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Myopia and saliency in renewable resource management

Daniel Gregg and John Rolfe†

An important challenge in managing renewable resources is to understand why owners and managers sometimes make decisions that deplete resources and future earnings, such as when graziers allow pastures and land condition to be degraded. In this paper, we test two potential reasons for unsustainable management practices, myopia and salience, with each explaining why resource managers may exhibit impatience in harvest decisions. Myopia is associated with decision makers placing lower weight on future outcomes than would be implied by their pure time preference. Salience is associated with overweighting of consumption 'now', implying inconsistency in time preferences. To test for these effects on renewable resource management, an incentivised, dynamic field experiment was carried out with rangeland grazing enterprise owners in north-eastern Australia that related management choices with uncertain rainfall events to both profits and land condition over time. Results demonstrate that respondents exhibiting myopia/salience in their choices tended to achieve lower cumulative scores in the experiment, as well as lower land conditions on their properties as measured with remote sensing data. Our results explain why there may be persistent optimisation failures by resource owners that reduce both profits and environmental outcomes.

Key words: bounded rationality, experimental economics, field experiment, grazing, Great Barrier Reef, renewable.

1. Introduction

Renewable resources under private control, such as private forests and agricultural lands, sometimes exhibit degradation even though these outcomes are suboptimal for the resource holder. Resource holders reduce the stock of their resource, and future harvests, by actions such as overharvesting (e.g. forestry) or over-stocking (e.g. grazing on pastures) that reduce the net present value of the enterprise. Clark (2010) shows that these behaviours are often driven by impatience of the resource owner with equilibrium 'optimal' resource stock levels being lower the higher is impatience, *ceteris paribus*. However, there is increasing evidence that a large portion of impatience is not derived from a pure time preference but rather is driven by behavioural factors or by bounded rationality (Ballinger *et al*. 2011; Brown *et al*. 2009). Furthermore, in many cases regarding the management of renewable natural resources there is jointness with public goods, such as for biodiversity or water quality impacts, in addition to private values over the flow of benefits from the resource in question. Improving the sustainability of privately held

† Daniel Gregg (email: daniel.gregg@adelaide.edu.au) is with Centre for Global Food and Resources, University of Adelaide. John Rolfe is with Central Queensland University.

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renewable resources thus may lead to both private and public welfare gains (e.g. Star *et al*. 2013). Despite clear and substantive impacts of behavioural factors in measures of revealed impatience (e.g. Brown *et al*. 2009) little is known about how these aspects of choice impact on decisions in the setting of renewable natural resources, nor the relative importance of different behavioural factors in dynamic choice.

In this paper we use a field experiment to consider two sources of impatience in dynamic decisions regarding renewable natural resources. One source, myopia, is captured by allowing for bounded rationality (Simon 1955; Heiner 1983), which causes the decision makers to place lower weight on future outcomes than would be implied by their pure time preferences. The other source of impatience, salience, is captured using quasi-hyperbolic preferences, which allow the decision maker to have inconsistent time preferences (Laibson 1997). These aspects have been widely tested in laboratory experiments (e.g. Haiyan and Ausubel 2004; Brown *et al*. 2009; Ballinger *et al*. 2011), but have received little attention in applied settings (i.e. field experiment settings).

Laboratory experiments have provided major contributions to the understanding of human behaviour in markets, with respect to risk and uncertainty and, slowly but increasingly, with respect to dynamic optimisation (Falk and Heckman 2009). However, applied researchers are increasingly finding that laboratory experiments alone may have low predictive capacity for behaviours in the 'real-world' (Roe and Just 2009). Even when laboratory methods have been taken to the field they have often been found to be of limited relevance to actual behaviours or the outcomes of those behaviours for the sample against which they have been applied, although this may be related to particular methods (Csermely and Rabas 2016). These results have led to an increasing realisation that applied research needs to both consider populations of interest and to incorporate appropriate context (framing) in experimental studies to access mental processes governing behaviours which are relevant to the issue of interest (Harrison and List 2004).

We examine the impact of myopia and salience on choices in the context of privately owned renewable resources using a framed field experiment involving a dynamic choice problem. Our study exploits a naturally dynamic setting, the management of pastures on rangelands grazing properties in close proximity to the World Heritage-listed Great Barrier Reef (GBR). The GBR is being considered for designation as 'at-risk' amongst World Heritage-listed assets, in part because of high pollutant loads, including sediments, from agriculture. Studies have shown that the vast majority of sediment is generated by over-stocking and poor grazing land management that also reduce resource quality (Star *et al*. 2013, 2015). Behaviours in these contexts may be driven by a complex set of factors, but recent work indicates that bounded rationality and behavioural aspects may be important (Rolfe and Gregg 2015). Our results support this linkage between nonrationality in decision-making to environmental degradation and lower profitability. In particular, we show that myopia and salience factors have significant explanatory power for decisions made by respondents and have real-world consequences for land conditions.

We make three important contributions to the literature. First, we make a methodological contribution by demonstrating the development and application of a model that explicitly allows for both myopia and salience simultaneously in dynamic decision-making. This allows us to measure these two sources of behavioural bias independently of each other and independently of pure time preference. Our second contribution is to show how a framed field experiment can be designed to measure these influences directly with landholders, through the application of a type of dynamic experiment involving 'stocking' and 'harvest' choices under risk. Third, we demonstrate that myopia and salience exist in resource decisions about land management and may underpin issues of land degradation and pollution into the GBR from the pastoral sector.

The remainder of the paper is set out as follows. In Section 2, we develop a simple representation of choices in dynamic settings that are affected by bounded rationality (myopia) and behavioural aspects (salience). In Section 3, we describe an incentivised dynamic choice field experiment involving hypothetical land condition, land condition-dependent profits and stochastic rainfall outcomes. The experiment was answered by 51 rangelands enterprise owners and managers operating in north-eastern Australia. A structural decision model that allows formal testing for the presence of myopia and salience effects is described in Section 4. Section 5 provides an outline of the data generated by the experiment and associated data used for posthoc analysis. Section 6 presents the results and Section 7 provides conclusions.

2. Conceptual background and supporting literature

Analysis of real-life revealed preferences commonly indicates the presence of nonrational decision-making in complex dynamic decision problem. For example, Arcidiacono *et al.* (2007) showed that older people applied discount rates in the order of 30 per cent to smoking choices, indicating very high levels of impatience, potentially associated with factors other than pure time-preference. Similarly, Miranda and Schnitkey (1995) showed that dairy producers' herd replacement decisions exhibited high levels of discounting beyond market rates and returns to capital in the dairy industry. Haiyan and Ausubel (2004) found evidence of salience in choice experiments on use of credit cards and savings decisions. More generally, Laibson *et al.* (2007) found hyperbolic intertemporal preferences explain consumption better than the simple exponential model using aggregate consumption data. Substantial evidence for myopia and salience effects also exists amongst studies of choices made in dynamic decision problems in laboratory experiments. Brown *et al.* (2009) show that decisions over time-differentiated outcomes generally exhibit myopia and salience effects, whilst Ballinger *et al.* (2011) present evidence of myopia in consumption-savings decisions and link this to decreasing cognitive ability of agents.

Despite the research on dynamic decision problems over the last 30 years, no studies have generated results involving a model that explicitly allows for both myopia and salience simultaneously in dynamic decision-making. Brown *et al.* (2009) employed a simple savings experiment to test myopia and learning effects on bounded rationality over consumption of beverages by thirsty subjects. Ballinger *et al.* (2011) only consider myopia in a dynamic savings/investment laboratory experiment. However, the separation between tests of bounded rationality and salience (Brown *et al.* 2009) largely precludes formal measurement of myopia and salience in an integrated model, whilst the laboratory setting limits generalisation of findings to real-world behaviour and has focused only on myopia (e.g. Ballinger *et al.* 2011) or salience effects (Dohmen *et al.* 2011; Charness *et al.* 2013; Richards and Green 2015).

Applied research, such as Miranda and Schnitkey (1995), Arcidiacono *et al.* (2007) and Skinner (2007), generally fails to adequately separate time preference from behavioural aspects or from bounded rationality due to limitations on joint identification of time preference and risk preference when independent verification of one or the other cannot be undertaken (Rust 1994; Andersen *et al.* 2008). There is, thus, an interest and need to develop a model of myopic and salience-affected behaviour that allows for simultaneous identification of these two sources of behavioural bias independently of each other and independently of pure time preference.

A useful starting point is to consider the standard rational choice function for a 3-period[1] intertemporal decision problem to represent the time preference function:

$$U(c_0, c_1, c_2) = \beta_0 U(c_0) + \beta_1 U(c_1) + \beta_2 U(c_2)$$

where:

$U(\cdot)$ = instantaneous utility function.

$$\frac{d^2 U(c_t)}{dc_t^2} < 0$$

c_t, consumption in period t, β_t, discount factor in period t.

$$\sum c_t \leq C$$

Under the standard (exponential) model of discounting, the discount factor is given by a reciprocal function of the discount rate (δ):

[1] A 3-period formulation is needed to identify salience effects in addition to myopia effects.

$$\beta_t = \frac{1}{(1+\delta)^t} \text{ for } \delta \geq 0$$

This formulation of the intertemporal choice problem generates maximal lifetime utility when the marginal utility for consumption in period 1 is equal to the discounted marginal utilities of consumption in periods 2 and 3. Assuming that consumption in the three periods must add to some constant ($c_0 + c_1 + c_2 = C$) and that the agent can consume as much as they want in any period. The consumption decision is governed solely by the discount rate where we have the following characterisation of rational consumption choices:

$$\begin{array}{lll} c_0 = c_1 = c_2 & \text{for:} & \delta = 0; \\ c_0 > c_1 > c_2 & \text{for:} & 0 < \delta < \infty; \text{ and} \\ c_2 = c_3 = 0 & \text{for} & \delta = \infty. \end{array}$$

More generally, consumption in period 0 is increasing in the discount rate, meaning that saving for future periods is decreasing in the discount rate. Clark (2010) shows that this is also pertinent for renewable resources, which have a potentially infinite total consumption across time; higher discount rates for the manager of these resources lead to higher initial harvests, lower equilibrium stock levels and lower equilibrium maximum sustainable (economic) yields.

Theoretical (Brown and Lewis 1989) and empirical results (e.g. Arcidiacono *et al.* 2007; Brown *et al.* 2009) suggest that impatience may include myopia (bounded rationality) as well as time preference in complex decision problems. In such cases, preferences over time-differentiated utility streams are functions of myopia as well as time preference. Using the standard exponential functional form for discounting, we represent this using:

$$U(c_0, c_1, c_2) = \bar{\beta}_0 U(c_0) + \bar{\beta}_1 U(c_1) + \bar{\beta}_2 U(c_2),$$

where:

$$\gamma = \text{myopia}$$

$$\beta_t = f(\text{time preference}) = \frac{1}{(1+\delta)^t} > \frac{1}{(1+\delta+\gamma)^t} = g(\text{time preference, myopia}) = \bar{\beta}_t.$$

The representation above conforms to the assertion of Brown and Lewis (1989) that myopia implies impatience but impatience does not imply myopia. In other words, when myopia is present, the decision function is more impatient than implied by preferences alone. This means that impatience is comprised of at least two components – one factor associated with pure time preference (intertemporal utility) and another with failure in dynamic optimisation leading to choices reflecting higher impatience than is privately optimal for the agent.

Bounded rationality caused by complexity of dynamic optimisation is not the only factor potentially affecting impatience. Salience occurs when the discount rate underpinning harvest decisions is inconsistent with (is higher than) other time preferences for future consumption (Brown *et al.* 2009). This form of choice is often represented as hyperbolic discounting in which agents have dual 'selves' (Thaler and Shefrin 1981; Harris and Laibson 2001): one 'self' is affected by the saliency of current rewards ('bird in the hand') whilst the other is long-sighted and considers the utility of current choices over the longer term ('two in the bush'). When an agent is affected by the salience of current rewards, they will tend to have a higher preference for current consumption over future consumption; however, when these rewards are delayed, the long-sighted decision process 'wins' the rights to decision-making. The level of salience is then a function of the tendency of the agent to use their myopic 'self' in making trade-offs between current and future consumption.

A common representation of salience in economic models of choice is via a quasi-hyperbolic function (Laibson *et al.* 2007), in which agents are assumed to weight the current period consumption more highly than later periods. This is typically represented by appending a weighting parameter to the current periods' consumption, which serves to inflate current-choice utility:

$$U(c_0, c_1, c_2) = \lambda \bar{\beta}_0 U(c_0) + \bar{\beta}_1 U(c_1) + \bar{\beta}_2 U(c_2)$$

where:

$$\lambda \geq 1 = \text{salience effect.}$$

This formulation clearly shows that consumption in $t = 0$ is increasing in λ, whilst consumption in periods $t \neq 0$ is decreasing in λ. The impact of this form of salience is fleeting. An agent who faces a choice involving allocation of consumption between periods 1 and 2 will not be affected by this form of salience. As a result, the hyperbolic model of time preferences allows representation of preference inconsistency over time-differentiated consumption options.

By combining myopia and salience effects into a single model of choice, these aspects can be represented more generally for a given sequence of choices, as:

$$U(c) = \lambda \bar{\beta}_0 U(c_0) + \sum_{t=1}^{T} \bar{\beta}_t U(c_t)$$

The discussion above relates myopia and salience effects as impacts on time preferences in a decision function over time. As myopia and salience effects become greater, the net value of consumption over time falls. Thus, there are private benefits to reductions in myopia and salience effects. Where there are additional biodiversity or externality issues, then there will be additional public values for reduced myopia and salience exhibited by a private resource owner. This provides a clear impetus for public intervention in the management of privately owned renewable natural resources that may be subject to myopia and salience effects.

3. Experiment

The experiments were run in central Queensland (Australia) in 2012 with owners and managers of rangelands grazing enterprises. Initially, 54 managers were involved in homestead visits with 51 completing the two experiments outlined here. Respondent enrolment was undertaken using an initial email contact with a follow-up telephone call using details from a private consulting firm and from government extension services. Respondents were thus self-selected from a pool of managers who were likely to be more engaged in grazing land management extension services relative to average enterprise managers in the industry. Because of this and our small sample size (51 producers) relative to the total number of producers in the region (approximately 3,500), it is unlikely that the sample is fully representative of the population (Gregg and Rolfe 2016a).

The experiment was framed for beef cattle producers in extensive grazing systems in Queensland, where overgrazing can lead to pasture degradation and poor groundcover, reducing both future grazing conditions and increasing sediment runoff. Managers/owners were largely male (2 of 49 were not) and had an average of 34-years industry experience (minimum of 8 years and maximum of 60 years). 69 per cent of the sample had children with most of these (88 per cent) considering succession planning.

Management in these extensive grazing systems is complex because of highly variable climatic conditions and poorly understood pasture response mechanisms. Beef producers make choices about stocking rates that balance production gains in the short term against risks of pasture degradation and lower production in the longer term, with damage to pastures generally occurring during drought periods.

Two experiments were designed for each producer to complete, involving almost identical response functions and 20 sequential choices each. The first experiment was a static choice task, where participants made 20 separate choices between stocking rates, profits and land condition under varying probabilities of low, medium and high rainfall outcomes (Gregg and Rolfe 2016a). The second task involved dynamic changes over the 20 periods, in which choices were linked via the land condition variable which changed depending on the stocking rate and the rainfall outcome in each period. The first-choice task was used to familiarise participants with the experiments and identify risk preferences, whilst the second-choice task was used to identify myopia and salience effects.[2]

Choice tasks were framed as a grazing management scenario. The discrete dynamic choice task utilising all of the above information was displayed as presented in Figure 1 with respondents beginning at choice 1 populated using a

[2] Conduct of the two separate tasks allowed us to address the issue identified by Andersen *et al*. (2008) that it is not possible to jointly identify risk preferences and myopia in a single experiment task.

random starting point for land condition and making 20 sequential choices. Respondents were allowed to undertake trial choices before beginning the task. The first static choice task was presented in the same format but did not involve details regarding future land condition. Experiment instructions were verbal and based on a straight-forward outline that rewards would be calculated based on performance relative to a computer player over a task lasting for 20 decision periods. The experiment application,[3] a screen capture of which is shown in Figure 1, provided all details needed to make informed choice, and respondents were provided with a chance to practice the task prior to undertaking it. Further details on the experiment design can be found in Gregg and Rolfe (2016b).

The dynamic choice task can be characterised as having three key components: rainfall risk, state-dependence and decision dynamics. The combination of the chosen management alternative (conceptually linked to stocking rate), the current state (linked to land condition), and the stochastic rainfall outcome defined a new state for the next choice and the profit in the current period. In the static choice experiment there were no such linkages between the tasks

The choice options were simplified for each set to make the decisions tractable. The management alternatives were framed as ‘A’, ‘B’ and ‘C’ rather than ‘low’, ‘medium’ and ‘high’ stocking rates to reduce other influences on decisions. Rainfall for the next period was shown as low, average and high outcomes, with probabilities of each adding to 100 per cent. Outcomes of each management and weather outcome were defined in terms of potential profit and land condition, which was based on a land condition framework familiar to all respondents, the ‘ABCD’ framework (Karfs *et al.* 2009). The framework is defined in terms of both ecosystem resilience/health and in terms of productive capacity, thereby providing a direct linkage for managers to environmental function and profit potential on their land (Figure 2).

In both experiments, a starting state and probabilities of events were selected randomly. The respondent then selected one of three possible alternatives associated with three different possible payoff and future state outcomes. A random number was drawn which determined the stochastic outcome. The chosen alternative event combination was associated with a payoff value and credited to the respondents’ record, which accumulated over the sequence of 20 choices. In the dynamic experiment, the choices also influence the state variable for each successive outcome, and by implication, future trade-offs. Parallel to this, profits for the ‘computer’ were estimated by selecting the best option in each set without considering dynamic factors.

To generate the dynamic state variable, the ABCD land condition framework shown in Figure 1 was modified to allow for three levels within each land condition designation, namely {A+, A, A−}; {B+, B, B−}; {C+, C, C−}; {D+, D, D−}. These levels were aligned with a monotonically

[3] This is available from the corresponding author on request.

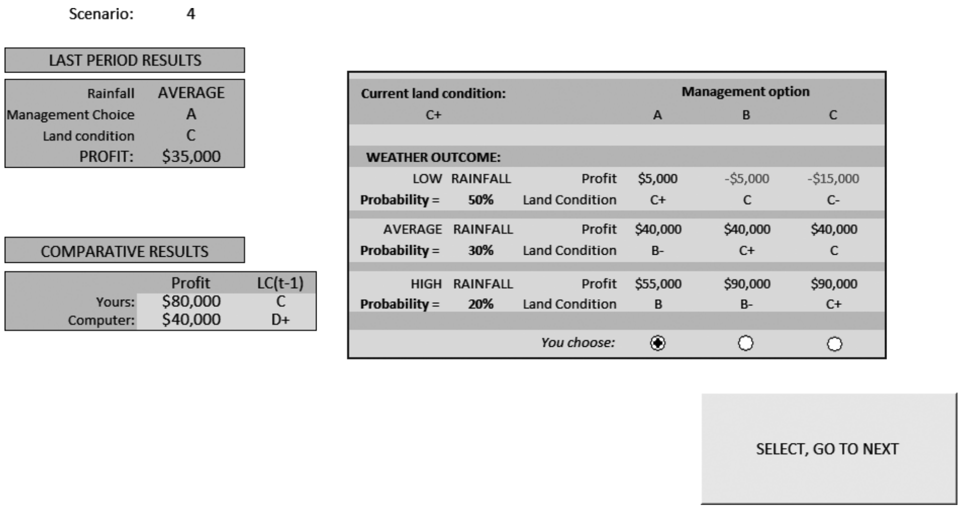

Figure 1 Screen grab of choice experiment as presented to respondents.

Land parameter:	A Condition	B Condition	C Condition	D Condition
Soil	Good condition, no erosion	Minor erosion	Obvious erosion	Severe erosion or scalding
Pasture	Good coverage by 3P grasses. <30% bare ground in most years	Increase in non-3P grasses. Between 30-50% bare ground in most years.	Large quantities of non-3P grasses. >50% bate ground in most years.	General lack of perennial grasses. Majority bare ground in most years.
Woodland	None or very early signs of woodland thickening.	Some thickening in woody plants.	General thickening in density of woody plants.	Thickets of woody plants cover much of the area.
Carrying Capacity		75% of A condition carrying capacity.	50% of A condition carrying capacity.	20% of A condition carrying capacity.

Figure 2 Description of the ABCD land condition framework.*Source:* Karfs *et al.* (2009). *Note:* 3P refers to 'productive, palatable and perennial' grasses considered ideal in rangelands grazing environments in Australia.

increasing payoff distribution with the A+ state involving the greatest potential profit levels and the D– state the lowest potential profit levels.

Each of the three alternative actions in each choice (options 'A', 'B' and 'C') was associated with, in order, increasing variance in payoffs, increasing expected value of payoffs, and decreasing future land condition values (decreasing future payoff possibilities). Thus, in general, a choice of alternative 'A' involved lower expected instantaneous profits, a higher future land condition (than the alternative choices) and lower variance of expected instantaneous profits. On the other hand, alternative 'C' involved higher

Table 1 Payoffs and future land condition outcome conditional on current land condition, rainfall and strategy choice

Land condition	Strategy:	Conservative ('A')			Average ('B')			Intensive ('C')		
	Rainfall:	Low	Average	High	Low	Average	High	Low	Average	High
A+		\$45,000 A+	\$75,000 A+	\$95,000 A+	\$60,000 A	\$105,000 A+	\$180,000 A+	\$55,000 A–	\$110,000 A	\$235,000 A+
A		\$40,000 A	\$70,000 A+	\$95,000 A+	\$50,000 A–	\$95,000 A	\$165,000 A+	\$45,000 B+	\$95,000 A–	\$200,000 A
A–		\$35,000 A–	\$65,000 A	\$90,000 A+	\$40,000 B+	\$80,000 A–	\$150,000 A	\$30,000 B	\$85,000 B+	\$175,000 A–
B+		\$25,000 B+	\$60,000 A–	\$80,000 A	\$30,000 B	\$70,000 B+	\$135,000 A–	\$20,000 B–	\$75,000 B	\$150,000 B+
B		\$20,000 B	\$50,000 B+	\$75,000 A–	\$20,000 B–	\$60,000 B	\$120,000 B+	\$10,000 C+	\$60,000 B–	\$130,000 B
B–		\$10,000 B–	\$45,000 B	\$65,000 B+	\$5,000 C+	\$50,000 B–	\$105,000 B	–\$5,000 C	\$50,000 C+	\$110,000 B–
C+		\$5,000 C+	\$40,000 B–	\$55,000 B	–\$5,000 C	\$40,000 C+	\$90,000 B–	–\$15,000 C–	\$40,000 C	\$90,000 C+
C		–\$5,000 C	\$35,000 C+	\$45,000 B–	–\$15,000 C–	\$30,000 C	\$75,000 C+	–\$25,000 D+	\$25,000 C–	\$65,000 C
C–		\$10,000 C–	\$30,000 C	\$35,000 C+	–\$30,000 D+	\$20,000 C–	\$60,000 C	–\$40,000 D	\$15,000 D+	\$45,000 C–
D+		–\$15,000 D+	\$20,000 C–	\$25,000 C	–\$40,000 D	\$5,000 D+	\$45,000 C–	–\$55,000 D–	\$5,000 D	\$25,000 D+
D		–\$25,000 D	\$15,000 D+	\$15,000 C–	–\$50,000 D–	–\$5,000 D	\$30,000 D+	–\$70,000 D–	–\$10,000 D–	\$5,000 D
D–		\$30,000 D–	\$10,000 D	\$5,000 D+	–\$65,000 D–	–\$15,000 D–	\$15,000 D	–\$85,000 D–	–\$20,000 D–	–\$15,000 D–

expected instantaneous profits (in all but the lowest land conditions), lower future land condition (than the alternative choices) and higher variance of expected instantaneous profits. Alternative 'B' was located between these two extremes. Table 1 presents the combinations of payoffs and future land conditions for each land condition variable that might be selected within the experimental design conditional on choice and 'rainfall' (the variable inducing stochasticity).

To ease cognitive burden in the dynamic task, the distribution of rainfall probabilities was limited to three possible 'seasonal' values – 'poor', 'average' and 'good'. These values were randomly allocated to each choice with predefined probabilities. The probability distributions of weather outcomes dependent on seasonal types are shown below in Table 2 – these were made known to participants prior to their beginning the experiment.

The experiments were generally undertaken at participants' properties. Instructions were verbal and involved describing the structure of the experiments and that they were being asked to participate to help develop an understanding of aspects of decision-making over systems which were similar to those they typically manage in their normal operations. It was emphasised that the experiment was not designed to generate predictions about how they manage their properties and responses would be anonymous. Participants were given the opportunity to practice the experiments prior to starting each one and were encouraged to explore the response function underlying the experiment.[4]

The experiment involved a performance-dependent reward incentive of up to 75 Australian Dollars based on a performance function similar to that in Ballinger *et al.* (2011). Our testing of the experiment prior to its extension led us to develop a simple payoff function defined as the ratio of the participants' total profit from the experiment and 2 times the 'computer' total profit for the experiment. Specifically, the reward function for this experiment was:

$$\text{Reward payment} = \min\left[\$75 \times \left(\frac{\text{Total final sum of participant choice profits}}{2 \times \text{Total final sum of 'computer' choice profits}}\right), \$75\right].$$

Table 2 Season types and presented rainfall probabilities for the dynamic choice task

	Presented probabilities of rainfalls		
Season type	Low	Average	High
'Poor'	0.50	0.30	0.20
'Average'	0.33	0.33	0.33
'Good'	0.10	0.25	0.65

[4] The experiments are available on request from the corresponding author and comprise 3 Microsoft Excel files with Macros.

Whilst all respondents were eager to play the game and to 'beat' the computer in what they regarded as an exercise that they should be 'good' at, only six respondents were able to achieve the payoff-limited benchmark of \$75. The distribution of reward scores appears normally distributed with a mean reward score of 85 per cent of the benchmark.

Additional data on land condition were also sourced for each grazing property. The remotely sensed ground cover index used for this component is a commonly used indicator of the land condition framework (Bastin *et al.* 2002) used in this experiment which is recognised to provide a measure of both environmental health and carrying capacity, or profit potential, for a given property (Karfs *et al.* 2009)

4. Analysis

The choices made by respondents were analysed in terms of the expected returns in all future periods. A constant relative risk aversion (CRRA) function[5] was specified for the instantaneous utility function based on outcomes from combinations of the state variable (s), respondent choice (j) and stochastic rainfall realisation (e) at choice t of $T = 20$:

$$U(x_{j,s,t,e}) = \frac{x(j_{s,t,e})^{1-\alpha}}{1-\alpha}$$

$$\mathrm{EU}_{j,s,t} = \sum_{e=1}^{3} P(e_t)U(x_{j,s,t,e})$$

where:

$U(x_{j,s,t,e})$ = Utility of outcome x from choice j under state s in time t for event e;

$x(j_{s,t,e})$ = Value of outcome from choice j under state s in time t for event e;

α = Relative Risk aversion coefficient.

The full decision function for the dynamic choice problem, in the general case allowing for the presence of myopia and salience effects, was estimated using a discount factor based only on myopia and a salience factor outlined in Section 2. The myopia factor was estimated as an exponential function with:

$$\beta_t = \frac{1}{1+\gamma},$$

[5] Hypothetical payoff values were normalised to the 0–1 interval allowing calculation of the CRRA form (which is not defined for negative payoffs). We utilised the contextual utility stochastic choice function of Wilcox (2011) which facilitates extension of results to other contexts (i.e. outside of the 0–1 interval or which involve tradeoffs across this whole range). This is outlined in more detail in the next section.

$$\gamma = \text{myopia}.$$

The experiment design was such that there was no pure time preference in responses to the dynamic choice task allowing attribution of contributions of the discount factor β to myopia alone. The intrachoice utility function based on myopia and salience effects yielded a value function for each choice j and at each stage t of the decision process provided by the solution to the Bellman equation[6] :

$$V(j_{s,t,e}) = \lambda U(x_{j,s,t,e}) + \max\left[\sum_{t'=t+1}^{20} \beta \mathrm{EU}_{t'} | e_t, j, s\right]$$

$$\mathrm{EV}_{j,s,t} = \sum_{e=1}^{3} P(e_t) V(j_{s,t,e})$$

where: λ = Salience effect; β = myopia factor.

$$\mathrm{EU}_{t'} = \sum_{e_{t'}=1}^{3} p(E[e_{t'}]) U(X_{j,s,t',e})$$

The functions outlined above indicate the resultant decision equation involves identification of three decision function parameters: the relative risk aversion coefficient within the instantaneous utility function (α); the myopia factor (β); and the salience factor (λ).

To represent intertemporal choice using the Bellman equation, it is necessary that the decision maker knows all of the relevant parameters of the model (Cogley and Sargent 2008). This aspect is implicit in the expectation over future events shown in the value function above. To meet this requirement, two identifying assumptions were made that allowed formulation of an exact solution to the Bellman equation. Firstly, we assumed future weather outcomes ('poor', 'average' and 'good' seasons) were equally likely. This was explained to participants (seasons were randomly chosen) and is a relatively benign assumption.

The second identifying assumption involved the expectation that participants were able to know the state-dependent payoff vectors, or at least their expected utility equivalents, for each state of nature. This second assumption is somewhat less benign. We justify it on the basis: (1) participants undertook a static choice task involving 20 choices with exactly the same state-dependent function immediately prior to the

[6] Details on the solution to the Bellman equation are provided in Rust (1994).

dynamic task and were encouraged to take note of the state-dependent payoff matrices in order that they could utilise this information; (2) participants were able to practice both choice tasks prior to starting to understand the state-dependent payoff matrices implicit in the response function; and (3) assuming equal weather outcomes implies the real burden on memory of state-dependent payoffs reduces to 12 expected utility outcomes for the 12 possible land condition states. Combining this with the fact (known to participants) that the expected value of payoffs was monotonically increasing in the state variable implies the true burden on rationality implied by the identifying assumption of knowledge of the state-dependent response function was not as great as might be thought. In particular, whilst participants may not have been able to directly quantify an expected value of outcomes for each land condition level, it is reasonable to assume they at least knew that higher land conditions were associated with monotonically increasing expected values of profits and that higher land conditions first-order stochastically dominated lower land conditions.

Four models were considered which allowed formal testing for the presence of myopia and salience effects and allowed nesting of the rational choice function in all nonrational forms. Specifically, functional forms for the value function considered for responses to the dynamic task were as follows:

Model	Restrictions	Description	Nests
(a)	$\lambda = 1$, $\beta = 0$	Rational choice model	None
(b)	$\lambda = 1$	Myopia model	(a)
(c)	$\beta = 0$	Saliency model	(a)
(d)	No restrictions	Myopia and saliency model	(a), (b), (c)

Within this framework, (a), (b) and (c) are nested with (d), allowing formal statistical testing for the hypothesis that:

> (H1) Agents tend to use decision functions incorporating bounded rationality and behavioural aspects in dynamic decision problems. Evidence for this would be provided by a statistical preference for models (b), (c) and/or (d) over model (a). This hypothesis was tested using pooled data.

Fifty-one individual-level models were estimated for each respondent using the most general specification (d) to consider the effects of myopia/saliency on decision performance. The hypotheses for this component were as follows:

> (H2) Myopia and/or salience effects lead to lower decision performance and lower utility as measured by rewards received in the field experiment. Evidence for this hypothesis was considered using a secondary regression of reward scores on estimated myopia and salience parameters.

(H3) Individuals with higher levels of myopia/salience will tend to employ more impatient resource management strategies. This hypothesis was considered using secondary regressions of a remotely sensed measure of land condition on estimated myopia and salience parameters.

A nonlinear multinomial logit model was used to model the choice probabilities for each respondent in two ways. Firstly, the sample-level models were estimated by poling data for all respondents across both tasks (static and dynamic). Secondly, individual-level models were estimated pooling data for the two tasks for each respondent individually. Following Moffat (2005) and Gregg and Rolfe (2016a), we allowed for incorrect specification via the inclusion of a 'Fechnerian' error term. The Fechnerian error generates a scaling of the choice probabilities based on the precision of the model. For sample-level models, a separate error term was estimated for each of the 20 choices in each of the static and dynamic tasks (40 error term estimates) which allowed for examination of the precision of each of the estimated models across choices.

The contextual utility (CU) model of Wilcox (2011) was also used to account for the relatively large range of different contexts presented to experiment respondents which were associated with the different land condition states. The CU model allows estimation of a value function which is valid for a normalised 'context' which can then be extended to other normalised contexts. Wilcox (2011) shows that this model is preferred to the strict utility models associated with the homoscedastic multinomial logit and the Fechnerian error multinomial logit models whilst Andersen *et al.* (2008) show that they can be combined yielding a specification which incorporates both some potential for specification error and the context of the experiment. The CU model is particularly pertinent in the case presented here due to the significantly different contexts facing respondents early in the dynamic task compared to later in the dynamic task. The CU model scales the value of prospects by the range of utilities amongst all prospects within a choice generating a stochastic model directly from the structural utility specification. Combining the multinomial logit model with Fechnerian errors and the CU model, we can represent the probability that a respondent i chooses alternative j for choice t as (i subscripts are suppressed):

For static choices:

$$P(j,s,t) = \frac{e^{\mathrm{EU}_{jst}/\mu_s/\sigma_{1t}}}{\sum_{j=1}^{J} e^{\mathrm{EU}_{jst}/\mu_s/\sigma_{1t}}}$$

For dynamic choices:

$$P(j,s,t) = \frac{e^{\mathrm{EV}_{jst}/\mu_d/\sigma_{2t}}}{\sum_{j=1}^{J} e^{\mathrm{EV}_{jst}/\mu_d/\sigma_{2t}}}$$

Where: $P(j,i,t)$ = probability that individual i chooses alternative j in choice t; σ_{kt} Fechnerian error term for k = 1 for static and k = 2 for dynamic experiment in tth choice; $\mu_s = \max(U_{s,t,e}) - \min(U_{s,t,e})$; $\mu_d = \max(V_{s,t,e}) - \min(V_{s,t,e})$.

The final log-likelihood was derived by stacking choice data from static and dynamic tasks and calculating the log-likelihood based on the addition of the log-likelihood for the static choices and the log-likelihood for dynamic choices. The log-likelihood is shown below:

$$\ln \ell_i = \sum_{t_1=1}^{T_1=20} I(y_{1,t_1} = j_{1,t_1}) \ln \frac{e^{\mathrm{EU}_{jst_1}/\mu_s/\sigma_s}}{\sum_{j=1}^{J} e^{\mathrm{EU}_{jst_1}/\mu_s/\sigma_s}} + \sum_{t_2=1}^{T_2=20} I(y_{2,t_2} = j_{2,t_2}) \ln \frac{e^{\mathrm{EV}_{jst_2}/\mu_d/\sigma_d}}{\sum_{j=1}^{J} e^{\mathrm{EV}_{jst_2}/\mu_d/\sigma_d}}$$

where: $I(y_{1,t} = j_{1,t})$ = indicator function for respondent static choice in t = alternative j in t; $I(y_{2,t} = j_{2,t})$ = indicator function for respondent dynamic choice in t = alternative j in t.

The log-likelihood for the individual-level models was based on the most general value function, model (d), but with only two Fechnerian error terms estimated: one for the static task responses; and one for the dynamic task responses. To estimate all functions, it was necessary to solve a backward induction algorithm for the EV function outlined above at each update of the parameters in the maximum likelihood function.

The models were estimated using a custom multinomial logit function[7] written in the free R statistical program (R Development Core Team 2013). The likelihood function was maximised using the Broyden, Fletcher, Goldfarb and Shanno algorithm in the maxLik library (Toomet *et al.* 2010). Numerical gradients were used to calculate standard errors. Starting values were varied and global maximisation methods (e.g. simulated annealing) were used to check for likely starting values when initial maximisation failed.

5. Data

A total of 51 respondents answered the dynamic experiment.[8] On average, most people chose option 'B' representing an alternative which was neither conservative (saving) nor intensive (consumptive). Respondents tended to choose more conservatively in Experiment 2 (the dynamic experiment than in Experiment 1 as expected. Table 3 presents simple statistics associated with these patterns.

Correlations between a range of variables from Experiment 2 were also considered and are presented in Table 4. Prior expectations were that the starting point of the experiment ('LC_START') should not matter much for reward scores ('SCORE') due to the use of a score based on performance relative to a computer-based agent. This is borne out by the data with correlations between the starting point and the end difference in land

[7] Estimation code can be provided by contacting the corresponding author.

[8] The focus in all results sections is on answers to the dynamic experiment, and we will refer to all results in general as referring to results associated with that experiment unless explicitly stated.

Table 3 Frequency of choices for each alternative in Experiment 1 and Experiment 2

	A (conservative choice)	B (medium choice)	C (unconservative choice)
Sum in Experiment 1	333	446	241
Sum in Experiment 2	348	515	157
Proportion in Experiment 1	0.33	0.44	0.24
Proportion in Experiment 2	0.34	0.50	0.15

Table 4 Correlation coefficients (Pearson Rho) for choices, land condition, rain score and reward scores for Experiment 2

	COUNT_A	COUNT_B	COUNT_C	LC_START	LC_DIFF	RAIN_SCORE	SCORE
COUNT_A		−0.77***	−0.34**	0.55***	0.56***	−0.52***	0.46***
COUNT_B			−0.34**	−0.2	−0.25*	0.23	−0.31**
COUNT_C				−0.52***	−0.46***	0.43***	−0.2
LC_START					0.9***	−0.01	0.16
LC_DIFF						0.12	0.17
RAIN_SCORE							−0.39***

Note: stars indicate significance at the 1% ('***'), 5% ('**') and 10% ('*') levels. No stars indicate the relationship is not significant at any standard level.

Table 5 Summary of reward scores and land condition indices for respondents

	Reward score (max reward when ≥ 1)	Ground cover in year of experiment (2012)	Ground cover in previous year	Last 3 years average ground cover	Last 5 years aver age ground cover	Variance of ground cover
Minimum	0.59	71.9	60.2	70.0	66.7	8.4
25th Percentile	0.76	87.1	77.1	81.9	77.3	22.5
Median	0.86	92.1	83.0	87.1	83.1	35.2
75th Percentile	0.93	94.1	89.5	90.6	86.9	58.1
Maximum	1.19	97.5	94.5	95.6	92.3	217.0
Mean	0.86	90.4	82.4	85.8	81.6	50.2
SD	0.14	5.4	8.0	6.0	6.8	48.4

condition being insignificant. 'Bad luck' in the form of relatively higher incidences of a 'LOW rainfall' outcome was inversely related to reward score as indicated by the variable 'RAIN_SCORE'.[9] However, as expected, a lower

[9] RAIN_SCORE was calculated as the sum over 20 choices for each respondent where LOW rainfall was recorded as equal to −1, AVERAGE rainfall was recorded as 0 and HIGH rainfall was recorded as +1. Thus, each respondent could potentially have a minimum of −20 and a maximum of +20 for this score, although these are both highly unlikely (minimum for the sample was −9, maximum was +8, and the mean was +0.39).

RAIN_SCORE is associated with a lower frequency of conservative choices ('option A') and vice versa for intensive choices ('option C'). Reward scores ('SCORE') are positively correlated with the number of conservative choices suggesting that many respondents failed to choose the conservative choice often enough (i.e. these results indicate returns to conservative choices are strongly positive on average whilst they are negative or zero for the other options).

The summary of choices and their correlations above suggest that respondents did respond to experimental inducements at least roughly correctly as shown by the correlations with 'RAIN_SCORE' but that they may have failed to fully optimise their dynamic choice problem (as indicated by the correlations between 'SCORE' and choice variables).

Of those responding to the experiment, 49 had remotely sensed ground cover available for comparison between estimated myopia levels and real-life land condition. Table 5 below presents a summary of a range of data series for the sample used in this research.

The sample presented here involves a wide range of reward scores from the experiment and appears to involve substantial heterogeneity in ground cover levels across a variety of measures and in the variance of ground cover.

6. Results

H1: Agents tend to use decision functions incorporating bounded rationality and behavioural aspects in dynamic decision problems.

Choice frequencies for the three alternatives chosen by participants across the 20 periods in the second experiment are shown in Figure 3. The observed pattern appears to show that dynamic considerations played a part in respondents' decision-making in this experiment. Participants clearly showed a preference for more conservative choices (choosing lower profits in the current choice to allow for potentially greater profits in future choices) at the beginning of the experiment and a preference for more intensive choices towards the end of the experiment.

To compare performance of models at the sample level, the estimated error terms for each of the models were plotted against the choice sequence (Figure 4). The Fechnerian error is an indicator of model precision; the lower the Fechnerian error, the more precisely the postulated response function fits the data. As expected, the levels of Fechnerian error terms were considerably higher across choice periods for the rational choice model (no myopia or salience) than for the models incorporating myopia and/or salience. The rational choice Fechnerian error terms clearly converged towards those incorporating nonrational processes as the last choice approached. Considering only the nonrational models, there were generally higher levels in the Fechnerian errors in the earlier and later choices, indicating the choices during the middle of the experiment were better approximated by the myopic functional forms than at the beginning and end.

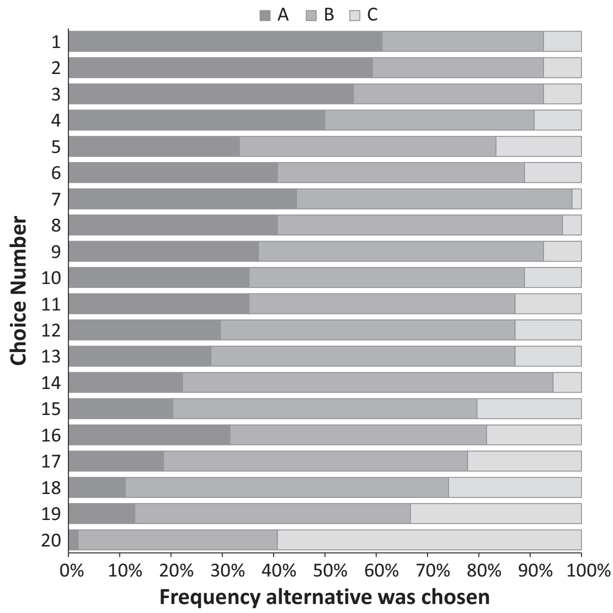

Figure 3 Choice frequencies across choice numbers.

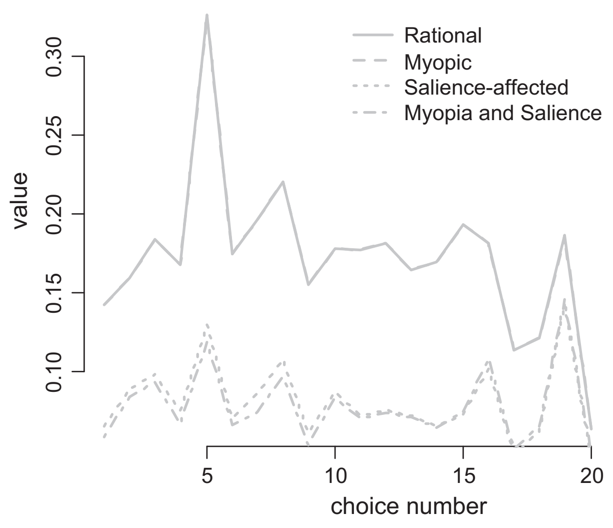

Figure 4 Fechnerian error trends over the 20 choices.

Table 6 presents the results for the decision function parameters from the estimation of these models. Consistent with the results shown in Figure 4, models (b), (c) and (d) in Table 6 provide a better fit to the data than the model (a) which assumes rational decision-making. The combination of the qualitative evidence depicted in Figure 4 and the clearly superior performance of nonrational decision function formulations shown in Table 4 provide support for the presence of myopic/salience-affected decision rules utilised by the participants in this experiment.

Table 6 Estimation results for sample-level models

Model:	(a)	(b)	(c)	(d)
Value function	EU	EU	EU	EU
Myopia?	N	Y	N	Y
Salience?	N	N	Y	Y
Alpha (CRRA)	0.72*** (0.08)	0.78*** (0.07)	0.84*** (0.04)	0.82*** (0.05)
Beta (myopia, lower is more myopic)	–	0.68*** (0.01)	–	0.81*** (0.06)
Lambda (salience, higher is more salience-affected)	–	–	3.75*** (0.24)	1.84*** (0.49)
N	2,040	2,040	2,040	2,040
K	41	42	42	43
Log-likelihood	−1384.25	−1279.20	−1279.90	−1273.86
AIC	2,850	2,642	2,644	2,634
BIC	3,081	2,878	2,880	2,875

Likelihood ratio tests firmly reject the rational decision model against all generalisations considered (models b, c and d at the 1 per cent level of significance for all comparisons). However, there is not any clear difference between the myopic formulation over a salience-affected formulation in the results of Table 6 providing no evidence, at least at the sample level, of whether behavioural aspects or bounded rationality aspects of choice are more important in this case. The likelihood ratio test rejects restrictions of the most general model (a) to model (b) or model (c) at the one per cent level of significance, indicating that, for the data presented here, myopia and salience effects are likely to both be present, at least regarding mean effects across the sample. All parameters are significant at the one per cent level of significance. The results here provide strong support for hypothesis H1, that is that respondents tend to employ nonrational decision functions.

Using the availability of 40 observations for each individual (20 from the static task of the experiment and 20 from the dynamic task), 51 individual models were estimated for the participants using the structural decision function of model (d) but with a single Fechnerian error term for choices made in the static task and another Fechnerian error term for those made in the dynamic task (5 parameters in total). Distributions for each of the decision function parameters are shown in Figure 5.[10]

> H2: Myopia and/or salience effects lead to lower decision performance and lower utility as measured by rewards received in the field experiment.

[10] Note for all data presented in this section two outliers were removed, one for a reward value of 2.9 and one for a salience value of 14 (almost 3 times larger than the next highest value). Two respondents also did not have ground cover data and so were not included in the regression analyses following.

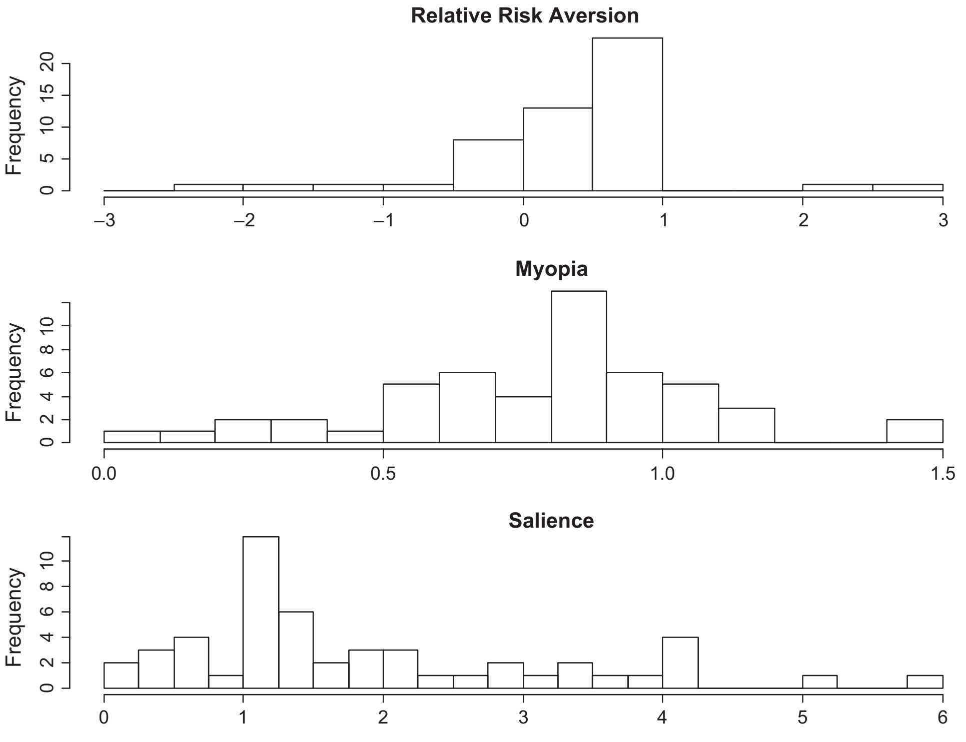

Figure 5 Distributions of estimated parameters from individual models.

Table 7 Regressions of reward scores on estimated decision function parameters

	Reward score = *f*(*x*)			
	Estimate	SE	*t* Value	Pr(>|*t*|)
Intercept	0.71***	0.05	13.30	0.00
RRA	−0.01	0.02	−0.35	0.73
Beta (myopia)	0.3***	0.07	4.60	0.00
Lambda (salience)	−0.05**	0.02	−2.67	0.01
N	49			
R-squared	0.33			
Log-Likelihood	38.14			

Note: A beta value equal to 1 indicates no myopia is present whilst a beta value equal to 0 indicates complete myopia. On the other hand, a value for Lambda of 1 indicates no salience and >1 indicates salience. This means: (1) impatience will be higher the lower is beta (this corresponds to higher myopia); (2) impatience will be higher the higher is Lambda (corresponding to higher salience). As a result, our hypotheses posit an expectation that the relationship for reward performance or land condition to beta is positive (myopia decreases these) and to Lambda is negative (salience also decreases these).

The results of regressions with decision performance (score relative to computer) on relative risk aversion, myopia and salience-effects are shown in Table 7. Risk preferences have no significant impact but both myopia and salience are significant factors affecting decision making.

As expected, the higher is myopia-induced impatience as measured by the impatience factor, the lower are rewards from decision-making in the experiment. The effects appear substantial – a completely myopic respondent will have a reward score approximately 30 per cent lower than a respondent who is not myopic. The mean value of the myopia factor in the sample was 0.79 indicating that the decision 'cost' of myopia for respondents in this sample accruing from the presence of myopia was 6.3 per cent of the potential reward amount (0.3 (1 – 0.79)). However, the lowest estimated myopia parameter was approximately 0.07 indicating substantial costs for a subset of respondents (in the order of 28 per cent of potential rewards).

The effect of salience is also substantial – a respondent who values current consumption at twice the rational choice level ($\lambda = 2$) will have a reward score approximately 4 per cent lower than that of a respondent with $\lambda = 1$ (i.e. with no salience effect). The mean value of λ in this sample was 1.83 indicating a mean 'cost' of salience effects in the sample of approximately 3 per cent of the potential reward amount. However, again, this belies the fact that some respondents presented with high levels of salience – in the order of λ between 3 and 5 for 11 graziers with one outlier (removed for regression analysis) in the order of $\lambda = 14$. For these graziers, the 'cost' of salience effects was in the order of 8–14 per cent of potential rewards.

These results provide clear support for hypothesis H2: that respondents affected by myopia and/or salience effects will tend to have substantially lower decision-making performance than respondents who are not affected by these factors. Given the contextualisation of the experiment in terms of range stocking decisions and land condition, this also suggests that bounded rationality may play an important part in the management of these renewable resources. We also note that these impact estimates are likely to be conservative due to the comparison to a potential reward function which was right-truncated.

> H3: Individuals with higher levels of myopia/salience will tend to employ more impatient resource management strategies.

The results of regressions with land condition (remotely sensed ground cover) on relative risk aversion, myopia and salience effects are shown in Table 8.

The results for the impact of decision function variables on ground cover, as an index of land condition on respondents' properties, indicate that the contextualised experiments here provide substantial predictive ability for highly variable and long-term management outcomes associated with grazing land management, namely land condition, as indicated by ground cover levels. The impact of myopia on land condition is both significant and substantive in this case; a completely myopic respondent will have, on average, 10 per cent lower ground cover than a respondent who does not employ a myopic decision function. Similarly, a respondent with a lambda value of 2 will have, on average, approximately 2.2 per cent less ground cover

Table 8 Regressions of ground cover on estimated decision function parameters

	Ground cover = $f(x)$			
	Estimate	SE	t Value	$\Pr(>\|t\|)$
Intercept	78.7***	3.56	22.11	0.00
RRA	−0.30	1.49	−0.20	0.84
Beta (myopia)	10.19**	4.39	2.32	0.03
Lambda (salience)	−2.26**	1.05	−2.15	0.04
N	49			
R-squared	0.14			
Log-Likelihood	−164.16			

than if they were rational. Given the levels of myopia and salience in the sample, these are substantive effects. They can be seen to be major factors in the management of rangelands pastures for sustainable profit or for the generation of externalities such as sedimentation. These results provide strong support for hypothesis H3; that myopia and salience effects estimated for individuals from choices made in our experiment explain aspects of decision-making regarding grazing land management for respondents as reflected in a measure of land condition on respondents' properties.

7. Conclusions

Suboptimality in decision-making is viewed in the economic literature from two substantially different perspectives – that of irrationality and inconsistency and that of bounded rationality and restrictiveness of assumptions embodied in the 'optimal' decision function. In this paper, we explored the implications of these decision theories with respect to their implications for renewable resource management by outlining a simple model of choice in dynamic decision problems incorporating salience effects (a behavioural theory of choice) and myopia (associated with bounded rationality). The model was tested using an incentivised, framed field experiment undertaken with managers of rangeland grazing properties in north-eastern Australia, many of whose properties are located in catchments which drain into the World Heritage-listed GBR lagoon.

The results provide strong evidence for impacts of both behavioural and bounded rationality effects on choice.[11] Myopic behaviours, estimated from choices in the experiment, are strongly associated with both poorer decision performance and with lower levels of land condition in our sample. Given the importance of land condition as a factor influencing both the carrying capacity of land and the contribution of sediments to streams potentially

[11] As the participants in the experiments were graziers who had voluntarily engaged in a grazing land management courses or government extension services for range management, it is possible that other graziers may exhibit larger levels of irrational choices.

flowing to the GBR, results suggest there are joint private and public benefits to improving decision-making amongst managers of grazing land. Behavioural effects (salience) were somewhat less important as factors influencing land condition but were significant in both predicting respondents' decision performance and the land condition on their properties.

The experimental results also show that properly contextualised field experiments, undertaken with the populations of interest directly, can provide detailed insights into behaviours which are relevant to the context being explored. The results suggest a greater emphasis should be placed on exploring bounded rationality in resource management settings to ensure that efficient policies are developed which do not presume perfect rationality in decision-making of the managers of these resources.

The results here are based on what might be considered a small dataset for generalisation, even though it is relatively large for a field experiment with agricultural producers. The approach is based on testing theory in a hypothetical context (framed field experiment) and in a real context (relation to real-world outcomes). From this perspective, we note that our sample is well beyond what might be considered 'large' from the perspective of the Central Limit Theorem. As a result, and due to earlier findings of Brown *et al*. (2009) and Ballinger *et al*. (2011), we have some confidence in stating that our results indicate that myopia and salience are major factors affecting dynamic optimisation in our sample. However, we caution against making inferences such as 'all managers are failing to optimise their farms'. We make no claim on aspects such as these given the high level of heterogeneity between managers and between farms and given we do not have what could be considered a representative sample. These are obviously questions to be explored, with this study as a starting point.

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