Agricultural Decision Making in the Argentine Pampas: Modeling the Interaction between Uncertain and Complex Environments and Heterogeneous and Complex Decision Makers

Guillermo Podestá[1], Elke U. Weber[2], Carlos Laciana[3], Federico Bert[4], and David Letson[1]

[1] Rosenstiel School of Marine and Atmospheric Science, University of Miami, USA
gpodesta@rsmas.miami.edu, dletson@rsmas.miami.edu

[2] Columbia University, Department of Psychology and Graduate School of Business, and Center for Research on Environmental Decisions (CRED), USA
euw2@columbia.edu

[3] Facultad de Ingeniería, University of Buenos Aires, Argentina
clacian@fi.uba.ar

[4] Facultad de Agronomía, University of Buenos Aires, Argentina
fbert@mail.agro.uba.ar

Summary. Simulated outcomes of agricultural production decisions in the Argentine Pampas were used to examine "optimal" land allocations among different crops identified by maximization of the objective functions associated with expected utility and prospect theories. We propose a more mathematically tractable formulation for the prospect theory value-function maximization, and explore results for a broad parameter space. Optimal actions differ among some objective functions and parameter values, especially for land tenants, whose enterprise allocation is less constrained by rotations. Our results demonstrate in a nonlaboratory decision context that psychologically plausible deviations from EU maximization matter.

1 Introduction

The world faces the dual challenge of feeding a burgeoning 21st century population of perhaps 9 billion, while at the same time not depleting its ecosystems that sustain life and well-being. In recent decades, agricultural output succeeded in outpacing human population growth and has reduced famine. As the food supply must continue to expand, however, it must do so with reduced environmental consequences [29]. New environmental information and its innovative usage will be central to this expansion.

Agricultural stakeholders consistently rank climate variability among the top sources of risk to production or profits. The use of climate information worldwide is evolving. Whereas decisions used to be based on analysis of historical records, now there is an increasing capability to monitor and predict seasonal regional climate. The increase in scientific and technological capabilities, an increasing appreciation for the importance of climate on human endeavors (including sustainable development, poverty mitigation, and food security), and a greater demand for climate information are all providing greater incentives for the provision of climate services, which can be defined as the timely production and delivery of useful climate data, information, and knowledge to decision makers [7,30].

On seasonal-to-interannual scales, the El Niño–Southern Oscillation (ENSO) phenomenon is the major single source of climate variability in many parts of the world [38]. The emerging ability to forecast regional climate based on ENSO [2,11,23] offers agricultural decision makers the opportunity to mitigate unwanted impacts and take advantage of expected favorable conditions [15,18,27,28]. However, any efforts to foster effective use of climate information and forecasts in agriculture must be grounded in a firm understanding of the goals, objectives, and constraints of decision makers in the target system, for three reasons.

First, climate data, forecasts, and technical assistance with the use of climate information are often publicly provided and highly subsidized. Estimates of the economic value of climate information and forecasts help justify investments in such publicly provided technology and infrastructure by comparing rates of return to those available from investments in other innovations. Research that estimates value of information (VOI) by simulating optimal forecast responses can provide useful insights, but actual use of climate information in agricultural production decisions and the production decisions themselves will most likely deviate from the prescriptions of normative models. Tests and validations of alternative descriptive models of risky decision making and probabilistic information use are thus crucial to obtaining realistic estimates of the value added from climate information. Estimates of the value of climate information should be based on alternative models closely linked to observed decision processes. The impact of alternative assumptions about decision processes and goals needs to be examined.

Second, the goals and objectives of farmers' decisions (i.e., their objective functions, in decision-theoretical terms) influence how climate information (both historical data and forecasts) is used. In turn, this has implications for how climate information should be presented and communicated (i.e., the design of climate forecasts and tutorials on climate information use). Decisions on the current contents and formats of climate forecasts make implicit assumptions about what farmers are trying to achieve and how such information will be used. It will be useful to make these assumptions explicit and put them to test. The probabilistic nature of climate forecasts needs emphasis and explanation for all users, as probabilistic thinking is a relatively recent evolutionary accomplishment [13] and not something that comes naturally to even highly trained professionals [8]. Nevertheless, the expectation of a deterministic forecast that will turn out to be either "correct" or "false" is especially damaging in situations where the decision maker will experience postdecisional regret after believing that she acted on a "false" forecast. Better understanding of the outcome variables that matter to farmers also will provide guidelines on whether and how best to "translate" climate forecasts. If, for example, crop yields or the costs of production input get particular attention, it makes sense to "translate" a climate forecast into the agronomic yield and/or cost implications that it holds.

Third, decision makers in numerous domains have been shown to have poor insight into their own decision processes and goals and objectives. This offers opportunities for interventions to help farmers to enhance their decisions. When made aware of the objective function and goals implicit in their past decisions, decision makers tend to react in one of two ways. Some are surprised by identified objectives and the associated cues or information they are using in their decisions. Furthermore, once aware of these objectives and cues, these decision makers may wish they were not using them: examples may include unconscious gender discrimination in hiring decisions, or possibly crop yield maximization rather than profit maximization in farm production decisions. Other decision makers may concur with identified goals, objectives, and their associated information cues once made apparent to them, and refuse to give up on them (e.g., greater sensitivity to losses than to gains), even if they violate normative models. Identification of objective functions and decision goals will provide feedback to farmers about their implicit decision processes, which can then be reviewed and either explicitly acknowledged and accepted, or rejected, leading to the modification of decision processes.

2 Background

2.1 Choice Theories: Expected Utility and Prospect Theory

The work by von Neumann and Morgenstern [40] provided an explicit formulation of expected utility (EU) and an axiomatic foundation. Subsequent extensions and variations are described by Schoemaker [37]. The EU model has been central in the analysis of choice under risk and uncertainty. It has been successful not only because of its compelling axiomatic foundation and ability to describe economic choices, but also because of its mathematical tractability [41]. Despite its obvious strengths, EU maximization as the (sole) objective of risky choice has encountered some opposition in recent years. There is both experimental and real-world evidence that individuals often do not behave in a manner consistent with EU theory [4,24]. A central assumption of EU theory is that the utility of decision outcomes is determined entirely by the final wealth they generate regardless of context, that is, that it is an absolute or reference-independent construct. Yet, decision-makers' evaluation of outcomes appears to be influenced by a variety of relative comparisons [19].

Prospect theory (PT) [20] and its modification, cumulative prospect theory [9,39], currently have become the most prominent alternatives to EU theory. Prospect theory formalizes one type of relative comparison observed when decision makers evaluate the utility of decision outcomes. Its value function $V(\cdot)$ is defined in terms of relative gains or losses, that is, positive or negative deviations from a reference point. Value therefore is determined by changes in wealth, rather than reference-independent states of wealth as in utility theory [19]. Furthermore, the value function for losses is steeper than the value function for gains, resulting in a sharp kink at the reference point. This feature of the value function models the phenomenon of loss aversion, that is, the observation that the negative experience or disutility of a loss of a given magnitude is larger than the positive experience or utility of a gain of the same magnitude. Empirical studies have consistently confirmed loss aversion as an important aspect of human choice behavior [4,5,36]. Rabin [33] emphasized the growing importance of loss aversion as a psychological finding which should be integrated into economic analysis.

2.2 EU Formulation

We define a risky prospect $q = (p_1, w_1; \ldots; p_n, w_n)$ as the ensemble of possible wealth/outcome values w_i with associated probabilities p_i that are nonnegative and add up to one. A common formulation (p. 104 of [16]) states that a decision maker evaluates the expected utility of prospect q as

$$EU(q) = \sum_i p_i u(w_i) \ . \tag{1}$$

The following real-valued utility function $u(\cdot)$ is given by Pratt [32] as

$$u(w) \propto \begin{cases} \frac{w^{1-r}}{1-r} & \text{if } r \neq 1 \\ \ln w & \text{if } r = 1 \end{cases} , \tag{2}$$

where r is the coefficient of constant relative risk aversion (CRRA). CRRA implies that preferences among risky prospects are unchanged if all payoffs are multiplied by a positive constant [16]. The curvature of the utility function, defined by parameter r, captures all information concerning risk attitude.

2.3 Prospect Theory Formulation

In prospect theory [20], the subjective value of a prospect is defined as

$$V(q) = \sum_i \Omega(p_i) v(\Delta w_i) \ , \tag{3}$$

where Δw_i represents the difference between outcome w_i and a reference point w_{ref}, a free parameter that separates perceived gains from perceived losses.

The subjective evaluation of this difference can be expressed as suggested by Tversky and Kahneman [39], using for simplicity the same exponent for losses and gains (which tends to be a good approximation based on empirical estimates of the two parameters and which can, of course, be changed to the more general case, if so desired). That assumption allows us to write the PT value function in the following more compact form

$$v(\Delta w) = \sum h(\Delta w)|\Delta w|^{\alpha} \,, \tag{4}$$

where function $h(\Delta w)$ is the step function

$$h(\Delta w) = \begin{cases} 1 & \text{if } \Delta w \geq 0 \\ -\lambda & \text{if } \Delta w < 0 \end{cases} \,, \tag{5}$$

and λ is a parameter ($\lambda > 1$) that reflects the degree of loss aversion. The exponent α in (4) ranges between 0 and 1 and describes the nonlinearity of the value function. Because of the discontinuity at the reference point, the exponent describes the degree of risk aversion (concavity) in the gains region and the degree of risk seeking (convexity) in the losses region.

The evaluation of risky prospects is based on subjective probability weights that typically do not correspond to the objective probabilities. Tversky and Kahneman [39] propose the nonlinear function $\Omega(p)$,

$$\Omega(p) = \frac{p^{\gamma}}{\left(p^{\gamma} + (1 - p^{\gamma})\right)^{1/\gamma}} \,, \tag{6}$$

to model the subjective weight of event probabilities, which overweights objective probabilities for outcomes at the extremes of the distribution of possible outcomes and underweights outcomes in the middle. The value of $\Omega(p)$ depends on positive parameter γ, which must be empirically estimated.

3 A Case Study

We compare and contrast the objective functions or choice criteria associated with expected utility and prospect theory in a real-world optimization problem in agricultural management. The decisions examined are related to the production of cereals and oilseeds in the pampas region of central-eastern Argentina, one of the most important agricultural regions in the world [14].

In particular, we examine the nature and magnitude of differences among simulated agricultural production decisions identified as “optimal” by maximization of the objective functions associated with EU and PT. EU maximization is a widely used criterion in agricultural economics, and thus is a useful benchmark against which to compare the results of other objective functions. We argue that as proven and mathematically tractable alternatives to the EU model become available, agricultural and resource economists should at least begin to consider alternative objective functions and explore how they might improve analysis and insight [41].

The case study is organized as follows. First, we describe the agricultural production systems in the target region. We then define a set of cropping enterprises that encompasses a realistic range of initial soil conditions and management options for the typical crops in the region, namely maize, soybean, and a wheat–soybean doublecrop (wheat followed during the same cropping cycle by a shorter-cycle soybean). Next we describe how yields and economic returns are simulated for each cropping enterprise using historical climate data, biophysical models, and realistic cost estimates. These results are subsequently used as input to optimization procedures. Finally we show and discuss optimal enterprise allocation for the two objective functions considered.

3.1 The Area of Study

The geographic focus of this study is the region of central-eastern Argentina known as the pampas, one of the most productive agricultural areas in the world [14] and of major importance to the Argentine economy (51% of exports, and 12% of GDP over 1999–2001, [6]). The climate, soils, and cropping systems of the Argentine pampas have been characterized by Hall et al. [14]. In particular, we focus on the region near Pergamino (33° 56′ S, 60° 33′ W), the most productive subregion of the pampas [31]. Two characteristics of agricultural production in the study region have implications for the optimization described below. First, agriculture in the Pampas is market-oriented and technology-intensive. As a consequence, a broad spectrum of agronomic management options exists and can be explored in the optimization process. Second, a considerable proportion of the area currently farmed is not owned by the farmers exploiting it. Very short land leases (usually one year) provide incentives for tenants to maximize short-term profits via highly profitable crops. In contrast, landowners tend to rotate crops to steward long-term sustainability of production and soil quality [22]. Given the differences in decision-making goals and constraints between landowners and tenants, we model the two groups separately.

3.2 Crop Enterprises

We defined 64 different cropping enterprises that reflect a realistic range of cultivation options for the study area. Each enterprise involves the combination of (a) a given crop (maize, full-cycle soybean, and wheat–soybean), (b) various agronomic decisions (cultivar/hybrid, planting date, fertilization options), and (c) a set of initial conditions (water and nitrogen in the soil at planting) that result from previous production decisions. That is, several enterprises may be associated with the same crop, although involving different management options.

3.3 Simulation of Yields: Agronomic Models

Yields for each enterprise were simulated using the crop models in the decision support system for agrotechnology transfer (DSSAT) package [17]: generic-CERES [34] for maize and wheat, and CROPGRO [3] for soybean. These models have been calibrated and validated under field conditions in several production environments including the pampas [12,25,26]. The information required to run the DSSAT models includes: (i) daily weather data (maximum and minimum temperature, precipitation, solar radiation), (ii) "genetic coefficients" that describe physiological processes and developmental differences among crop hybrids or varieties, (iii) a description of crop management, and (iv) soil parameters, including soil moisture and N content at the beginning of simulations. Historical (1931–2003) daily weather data for Pergamino provided information about category (i). Genetic coefficients, the management options that defined the enterprises, and likely ranges of initial soil conditions were provided by the Asociación Argentina de Consorcios Regionales de Experimentación Agrícola (AACREA), a nonprofit farmers' group (similar in goals to the U.S. Agricultural Extension Services) that partnered with us in this study. Simulations assumed no irrigation, a very infrequent practice in the pampas. For each enterprise, 72 simulated yields were obtained (one for each cropping cycle in the 1931–2003 historical weather record used).

3.4 Simulation of Economic Outcomes

Economic outcomes were simulated for a hypothetical 600-hectare farm, the median size of AACREA farms in the Pergamino region. We computed net economic returns per hectare π_{ij} for year i and enterprise j as the difference between income and costs:

$$\pi_{ij} = Y_{ij}P_j - (F_j + V_{ij} + S_i + T_i) \,. \tag{7}$$

Gross incomes per hectare $Y_{ij}P_j$ were the product of simulated yield for a year and enterprise (Y_{ij}) and a constant output price for each crop (P_j). Assumed output prices were the median of 2000–2005 prices during the month when most of the harvest is marketed (April, May, and January for maize, soybean, and wheat, respectively). After deducting export taxes charged by the Argentine government, these prices were 78.9, 166.0, and 112.0 US \$ ton^{-1} for maize, soybean, and wheat, respectively.

Four different kinds of costs were involved in the computation of net returns per hectare: (i) *Fixed costs* F_j for enterprise j are independent of yield. For landowners, fixed costs included: (a) crop production inputs (e.g., fertilizer, seed, field labor), and (b) farmer's salary, health insurance, and a fixed fiscal contribution. For land tenants, fixed costs also included (c) land rental (assumed to be 232.5 \$ ha^{-1}, equivalent to the price of 1.4 tons of soybean) and (d) management costs (12 \$ ha^{-1}). (ii) *Variable costs* V_{ij} are a function of yield on year i for enterprise j. These costs included: (a) harvesting costs, estimated as 8% of gross income ($Y_{ij}P_j$), (b) transportation costs (about 10 \$ ton^{-1}), and (c) sales tax and commissions, estimated as 8% of gross income. Variable costs were the same for landowners and tenants. (iii) *Structural costs* S_i are applicable only to landowners and covered: (a) maintenance of farm infrastructure, (b) real estate taxes, and (c) management and technical advice. Structural costs are independent of farm activities or enterprise yields. For the sake of simplicity, however, they were approximated following a criterion used by AACREA: they were a percentage (23%, 18%, and 20% for maize, soybean, and wheat–soybean, respectively) of income per ha after subtracting variable costs ($Y_{ij}P_j - V_{ij}$). Because structural costs are incurred even if part of the farm is not cultivated, an implicit but not unreasonable assumption, given the high costs of land around Pergamino, is that the entire 600-ha area of the hypothetical farm is cultivated. (iv) *Income tax* T_i applies equally to landowners and tenants and was computed as follows.

$$T = \begin{cases} b(\overline{\pi} - a) + c & \text{if } \overline{\pi} \geq a \\ c & \text{if } \overline{\pi} < a \end{cases} , \tag{8}$$

where a is a threshold income above which farmers pay an average tax rate $b = 0.32$. Below a, farmers pay a minimum tax assumed to be 59.33 \$ ha^{-1}. To simplify calculations, an average annual income $\overline{\pi}$ of 177.5 \$ ha^{-1} (57.6 \$ ha^{-1}) was assumed for owners (tenants).

3.5 Optimization Procedure

A whole farm production model was used to identify optimal decisions for the objective functions associated with EU and prospect theories. The choice variable in the optimization is the vector $\mathbf{x} = (x_1, \ldots, x_{64})$ that includes the area in the 600-hectare hypothetical farm allocated to each of the 64 alternative cropping enterprises considered. Different land amounts allocated to the 64 enterprises were considered by the optimization of each objective function. The optimization was performed using algorithm MINOS5 in the GAMS software package [10].

For comparability, all objective functions are expressed in terms of a decision-maker's wealth, either in an absolute sense (for EU and regret-adjusted EU), or as a difference from a specified reference level (in prospect theory). The total wealth of a decision maker at the end of cropping year i is

$$w_i = w_0 + \pi_i , \tag{9}$$

where w_0 is the decision-maker's initial wealth (i.e., prior to production decisions for year i) and π_i is the farmwide income during year i, after deducting costs. Farmwide income π_i is calculated as

$$\pi_i = \sum_{j=1}^{m} x_j \pi_{ij} , \tag{10}$$

where π_{ij} is the net margin for year i and enterprise j (7) and x_j is the amount of land allocated to enterprise j (i.e., a component of the land allocation vector $\mathbf{x}$).

Expected Utility Optimization

The expected utility (1) of final wealth can be expressed as:

$$EU(\mathbf{x}) = \sum_{i=1}^{n} p_i u\left[w_i(\mathbf{x})\right] \ , \tag{11}$$

where p_i is the probability of a given climate scenario for year i. A climate scenario is defined as the climate conditions over an entire production cycle. We assume that all climate scenarios in the historical record have the same probability (i.e., $p_i = 1/n$, where n is the number of cropping cycles in the historical climate data, in this case, 70 years). Therefore, we can write

$$EU(\mathbf{x}) = \frac{1}{n}\sum_{i=1}^{n} u\left[w_i(\mathbf{x})\right] \ . \tag{12}$$

The next step is the optimization

$$\max_{\mathbf{x}} EU(\mathbf{x}) = EU(\mathbf{x}^{\star}) \ , \tag{13}$$

where $\mathbf{x}^{\star} = (x_1^{\star}, \ldots, x_{64}^{\star})$ indicates the proportion of land allocated to each enterprise that maximizes the value of EU.

Prospect Theory Value Optimization

In prospect theory, value is defined by changes in wealth rather than reference-independent wealth states. Outcomes w_i are evaluated as gains or losses with respect to reference value w_{ref}:

$$\Delta w_i = w_i - w_{ref} \ . \tag{14}$$

One plausible reference value of wealth that determines whether a farmer thinks of another wealth level as a gain or a loss is the income w_r that a farmer could achieve with minimal effort (e.g., by renting his land) added to the decision-maker's initial wealth:

$$w_{ref} = w_0 + w_r \ . \tag{15}$$

Combining (9) and (14) with (15) we obtain:

$$\Delta w_i = \pi_i - w_r \ . \tag{16}$$

The total value function for prospect theory (3) then can be rewritten as

$$V(\mathbf{x}) = \sum_{i=1}^{n} \Omega(p_i) v[\Delta w_i(\mathbf{x})] \,. \tag{17}$$

As for EU, all climate scenarios are assumed to have the same probability (i.e., $p_i = 1/n$), therefore $\Omega(p_i)$ is independent of i. Rewriting (17), we obtain

$$V(\mathbf{x}) = \sum_{i=1}^{n} \Omega\left(\frac{1}{n}\right) v[\Delta w_i(\mathbf{x})] \,, \tag{18}$$

which indicates that the constant $\Omega(1/n)$ is irrelevant for the optimization; thus one need not worry about the functional form of Ω. The optimization is performed in a way analogous to (13):

$$\max_{x} V(\mathbf{x}) = V(\mathbf{x}^{\star}) \,. \tag{19}$$

Optimizing the value function with the GAMS software [10] available to us was problematic because of the discontinuity of function $h(\cdot)$ (defined in (9)) at $\Delta w_i = 0$ (where prospect theory's value function has a sharp kink and is not differentiable). To address the problem, we used a continuous function $\tilde{h}(\cdot)$ that is numerically equivalent to $h(\cdot)$:

$$\tilde{h}(x) = 1/2\left[1 - \lambda + (1 + \lambda)\tanh(\varrho x)\right] \,, \tag{20}$$

where ϱ is an arbitrary parameter such that $\varrho > 1$; large values of ϱ (we used $\varrho = 10$) reproduce function $h(\cdot)$ more closely.

3.6 Optimization Constraints

Allocation of land to cropping enterprises differs for landowners and tenants in the Pergamino region. Landowners tend to adhere to a rotation of crops that offers advantages for soil conservation and control of pests and diseases [22]. In contrast, land tenants seek high profits during short leases (usually one year) and thus usually select enterprises with the greatest economic returns. The clear differences in enterprise allocation between land tenure regimes suggest that we explore optimal decisions separately for landowners and tenants.

With three major cropping systems (maize, soybean, and a wheat–soybean double crop) the rotation advocated by AACREA allocates about 33.3% of the land to each of these cropping systems in a given year. To allow owners some flexibility in land allocation, we introduced two constraints in the optimization procedure: land assigned to a crop could be no less than 25%, or more than 45% of the farm area. These constraints did not apply to land tenants, who could allocate the entire farmed area to a single crop. The lack of allocation constraints is consistent with the observed increase in monocropping of soybean that has occurred in the pampas in the last few years [35]. A final constraint specified that 100% of the land had to be assigned to some enterprise (i.e., no land could be left without cultivation).

3.7 Parameter Space Explored for Each Objective Function

Each objective function has a set of parameters. In some cases, the value of a given parameter describes a personality characteristic (e.g., degree of risk aversion or loss aversion) that may vary among decision makers. With no widely accepted values for parameters, a broad range of plausible values should be considered. In this section, we describe and justify our choice of central (or nominal) parameter values.

Expected Utility

The expected utility function has two parameters: (i) the decision-maker's initial wealth w_0 and (ii) the risk-aversion coefficient r. Initial wealth w_0 is defined as liquid assets. For landowners, this quantity was estimated as 40% of the value of the farm land. The definition is based on the assumption that a farmer will not sacrifice future income potential by selling crop land, but can borrow up to 40% of her land value. The 1994–2003 average value of land for Pergamino was 3541 \$ ha^{-1}, making w_0 equal to 1400 \$ ha^{-1} (3541 \$ ha^{-1} $\times$ 0.4). For land tenants, we assumed a w_0 value of 1000 \$ ha^{-1}, the liquid assets required to finance two complete cropping cycles (i.e., in case of a total loss in one cycle, the farmer still has capital to fund a second cycle). For the risk-aversion coefficient r, we followed Anderson and Dillon's [1] classification: 0.5 is hardly risk averse; 1.0, somewhat risk averse (normal); 2.0, rather risk averse; 3.0, very risk averse; and 4.0, extremely risk averse. We also included risk indifference by considering r values of 0.0. The range of r values was the same for owners and tenants.

Prospect Theory Value Function

The value function is defined by (i) a reference wealth w_r that separates outcomes perceived as gains and losses, (ii) a risk preference parameter α, and (iii) a loss aversion parameter λ that quantifies the relative impact of gains and losses. The combination of all three parameters defines risk aversion in PT. For landowners, w_r was estimated as the income easily achieved by renting out the land instead of farming it. This value of w_r was estimated to be 232.5 \$ ha^{-1} (a rental fee of 1.4 ton ha^{-1} of soybean times a price of 166 \$ ton^{-1}). For land tenants, w_r was estimated as the income obtained by placing the tenant's initial wealth ($w_0 = 1000$ \$ ha^{-1}, as described for EU) in a bank for six months (the duration of a cropping season) at an annual interest of 4% (representative of current rates in Argentina). The nominal w_r value, then, was 20 \$ ha^{-1}. For the risk-aversion parameter α and the loss-aversion parameter λ, we used the values empirically estimated by Tversky and Kahneman [39] of 0.88 and 2.25, respectively, for both owners and tenants, but also explored a broader range of values.

4 Results

This section describes the land allocations (i.e., the proportion of land assigned to different enterprises) identified as optimal for each objective function. Only seven out of 64 possible cropping enterprises were selected by the various optimizations.

4.1 EU Maximization

Landowners

The enterprise allocation that maximized expected utility for landowners was constant for the full range of initial wealth and risk aversion values explored (Figure 1). The maximum area allowed for one crop by the optimization constraints defined for owners (45% of total land) was allocated to full-cycle soybean Soy14, the enterprise with the highest average economic returns ($\overline{x}$ = 188.1 \$ ha^{-1}) over the 70 simulated cropping cycles. Conversely, the minimum area required by constraints (25%) was for maize, the crop with lowest average profits. Ma23, the enterprise with the highest average profits for this crop ($\overline{x}$ = 116.5 \$ ha^{-1}) was selected. The remainder of the area (30%) was allocated to the wheat–soy enterprise SW21, which had average profits between those of full-cycle soy and maize ($\overline{x}$ = 168.8 \$ ha^{-1}). The stability of results for all parameter combinations illustrates the importance of ecological or logistic constraints associated with maintaining a crop rotation: these constraints clearly override any financial or personality characteristics of a decision maker.

Land Tenants

For land tenants, only two enterprises (full-cycle soybean Soy14 and wheat–soybean SW21) were involved in the maximization of expected utility. Because of the markedly lower economic profits of maize (due to higher production costs and low prices) and the lack of areal constraints for tenants, this crop did not appear at all in the optimal land allocations.

The relative proportions of the two selected enterprises (Soy14 and SW 21) depended on the combination of parameters. Figure 2 has four panels with increasingly higher levels of risk aversion r (from top to bottom). In each panel, the optimal allocation of land is shown as a function of initial wealth w_0. For a risk-neutral decision maker ($r = 0$; Figure 2, upper panel), the optimal action was to allocate the entire area to the double crop enterprise SW21; this result is constant for the entire range of values considered for w_0. Because the decision maker is risk-neutral, the selection of SW21 was based only on its higher mean profit relative to Soy14 (77.6 \$ ha^{-1} versus 69.4 \$ ha^{-1}), and ignored the higher risks associated with the considerably larger dispersion of profits (122.0 \$ ha^{-1} versus 89.0 \$ ha^{-1} for Soy14). For moderate risk aversion

Fig. 1. Land allocation (as proportion of the hypothetical 600-ha farm) that maximizes expected utility for landowners. The selected combination of enterprises is constant for all initial wealth w_0 and risk aversion r.

values ($r = 1.0$; Figure 2, second panel from top) and low w_0 (below about 1100 \$ ha^{-1}), the optimal action involved about 75% of the land allocated to SW21 and about 25% to Soy14. For higher w_0 values, the optimal action was to allocate the entire area to the double crop enterprise SW21. When slightly higher amounts of risk aversion are considered ($r = 1.5$; Figure 2, third panel from top), the optimal action involved diversification of enterprises for most values of w_0. For low w_0, diversification is highest: 60% of the land was allocated to SW21 and 40% to Soy14. As w_0 increases (and, thus, decision makers can afford higher financial risks), the proportion of land assigned to SW21 grew until this enterprise occupied the entire area, resembling results for risk-neutrality. In other words, increasing initial wealth compensates, to some degree, for the effects of risk aversion. Finally, for a highly risk-averse decision maker ($r = 3.0$; Figure 2, bottom panel), the optimal land allocation was fairly conservative, as maximum crop diversification (comparable proportions of SW21 and Soy14) prevailed throughout the w_0 range.

4.2 Prospect Theory

Landowners

The land allocation that maximized PT's value for landowners was fairly similar to results for EU. As for EU, full-cycle soybean Soy14 was the enterprise with the largest area (45%). The area allocated to maize (25%) was again the minimum required by optimization constraints. Unlike EU, though, three different maize enterprises (Ma21, Ma23, and Ma24) were selected for

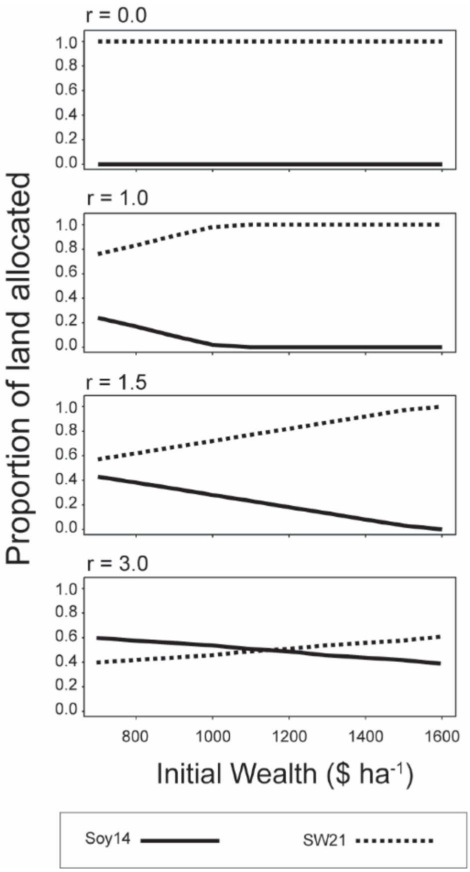

Fig. 2. Land allocation (as proportion of the hypothetical 600-ha farm) that maximizes expected utility for land tenants. The four panels show the results for risk neutrality ($r = 0$, upper panel), small risk aversion ($r = 1.0$), moderate risk aversion ($r = 1.5$), and pronounced risk aversion ($r = 3.0$, bottom panel), in each case plotted as a function of initial wealth w_0.

different portions of the parameter space (figure not shown). All three enterprises had very similar average returns (113.2, 116.5, and 116.3 \$ ha^{-1} for Ma21, Ma23, and Ma24, respectively). The maize enterprise with the highest dispersion (Ma21, SD = 106.8 \$ ha^{-1}) prevailed for risk-seeking parameter combinations, whereas the less variable enterprise (Ma23, SD = 84.1 \$ ha^{-1}) was characteristic of moderate and high-risk aversion. Ma21 only appeared for intermediate reference wealth and lower risk preferences. Nevertheless, Kolmogorov–Smirnov tests showed that distributions of economic returns for the three maize enterprises were not significantly different from one another, therefore any differences in land allocation to maize can be considered minor. The wheat–soy double crop (in most cases, enterprise SW21, but also SW20) occupied the remaining area. As for EU, results are consistent with the relative average profitability of each crop. Furthermore, the similarity with EU results suggests that constraints associated with maintaining the crop rotation prevail over personality characteristics, and thus optimal allocations are similar even for fairly different objective functions.

Land Tenants

Just as for EU, the land allocation that maximized prospect theory's value function for tenants involved two enterprises: full-cycle soybean (Soy14) and wheat–soybean (SW21). As for EU, the specific proportions of these enterprises depended on the combination of parameters. The top-left panel of Figure 3 ($w_r = 10$ \$ ha^{-1} and $\lambda = 1.00$) can be used as a reference to discuss the consequences of varying prospect theory's parameters. In this panel, there is no loss aversion. Also, a low level of reference wealth puts most outcomes into the domain of gains, where low α values imply a more risk-averse decision maker. As a result, a diversified land allocation including two enterprises (Soy14 and SW21) is selected. As α increases and the decision maker becomes less risk-averse, the allocation switches toward an increasingly higher proportion of the more profitable but riskier SW21, until monoculture is reached.

As we move along the top row of Figure 3, we detect a mixture of the two dominating enterprises in the central and right-top panels. Nevertheless, there is always a higher proportion of the less-risky Soy14. The conservative land allocations reflect the effect of increases in loss aversion. If we move down the left column of Figure 3, the switch from diversification to a monoculture of SW21 begins at progressively lower values of α. This is due to the fact that as w_r increases, an increasing proportion of outcomes is perceived as losses, in which case α indicates risk-seeking. Risk-seeking to risk-neutral decision makers choose the riskier option (SW21) in search of higher profitability, and thus enterprise selection in the bottom-left panel is identical to that of risk-neutral EU maximizers (top panel in Figure 2).

This pattern is also apparent in the middle-bottom panel of Figure 3, where we now also have loss-aversion ($\lambda = 2.25$). The high reference wealth ($w_r = 80$ \$ ha^{-1}) implies that a high proportion of outcomes are perceived as losses. For low α values, the decision maker is more risk-seeking and thus selects riskier SW21 in order to attain higher profits and get out of the domain of losses. As α increases, risk-seeking decreases and the selected allocation becomes diversified, as loss aversion now takes effect. The result is a higher proportion of the less variable enterprise Soy14. When loss aversion is even stronger, as in the right column of Fig 3 ($\lambda = 3.50$), this effect takes over and dictates diversification across the whole range of α, and even more so for higher levels of reference wealth, as more outcomes are in the domain of losses and hence subject to loss aversion.

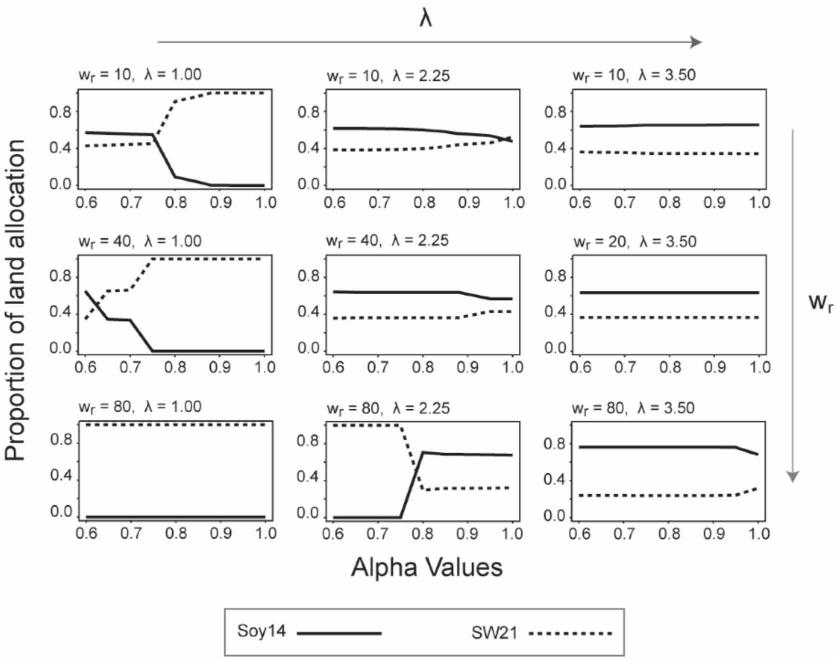

Fig. 3. Land allocation (as proportion of the hypothetical 600-ha farm) that maximizes prospect theory's value function for land tenants. The different panels correspond to combinations of w_r (reference wealth in \$ ha^{-1}, increasing from top to bottom) and λ (loss aversion parameter, increasing from left to right). In each panel, the optimal allocation of land is shown as a function of the risk aversion coefficient α.

5 Discussion

Our results demonstrate in a nonlaboratory decision context that, in some cases, psychologically plausible deviations from EU maximization lead to differences in optimal land allocation decisions. As an example, for nominal or central values of parameters (considered typical of many decision makers), EU maximization generally suggests that tenants should allocate a much greater proportion of land to the riskier SW21 enterprise than in PT value maximization. The loss aversion that is essential in PT's formulation dictates more conservative strategies (predominance of Soy14) for this objective function. Nevertheless, in situations where there are prescribed constraints to land allocation (e.g., those associated with maintaining an ecologically sound crop rotation), results are very similar for quite different objective functions (EU and PT's value) and for a broad range of personality and economic characteristics of decision makers. This consistency is an illustration of one of the important goals of institutions and/or social norms, namely, to make behavior more predictable.

Optimization of any utility or value function reflects a tradeoff between the expected profits of an enterprise and its risk or dispersion of outcomes. It is interesting to see that different objective functions shape the nature of this tradeoff in different ways that are consistent with the characteristics of each function. In EU optimization, more risk-averse land allocation is encouraged by differences in risk-aversion as indicated by parameter r, and by lower initial wealth w_0. In contrast, in PT's value optimization, risk-averse behavior is encouraged by a lower reference wealth (that divides the perception of returns into gains versus losses) and much more by the individual loss aversion parameter λ than by the individual risk preference parameter α. The importance of loss aversion is not surprising, given the centrality of this process in PT. Similarly, more risk-seeking land allocation is encouraged by different processes and parameters under the different objective functions. For EU maximization, both parameters r (less risk aversion) and w_0 (greater initial wealth) are deciding factors (top panel and right end of middle panel of Figure 2). In PT value optimization, on the other hand, less risk-averse land allocations come about when the decision maker has no loss aversion but a high reference value, with the result that most outcomes are in the domain of losses, in which choices are either risk-seeking or at best risk-neutral (bottom left panel of Figure 3).

5.1 Relevance of Results

We envision three main applications of the work presented here. First, an improved understanding of individual differences in preferences and objective functions (when they induce different optimal land allocations) may allow the development of agronomic advice tailored to the personality characteristics of different types of farmers. Such advice will be more effective than the common “one size fits all” agronomic recommendations. Second, knowledge of individual preferences may be helpful to guide the framing and to assess the acceptability of regional or national policies of agricultural sustainability (e.g., policies that encourage crop diversification). Finally, an understanding of production decisions in agriculture may contribute to a better understanding and thus better planning and implementation of a range of related issues, such as adoption of technological innovations and adaptation to climate change.

Acknowledgments

This work was supported by an NSF Biocomplexity in the Environment grant (BE-0410348), an NSF Center grant under the Decision Making under Uncertainty Initiative (SES-0345840), and a NOAA Human Dimensions grant (GC04-159). F. Bert is supported by a doctoral fellowship from Argentina's Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET). The authors are grateful to the management, technical advisors, and farmer members of the Asociación Argentina de Consorcios Regionales de Experimentación Agrícola for their commitment to this research.

References

1. J. R. Anderson and J. L. Dillon. *Risk Analysis in Dryland Farming Systems.* Number 2 in Farm Systems Management Series. FAO, Rome, 1992.
2. A. G. Barnston, M. H. Glantz, and Y. He. Predictive skill of statistical and dynamical climate models in SST forecast during the 1997–98 El Niño episode and the 1998 La Niña onset. *Bulletin of the American Meteorological Society*, 80:217–243, 1999.
3. K. J. Boote and J. W. Jones. Simulation of crop growth: CROPGRO model. In R. M. Peart and R. B. Curry, editors, *Agricultural Systems Modeling and Simulation*, pages 651–692. Marcel Dekker, New York, 1998.
4. C. Camerer. Prospect theory in the wild. In D. Kahneman and A. Tversky, editors, *Choice, Values, and Frames*, pages 288–300. Cambridge University Press, New York, 2000.
5. C. Camerer. Three cheers—psychological, theoretical, empirical—for loss aversion. *Journal of Marketing Research*, 42:129–133, 2005.
6. D. Díaz. Una fábrica de empleos. *Clarín Rural*, page 4, 2002.
7. J. A. Dutton. Opportunities and priorities in a new era for weather and climate services. *Bulletin of the American Meteorological Society*, 83:1303–1311, 2002.
8. D. M. Eddy. Probabilistic reasoning in medicine: Problems and opportunities. In D. Kahneman, P. Slovic, and A. Tversky, editors, *Judgment Under Uncertainty: Heuristics and Biases*, pages 249–267. Cambridge University Press, New York, 1982.
9. H. P. Fennema and P. P. Wakker. Original and cumulative prospect theory: A discussion of empirical differences. *Journal of Behavioral Decision Making*, 10:53–64, 1997.
10. P. E. Gill, W. Murray, B. A. Murtagh, M. A. Saunders, and M. Wright. GAMS/MINOS. In *GAMS–The Solver Manuals*. GAMS Development Corporation, 2000.
11. L. Goddard, S. Mason, S. Zebiak, C. Ropelewski, R. Basher, and M. Cane. Current approaches to seasonal-to-interannual climate predictions. *International Journal of Climatology*, 21:1111–1152, 2001.
12. E. Guevara, S. Meira, M. Maturano, and G. Coco. Maize simulation for different environments in Argentina. In *International Symposium: Modelling Cropping Systems*, pages 193–194. European Society of Agronomy, University of Lleida, Catalonia, Spain, 1999.
13. I. Hacking. *The Emergence of Probability.* Cambridge University Press, New York, 1975.
14. A. J. Hall, C. M. Rebella, C. M. Ghersa, and J. P. H. Culot. Field crops systems of the Pampas. In C. J. Pearson, editor, *Field Crops Systems: Ecosystems of the World*, pages 413–449. Elsevier, Amsterdam, 1992.
15. G. Hammer, J. Hansen, J. Phillips, J. Mjelde, H. Hill, A. Love, and A. Potgieter. Advances in application of climate prediction in agriculture. *Agricultural Systems*, 70:515–553, 2001.

16. J. B. Hardaker, R. B. M. Huirne, J. R. Anderson, and G. Lien. *Coping with Risk in Agriculture*. CABI Publishing, Cambridge, MA, 2004.
17. J. Jones, G. Tsuji, G. Hoogenboom, L. Hunt, P. Thornton, P. Wilkens, D. Imamura, W. Bowen, and U. Singh. Decision support system for agrotechnology transfer. In G. Tsuji, G. Hoogenboom, and P. Thornton, editors, *Understanding Options for Agricultural Production*, chapter Dordrecht, The Netherlands, pages 157–177. Kluwer, Boston, 1998.
18. J. W. Jones, J. W. Hansen, F. S. Royce, and C. D. Messina. Potential benefits of climate forecasting to agriculture. *Agriculture, Ecosystems and Environment*, 82:169–184, 2000.
19. D. Kahneman. Perspective on judgment and choice: Mapping bounded rationality. *American Psychologist*, 58:697–720, 2003.
20. D. Kahneman and A. Tversky. Prospect theory: An analysis of decision under risk. *Econometrica*, 47:263–291, 1979.
21. C. E. Laciana and E. U. Weber. Using prospect theory in optimization problems. Technical report, Department of Psychology, Columbia University, New York, 2005.
22. B. Leteinturier, J. L. Herman, F. D. Longueville, L. Quintin, and R. Oger. Adaptation of a crop sequence indicator based on a land parcel management system. *Agriculture, Ecosystems & Environment*, 112:324–334, 2006.
23. S. J. Mason, L. Goddard, N. E. Graham, E. Yulaeva, L. Sun, and P. A. Arkin. The IRI seasonal climate prediction system and the 1997/98 El Niño event. *Bulletin of the American Meteorological Society*, 80:1853–1873, 1999.
24. D. McFadden. Rationality for economists? *Journal of Risk and Uncertainty*, 19:73–105, 1999.
25. S. Meira, E. Baigorri, E. Guevara, and M. Maturano. Calibration of soybean cultivars for two environments in Argentina. In *Global Soy Forum*, Chicago, IL, August 1999.
26. J. L. Mercau, J. L. Dardanelli, D. J. Collino, J. M. Andriani, A. Irigoyen, and E. H. Satorre. Predicting on-farm soybean yields in the pampas using CROPGRO-Soybean. *Field Crop Research*, 100:200–209, 2007.
27. J. Mjelde, H. Hill, and J. Griffiths. A review of current evidence on climate forecasts and their economic effects in agriculture. *American Journal of Agricultural Economics*, 80:1089–1095, 1998.
28. J. Mjelde, T. Thompson, C. Nixon, and P. Lamb. Utilizing a farm-level decision model to help prioritize future climate prediction research needs. *Meteorological Applications*, 4:161–170, 1997.
29. National Research Council. *Our Common Journey: A Transition Towards Sustainability*. National Academy Press, Washington, DC, 1999.
30. National Research Council. *A Climate Services Vision: First Steps Toward the Future*. National Academy Press, Washington, DC, 2001.
31. J. Paruelo and O. Sala. Effect of global change on Argentine maize. *Climate Research*, 3:161–167, 1993.
32. J. W. Pratt. Risk aversion in the small and in the large. *Econometrica*, 32:122–136, 1964.
33. M. Rabin. Psychology and economics. *Journal of Economic Literature*, 36:11–46, 1998.
34. J. Ritchie, V. Singh, D. Godwin, and W. Bowen. Cereal growth, development and yield. In G. Tsuji, G. Hoogenboom, and P. Thornton, editors, *Understanding*

Options for Agricultural Production, pages 79–98. Kluwer Academic, Dordrecht, The Netherlands, 1998.

35. E. H. Satorre. Cambios tecnológicos en la agricultura actual. *Ciencia Hoy*, 15:24–31, 2005.
36. U. Schmidt and H. Zank. What is loss aversion? *Journal of Risk and Uncertainty*, 30:157–167, 2005.
37. P. J. H. Schoemaker. The expected utility model: its variants, purposes, evidence and limitations. *Journal of Economic Literature*, 20:529–563, 1982.
38. K. E. Trenberth and D. P. Stepaniak. Indices of El Niño evolution. *Journal of Climate*, 14:1697–1701, 2001.
39. A. Tversky and D. Kahneman. Advances in prospect theory, cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, 5:297–323, 1992.
40. J. von Neumann and O. Morgenstern. *Theory of Games and Economic Behavior*. Princeton University Press, Princeton, NJ, 1944/1947.
41. R. T. Woodward. Should agricultural and resource economists care that the subjective expected utility hypothesis is false? In *Meeting of the American Agricultural Economics Association*, Salt Lake City, UT, August 1998. `http://agecon2.tamu.edu/people/faculty/woodward-richard/paps/AAEA98-Uncertainty.pdf`.