches are sometimes referred to as "on" options, which have a timeliness aspect, and "in" options, which have technical engineering and design adjustments enabling options within operations.

Some studies do apply ROA to water storage, either for hydropower (Kim et al., 2017, Steinschneider & Brown, 2012) or reservoirs for other uses (Sturm et al., 2017). Again the analysis is either on or in options: Kim et al. (2017a) apply 'in' options to look at the optimal sequential expansion of rainwater harvesting tanks.

Kim et al. (2017b) assess the economic benefit of adapting hydropower plants to climate change in South Korea. They assess whether to build a hydropower plant under either RCP 4.5 or RCP 8.5, with no uncertainty considered within each RCP. The climate change risk is in the form of the quantity and timing of runoff and extreme weather events, including floods and droughts. They use a similar approach as Gersonius et al. (2013) to determine the probability, and for the volatility, a ratio of best/worst case. The best case is created assuming that the energy production and tariff increase to maximum, whereas investment and operating and maintenance costs decrease to minimum compared with those of the moderate case. The findings indicate that under RCP 8.5 the investment should not go ahead, as the investment cost exceeds the economic payoff.

Steinschneider and Brown (2012) apply ROA to compare different adaptation strategies for a hydropower facility in the US under a range of possible future climates. The utility of these adaptation strategies are tested with and without the availability of a real option water transfer. The first strategy assumes stationary climate conditions will persist into the future and conditions reservoir operations on the historic record. The second strategy optimises operations for the mean projections of future climate as simulated by the GCMs. The third strategy dynamically manages the system for short term climate variability using seasonal hydrologic forecasts. For the third strategy, the authors suggest using seasonal hydrologic forecasts in combination with ROA-style hedging rather than trying to use long-term projections which are highly uncertain. The real option is the possibility to transfer water between the water supply agency and a nearby flood control reservoir that is established to augment supply in times when water is over-allocated and shortages are imminent.

The study indicates that seasonal hydrologic forecasts are a promising adaptation to nonstationary hydrology, even without the support of a risk hedging option. Surprisingly, the option approach enabled even a stationary assumption to perform well in the future, suggesting that option instruments alone can act as a robust adaptation mechanism.

Sturm et al. (2017) apply ROA options to compare the prices of water storage and no water storage. They use an option pricing approach, i.e a simplified Black-Scholes formula to evaluate strategic decisions, applying it to two examples, one of which is water storage. They replace the finance variables in the formula with climate variables, using the example of the development of water storage through a system of rivers, dams and reservoirs for California, and compare the option price of storage and no storage ad examine the difference.

The purpose of applying ROA in the context of climate change is to assist in making decisions when there is uncertainty involved. ROA assumes that the uncertainty is dynamic rather than deep and while it will not completely resolve over time, the probability distribution will be adjusted in future as time series of data grow longer, 'low-data' methods are developed and model uncertainties in climate and hydrological models are reduced. This agreement on probabilities does mean the technique is vulnerable to bias, gridlock and brittle decisions (Kalra et al., 2014), but still provides advantages over traditional non-flexible approaches.

Some large-scale modelling assessments have developed probability-like projections, notably the UKCP09 projections (Murphy et al., 2009), however these only sample climate model uncertainty (i.e. a probability distribution function (pdf) for each separate emission scenario), rather than a single pdf of the overall envelope of difference scenarios and all climate models together. In this study we develop an approach to assign probabilities to a range of climate model and climate scenario combinations.

3. New Zealand climate projections and uncertainty

Climate change is already affecting New Zealand with downstream effects on the natural environment, the economy, and communities. In the coming decades, climate change is highly likely to increasingly pose challenges to New Zealanders' way of life.

In general, New Zealand can expect ongoing warming throughout the 21st century, as well as changes to extreme temperatures. Extreme warm temperatures and heatwaves are likely to be more common in the future, and extreme cold temperatures and frosts are likely to decrease. In addition, rainfall patterns may change across the country, with the west and south of New Zealand becoming wetter and the north and east of the North Island becoming drier. Some areas may not experience much change in total annual rainfall, but the seasonality when rainfall occurs may change, i.e. summers may become drier and winters may become wetter (Figure 1). The intensity of extreme rainfall is likely to increase in a warmer climate. Winds are also likely to increase across

central New Zealand, particularly in winter.

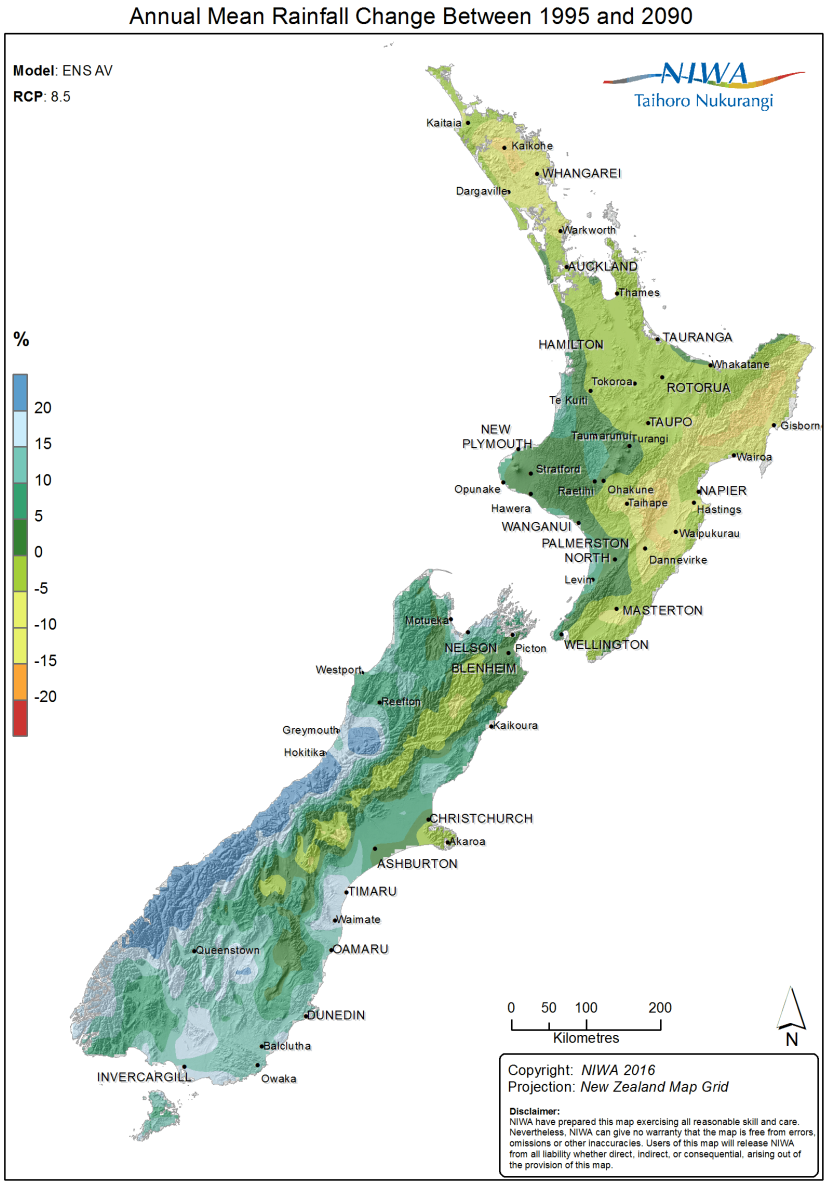

Figure 1 : Annual mean rainfall change (in %) between 1995 and 2090, under the highest IPCC Representative Concentration Pathway (RCP8.5).

These changes are likely to have significant impacts on the country's water cycle. This in turn will affect the availability of water for irrigation and crop demand for irrigation, and as such affect New Zealand's agricultural systems.

Increasing temperatures will impact pasture grass and crop growth, as plant phenological development may occur at a faster rate. The pasture growth season may extend into the cooler part of the year as the climate warms, and higher concentrations of carbon dioxide in the atmosphere means that pasture may grow more vigorously when it is not constrained by temperature or water availability.

Extreme heat affects the rate of evapotranspiration, or the uptake of water by plants. Therefore, increases to extreme heat may affect water availability and increase the amount of water needed for irrigation, as under hot conditions plants use more water than usual. Extreme heat may also result in current varieties of crops and pasture becoming unsustainable if they are not suited to growing in hot conditions.

Reductions in cold conditions may have positive impacts for diversification of new crop and grass varieties that are not able to currently be grown in cooler parts of New Zealand. However, future warmer temperatures may increase the risk from pests (plants and animals) and diseases. Currently, many pests are limited by New Zealand's relatively cool conditions, so that they cannot survive low winter temperatures, and therefore their spread is limited (Kean et al., 2015). Under a warmer climate, these pests may not be limited by cold conditions and therefore cause a larger problem for farmers and growers in New Zealand.

Increases in extreme rainfall event magnitudes may impact agriculture and horticulture in several different ways. Slips on hill country land may become more prevalent during these events, and soil erosion may also be exacerbated by increasing drought conditions followed by heavy rainfall events (Basher et al., 2012). This has impacts on the quality of soil, the area of land available for production, and other impacts such as sedimentation of waterways (which can impact flooding and water quality). Slips may also impact transport infrastructure (e.g. roads, farm tracks) which may in turn affect connectivity of farms and orchards to markets.

3.1. Simplifying complexity

A degree of simplification, aiming at reducing the complexity of the results, is necessary to convey and frame the science appropriately for diverse audiences. Those simplifications can be achieved in a number of ways such as: i) conveying the effects in summary qualitative terms rather than quantitative; ii) confining the suite of dependent variables reported; ii) choosing to convey spatial or temporal averages of summary statistics (e.g. minimum flows to support water allocation process); iii) selecting only a subset of GCMs (e.g. choosing GCM that better represent historical observation); iv) defining a limited set of scenarios to serve as RCPs (e.g. planning for the worst case scenario); v) selecting only a subset of defined scenarios/RCPs; vi) averaging results across the GCMs; or vii) combing results across RCPs by treating RCPs probabilistically rather than separately

Of the simplifications listed above, the most challenging is where RCPs are probabilistically combined to represent end-user perception of future emission scenario. RCPs were defined to represent plausible and distinct scenarios along a continuum of multi-dimensional possibilities, helping to clarify how the climate may be driven in the future. They are based on a number of assumptions and simplifications about how society will behave and what technologies will become available. They

help to highlight implications of climate change mitigation, but are currently a source of uncertainty and complexity to guide adaptation decision making.

Despite the substantial knowledge encapsulated by the modelling chain used to generate models and datasets, due to their nature errors and uncertainties remain and can influence interpretation and analysis results. Uncertainties related to climate change fields are discussed in detail in Ministry for the Environment (2018).

3.2. Hydrological uncertainties due to Global Climate Model uncertainty

Multiple GCMs are used in order to encapsulate a plausible range of physical interpretations of the climate system given uncertainties in climate science. The IPCC assessment contains an ensemble of more than 41 GCMs. NIWA selected 41 to be used in New Zealand, but the number of simulations available varied with RCP – only 23 for RCP2.6, but the full 41 for RCP8.5 and this historical period ending 2005. Thus among those GCMs, a subset of 23 GCMS was established to be used in New Zealand for the four RCPs (Ministry for the Environment 2016). A further subset of six GCMs to be used for dynamical downscaling was established representing the wide range of potential climate condition across New Zealand for each RCP (Ministry for the Environment, 2018). Each GCM will invariably produce a unique and different hydrological outcome. To illustrate the potential variability of these outcomes,

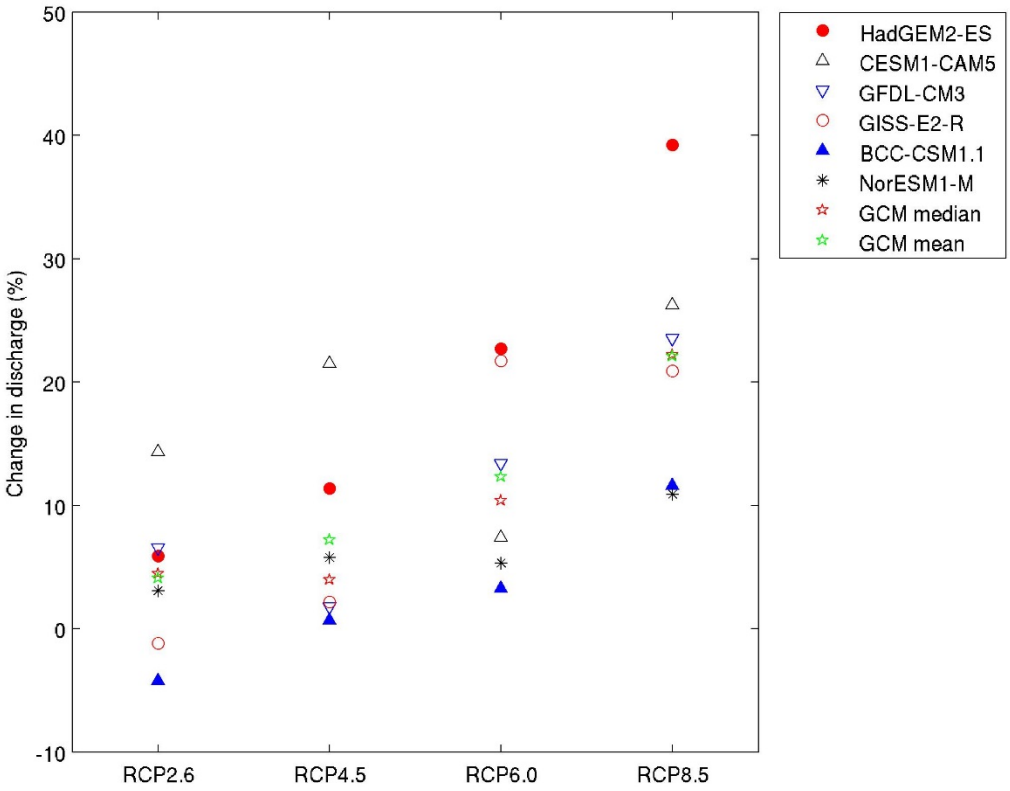

Figure 2 illustrates the variation across GCMs and RCPs for the change in mean discharge in the Waikato river for each individual GCM and RCP as well as the mean and median of GCM results. For the lower three RCPs, the variation among GCMs is greater than the variability among RCPs. Differences in the distribution of the GCM results for a given RCP also affect the relative position of the GCM mean and median: while the GCM mean increases monotonically across RCPs, the GCM median does not.

The GCM hindcasts are also biased to a degree. This is addressed through the bias correction and downscaling described by Sood (2014).

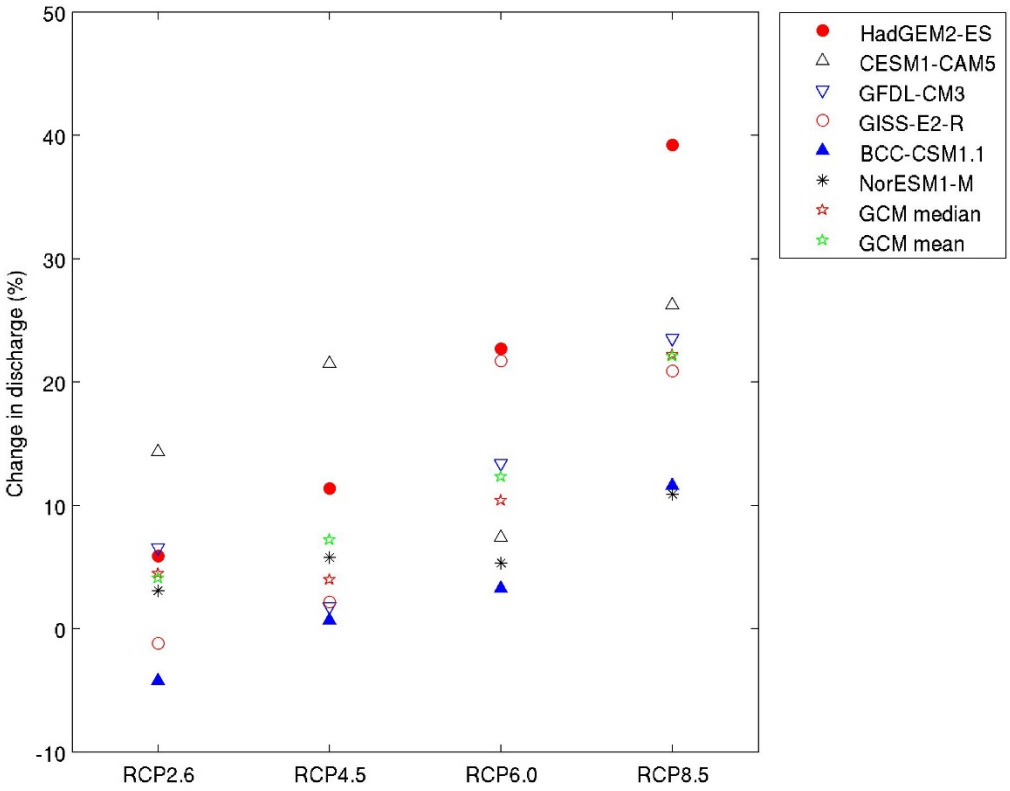

Figure 2: Change in mean discharge by end of the century at the outlet of the Waikato River for individual GCMs and RCPs, including GCM means and medians.

4. The case study used in this project

In this study, we focus on the uncertainty relating to future water availability for agriculture in New Zealand. Water availability for irrigation, industry and domestic use is currently under considerable pressure in NZ, and is likely to increase further with extreme events (droughts) and increased rainfall variability under climate change, combined with ever-increasing demand. Increasing requirements to leave more water in lowland stream and aquifers for environmental values (Ministry for the Environment and Ministry for Primary Industries 2018) means that new thinking is required to bring reliability of supply to acceptable levels. Water storage is a potential adaptive measure, harnessing rainfall and water fluxes in periods of excess for use when less is available, and improving the reliability of supply. Storage facilities are a significant investment however, and standard decision-making approaches (such as cost-benefit analysis), using a specified climate change scenario in order to identify a single optimal adaptive strategy, may lead to sub-optimal decisions.

Dittrich et al. (2016) provide advice on the choice of robust approach in different contexts, and recommend that ROA is most appropriate for large capital infrastructure investments. ROA is suited for (partly) irreversible investments with long life-times and sensitivity to climate conditions when there is a significant chance of over- or underinvesting combined with an opportunity cost to waiting, i.e. if there is a need for action in the present. We will therefore apply ROA for the appraisal of water storage, as it meets these criteria. ROA enables uncertainty to be considered, and explicitly places a value on flexibility. If the investment was partially or completely reversible, i.e. no sunk cost was incurred, there would be no value in delaying the investment or setting it up with flexibility.

By applying ROA we will identify how to sequence the construction of the water storage measure or scheme so that it is able to provide a reliable future supply of water in a way that minimises the expected life-time cost of the system.

Current guidance for sizing irrigation reservoirs does not consider future climate change in depth. For example, Figure 3 from IrrigationNZ illustrates the main factors to be considered when sizing an irrigation pond and recommends considering the current local climate, but does not mention potential future changes, nor any uncertainty regarding those. The current National Policy Statement on Freshwater Management (New Zealand Government 2014,) requires water resource managers to consider the "foreseeable impact of climate change" (pgs.12 and 15) as part of their decision-making process. If a resource consent is required for constructing an irrigation reservoir, this type of consideration does need to be demonstrated, but there is no specification regarding time horizons, different scenarios, or the inclusion of uncertainty.

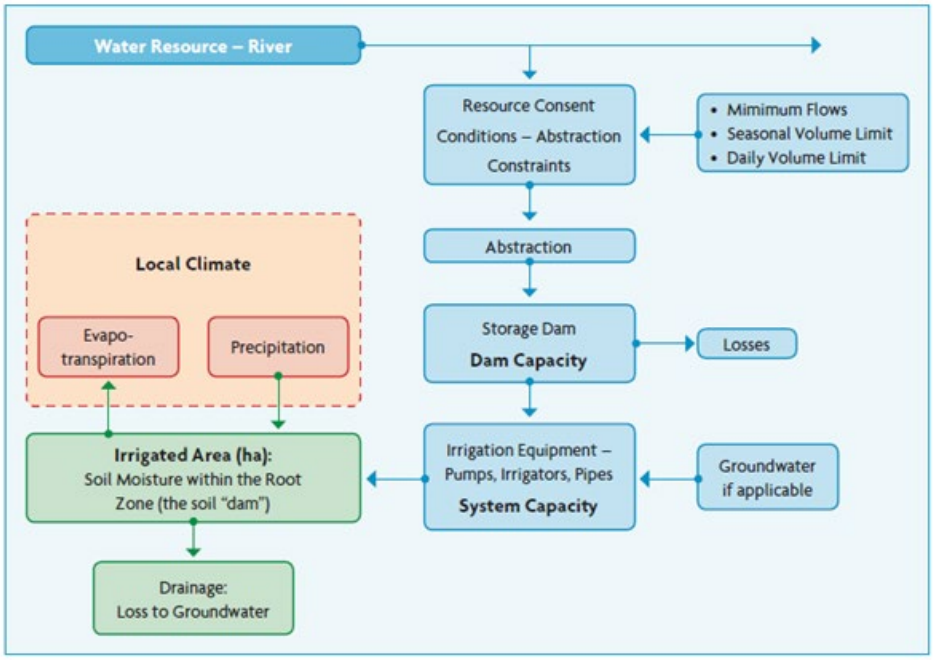

Figure 3 The main factors to be considered when sizing an irrigation pond (Irrigation NZ 2017)

By applying ROA, we will not obtain one strategy but a strategy that can be adjusted over time depending on the climate change outcomes observed over time, i.e. extending the capacity of the reservoir. Thus, ROA ensures that resources can be used more efficiently by considering a wide range of potential outcomes now and determining the best possible strategy for any of these contingent scenarios.

We use a case study to demonstrate the applicability of ROA as a potential investment appraisal tool for adaptation to climate. We focus on water availability in the dairy sector, one of the larger consumers of water resources in New Zealand (Rajanayaka et al., 2010), and which has become increasingly reliant on water storage over the last two decades. The case study was chosen based on the following criteria:

- Land cover chosen is dairy dry land to represent the dairy sector;
- The case study should be located in an area that fits the hydrological model assumption (i.e. not located in coastal areas where groundwater could play a major role);
- The case study should be located in an area that is currently experiencing water stress to support agricultural activities;
- The case study should be located in a high productive location where climate changes are expected to be relatively consequent and described as follow:
- Mean summer flow is going to decrease by at least 20% (compared to current simulated conditions) across all scenarios;
- Summer soil moisture deficit has increased by at least 10% by the end of the Century under RCP8.5.

As a result, a catchment was identified in the Canterbury area that meets these criteria in collaboration with Deep South National Hydrology project team. The catchment is located at nzreach id 13055784 (branch of Rangitata), approximately 40 km north-west of Hinds in mid-Canterbury (Figure 4). We stress however, that beyond the selection of the location, all of the other assumptions are purely hypothetical, i.e. this analysis is not being carried out for an investment decision in reality.

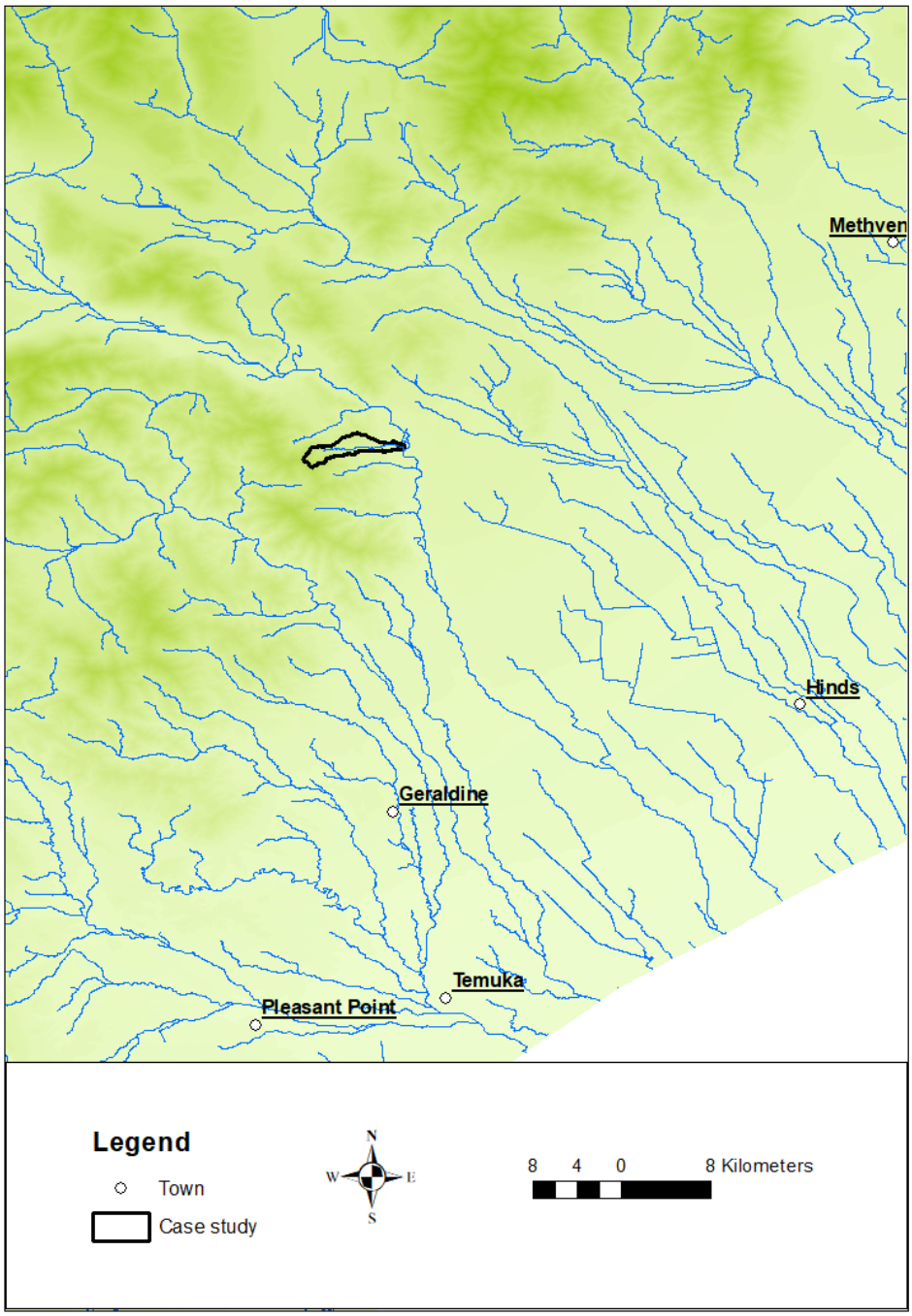

Figure 4: Case study location (black outline polygon). Topographic information provided by green background.

5. Data and Methods

In this section we describe the methodology used to carry out the ROA. Before the ROA itself can be carried out, the hydrological analysis must first be conducted. We describe the data and methods used for that first, before moving on to describe the ROA method.

5.1. Climate modelling

Assessing the potential adaptation pathway over the 21st century for primary industry in the face of impacts of climate change can be carried out using continuous hydrological modelling driven by climate change projections from a suite of models associated with economic assessment provided by ROA. The data, models and methods are described below.

The primary input for the hydrological and economic assessments is climate data generated from a suite of Regional Climate Model (RCM) simulations with sea surface forcing taken from Global Climate Models (GCMs). These coupled climate models are driven by natural climate forcing such as solar irradiance and historical and modelled anthropogenic forcing driven by emissions of greenhouse gases and aerosols based on 4 Representative Concentration Pathways (RCPs), but are otherwise free-running in that they are not constrained by historical climate observations applying data assimilation. As part of the fifth IPCC assessment report (AR5) (IPCC 2014), NIWA assessed up to 41 GCMs from the AR5 model archive for their suitability for the New Zealand region. Validation of those GCMs was carried out through comparison with large scale climatic and circulation characteristics across 62 metrics (Ministry for the Environment 2018). This analysis provided performance-based ranking based on New Zealand's historical climate. The GCMs were then used by NIWA to drive statistically based regional climate simulations for performing change impact assessments across New Zealand. The six best performing independent models, where projections across all four RCPs were available (van Vuuren et al. 2011), were selected for dynamical downscaling; that is, sea surface temperatures (SST) and sea ice concentrations from the six models are used to drive an atmosphere-only global circulation model, which in turn drives a higher resolution Regional Climate Model (RCM) over New Zealand. The output data fields are bias-corrected relative to a 1980-1999 climatology and subsequently further downscaled to an approximate 5 km grid (Sood 2014). The RCM output (bias-corrected and downscaled to 5 km) is then provided as input to a hydrological model which produces soil moisture and river flow.

The NIWA dynamical procedure involves a free-running atmospheric GCM (AGCM) (i.e., not constrained by historical observations), in this case HadAM3P (Anagnostopoulou et al. 2008), forced by SST and sea ice fields from the Coupled Model Intercomparison Project Phase 5 (CMIP5) models (Ackerley et al. 2012). Due to the nature of the climate runs for each GCM, year-to-year variability in the models does not correspond with observed variability. As such they are a deterministic consequence of the initial conditions and the solar and anthropogenic drivers. Further details on the validation of the six GCMs can be found in Sood (2014) and Ministry for the Environment (2018). Model and parameter uncertainty are discussed in the Uncertainties and limitation section.

The downscaled climate data used here run from 1971 to 2100. From 2005 onward, as per IPCC recommendations, each GCM is in turn driven by four RCPs that encapsulate alternative scenarios of

radiative forcing and reflect alternative trajectories of global societal behaviour with regard to greenhouse gas emissions and other activities. The range of RCPs used can help shed light on the utility of climate change mitigation. Descriptions and trajectories of the four RCPs are provided in Table 1 and Figure 5. By mid-century, the temperature trajectory of RCP2.6 is the coolest and RCP8.5 the warmest, with RCP4.5 and RCP6.0 producing intermediate warming. While RCP6.0 ends the century with more forcing than RCP4.5, early and mid-century it is RCP4.5 that has higher greenhouse gas emissions and a stronger radiative forcing; this is somewhat reflected by the mid-century temperature change ranges for the New Zealand seven-station network (Table 1). RCP6.0 overtakes RCP4.5 after the middle of century. The climatic and hydrological effects of the RCPs are not simply a linear or monotonic progression from the lowest to highest RCP. Furthermore, the spatial patterns of climatic change across New Zealand are different from RCP to RCP.

Table 1: Descriptions of the Representative Concentration Pathways (RCPs). Temperature changes are the GCM mean (°C) and, in brackets, the likely ranges.

Representative Concentration Pathway	Description	Seven-station temperature change (Ministry for the Environment 2016)		Global surface temperature change for 2081-2100 (IPCC 2014, Table 2.1)
		2031-2050	2081-2100	
RCP2.6	The least change in radiative forcing considered, by the end of the century, with +2.6 W/m^2 by 2100 relative to pre-industrial levels.	0.7 (0.2, 1.3)	0.7 (0.1, 1.4)	1.0 (0.3, 1.7)
RCP4.5	Low-to-moderate change in radiative forcing by the end of the century, with +4.5 W/m^2 by 2100 relative to pre-industrial levels	0.8 (0.4, 1.3)	1.4 (0.7, 2.2)	1.8 (1.1, 2.6)
RCP6.0	Moderate-to-high change in radiative forcing by the end of the	0.8 (0.3, 1.1)	1.8 (1.0, 2.8)	2.2 (1.4, 3.1)

	century, with +6.0 W/m^2 by 2100 relative to pre-industrial levels.			
RCP8.5	The largest change in radiative forcing considered, by the end of the century, with +8.5 W/m^2 by 2100 relative to pre-industrial levels.	1.0 (0.5, 1.7)	3.0 (2.0, 4.6)	3.7 (2.6, 4.8)

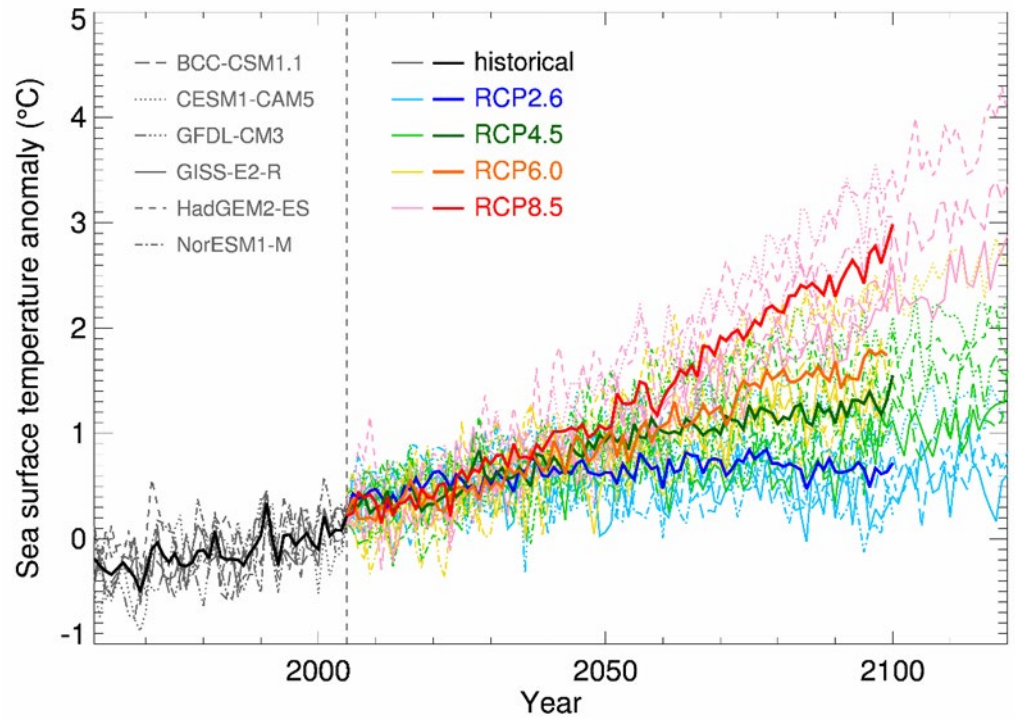

Figure 5: Bias-adjusted SSTs, averaged over the RCM domain, for 6 CMIP5 global climate models (2006-2120), the historical simulations (1960-2005), and four future simulations (RCPs 2.6, 4.5, 6.0 and 8.5), relative to 1986-2005 (Sood 2015). Individual models are shown by thin dotted or dashed or solid lines (as described in the inset legend), and the 6-model ensemble-average by thicker solid lines, all of which are coloured according to the RCP pathway.

5.2. Hydrological modelling

In order to assess the potential impacts of climate change on agricultural water resource, a hydrological model is required that can simulate soil moisture and river flows continuously and under a range of different climatic conditions, both historical and future. Ideally the model would also simulate complex groundwater fluxes but there is no national hydrological model capable of this at present. Because climate change implies that environmental conditions are shifting from what has been observed historically, it is advantageous to use a physically based hydrological model over one that is more empirical, with the assumption that a better representation of the biophysical processes will allow the model to perform better outside the range of conditions under which it is calibrated.

The hydrological model used in this study is TopNet (Clark et al. 2008), which is routinely used for surface water hydrological modelling applications in New Zealand. It is a spatially semi-distributed, time-stepping model of water balance. It is driven by time-series of precipitation and temperature, and of additional weather elements where available. TopNet simulates water storage in the snowpack, plant canopy, rooting zone, shallow subsurface, lakes and rivers. It produces time-series of modelled river flow (without consideration of water abstraction, impoundments or discharges) throughout the modelled river network, as well as evapotranspiration, and does not consider irrigation. TopNet has two major components, namely a basin module and a flow routing module.

The model combines TOPMODEL hydrological model concepts (Beven et al. 1995) with a kinematic wave channel routing algorithm (Goring 1994) and a simple temperature based empirical snow model (Clark et al. 2008). As a result, TopNet can be applied across a range of temporal and spatial scales over large watersheds using smaller sub-basins as model elements (Ibbitt and Woods 2002; Bandaragoda et al. 2004). Considerable effort has been made during the development of TopNet to ensure that the model has a strong physical basis and that the dominant rainfall-runoff dynamics are adequately represented in the model (McMillan et al. 2010). TopNet model equations and information requirements are provided by Clark et al. (2008) and McMillan et al. (2013).

For the development of the National TopNet used in this application, spatial information in TopNet is provided by national datasets as follows:

- Catchment topography based on a nationally available 30 m Digital Elevation Model (DEM);
- Physiographical dataset based on the Land Cover Database version two and Land Resource Inventory (Newsome et al. 2000);
- Soil dataset based on the Fundamental Soil Layer information (Newsome et al. 2000); and
- Hydrological properties (based on the concept of River Environment Classification version one- REC1 (Snelder and Biggs 2002).

The method for deriving TopNet's parameters based on GIS data sources in New Zealand is given in Table 1 of Clark et al. (2008). Due to the paucity of some spatial information at national/regional scales, some soil parameters are set uniformly across New Zealand. Because of the model

assumptions soil and land use characteristics within each computational sub-catchment are homogenised. This results in soil characteristics and physical properties of different land uses, such as pasture and forest, to be spatially averaged, and the hydrological model outputs will be an approximation of conditions across agricultural land uses.

Hydrological simulations are generated over the period 1971 to 2100, with the spin-up period 1971 excluded from any subsequent the analysis. The climate inputs are stochastically disaggregated from daily to hourly time steps for model requirements. Hydrological simulations are based on the REC version 1 network aggregated up to Strahler[1] catchment order three (approximate average catchment area of 6 km^2) to reduce simulation times and data sizes to manageable levels while still providing useful information; residual coastal catchments of smaller stream orders remain included. The simulation results comprise hourly time-series of various hydrological variables for each computational sub-catchment, and for each of the six GCMs and four RCPs considered.

NIWA, in collaboration with Aqualinc, refined the national scale analysis of climate change impacts on water availability (Collins and Zammit 2016), by considering the effects of climate change alone on irrigation demand, and by considering when effects may become discernible from or significantly different to current climate variability (Collins et al 2019). This was carried out by coupling previous simulations with an irrigation water demand model, IrriCalc (Allen et al. 1998). The assessment focussed on areas that are currently under irrigation and for simplicity assumed that land use stays fixed.

As a result of climate change, mean river flows during the irrigation season are projected to increase across many but not all irrigated areas in the South Island with Southland and parts of Central Otago showing the first substantial signs by mid-century (2039-2049). Irrigation water demand is projected to increase across most of New Zealand, with effects emerging by mid-century in the North Island and later (2080-2099) in the South Island.

From a water management aspect, irrigation restrictions are expected to occur earlier in the year, mostly for the North Island, but only after the middle of the century and largely only for the extreme warming scenario. At the same time, irrigation restrictions are expected to stop earlier during the water year, although the shifts are neither as widespread nor as large as with the change on the onsets of irrigation restrictions. This shift in the onset and offset of the irrigation restrictions results in a minimal change in the duration of the irrigations restrictions, but the frequency of irrigation restrictions tends to increase over the course of the century with the North Island and northern South Island irrigated areas hardest hit.

Reliability of river water supply (the average fraction of time during each irrigation season that the river flow is too low and thus irrigation is restricted) tends to decline during the century but largely only by late-century and for the extreme climate change scenario (Figure 6).

[1] Strahler order describes river size based on tributary hierarchy. Headwater streams with no tributaries are order 1; 2nd order streams develop at the confluence of two 1st order tributaries; stream order increases by 1 where two tributaries of the same order converge.

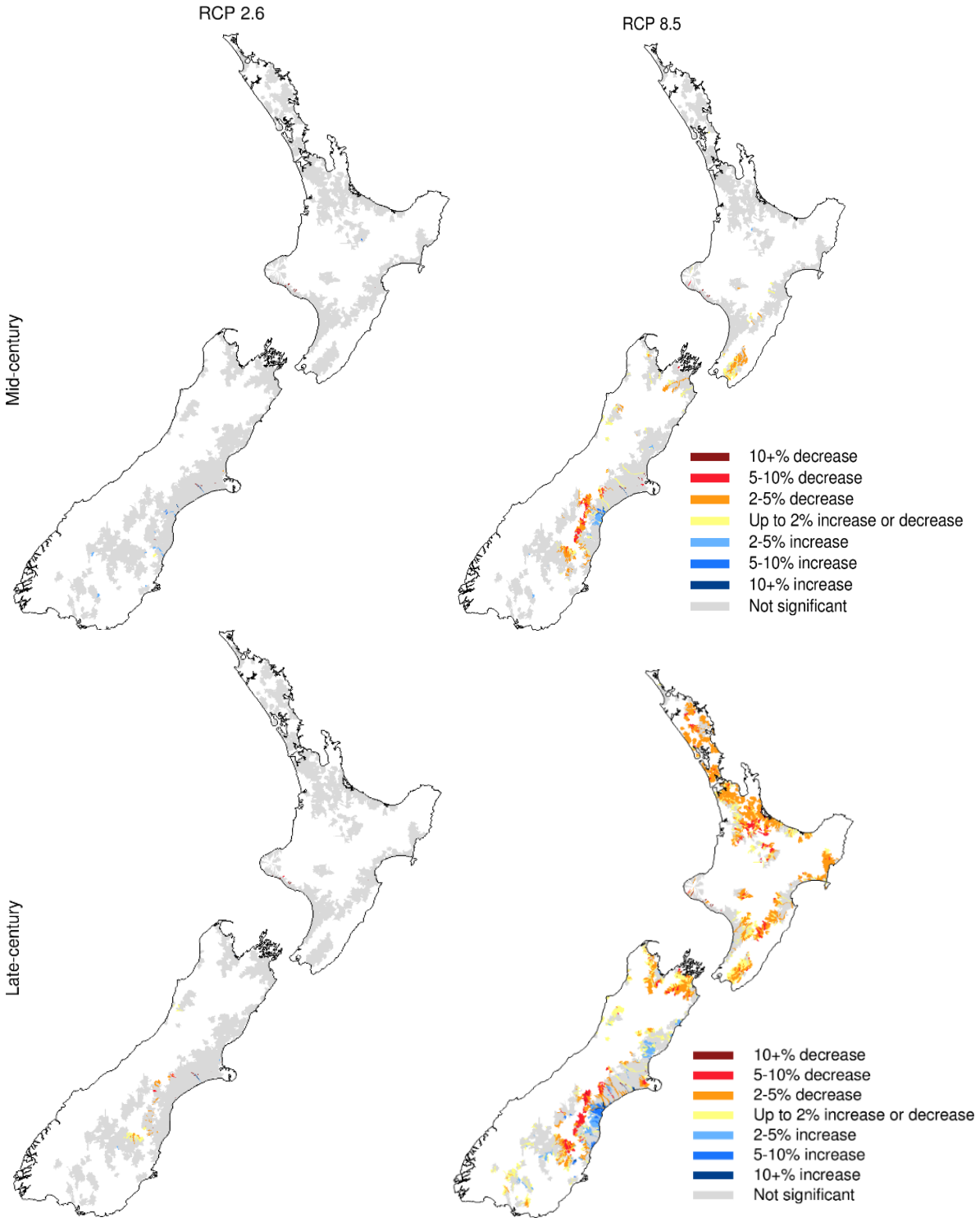
RCP 2.6
RCP 8.5
Mid-century
Late-century
10+% decrease
5-10% decrease
2-5% decrease
Up to 2% increase or decrease
2-5% increase
5-10% increase
10+% increase
Not significant
10+% decrease
5-10% decrease
2-5% decrease
Up to 2% increase or decrease
2-5% increase
5-10% increase
10+% increase
Not significant

Figure 6: Mid- and late-century changes in river reliability of supply (Collins et al. 2019).

5.3. Water demand, water availability and reliability of supply

5.3.1 Water demand and availability

A hypothetical dairy farm of 200 ha in size was used to determine the water demands for this study. It was assumed that irrigation season spans from September to April. Irrigation water is applied at 90% efficiency to meet the soil-moisture deficit, when water is available. A stock rate of 4 cows/ha was used with an average daily water demand of 70 litres/day/cow for stock water and dairy shed cleaning, washing and milk cooling (Stewart and Rout, 2007). We assume that the current stocking rate and production will continue into the future.

Given that the study area is located within the Canterbury region, Environment Canterbury allocation rules were used to determine the available water for irrigation and associated activities. Canterbury Land and Water Regional Plan (ECan, 2017) Rule 5.123.2 states that:

Unless the proposed take is the replacement of a lawfully established take affected by the provisions of section 124-124C of the RMA, if no limits are set in Sections 6 to 15 for that surface waterbody, the take, both singularly and in addition to all existing consented takes meets a flow regime with a minimum flow of 50% of the 7-day mean annual low flow (7DMALF) as calculated by the CRC and an allocation limit of 20% of the 7DMALF.

Based on the above rule, the minimum flow and primary run-of-river allocation for the stream are 16.6 and 6.7 litres/sec, respectively. It is also assumed that further high stream flows between the median flow and three times the median flow is available for harvesting and storing in a reservoir.

5.3.2 Reliability of supply and reservoir sizing

Four key factors are generally considered to quantify the reliability of supply-demand (Robb and McIndoe, 2001). These are:

1. Severity – size or amount of restriction;
2. Frequency – how often the restrictions occur;
3. Duration – how long the restrictions last; and
4. Timing – when restrictions occur.

On any day during the irrigation season, the supply of available water from the storage can be compared with the demand for irrigation. If water supply from the storage equals or exceeds demand, reliability is 100%. If demand exceeds water supply, reliability is calculated by dividing supply by demand to give a supply/demand ratio. The daily ratios can be combined into weekly, monthly, seasonal (spring, summer, autumn), irrigation season or annual figures.

In general, it is neither economically attractive nor is sufficient water available to develop a large storage to meet high level of reliability (e.g. >95%) when water is sourced from a small stream. Therefore, the capacity of the storage has been designed to meet average annual supply/demand

ratio of 80%. The unmet demand needs to be met with alternative supplies such as supplementary feed.

5.4. The ROA

We begin by providing an overview of the ROA process and the necessary steps, and describe the relevant methods within each of these.

The ROA decision problem for a multinomial decision-tree method is structured based on the following steps, following Gersonius et al. (2013) and Dittrich et al. (2019):

1. Specify the decision tree

2. Identify the potential options

3. Formulate the optimisation objective

4. Solve the optimisation problem

5.4.1. Specify the decision-tree

The decision problem can be illustrated in a decision-tree, where the branches represent potential pathways of available water under the different RCP/GCM combinations. The nodes describe the water storage sizes constructed, depending on the different water availability outcomes.

For this study we specify a decision tree with two decision-points (2018 and 2050), with four potential outcomes between 2018 and 2050 and for each of these, a further four potential outcomes by 2090, when we conclude the analysis. Depending on the type of decision to be made and the context, more decision points could be selected, but this would increase the complexity. Thus for the present study we construct a decision-tree with 256 (4^4) branches.

5.4.2. Determine the probabilities of each branch

Determining the different branches of the decision-tree is one of the major parts of the ROA methodology, and one of the most challenging and contested in the context of climate change (Kalra et al. 2014). Most studies make simplifying assumptions that avoid making assumptions regarding the likelihood of different climate scenarios. Several studies (Abadie et al., 2017; Gersonius et al., 2013) assume the different climate scenarios are equally likely. Jeuland and Whittington (2014) do not assign probabilistic weights to the respective scenarios, but transform indicators into relative measures of downside, expected, and upside performance, but they go on to use Robust Decision Making (a different approach) to compare across scenarios. Kim et al. (2014) calculate the probabilities through the standard deviation which are influenced by the percentiles of the rainfall distribution. However the formula for the volatility assumes that the changes in climate are normally distributed. Kim et al. (2017) use two RCPs independently, both of which were considered certain. This does not provide information for considering the likelihood of each RCP. In a very different approach, Sanderson et al. (2016) use historical climate data from another location as an analogue for how the climate may become in the case study location.

In this study, the combination of RCPs and GCMs provides a 24-members ensemble of potential futures. To help inform decision-makers concerned with adaptation, it is necessary to define a conceptual approach that summarises the range of projections in a simpler framework outlining the range of plausible pathways a key decision variable (in this case water availability) may take. The term pathway is used to describe the evolution of a single variable over time (i.e. trajectory), not the propagation of information along a causal chain. This procedure enables probabilities to be assigned explicitly using "perceived" probabilities to both GCMs and RCPs.

The framework is illustrated hereafter using a probabilistic approach based on the following assumptions:

- No assessments have been made on the relative plausibility of the six GCMs used thus far for climate change projections in the New Zealand region, and so in the absence of more specific information we treat each as being equiprobable.
- The relative plausibility or the RCPs, however, are not as unknown. The two end-member RCPs (2.6 and 8.5) are both considered less likely than the two middle range RCPs (4.5 and 6.0) (see Table 2).

To simplify the application of the framework, while providing enough granulometry for future decision makers, we collapse the potential 26 futures into 4 states, which correspond to a discrete, non-overlapping range of simulated hydrological conditions encountered over the time period considered. For simplicity, the full range of future hydrological conditions is divided in four equal bins, representing the maximum size of the reservoir needed to meet the water demand over the time period for the reliability of supply chosen.

Table 2: Two scenarios of relative perceived probabilities for the four RCPs

RCP	***Equiprobable***	***Non-equiprobable***
2.6	0.25	0.15
4.5	0.25	0.35
6.0	0.25	0.35
8.5	0.25	0.15

5.4.3. Identify the potential options

In this context of this case study, flexibility comes from the size and potential expansion of the reservoir depending on the future climate. The reservoir sizes in the different time periods are presented in Table 3.

Table 3 - Probabilities and storage sizes for each of the quartile bins, in 2050 and 2090

2050					2090				
		probability					probability		
GCM/RCP		Equi	Non-equi	Average storage size (m3)	**GCM/RCP**		Equi	Non-equi	Average storage size (m3)
GCM1RCP3	Bin 1	0.45833	0.40833	59875	GCM3RCP3	Bin 1	0.4817	0.5417	173500
GCM3RCP4					GCM6RCP1				
GCM2RCP3					GCM3RCP4				
GCM4RCP3					GCM2RCP3				
GCM5RCP4					GCM5RCP1				
GCM4RCP1					GCM4RCP4				
GCM3RCP3					GCM3RCP1				
GCM3RCP1					GCM1RCP3				
GCM1RCP1					GCM1RCP1				
GCM5RCP1					GCM2RCP1				
GCM1RCP4					GCM3RCP2				
GCM5RCP3	Bin 2	0.25	0.316667	117250	GCM5RCP4				
GCM6RCP2					GCM4RCP3				
GCM4RCP4					GCM1RCP2	Bin 2	0.225	0.2083	340000
GCM1RCP2					GCM6RCP3				
GCM3RCP2					GCM6RCP4				
GCM2RCP2					GCM1RCP4				
GCM6RCP4	Bin 3	0.20833	0.191667	174625	GCM5RCP3				
GCM5RCP2					GCM6RCP2	Bin 3	0.1417	0.125	506500
GCM2RCP1					GCM2RCP2				
GCM6RCP3					GCM4RCP1				
GCM2RCP4					GCM2RCP4	Bin 4	0.1417	0.125	673000
GCM6RCP1	Bin 4	0.08333	0.08333	232000	GCM5RCP2				
GCM4RCP2					GCM4RCP2				

5.4.4. Formulate the optimisation objective

The next step is to formulate the optimisation objective, which is to maximise the net present value of the storage investment:

$$C = \max_{Z_t} \quad \sum_{y_{1=1}}^{Y_t} \frac{B(X_t) - I(X_t}{(1+\delta)^{y_t - y_1}} \tag{1}$$

Where

C = Net present value of the total investment

$I(Z_t)$ = Investment costs

$B(X_t)$ = Value of the benefits

δ = Discount rate

Z_t = Decision variable (e.g investment in additional storage capacity at the decision nodes)

X_t = Stock variable (i.e. the total storage capacity at year t)

Damage occurs if the water storage constructed is insufficient to meet the needs of the farm in that time period. Additional investment Z_t is realised by expanding the size of the reservoir at two decision points, at time = 1 and 2 (corresponding to 2018 and 50), i.e

$$X_t = X_{t-1} + Z_t \tag{2}$$

To maintain production, the storage capacity needs to be above α

$$q_{tu}\,(X_{t-1} + Z_t) \geq \propto \tag{3}$$

Where α has been identified from the hydrological analysis and q_{tu} is an estimate of the probability associated with 80% reliability of supply at time *t* based on a particular climate, *u*.

Cost calculations

The cost values used in this study were obtained from personal communication with an irrigation reservoir contractor based in Christchurch.

The investment costs of constructing a reservoir consist of the one-off construction costs (design, labour and materials). For the purposes of this study we assume construction costs are between $3 – $6/m^3 and conduct sensitivity analyses around these (Densem, pers comm).

Other potential costs not included here include the cost of consent and potentially geotechnical investigations that may be required in reality. There are also likely to be annual maintenance costs, and potentially energy costs involved in pumping the irrigation water, if it is not a gravity based system. There is also the opportunity cost of the land, depending on the footprint of the dam, which we have not included in this analysis. More detailed analysis in future could explore the implications of these fuller costs.

We assume that extending an existing dam will add 35% onto the cost of construction (Densem, pers comm).

For some types of constructions, future extension would require different (and probably more costly) initial construction to keep the options open for future expansion. In the case of this type of

water storage, there is no difference in the construction in the first time period, although there would need to be sufficient surrounding land available to extend into.

Benefit calculations

The benefits of water storage in this example are the avoided production losses that would have occurred if no water was available (i.e. the avoided damage).

The relationship between water availability and production is complex with several contributing factors, and an entire research project could be devoted to understanding this in more detail. For the purposes of this project however, we make a number of simplifying assumptions in order to develop a relationship between water availability and dairy production.

Tait et al. (2005) find that a one standard deviation in soil moisture deficit (SMD) translates to a 3-5% change in milkfat production per cow. We used the mean monthly SMD for the historical period of 1986-2005 as a base from which to determine the projected standard deviation.

Monthly milkfat production data for the Canterbury region for 2018/19 (LIC and DairyNZ 2018) was used, and we assumed no production in May – July.

Using the relationship of 1Std dev = 4% reduction in Milkfat, we calculated monthly milkfat production over time resulting from the change in SMD. We added these to get the annual value and multiplied this by the herd size and milkfat price. We used a base price of $6/kg, and assumed it remains constant into the future, but use a range of milkfat prices to determine the sensitivity ($5-$7/kg).

The difference between these future annual milkfat prices and the base 2018/19 value was used to determine the value of the water storage. Without sufficient storage, SMD would increase, resulting in pasture and therefore production losses. An alternative method would be to keep production constant but assume the shortfall in pasture required the purchase of supplementary feed. The benefit would be the avoided feed costs.

The key parameters for the base case are summarised in Table 4

Table 4 Key parameters in case study

Parameter	Value
Construction cost	$3/m^3
Milk price	$6/l
Discount rate	6%
Herd size	800 cows

5.4.5. Solve the optimisation problem

Following Dittrich et al. (2019) we solve this optimisation problem in a spreadsheet using backward induction, beginning with the last decision to be made and working progressively back in time to the present.

In order to apply the backward induction, we first need to calculate the net present value for all 256 paths as if they were going to be implemented. Figure 7 shows part of the decision tree to illustrate this initial step. If path 1, (dotted line), eventuated, sufficient storage would be constructed in 2018 (investment decision I1a) to maintain production under changing water availability in the climate model and scenario combinations captured in bin A (25th quartile of the distribution) in 2050. Getting to 2050, the water availability turns out to correspond to bin A (outcome O1a), so no further storage is necessary to correct for a wrong decision in 2018 (I1=O1), and no damage cost has incurred. Instead, the reservoir is extended to continue to maintain production in 2090 corresponding to bin A (25th quartile) in 2090 (I2a). In 2090, this choice turns out to be correct (O2a), and no further expansion is necessary (I2=O2). The net cost of path 1 (P_1 cost in Figure 7) will therefore be the discounted cost of the reservoir construction I1 + I2. The net cost of path 2 (P_2 in Figure 7) is identical to path 1 with the difference that in 2090, the water requirements correspond to Bin B (50th quartile) (O2≠I2). This means two things; (1) that additional storage capacity will be required in 2090 to make up the difference between the capacity in 2050 and the actual storage capacity need in 2090 to prevent lost production, and (2), damage (lost production) from the lack of water occurs and causes additional cost.

In a second step, we carry out the backward induction. Backward, as it begins with the analysis of the last decision to be made and works from there to the original water storage investment decision. Our last (and in this case the second) decision relates to the investment made in 2050 anticipatorily adapting to possible outcomes in 2090. This step informs us which investment to make at I2 depending on the state we reach in 2050. By 2050, we will have constructed a reservoir for one of the four quartiles and one of the four possible outcomes of the changing water availability (the 25th, 50th, 75th or 100th quartile) will have been realised. This implies 16 possible states in 2050. We now have the choice of creating additional capacity I2 which corresponds to the 25th, 50th, 75th or 100th quartiles of the water requirements associated with the changing climate in 2090. For example, as illustrated in Figure 7, if we had constructed the reservoir for the capacity of the 25th quartile in 2018 and the water availability associated with the 25th quartile were actually realised in 2050, we can make the investments I2a (25th quartile),….I2d (100th quartile) in a next step. The outcomes O2a (25th quartile),…O2d(100th quartile) might occur in 2090 with the probabilities P_{AA2090}, P_{AB2090}, P_{AC2090} and P_{AD2090} respectively)(A refers to the water outcomes in the 25th percentile, B for the 50th percentile etc). Therefore, the expected cost for reservoir construction for the 25th percentile of the water availability in 2090 equals $P_{AA\,2090}P_1+P_{AB2090}P_2+P_{AC\,2090}P_3 + P_{AD2090}P_4$. P_1 to P_4 represent the total net cost of each path calculated in step 1. This process is carried out for the three other states in 2040 (50th, 75th or 100th quartile) to decide on I2. The quartile with the lowest expected cost will always be selected. The same procedure of obtaining the lowest net cost is carried out for the investment decision I1 in 2018. In other words, we find the lowest net cost by multiplying the probabilities P_{AA2050}….P_i with the respective lowest outcome for I2 and comparing them for each quartile.

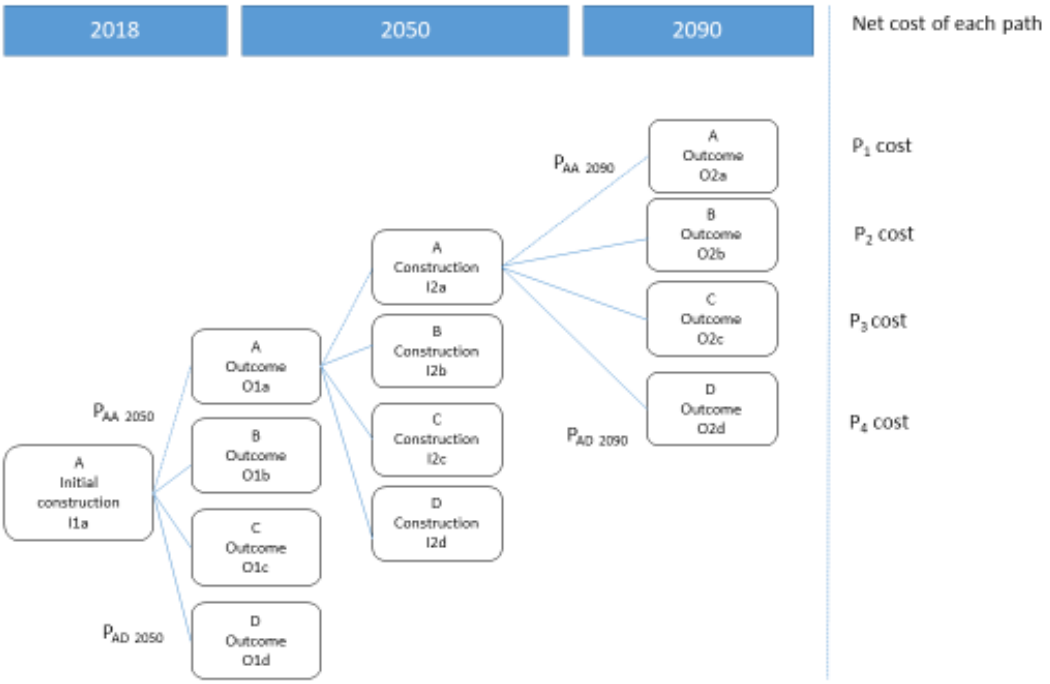

Figure 7 Illustration of backward induction for the decision problem (Branch A, one of four branches of the full decision tree)

6. Results

The hydrological modelling developed estimates of storage water requirements (assuming 80% reliability) from 2018 – 2049, and from 2050 – 2090, for all of the GCM/RCP combinations (Figure 8 and Figure 9). These are used as the inputs into the ROA, using the methods described in the previous section.

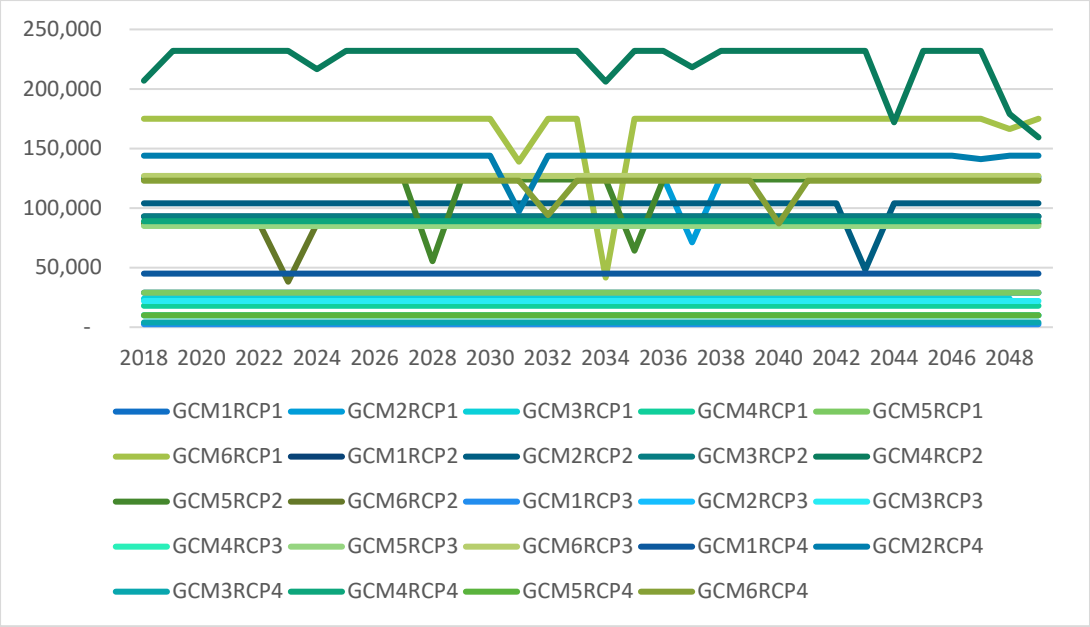

Figure 8 Storage water requirements (m3) for 80% reliability, 2018-2049

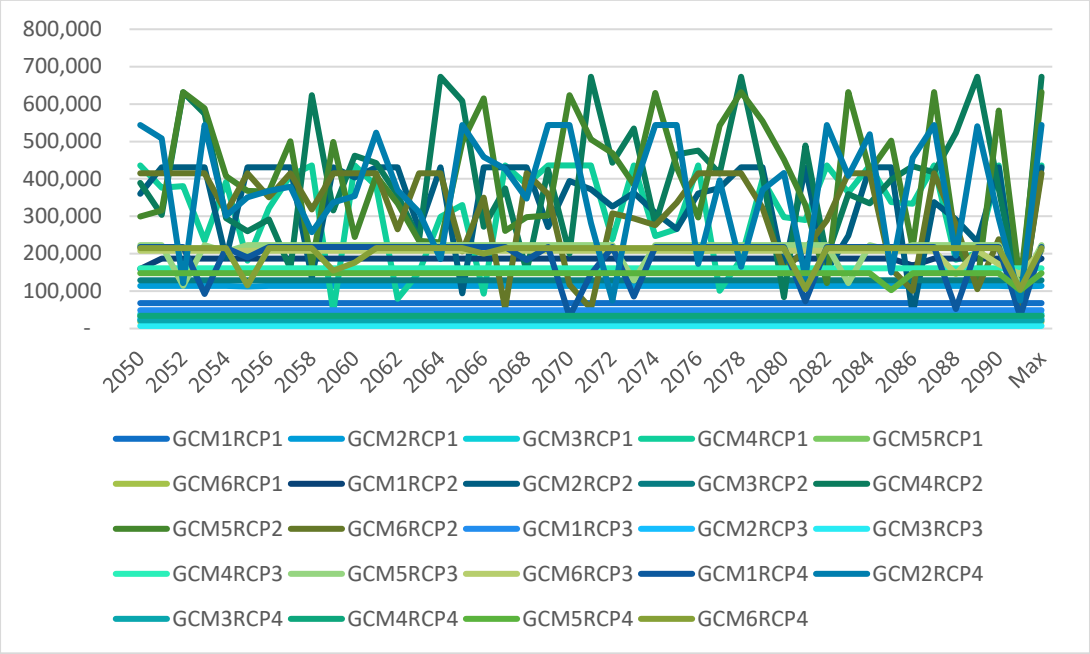

Figure 9 Storage water requirements (m3) for 80% reliability, 2050 - 2090

Initially only investment I_1 is implemented in 2018. Subsequently, expansion to the reservoir can be implemented in 2050, determined by the climate outcome of the first time period. Thus, the optimal investment decision today is influenced by the possibility of the decision-maker to adjust their decision at a future point in time based on the changing future water availability. For example, if water availability decreases in future more than what had originally been expected, the size of the reservoir can be increased in the most cost-effective way. The adjustment in 2050 cannot undo the cost of lost production (or increased costs) in the past, but it will seek to avoid those costs into the future. On the other hand, if water availability did not decrease significantly over time, valuable resources were saved by not constructing an unnecessarily large reservoir.

The suggested strategies under both the equi-probable and non-uniform RCP probabilities are presented in Table 5, and a selection of other scenarios varying parameters such as discount rate, milk price and construction cost. The reservoir size z_t corresponds to the quartiles of GCM/RCP combinations of water availability distribution in 2018 and 2050. In the base case of this example, assuming all RCPs are equi-probable, the initial decision would be to construct a reservoir for what corresponds to the 25th quartile of the water availability GCM/RCP combinations in 2018 (59 873m^3), the smallest of the reservoir sizes. The reservoir size decision in 2050 depends on the climate outcome in 2050, i.e. how much water storage is required to maintain production in a changing climate – which GCM/RCP combinations have been observed over time by 2050. The second decision in this example will be to choose the 25th percentile, the smallest increase in storage size. For the other possible outcomes in this case, the most cost effective choice is to build for the 25th percentile in 2050. However, when we consider the distributed probability scenario, where RCPs 2.6 and 8.5 are assumed less likely to occur, the decision changes. In this case, the correct decision in 2018 is to build for the 50th percentile in 2018, and the 25th in 2050.

In the second scenario, we use a discount rate of 3% (consistent with public sector discount rates in the United Kingdom for example) as a comparison. For both the equi-probable and distributed probability scenarios, the correct decision in 2018 is to build for the 75th percentile (i.e. a larger investment is more cost-effective with a lower discount rate). For the decisions in 2050, the correct decision is to choose to build for the 25th percentile (the smallest additional storage).

In the third and fourth scenarios, we increase and decrease the milkfat price respectively. An increase in milkfat price by $1/kg implies that the initial storage size should be for the 50th percentile in both probability assumptions, and the 25th percentile in 2050. For the lower milk price, the correct decision is now to construct the smallest reservoir in 2018 and make the smallest expansion in 2050.

The final scenario uses a higher per metre construction cost ($4/m^3). In this case, for both the equi-probable and distributed probabilities, the correct decision is to build for the 25th percentile in 2018 and again in 2050.

We compare the expected NPV of the most cost effective pathway with the NPV of constructing a reservoir for the worst case in both time periods (i.e. the 100th percentile in 2018 and again in 2050). This illustrates the economic benefits of conducting an ROA, which allows the most cost-effective strategy to be identified.

Table 5 Results – showing the most cost-effective strategies in terms of construction for a particular climate outcome percentile at the two time periods, 2018 and 2050. "Strategy" refers to the most cost-effective strategy at that decision point, and "Outcome" refers to the possible outcomes in 2050 from the preferred strategy in 2018.

		1) base case		2) 3% DR		3) $7 milk price		4) $5 milk price		5) $4 constr. cost	
Decision point		equi	non-equi	equi	non-equi	equi	non-equi	equi	non-equi	equi	non-equi
		strategy		*strategy*		*strategy*		*strategy*		*strategy*	
2018		25th	50th	75th	75th	50th	50th	25th	25th	25th	25th
2050		*Strategy*	*Strategy*	*Strategy*	*Strategy*	*Strategy*	*Strategy*	*Strategy*	*Strategy*	*Strategy*	*Strategy*
Outcome	25th	25th	25th	25th	25th	25th	25th	25th	25th	25th	25th
	50th	25th	25th	25th	25th	25th	25th	25th	25th	25th	25th
	75th	25th	25th	25th	25th	25th	25th	25th	25th	25th	25th
	100th	25th	25th	25th	25th	25th	25th	25th	25th	25th	25th
Expected NPV		$171,481	$83,676	$159,425	$147,745	$143,824	$121,814	$124,705	$104,384	$135,310	$113,926
Expected NPV of building for worst case scenario		-$8,997	-$6,617	$17,259	$19,371	-$442	$1,202	-$17,552	-$14,437	-$29,106	-$24,462

7. Discussion

The analysis in general highlights the trade-offs involved between the costs associated with investing in a reliable water supply and the benefits provided. In some cases it will be more cost-effective to accept the losses in production in some years rather than building a large structure that will provide reliable water (at 80% reliability) in every year, but be very costly. In this section we discuss some of the specific implications of the results, and then discuss limitations and scope to develop the research further.

- Choice of probability distribution

The results illustrate that the assumptions made regarding the likelihood of future climates do make a difference to decision-making. In the base case, the choice of initial storage size changes from when we assume the RCPs are equi-probable (25th percentile) to when we assume that RCPs 2.6 and 8.5 are less likely. When the probabilities are distributed, the decision would be to construct the larger reservoir in 2018 (50th percentile). This is possibly due to the fact that the climate evolves differently over the course of the century under the different RCPs, with the impacts peaking earlier in the two central RCPs and then declining, meaning more water is required mid-century than later, while under RCP 8.5 the impacts increase over the course of the century. In both scenarios, the second decision is to extend for the 25th percentile in 2050, to ensure sufficient water availability out to 2090.

Although the other scenarios do not result in different pathways between the equi-probable and distributed probability scenarios, the differences in the base case do highlight the very real implications that assumptions regarding the likelihood of future changes have on decisions today. While ROA is an improvement on approaches such as cost-benefit analysis, which usually only consider one climate scenario, these differences emphasise the challenges of the need to "agree on assumptions" (Kalra et al. 2014). Given more recent evidence regarding our current climate trajectories, further analysis could examine the impact of assuming a lower likelihood in the two lower RCPs and a higher likelihood of RCPs 6.0 and 8.5.

- Choice of discount rate

Choosing a lower discount rate results in building for the 75th percentile in 2018, the largest size of all the scenarios considered here. In this scenario, the lower discount rate results in the benefits of having sufficient storage in the period between 2018 and 2050 justifying the larger construction. In 2050 however, the decision for all outcomes is still to build for the 25th percentile. This result demonstrates the importance of the choice of discount rate, with very real implications for investment decisions. For public sector projects with real public good benefits, there is a strong argument in favour of a lower discount rate, or one that declines over time (Stern 2007). For this type of project however, which generates primarily private benefits, remaining with the six percent rate is justified.

- Milk price

The base case assumes a constant milk price of $6/kg milkfat. In order to test the sensitivity of the results to this assumption, we also examined the effect of a $5/kg and $7/kg price (all held constant for the duration of the analysis). As might be expected, a higher milk price changes the choice of storage size in 2018 from the 25th percentile to the 50th percentile assuming equi-probable RCPs. Under the distributed probability assumption, the higher milk price does not change the decision in 2018 (which was also for the 50th percentile at the $6/kg milk price). The subsequent decisions are all for the 25th percentile though, as in the base case.

Lowering the milk price to $5/kg means that only the smallest storage size is chosen in 2018 and the smallest again in 2050, under both assumptions about likelihood. At this lower price a larger investment is not justified. The expected NPV is still positive though, demonstrating the benefits of water storage in this example.

For this application, in all of the scenarios, the correct choice in 2050 is to build for the 25th percentile, the smallest extension. Although there will be years in which the storage is not sufficient, the costs of lost production are not sufficient to justify the cost of larger storage. In other applications, whether different locations for water storage or different types of investments altogether, each pathway and decision point will be different.

Table 5 also shows the expected NPV for building water storage for the worst climate outcome in each of the scenarios, as a comparison with the most cost-effective. Most of these have negative expected NPVs, indicating the costs outweigh the benefits, but the scenarios with the lower discount rate do generate positive NPVs even with these larger sized reservoirs. The higher milk price and distributed probability scenario also generates a positive expected NPV. While these may be cost-effective investments under those assumptions, they are not the *most* cost-effective, and do not generate the maximum NPV.

7.1. Limitations and further work

The intention of this project was to demonstrate how ROA can help with large investment decisions under climate change in New Zealand, as there have been few applications of this in New Zealand to date. With water availability and irrigation being currently very topical, this seemed like an appropriate application. This project as such makes a number of simplifying assumptions, both in the hydrology and the economics, that leave scope for improvement in future work. We outline the main areas below.

7.1.1. Distinguishing climate change from climate variability

The GCMs used to drive the hydrological modelling are able to encapsulate long-term natural oscillations, such as the Interdecadal Pacific Oscillation (IPO). The IPO, as observed, has a periodicity on the order of 20 to 30 years, a period that extends beyond the time frames used to average hydrological results here. This can pose a problem in that hydrological differences between time periods (i.e., baseline, mid-century, and late-century) will reflect a combination of both gradual (but not linear) climate change as well as natural climate variation. If the simulated IPO during one projection period is out of phase from the other, then the resulting analysis would either exaggerate or downplay the effect of climate change. This effect has not been analysed, but it could be responsible for the non-monotonic trend often seen across

RCPs. RCP4.5 often stands out as exhibiting more severe changes than RCP6.0, which can be traced to higher mid-century temperature increases (Ministry for the Environment 2018). This may be due to inter-annual climate variability, due to higher radiative forcing of RCP4.5 compared with RCP6.0 in the early century, or a combination of both.

7.1.2. Hydrological model uncertainties

The TopNet model was designed to have a sufficiently comprehensive description of catchment hydrology to be used for the diverse range of landscapes and climate characteristics present in New Zealand. This results in a model that approximates all of the country's hydrology with the same set of hydrological process representations. TopNet is widely used in hydrological modelling applications in New Zealand; for example for operational flow forecasting (McMillan et al. 2013), to predict the hydrological impacts of climate change (Poyck et al. 2011; Zammit and Woods 2011), and for national water accounting (Collins et al. 2015).

At the start of the project the current limitations of the model include the lack of a dedicated glacier component (without coupling to a glacier energy balance model), no simulation of deep groundwater processes that transfer subsurface water between sub-catchments (Yang et al. 2016), and the use of a single ground water store in each catchment which restricts the possible recession behaviour (McMillan et al. 2011). Those limitations are currently being addressed by NIWA through improved conceptualisation and parametrisation of TopNet through the development of the New Zealand Water model. The TopNet model (used in this project) was assessed against a consistent suite of test procedures aiming to quantify spatial and temporal patterns in performance of representation of various part of typical hydrological signatures within a hydrological model (McMillan et al., 2016). The authors indicate that model performance varied in space and time with better scores in larger and medium-wet catchments, and in catchments with smaller seasonal variations. The authors further acknowledge that TopNet performance was not sensitive to connectivity to large groundwater systems, making the uncalibrated model suitable for national scale assessment.

Hydrological model uncertainty is usually associated with either model parameterisation or model structure. Uncertainty associated with model parameterisation is usually estimated using an ensemble of potential model parameters, while uncertainty associated with model structure is usually addressed using an ensemble of hydrological models. In this project the hydrological model is used in an uncalibrated form and neither of these uncertainties is addressed.

7.1.3. Land use coverage

The focus of the present study is on water resources relevant to agriculture, specifically water supply and soil moisture conditions. Results are reported only for parts of New Zealand that correspond to agricultural and irrigable land uses. Drawing from the Land Cover Database (LCDB v.2, Newsome et al. 2000) these include:

- Short-rotation cropland;
- Orchard, vineyard and other perennial crops;

- High-producing exotic grassland;
- Low-producing exotic grassland; and
- Depleted grassland.

Depleted grassland is included as it may have been or may once more serve as agricultural land. The full extent of these land uses is depicted in Figure 10, with a total area of 111,485 km^2. The hydrological model used as the basis for this project (New Zealand Water Model-Surface, previously referred as TopNet) is currently configured to use LCDB v.2, reflecting 2001 land cover, rather than the latest version, version four, which corresponds to 2011. There will be differences in land use between the two, and these may have hydrological consequences, although they are likely to be small in comparison with changes up to 2100. During the course of the simulations from 1971 to 2100, however, land use is kept constant. The purpose of this is for the hydrological assessment to isolate the effects of changing climate on the hydrological response.

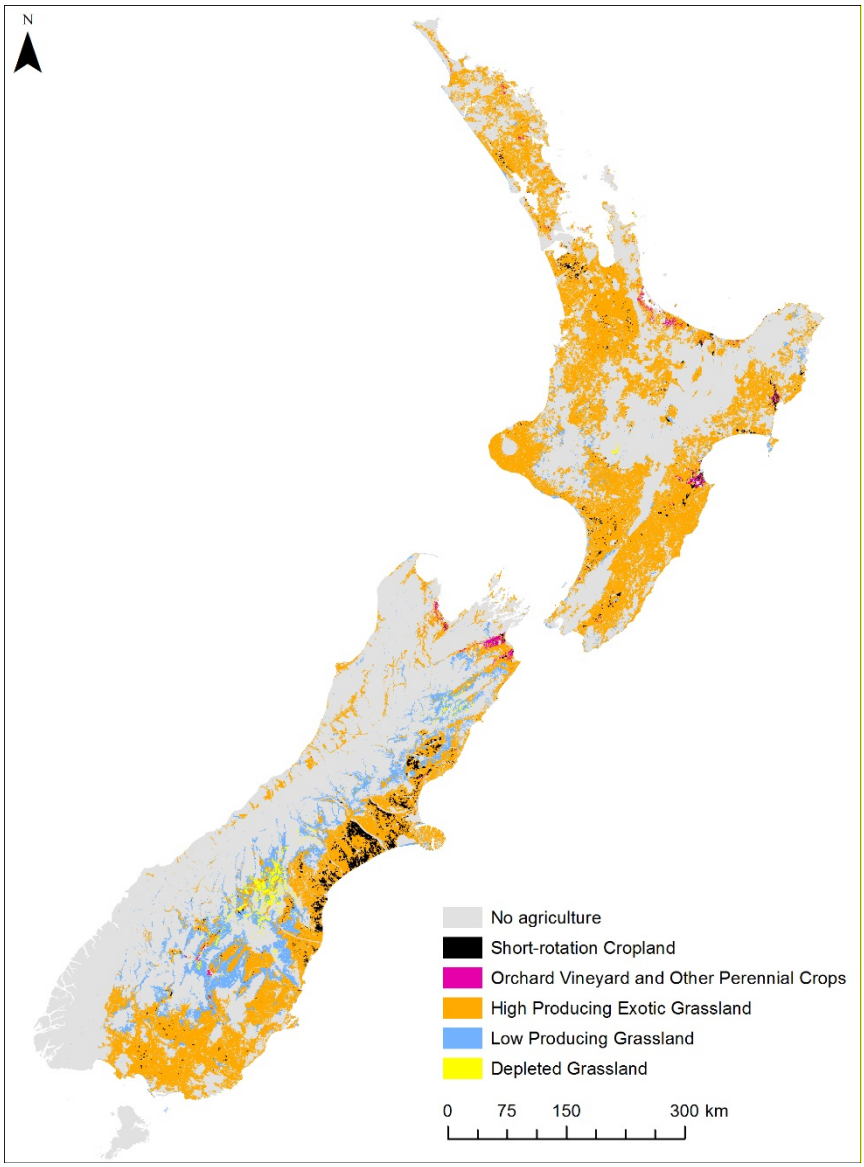

Figure 10 Agricultural land covers based on the LCDB version 2 (Newsome et al. 2000). Note however that there are many small areas of potential agriculture that cannot be seen at this scale.

7.1.4. Cost and benefit calculations

In further research there is scope to provide more detail in the development of the costs and benefits. As mentioned in the methodology section, the costs currently only include the cost of constructing the reservoir in the two time periods, but in more detailed analysis it would improve the accuracy to include the costs of consent, maintenance, energy if applicable, and the opportunity cost of the land used.

The calculation of benefits also leaves considerable scope for improvement. The current calculation relies solely on the relationship between soil moisture deficit and milkfat

production, which is dependent on a single study (Tait et al. 2005). Expanding the benefits to more accurately reflect the farm system profitability would reflect reality much better. Rather than accept the loss in production, farmers are much more likely to purchase supplementary feed to make up for the lost pasture. The costs of supplementary feed may be different from the value of the lost milkfat, and capturing these differences may change the outcomes of the different pathways.

In the current analysis we hold the price of milkfat constant over the entire time period. While this is of course unrealistic, predicting milk prices is another academic exercise entirely, with its own sources of uncertainty. But it would be possible to make different assumptions regarding the dynamics of milk prices to determine how much difference they make to the decision. It would be interesting to determine what milk price would justify a larger investment now (the increase to $7 analysed here was only sufficiently large to make a difference in the equi-probable assumption – although this may also reflect the way that benefits are calculated). Changing milk prices over time are a real risk for this type of investment, so understanding the implications of a fall in milk prices over time would undoubtedly be useful for the industry.

7.1.5. The ROA process

The ROA analysis itself could both usefully be expanded on or simplified. In terms of expansion, other questions to examine would be the inclusion of more, or different decision-nodes. More nodes increases the complexity of the analysis, but would provide greater flexibility. We did not include the option to do nothing, but in a further analysis this would be useful as one of the options. This would allow the decision-maker the ability to identify the value of delaying action, as well as understanding the size and sequence implications.

The analysis could also usefully be simplified to make the process more accessible to individual decision-makers. In its current form, this type of analysis would be very useful for a large-scale investment, probably by a collective rather than an individual. Although the analysis is relatively straightforward if the hydrological data is available (and conducted in a spreadsheet), it is still beyond the complexity most individuals are likely to undertake. However, if a 'tool' was available allowing the farmer to input their farm location and details of their farm business, and their preferred decision-points, the ROA process could be automated. Alternatively, the principles of not constructing for the worst case scenario and allowing flexibility to expand in future, could be adopted relatively easily without conducting the full analysis.

8. Conclusion

This study has demonstrated how ROA can be applied to identify the most cost-effective option for constructing an on-farm water storage reservoir under a changing climate. In this particular example, the most cost-effective option was to construct a reservoir for the most conservative climate change outcome in 2018, and in 2050. This avoids the expense of constructing a large reservoir that would cover the worst case climate outcomes, but where the benefits would not outweigh the costs. The decision to build for the smallest climate change is sensitive to a number of factors however, particularly the discount rate and the milk

price, both of which result in larger reservoirs being more cost-effective in the first time period. The decision is also sensitive to assumptions regarding the likelihood of future climate changes – when the higher and lower scenarios are assigned a lower likelihood, this changes the decision to a larger storage size in 2018. This analysis illustrates the benefits of ROA when the future is uncertain. It enables decision-makers to revise their decisions over time rather than locking themselves into a decision made now that has long-term consequences.

We used an example of water storage on a dairy farm to illustrate how ROA can be used, using the climate data available in New Zealand. We developed a method to use the range of 26 GCM/RCP combinations to generate estimates of likelihood. This method is suitable for application across a range of investment decisions in New Zealand, where the initial cost is large and the investment is at least partially irreversible. We believe that using ROA for these types of decisions will enable more cost-effective investment than cost-benefit analysis or other methods that use only a single climate scenario.

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