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Value of perfect ENSO phase predictions for agriculture: evaluating the impact of land tenure and decision objectives

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Abstract In many places, predictions of regional climate variability associated with the El Niño–Southern Oscillation phenomenon offer the potential to improve farmers' decision outcomes, by mitigating the negative impacts of adverse conditions or by taking advantage of favorable conditions. While the notion that climate forecasts are potentially valuable has been established, questions of when they may be more or less valuable have proven harder to resolve. Using simulations, we estimate the expected value of seasonal climate information under alternative assumptions about (a) land tenure (ownership vs. short-term leases) and (b) the decision maker's objective function (expected utility vs. prospect theory value function maximization),

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employing a full range of plausible parameter values for each objective function. This allows us to show the extent to which the value of information depends on risk preferences, loss aversion, wealth levels and expectations, as well as situational constraints. Our results demonstrate in a non-laboratory decision context that, in some cases, psychologically plausible deviations from expected utility maximization can lead to substantial differences in estimates of the expected value of climate forecasts. 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.

1 Introduction

1.1 Climate variations and decision making

A major scientific advancement of the twentieth century was the progress made in diagnosing, modeling and predicting seasonal climatic variations. Climate forecasts can affect peoples' behavior and, in turn, their livelihoods. Agriculture is one sector that may benefit from reliable forecasts of seasonal variability. Agricultural stakeholders consistently rank climate variability among the top sources of risk to production or profits (Harwood et al. 1999). Prediction of an impending wet growing season, for example, may encourage farmers to apply more fertilizer or select a less drought-tolerant crop. Improved decisions may enhance productivity, food security and social welfare. The way in which and the extent to which climate forecasts can improve decisions depend on the decision makers' constraints and objectives, as we demonstrate in this paper.

1.2 Forecast capabilities, value and use

Current understanding of sea surface temperature variability in the equatorial Pacific and its climatic impacts enables skillful, though imperfect, forecasts of future sea surface temperature anomalies (Landsea and Knaff 2000). Climate and crop yield variability associated with the El Niño–Southern Oscillation (ENSO) phenomenon can also be predicted with some skill (Mason et al. 1999; Goddard et al. 2001). ENSO is the greatest single source of climatic variability on seasonal-to-interannual scales in much of the world (Trenberth and Stepaniak 2001; Goddard et al. 2001) and results from the two-way interaction between the ocean and atmosphere in the tropical Pacific Ocean. ENSO involves two extreme phases: "El Niño" events and "La Niña" events; those time periods which do not fall in these extreme phases are labeled as "neutral" (Trenberth 1997). Links between ENSO-related climate variability and agricultural outcomes exist in many agricultural regions (Dilley 1997; Hsieh et al. 1999; Hammer et al. 2001; Naylor et al. 2001; Amissah-Arthur et al. 2002; Gimeno et al. 2002).

The value that climate forecasts may have under different decision circumstances (e.g., crops grown, resource conditions, production technologies) has become an important public policy concern. In this paper, we define the expected value of forecast information (EVOI) as the difference between the expected value of the outcome from an improved, forecast-assisted decision and the expected value of the outcome of a decision made without the forecast. In the developed world, climate data, forecasts and technical assistance often are provided and subsidized by the public sector (Glantz 2000). Estimated forecast value can help show if improved forecast provision and dissemination may offer more to society than other innovations, such as genetically modified seed varieties. Richard Katz's internet site (http://www.isse.ucar.edu/staff/katz/agriculture.html) offers reviews and summaries of numerous studies that estimate forecast value for agriculture. The mere existence of a technical innovation such as improved climate forecasts does not ensure its use (Schultz 1964), and forecast use has indeed advanced slowly (Trenberth 1997; Changnon and Kunkel 1999; Goddard et al. 2001).

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 two reasons. First, the goals and objectives of farmers' decisions (i.e., their objective functions, in decision-theoretic terms) influence how climate information (both historical data and forecasts) is used. In this paper we examine the differences identified as "optimal" by maximization of the objective functions associated with expected utility (EU) theory and prospect theory (PT). How climate information is used, in turn, has implications for how climate information should be presented and communicated, i.e., for the design of climate forecasts and tutorials of climate-information use. Decisions about the contents and formats of current climate forecasts make implicit assumptions about what farmers are trying to achieve and how such information will be used.

Second, decision makers in numerous domains often have poor insight into their own decision processes, goals and objectives (Camerer 1981; Dawes 1971; Dawes et al. 1989; Schoemaker and Russo 1993; Ebert and Kruse 1978; Wrights 1979). Keeney (1992) has provided broad theoretical support for the argument that thinking about one's decision objectives is an important component of effective decision making. This offers opportunities for interventions to help farmers enhance their decisions. When made aware of the objective function and goals implicit in their actions, decision makers tend to react in one of two ways. Some are surprised by identified objectives and the information they used in their decisions (Bond et al. 2008; Slovic and Lichtenstein 1968, supplementary materials). Further, once aware of these objectives and information use, these decision makers may wish they were not using them: examples may include crop yield maximization rather than profit maximization in farm production decisions. (e.g., List 2003). Other decision makers may concur with identified goals, objectives, and information used, once made apparent to them, and refuse to give them up (e.g., greater sensitivity to losses than to gains), even if they violate normative models (Samuelson 2004). Identification of objective functions and decision goals provides feedback about implicit decision processes, which can then be reviewed and either explicitly acknowledged and accepted, or rejected.

1.3 Objectives and contributions

The purpose of this paper is to evaluate the influence of an individual's decision goals upon EVOI. While the notion that climate forecasts are potentially valuable has been established, questions of when they may be more or less so have proven harder to resolve. In particular, the impacts of decision goals have only seldom received mention (e.g., Hansen 2002; Rubas et al. 2006; Meza et al. 2008). For comparative purposes, we gauge the effects of decision processes relative to those of wealth and land tenure regime, effects which have been examined elsewhere (e.g., Hammer et al. 2001). The point that the EU model does not adequately describe climate-sensitive decisions has also been made elsewhere but not specifically for PT in estimating EVOI (e.g., Jochec et al. 2001). If EVOI depends on the assumption of farmers' objective function and its parameters, then we should reconsider the validity of basing EVOI estimates exclusively or primarily on EU maximization as the objective function.

1.4 Approach

To test the robustness of climate-forecast value estimates to alternative objective functions and their parameter values, we simulate farm-level ENSO forecast value for existing rainfed cropping systems in the Pampas region of central-eastern Argentina. We compare simulated EVOI for a plausible range of parameter values for each objective function, reflecting individual differences in farmers' cognition and motivation. We assume farmers maximize either EU or PT value. To keep an already complex story manageable, we focus on the case of perfect ENSO phase forecasts, which assumes decision makers correctly anticipate ENSO phase but not daily weather. We examine decisions relate to production of cereals and oilseeds, i.e., a specific use of climate information in agricultural decision making. However, similarity in resource conditions (e.g., soils and rainfall), production scale, crops grown, land tenure regimes and high input technology in the Pampas to those in other major production areas, such as the Midwestern US, suggests broader relevance for our results. In the sections that follow, we discuss our case study, alternative objective functions that may underlie risky decision making, our empirical approach and findings.

2 Case study

The climate, soils and cropping systems of the Argentine Pampas have been characterized by Hall et al. (1992). We focus on the region near Pergamino (33°56′ S, 60°33′ W), the most productive sub-region of the Pampas (Paruelo and Sala 1993). Earlier evidence of forecast value in attitudinal (Letson et al. 2001), agro-climatological (Ferreyra et al. 2001; Podestá et al. 2002) and decision studies (Messina et al. 1999; Letson et al. 2005; Bert et al. 2006, 2007; Podestá et al. 2008) suggested Pergamino as a promising region for study.

The Pampean ENSO signal has been well documented. During the late spring (October–December) of La Niña events, maximum temperatures and radiation tend to be higher, while minimum temperatures and rainfall tend to be lower than normal; the opposite tends to occur in El Niño events, though less markedly (Grondona et al. 2000; Furrer and Katz 2007). The ENSO-related climatic impacts, in turn, affect crop yields. A clear association exists between maize and soybean yields and ENSO: high (low) yields are more likely during El Niño (La Niña) events (Podestá et al. 1999).

Two characteristics of agricultural production in the study region have implications for our analysis. 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. Second, a considerable proportion of the area currently farmed is not owned by the farmers exploiting it. Short land leases (usually one year) provide incentives for tenants to maximize short-term profits via highly-profitable crops. In contrast, land owners tend to rotate crops to steward long-term sustainability of production and soil quality (Leteinturier et al. 2006), which implies fewer opportunities to benefit from forecast use. Given the differences in decision making goals and constraints between land owners and tenants, we model the two groups separately.

Farmers in the Pampas can easily access forecasts of ENSO from the beginning of the decision-making process. Land assignment decisions start several months prior to sowing. When harvest of the previous cycle's summer crops is completed (March to April), preliminary land allocation decisions are made for the following season. The plans are executed as the sowing of each crop occurs (May for wheat, September for maize and November for soybean) and could be revised along this period. Since some ENSO events can be forecasted qualitatively only a few months in advance and occasionally after an event has begun (Landsea and Knaff 2000), farmers will be less than certain about an ENSO phase when making these decisions. After decisions about land assignment are made, farmers focus on crop management decisions. Decisions related to crop management are made 2 to 3 months prior to sowing (e.g., July to August for maize) but are often revised up to the period preceding planting (Bert et al. 2006, 2007).

At least four other studies have estimated the expected value of climate forecast for crop production in Pergamino. Royce et al. (2001) linked a widely used crop model, CERES-maize, to a simulated annealing algorithm and a partial budget calculator, to optimize crop management by ENSO phase. Messina et al. (1999) provided comparative estimates of the expected value of climate forecasts for Pergamino and Santa Rosa, a nearby but semi-arid location. Jones et al. (2000) estimated the potential economic value of climate forecasts for farm scale management decisions in Tifton, GA, for comparison with the estimates of Messina et al. (1999). Letson et al. (2005) extended Messina et al. (1999) by considering variability in historical crop prices and weather to explore EVOI dispersion. However, each study assumes that farmers are trying to maximize EU, and none examines the effect of alternative objective functions or crop selection constraints.

3 Theories of risky choice: expected utility and prospect theory

3.1 Missing motivations

Models of risky choice have an extensive history in economics. In this paper we examine the differences among simulated agricultural production decisions identified as "optimal" by maximization of the objective functions associated with EU and PT. Because of our interest in comparing objective functions, we discuss them in some detail here. Traditional EU maximization, further described below, is a widely used criterion in agricultural economics, and thus is a useful benchmark against which to compare the results of other objective functions. However, with the growing interest in PT as a theory of risky decision making, agricultural and resource economists have an exciting opportunity to explore how alternative objective functions might improve analysis and insight (Shaw and Woodward 2008). Notably, George Akerlof has recently explored the implications of utility functions dependent on norms, or decision makers' notions of what ought to be, to which he refers to as "missing motivations". Akerlof recommends that "economists observe decision makers as closely as possible, with the express intent of characterizing their motivation, and would use such characterization as the basis for modeling of economic structure" (Akerlof 2007, p. 57).[1]

3.2 Expected utility

The EU hypothesis assumes that individuals evaluate uncertain prospects according to their expected level of satisfaction or "utility" and is the predominant descriptive and normative model of choice under uncertainty in economics. Specifically, EU asserts that people maximize a probability-weighted average of the outcomes' utilities. To do so, a decision maker calculates the utility in each possible state and constructs a weighted average. The weights are the decision maker's estimate of the probability of each state. The expected utility is thus, in probabilistic terms, an "expectation." Empirically speaking, most decision makers exhibit risk aversion, meaning that they would rather take a certain amount of money than take a gamble with an expected payoff that is slightly larger than the certain amount.

We define a risky prospect q as the ensemble $i = (1,\ldots, n)$ of possible wealth outcomes w_i with associated probabilities p_i. The farm-wide economic outcome of each action vector $\vec{x}$ during cropping cycle i, π_i, is computed as:

$$\pi_i = \sum_{l=1} x_l \, \pi_{il} \tag{1}$$

where π_{il} is the net margin for year i and cropping alternative l and x_l is the amount of land allocated to cropping alternative l (i.e., a component of the land allocation vector $\vec{x}$), and the summation is across all possible cropping alternatives. The total wealth of a decision maker at the end of cropping cycle i is: $w_i = w_0 + \pi_i$, where w_0 is the decision maker's initial wealth (i.e., prior to production decisions for year i) and π_i is the farm-wide income during year i. A decision maker evaluates the EU of prospect q as:

$$E[U(q)] = \sum_i p_i u(w_i) \tag{2}$$

[1] George Akerlof has shown how insights from sociology and psychology could broaden the power of economics. In his Nobel Lecture (Akerlof 2001), he wrote: "Economics is a powerful tool, but like a microscope, it focuses attention on some aspects of reality (especially the role of prices in markets), while it also diverts attention from other aspects. There are still important areas of economics that are all but uncharted because of this limited focus. It is consistent with this interpretation that Daniel Kahneman, a leader in changing the focus of economics and one of last year's (2002) prize winners, is not only a trained psychologist, but also, has special expertise in human optical illusion."

One flexible form of utility function $u(\cdot)$ is given by Pratt (1964) as:

$$u(w) \propto \begin{cases} \dfrac{w^{1-r}}{1-r} & if\ r \neq 1 \\ \ln w & if\ r = 1 \end{cases} \tag{3}$$

where r is the coefficient of constant relative risk aversion (CRRA). CRRA implies that preferences among risky prospects will be unchanged if all payoffs are multiplied by a positive constant (Hardaker et al. 2004). The parameter r describes the curvature of the utility function and captures degree of risk aversion, e.g., $r = 0$ for risk neutrality and $r > 0$ for risk aversion.

The EU model has been central in the analysis of choice under risk and uncertainty, not only because of its compelling axiomatic foundation, but also because of its mathematical tractability (Shaw and Woodward 2008). Despite these strengths, there is both experimental and real-world evidence that individuals often do not behave in a manner consistent with EU theory (McFadden 1999; Camerer 2000). A central assumption of EU theory is that the utility of decision outcomes is determined entirely by the final, reference-independent wealth they generate. Yet, decision makers' evaluation of outcomes instead appears to be influenced by a variety of *relative* comparisons (Kahneman 2003).

3.3 Prospect theory

PT (Kahneman and Tversky 1979) and its modification, cumulative PT (Tversky and Kahneman 1992; Fennema and Wakker 1997) currently have become the most prominent alternative to the EU theory. PT formalizes one type of relative comparison observed when decision makers evaluate the utility of decision outcomes. In PT, a value function $V(\cdot)$ is defined by *changes in wealth* rather than reference-independent wealth states as in utility theory (Fig. 1; Kahneman 2003). Outcomes w_i are evaluated as gains or losses with respect to reference value w_{ref}: $w_i = \Delta w_i - w_{\text{ref}}$. 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, i.e., 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 (Schmidt and Zank 2005; Camerer 2000; Rabin 1998). Kahneman and Tversky (1979) define the subjective value of a prospect q as:

$$V(q) = \sum_i p_i v[\Delta w_i] \tag{4}$$

where Δw_i is the difference between the outcome w_i and the 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 (1992):

$$v(\Delta w) = h(\Delta w)|\Delta w|^{\alpha} \tag{5}$$

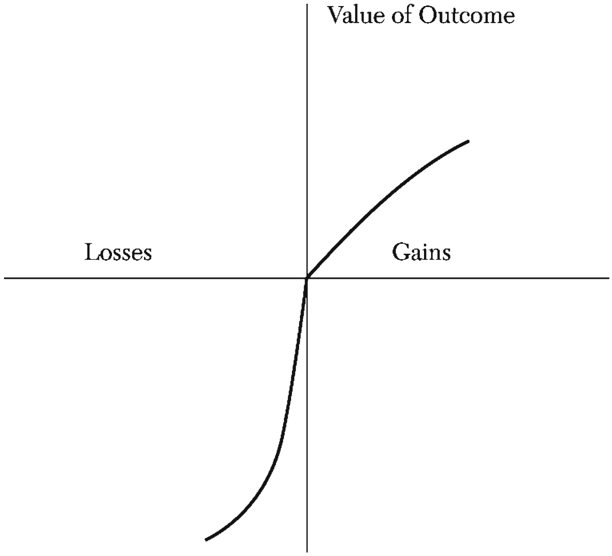


Fig. 1 The valuation of outcomes in prospect theory. The prospect theory (*PT*) value function passes (Eqs. 4, 5 and 6) through a reference point (w_{ref}), or status quo. Its s-shape indicates that risk preferences (α) over negative prospects are not a mirror image of their preferences over positive prospects. While decision makers are risk-averse over prospects involving gains, they are risk-loving over prospects involving losses. As the function's asymmetry implies, given the same variation in absolute value, there is a bigger impact of losses than of gains (loss aversion, λ). In contrast to expected utility theory, the PT value function measures losses and gains, not absolute wealth

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

$$h(\Delta w) = \begin{cases} 1 & if\ \Delta w \geq 0 \\ -\lambda & if \Delta w < 0 \end{cases} \tag{6}$$

and λ is a parameter ($\lambda > 1$) that reflects increasing loss aversion. The exponent α in Eq. 5 ranges between 0 and 1 and describes the curvature of the value function. Because of the discontinuity at the reference point, α describes the degree of risk aversion (concavity) in the domain of gains and the degree of risk seeking (convexity) in the domain of losses.

4 Empirical approach

4.1 Crop yield simulation

In collaboration with our regional stakeholders, we defined 64 different cropping alternatives (CAs) that reflect a realistic range of cultivation options for the study area (Bert et al. 2006, 2007). Several CAs are associated with the same crop, although involving different management options, as shown in Tables 1 and 2, where the monetary units are constant US dollars equivalent to the median of 2000–2005 prices. Each CA combines (a) a crop (maize, full-cycle soybean and wheat–soybean),

Table 1 Optimal CAs for land *owners*

Cropping alternative ID	Cropping alternative management				Economic returns for owners ($ ha^{-1})							
	Genotype	Planting date	Fertilizer added (kg N ha^{-1})	Row spacing (m)	All years		Neutral		El Niño		La Niña	
					Mean	SD	Mean	SD	Mean	SD	Mean	SD
Maize												
Ma20	DK752	Sep 15	75	0.70	112.7	101.6	128.3	95.5	150.3	46.1	44.0	119.8
Ma21			100		113.2	106.8	129.3	102.3	149.8	50.5	44.2	124.6
Ma23		Oct 15	75		116.5	84.1	131.2	70.0	132.9	63.6	67.5	111.8
Ma24			100		116.3	90.1	131.4	75.5	133.4	68.8	65.6	119.
Full-cycle soybean												
Soy13	DM4800	Oct 25	0	0.52	187.3	61.8	197.1	52.5	197.6	80.4	155.3	58.0
Soy14					188.1	60.7	197.8	51.3	198.2	78.4	156.3	58.0
Soy16		Nov 15			169.6	50.5	176.7	44.6	171.6	58.1	151.0	55.8
Wheat–soybean												
SW19	Scorpion[a] and DM4800[b]	Jun 10	40	0.19[a] 0.52[b]	162.1	83.4	167.5	79.2	224.1	67.7	97.5	60.1
SW20		Jun 10	60		167.3	84.7	171.6	81.8	229.7	68.6	105.4	61.3
SW21		Jun 10	80		168.8	85.0	172.2	83.1	230.0	69.5	110.3	62.5
SW24		Jul 10	80		148.3	80.3	146.0	80.2	205.2	67.0	106.8	65.0

The combination of management variables that define each CA is shown, along with mean economic returns (revenue minus costs) and their standard deviation (SD) over the 72 simulated cropping cycles. For the wheat–soybean double crop, the superscripts a and b indicate values for wheat and soybean, respectively

Table 2 Optimal cropping alternatives for land *tenants*

Cropping alternative ID	Cropping alternative management: Genotype	Planting date	Fertilizer added (kg N ha^{-1})	Row spacing (m)	Economic returns for tenants (\$ ha^{-1}): All years Mean	All years SD	Neutral Mean	Neutral SD	El Niño Mean	El Niño SD	La Niña Mean	La Niña SD
Maize												
Ma20	DK752	Sep 15	75	0.70	2.1	151.4	25.0	142.1	61.6	72.4	−102.2	176.2
Ma21			100		6.8	157.7	30.2	150.5	64.9	77.7	−97.4	181.7
Ma23		Oct 15	75		5.8	128.6	28.3	109.8	29.7	100.5	−68.9	165.6
Ma24			100		9.8	135.8	32.9	116.2	34.2	106.9	−65.7	175.6
Full-cycle soybean												
Soy13	DM4800	Oct 25	0	0.52	68.0	90.9	83.9	75.2	77.1	117.2	22.1	91.7
Soy14					69.4	89.0	85.2	73.1	78.5	114.0	23.9	91.5
Soy16		Nov 15			44.7	77.9	56.0	67.4	43.9	89.5	18.0	89.1
Wheat–soybean												
SW19	Scorpion[a] and DM4800[b]	Jun 10	40	0.19[a] 0.52[b]	62.3	121.7	71.3	115.2	152.7	89.4	−34.0	94.1
SW20		Jun 10	60		72.3	122.5	79.2	117.8	162.5	89.6	−18.6	96.6
SW21		Jun 10	80		77.6	122.0	82.9	118.7	165.1	91.1	−7.3	98.6
SW24		Jul 10	80		48.7	118.8	47.0	118.7	131.8	90.7	−15.5	101.4

The combination of management variables that define each cropping alternative is shown, along with mean economic returns (revenue minus costs) and their standard deviation (SD) over the 72 simulated cropping cycles. For the wheat–soybean double crop, the superscripts a and b indicate values for wheat and soybean, respectively

(b) various agronomic decisions (cultivar/hybrid choice, 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. Additional details on the crop simulation and farm decision model can be found in (Podestá et al. 2008).

Yields for each CA were simulated using the crop models in the Decision Support System for Agrotechnology Transfer package (Jones et al. 1998). These models simulate daily crop growth and development as a function of inputs such as management practices, weather, soils and cultivars. These models have been calibrated and validated under field conditions in several production environments including the Pampas (Guevara et al. 1999; Meira et al. 1999; Mercau et al. 2007). We used 1931–2003 daily weather for Pergamino (maximum and minimum temperature, precipitation and solar radiation) to run the models. Other inputs such as (1) genetic coefficients describing physiological processes and developmental differences among genotypes, and (2) soil conditions, including moisture and N content at the beginning of simulations, were provided by Asociación Argentina de Consorcios Regionales de Experimentación Agrícola (AACREA, www.aacrea.org.ar), a non-profit farmers' group that partnered with us in this study. For each CA, 72 simulated yields were obtained (one for each cropping cycle in the 1931–2003 historical weather record).

4.2 Farm decision models

4.2.1 Choice variables and solution method

Economic outcomes were simulated for a hypothetical 600-ha farm, the median size of AACREA farms in the region. We used a stochastic whole-farm crop and management choice model to capture the role of climate forecasts in decision making and to estimate their value. The choice variable in the optimization is the vector $\vec{x} = (x_1, \ldots, x_{64})$that reports the percentage of area of the 600-ha hypothetical farm allocated to each of the 64 CAs considered. Different land amounts allocated to the 64 CAs were considered by the optimization of each objective function. The optimization was performed using algorithm MINOS5 in the GAMS software package (Gill et al. 2000). We drew from a uniform distribution to assign starting values, to assure that model solutions were global maxima.[2] The Appendix gives a more detailed presentation of the model structure, assumptions and data sources.

We solved the farm model for two sets of objective functions, EU and PT, optimized with and without using ENSO-phase forecasts. Specifically, we calculated the expected value of a decision made based on a perfect forecast of ENSO phase, i.e., knowing with certainty which ENSO phase will occur, but taking into account weather variability within that given phase, because there is still an imperfect relationship between the ENSO phase and daily weather. We assumed the forecasting system is consistent with historical probabilities of the climatic conditions. To estimate EVOI, we compared the expected value of a decision made based on perfect ENSO information with that without this information. We used the farm model to:

[2]To set initial values for our land allocations, we randomly drew from a uniform distribution bounded by 0 and 1. We used this procedure to re-solve the model ten times for each value of r, w_0, λ, α and w_{ref}. In all cases, model solutions were identical up to three decimal places, with respect to the varying initial values.

(a) identify optimal decisions with and without ENSO information; and (b) simulate annual economic outcomes for the optimal decisions, with and without forecast use, for the length of our weather series.

4.2.2 Farm model constraints

Model constraints imposed by crop rotations warrant mention. Differences in goals and constraints between land owners and tenants require that we explore optimal decisions separately for these groups. 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: 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. A final constraint specified that no land could be left idle.

4.2.3 Parameter space explored for each objective function

Each objective function has a set of parameters. In some cases, a given parameter value describes a personality characteristic (e.g., risk aversion) that varies among decision makers. With no widely accepted values for parameters, a broad range of plausible values is considered, including available empirical estimates in the region. In this section, we describe and justify our choice of central (or nominal) parameter values (Table 3).

Expected utility The EU function has two parameters: (1) the decision maker's initial wealth w_0 and (2) the constant relative risk aversion coefficient r (Table 3). Initial wealth w_0 is defined as liquid assets, or borrowing ability. For land owners, this quantity was estimated as 40% of the value of the farm land. We assume a

Table 3 Range of parameters considered for each objective function

Objective function	Parameter	Land owners		Land tenants	
		Typical value	Values explored	Typical value	Values explored
Expected utility	Initial wealth (w_0)	\$1,400 ha^{-1}	\$900, \$1,400, \$1,900 ha^{-1}	\$1,000 ha^{-1}	\$700, \$1,000, \$1,400 ha^{-1}
	Risk aversion coefficient (r)	1.5	0.0, 0.5, 1.0, 2.0, 3.0, 4.0	Same as for land owners	
Prospect theory value function	Reference wealth (w_r)	\$232.5 ha^{-1} \$400 ha^{-1}	100, 232.5	\$20 ha^{-1}	\$5, \$20, \$50, \$80 ha^{-1}
	Risk preference (α)	0.88	0.60, 0.65, 0.70, 0.75, 0.80, 0.85, 0.88, 0.90, 1.00	Same as for land owners	
	Loss aversion (λ)	2.25	1.00, 2.25, 3.50	Same as for land owners	

farmer will not sacrifice future income potential by selling crop land, but can borrow up to 40% of his/her land value (see Messina et al. 1999). The 1994–2003 average land value in Pergamino was \$3,541 ha^{-1}, making w_0 equal to \$1,400 ha^{-1} (\$3,541 × 0.4 ha^{-1}), where the monetary units are constant US dollars equivalent to the median of 2000–2005 prices. In sensitivity analysis, we also allowed w_0 to take on the values of 900 and 1900. For land tenants, we assumed a w_0 value of \$1,000 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). In sensitivity analysis, we also allowed w_0 to take on the values of 700, 1,200 and 1,400. For the risk-aversion coefficient r, we followed the Hardaker et al. (2004) classification: 0.5 is hardly risk averse; 1.0, somewhat risk averse; 2.0, rather risk averse; 3.0, very risk averse; and 4.0, extremely risk averse. We also included risk indifference by considering $r = 0$. The range of r values (from 0 to 4) was the same for owners and tenants.

Prospect theory value function The PT value function is defined by (1) a reference wealth w_{ref} that separates outcomes perceived as gains and losses, (2) a risk preference parameter α, and (3) a loss aversion parameter λ that quantifies the relative impact of gains and losses (Table 3). The combination of all three parameters accounts for the choice phenomena or choice behaviors that need to be explained solely with reference to the risk aversion parameter in EU. For land owners, w_{ref} was estimated as the income easily achieved by renting out the land instead of farming it. This value of w_{ref} was estimated to be \$232.5 ha^{-1} (a rental fee of 1.4 tons of soybean per hectare times a price of \$166 ton^{-1}). In sensitivity analysis, we also allowed w_{ref} to take on the values of \$100 and \$400 ha^{-1}. For land tenants, w_{ref} was estimated as the income obtained by placing the tenant's initial wealth ($w_0 =$ \$1,000 ha^{-1}, as described for EU) in a bank for 6 months (the duration of a cropping season) at an annual interest of 4% (representative of current rates in Argentina). The nominal w_{ref} value, then, was \$20 ha^{-1}. In sensitivity analysis, we also allowed w_{ref} to take on the values of \$5, \$50 and \$80 ha^{-1}. For the risk-preference parameter α we explored nine values over its possible range, the 0–1 interval. For the loss-aversion parameter λ, we explored three values (1, 2.25 and 3.5) chosen to span the 95% percentile range empirically estimated in decision experiments in the region by Weber (2007).

5 Results

5.1 Land tenure, decision objectives and economic outcomes

Our linked modeling approach allowed us to consider several important hypotheses regarding the relationship between decision contexts and the EVOI. We are interested in the role of land tenure (owner managed vs. tenant managed) and of the differences in cognitive process assumed to underlie different objective functions (EU maximization versus PT value maximization), and we use three different dependent measures (land allocations, incomes, EVOI) to evaluate our model simulations. Those four permutations of land-tenure and decision objectives give us three testable hypotheses on whether land tenure or assumed cognitive process influences economic outcomes with regard to the use of climate-forecast information. Specifically, we wish to compare the degree of influence that land tenure and decision objective each impart on the selection of CAs, on the resulting incomes, and on EVOI.

We begin in Section 5.2 by reporting the optimal land allocations with and without forecast use, as determined by our farm model. These findings are intended to help build reader intuition for more detailed results that follow. Also in Section 5.2, we report results on income levels and relate them to the type of ENSO phase forecast issued (i.e., El Niño, neutral or La Niña) and to risk preference, and compare those between the two types of land tenure and two objective functions. Later, in Section 5.3, we report findings on EVOI and discuss how they relate to land tenure, decision process, the ENSO phase forecast and risk preference.

5.2 Land allocations and incomes

If assumptions regarding land tenure and decision processes and thus objective functions matter, they should at least influence farm CA choices. Tables 1 and 2 describe the available CAs prevalent in the case study region, by genotype, planting date, rate of nitrogen fertilization and row spacing. Tables 1 and 2 also offer the mean and standard deviation of simulated economic returns for each CA, across all 72 of the years in our data set and also by each ENSO phase. Comparative findings are offered for owner management (Table 1) and for tenant management (Table 2). Note that we include four maize alternatives, three for soybean, and four others for a wheat–soybean relay or double crop. For land owners, full-cycle soybean CAs are most profitable, except for El Niño years, when the wheat–soybean double crop CAs offer the highest returns. For land tenants, the reverse is true: the wheat–soybean double crop CAs offer the highest returns, except in neutral and La Niña years when the full cycle soybean CAs are most profitable.

Figure 2 displays the optimal CAs for each combination of land tenure and objective function (recall our assumptions about land owners, but not land tenants adhering to crop rotations, see Section 4.2.2). While land tenure appears to matter a great deal, the type of cognitive process has only a marginal influence. For brevity, and because of the similarity of our findings across the parameter space we considered, we show only representative cases in Fig. 2, i.e., $w_{\mathrm{ref}} = 232$, $\lambda = 2.25$ and $\alpha = 0.88$ for PT maximizing owners; $w_0 = 1{,}400$ and $r = 1$ for EU maximizing owners; $w_0 = 1{,}000$ and $r = 1$ for EU maximizing tenants; and $w_{\mathrm{ref}} = 20$, $\lambda = 2.25$ and $\alpha = 0.88$ for PT maximizing tenants (Podestá et al. 2008).

In the case of land tenants, with one exception, monocropping prevails because of the absence of crop rotation commitments. In neutral and La Niña events full cycle soybean CAs are the dominant choice, while wheat–soybean double CAs are dominant in El Niño years. The exception to monocropping is the PT maximizing farmer using climatology rather than the ENSO phase forecasts, who allocates 40% of land to the most profitable CA, a wheat–soybean double crop, and hedges against climate risk by allocating the remaining 60% to a full cycle soybean CA offering lower but more stable income. The PT/tentant using ENSO forecasts benefits most in El Niño years, when the income differential for phase specific versus climatological management is greatest [\$165.1 ha^{-1} vs. $(0.4 \times 77.6 + 0.6 \times 69.4)=$ \$72.7 ha^{-1}]. The forecast response strategies in the case of PT/tenants are to avoid hedging costs and are offensive in the sense that they take advantage of anticipated favorable conditions. In part, the PT/tenants are responding to lower w_{ref} levels that make

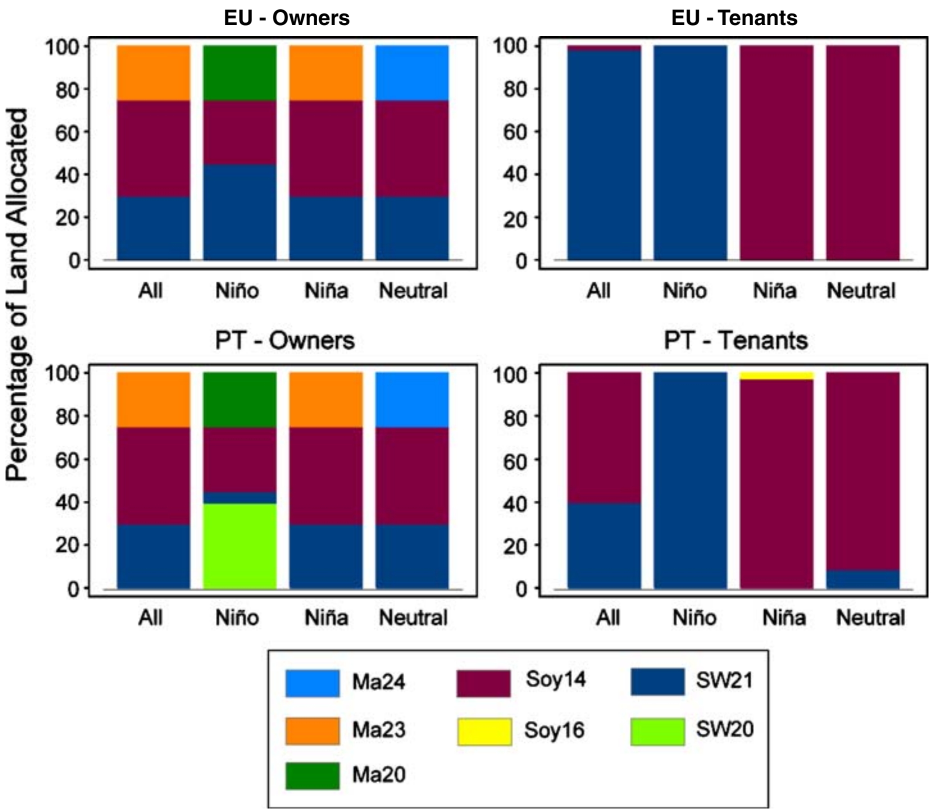
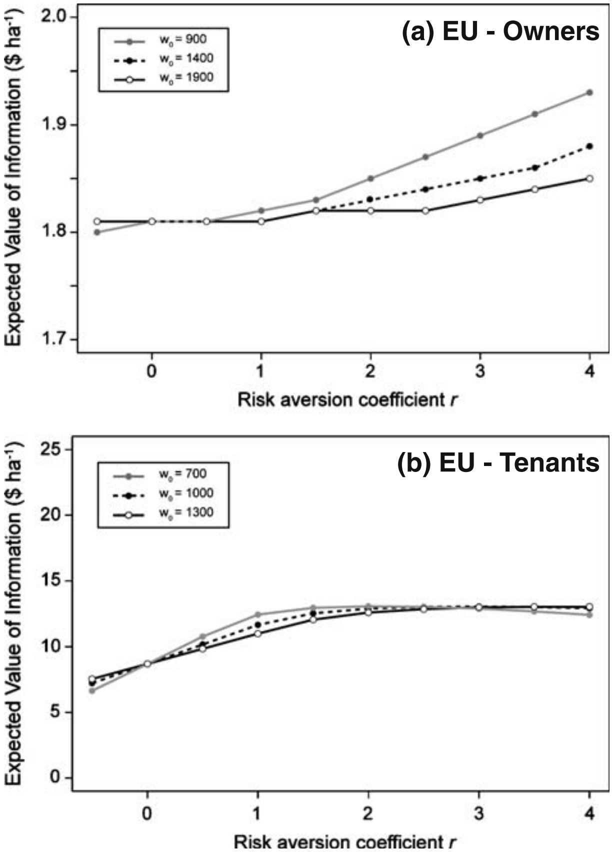


Fig. 2 Optimal land allocations for each combination of land tenure and cognitive process

losses relatively unlikely. The opposite is true in the case of EU/tenants, because the forecast response is defensive in selecting a full cycle soybean CA offering lower but more stable income.

In the case of land owners, the crop rotation commitments, by restricting the decision space, closely link the land allocations of the EU and PT maximizing farmers. In neutral and La Niña years, full cycle soybean CAs are the dominant choice, meaning they receive the maximum land allocation of 45%. In El Niño years, the wheat–soybean double crop CAs get the (maximum) 45% land allocation. In all cases, maize CAs are the least profitable and receive the minimum land allocation, 25%. The lone instance where the land allocations of the utility- and PT-maximizing farmers differ is in El Niño years, when the PT maximizing land owner opts for a slightly less profitable but more stable wheat–soybean CA. The land allocation findings in Fig. 2 are broadly consistent with known regional ENSO crop yield associations (Podestá et al. 1999; Table 3 and Fig. 3), as well as observed land allocations in the Argentine Agricultural Census (2002), and confirm our basic approach by replicating expert knowledge of regional decision making. A detailed comparison of our simulated land allocations with the 2002 observed allocations appears in Podestá et al. (2008) and is also available upon request from the corresponding author.

Fig. 3 EVOI in \$ ha^{-1} certainty equivalent units for EU and **a** land owners and **b** land tenants



Raising and stabilizing farm incomes is an important policy goal, so we are also interested in how assumptions regarding land tenure and decision processes might influence farm incomes. In general, economic returns per hectare are greater for owners, because of differences in fixed and structural costs, as shown in Tables 1 and 2, which implies that relaxing our rotational constraints on owners would merely replicate the tenant decisions. Because land tenure matters more than cognitive process in terms of optimal land allocations, we are not surprised to see that it does so as well for income levels, as indicated by the economic returns in Tables 1 and 2 and the land allocations in Fig. 2. For owners, income per hectare is about \$164 ha^{-1}, while for tenants income is about \$71 ha^{-1}. For brevity, and because of the similarity of our findings across the parameter space considered, we mention here only representative cases shown in Fig. 2, in comparing farm incomes optimized on climatology vs. that optimized on ENSO phase. For EU/Tenants, incomes for climatological and perfect phase information are \$69.4 and \$71.3 ha^{-1}. For PT/tenants, those incomes are \$72.7 and \$71.3 ha^{-1}. For EU/owners, those incomes are \$164.4 and \$163.5 ha^{-1}. For PT/Owners, those incomes are \$164.4 and \$164.2 ha^{-1}. In contrast, we see in the next section that the effects of both land tenure and decision objective parameter values are much larger upon EVOI.

5.3 Expected value of information

The next set of results is our estimated EVOI for each possible type of land tenure and cognitive decision process, expressed in certainty equivalent[3] dollars on a per hectare basis. The chief finding is that EVOI is three to five times higher for tenants than for owners, under EU and PT, since owners abide by crop rotations and have less flexibility to respond to climate forecasts. While higher EVOI is a welcome result, it must be balanced against the environmental degradation that accompanies monocropping. For illustrative purposes, we again highlight a few, representative cases: i.e., in Fig. 3a, $w_0 = \{900, 1{,}400 \text{ and } 1{,}900\}$ for EU owners; in Fig. 3b, $w_0 = \{700, 1{,}000 \text{ and } 1{,}300\}$ for EU tenants; in Fig. 4a, $w_{\text{ref}} = \{100, 232 \text{ and } 400)$ and $\lambda = \{1, 2.25 \text{ and } 3.5\}$ for PT owners; and in Fig. 4b, $w_{\text{ref}} = \{5, 20, 50 \text{ and } 80\}$ and $\lambda = \{1, 2.25 \text{ and } 3.5\}$ for PT tenants.

One way to interpret forecast responses is to note their direction, that is, whether the farmer uses ENSO forecasts primarily to avoid risk associated with adverse conditions (defensive response) or to seek more profits by taking advantage of favorable conditions (offensive response). In Fig. 2, for EU/tenants, farmers already are positioned to take advantage of El Niño events, because of favorable resource conditions, and use forecasts defensively to minimize income losses associated with neutral and La Niña events; in Fig. 3b, the associated EVOI estimate is \$12.00 ha^{-1}. The case of PT/tenants is less clear for the representative case shown in Fig. 2: farmers are diversified and would use forecasts offensively (more soy–wheat, less soy) to take advantage of expected favorable conditions in El Niño events but would also use forecasts defensively (more soy, less soy–wheat) in Niña and neutral events. Over the parameter space considered (Fig. 4b), however, EVOI increases with risk aversion, suggesting that PT/tenant forecast use is primarily defensive; the relevant EVOI estimate in Fig. 4b is \$15.00 ha^{-1}. Land owners also use forecasts offensively, to take advantage of favorable conditions, and shift land into riskier but more profitable soy–wheat CAs during El Niño events. The relevant EVOI estimates are in Fig. 3a for EU, \$1.80 ha^{-1} and in Fig. 4a for PT, \$1.80 ha^{-1}. Our estimates for tenants are consistent with those for the region reported in Messina et al. (1999), Royce et al. (2001), Jones et al. (2000) and Letson et al. (2005).

To discuss the sensitivity of EVOI with respect to changes in objective function parameters, we begin by noting that the far right point in the PT maximization diagrams (Fig. 4a, b), corresponding to $\alpha = 1$, is identical to the far left point, corresponding to $r = 0$, in the EU maximization diagrams (Fig. 3a, b). The cases of $\alpha = \lambda = 1$ and $r = 0$ are identical and equivalent to expected profit maximization.

In both cases of EU maximization (Fig. 3a, b), the EVOI rises, with few exceptions, with level of constant relative risk aversion, regardless of the level of initial

[3]The certainty equivalent is the amount of money the decision maker is willing to exchange for a given risky prospect. It is defined as the inverse of the utility function evaluated at the probability weighted average of the utilities. Since we evaluate the outcomes of farm decisions in terms of the final wealth they generate for the farmer, we compare the effect of different decisions (with or without climate information) in terms of wealth certainty equivalents. Formally, let $U[E(W)]$ be the level of utility associated with an expected level $\mathrm{E}(W)$ of a lottery promising different levels of wealth W. Let $E[U(W)]$ be the expected utility from the same lottery. The certainty equivalent of a wealth lottery is the level of wealth W_{CE} such that $U(W_{CE}) = E[U(W)]$ or $W_{CE} = U^{-1}\{E[U(W)]\}$.

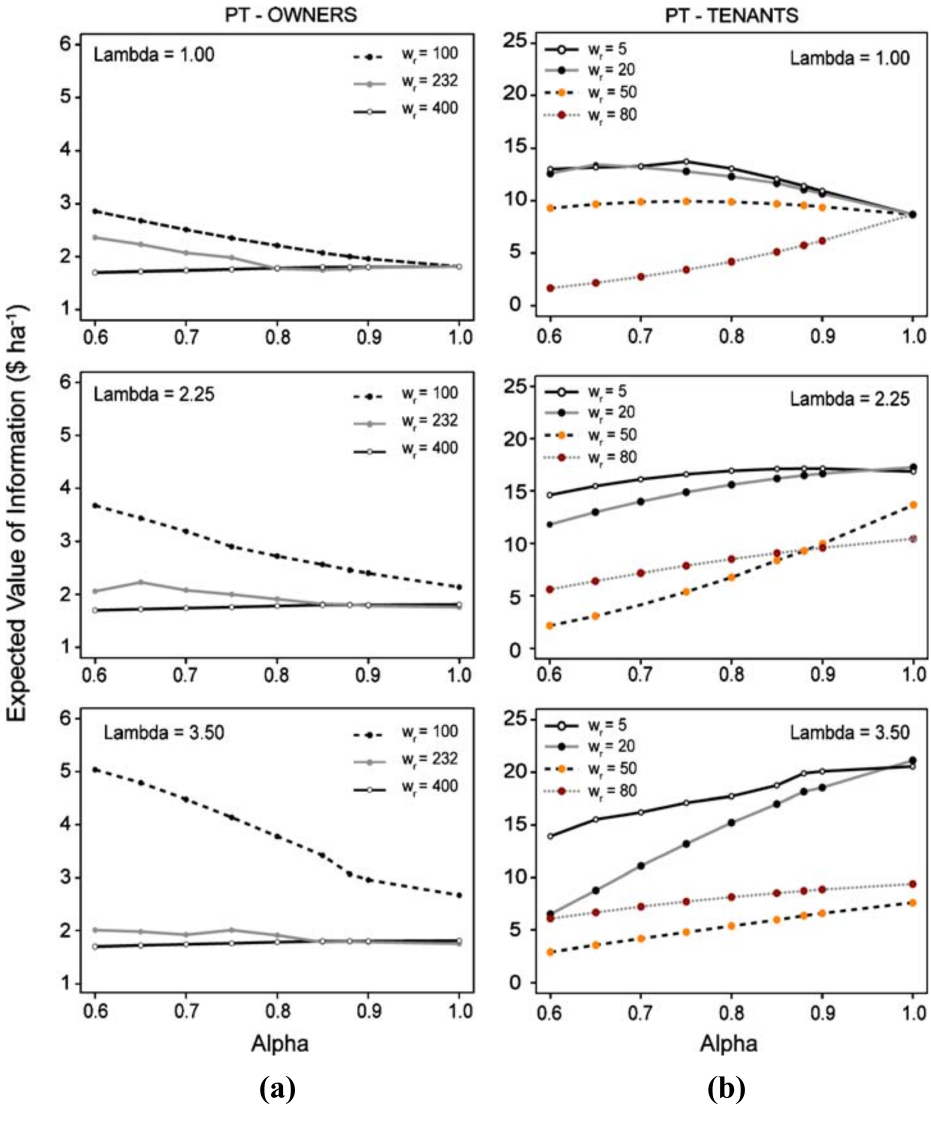


Fig. 4 EVOI in \$ ha^{-1} certainty equivalent units for PT and **a** land owners and **b** land tenants. For land owners (**a**), we show the representative cases for $w_{\text{ref}} = \{100, 232, 400\}$ and $\lambda = \{1, 2.25, 3.5\}$. For land tenants (**b**), we show representative cases for $w_{\text{ref}} = \{5, 20, 50, 80\}$ and $\lambda = \{1, 2.25, 3.5\}$

wealth we assume, a finding consistent with other published results (e.g., Messina et al. 1999; Letson et al. 2005). In the case of owner management (Fig. 3a), EVOI increases nearly monotonically with r. In the case of tenant management (Fig. 3b), the EVOI-risk aversion relationship is less consistent, with the EVOI increasing initially but then remaining constant for $r \geq 2$, since diversified land allocations tend to reduce effective climate forecast responses. The effect of different levels of initial wealth w_0 is minor throughout most of the range of risk preference and especially for tenant management. EVOI varies primarily because of the way in which similar sets of CAs are evaluated by an objective function with different parameter settings.

For PT owners and tenants (Fig. 4a, b), increases in the loss aversion parameter λ and decreases in the reference wealth parameter w_{ref} have the same effect that decreases in w_0 and increases in r had for the case of EU maximization. In essence, increases in loss aversion or decreases in reference wealth act to increase EVOI: higher λ values do so by weighing losses more heavily, losses that forecast use can help avoid, while lower w_{ref} values discourage risk hedging behavior, and increase decision flexibility, since lower income expectations imply a lower probability of losses (Podestá et al. 2008). On the other hand, α (where smaller values indicate more risk aversion in the domain of gains), exerts a more complex influence on EVOI. For tenants, the lack of crop rotations enables a higher EVOI but also allows a greater opportunity for rising λ or falling α to induce risk hedging. Since hedging behavior restricts the decision space, both forecast responses and EVOI diminish. For owners, greater risk concern (i.e., higher λ, lower w_{ref} and α) implies higher EVOI, as in the case of EU/owners.

6 Discussion

Similar land allocations and incomes, once evaluated by EU and PT, imply markedly different EVOI estimates. Since decision objectives exert more influence on EVOI in our case study, while land tenure does so for land allocations and income levels, one implication is that our findings in general are robust over the range of parameters we consider. The contrast between land allocations and incomes vs. EVOI as economic outcomes is a crucial one, since land allocations and incomes are observable, while EVOI is not. Even if engaging in similar CAs and earning similar incomes, the EU and PT farmers may have quite different EVOI perceptions. The implication is that decision goals are of fundamental importance, since observing or simulating land allocations and incomes alone is not enough to tell us EVOI.

Not surprisingly, the more descriptive PT model complicates efforts to prescribe advice. Because of the complex way in which PT evaluates risk, farm strategies (and policy interventions) are not as obvious (Fig. 4a, b). Risk aversion in the EU model is summarized by the parameter r, which suggests that small scale farmers might be targeted for technical assistance and use of complementary risk management tools. However, in a PT decision environment risk aversion may result from low income expectations (lower w_{ref}), curvature of the value function ($\alpha < 1$) and/or loss aversion ($\lambda > 1$), each of which may call for different actions. As experimental evidence continues to mount in support of PT as a descriptive model (e.g., Camerer 2000), those who facilitate agro-technology transfer (e.g., cooperative extension) may have more success if they address loss aversion and relative wealth changes, as they appear basic to forecast adoption decisions. One way to do so is to inform decision makers about their implicit decision processes. Changing user goals is not a legitimate policy objective but raising agricultural productivity and incomes traditionally has been.

Our EVOI estimates may contribute to comparisons with payoffs from alternative agricultural innovations, but such comparisons also require expenditure estimates, which are themselves laborious and beyond our scope. At least two studies have made such comparisons. Adams et al. (2003) estimate a 30% rate of return to

Mexican agriculture. Similarly, Sassone and Weiher (1999) report that investments in the TOGA ocean observing program have a rate of return of 13% to 26% for US agriculture. By comparison, rates of return to other agricultural innovations appear higher. While studies using different methods and coverage give a range of estimates, the consensus is that the payoff from the government's investment in agricultural research has been high (Fuglie and Heisey 2007). A recent review of 35 studies published over 1965–2005, reports a median rate of return of 45% (Huffman and Evenson 2006).

7 Conclusions

People perceive events and outcomes in ways that differ from standard assumptions in economics (McFadden 1999). Our results show in a non-laboratory decision context that psychologically plausible deviations from EU maximization may lead to differences in EVOI estimates. Climate variability and change must be assessed within the specific decision contexts in which they occur. Such a finding is consistent with traditional social science research on technology diffusion in agriculture. In his seminal (and Nobel prize winning) *Transforming Traditional Agriculture*, Schultz argues that agricultural technology is highly "location specific" and must be adapted to the cultural and resource conditions where applied (Schultz 1964). We concur with Meinke et al. (2006) who notes that the traditional reductionist approach to science has a tendency to create islands of knowledge in a sea of ignorance, with a stronger focus on analysis of scientific inputs rather than synthesis of socially relevant outcomes. The reductionist approach may be the principal reason why intended end users of climate information generally fail to embrace what climate science has to offer.

To make climate forecasts more useful, both the effects of land tenure and cognitive decision processes warrant careful attention, since the two may have conflicting policy implications. We have argued elsewhere that effective use of climate forecasts requires well-functioning forecast generation, communication and application (Podestá et al. 2002; see also Pielke et al. 2000). Appreciating the role of each of the three components in conditioning EVOI can help identify priority needs in these three parallel processes. For example, slow rates of climate-forecast adoption (i.e., strict adherence to crop rotations), despite the EVOI estimates reported here and elsewhere may be a rational response to concerns about long term soil degradation from soybean monocropping. Or would-be users' reluctance may simply reflect a benefit of forecast use that does not compensate for the more complicated adaptive management it requires. If so, public investments to raise EVOI, by increasing forecast skill, may be justified. On the other hand, if risk preferences are as complex as portrayed by PT that might also deter forecast adoption and would call for different public investments, e.g., improving forecast comprehension (communication) or learning how to use climate forecasts in coordination with more traditional risk management tools, e.g., crop insurance (application).

While we have assumed perfect ENSO phase forecasts here as a convenient fiction, we do relax this assumption elsewhere in our work. Following Kite-Powell and Solow (1994), it is fairly simple to include uncertainty in the occurrence of an ENSO phase. As climate forecasting systems improve globally, so will quantitative predictions of expected regional climate conditions (one determinant of EVOI). Our simulation framework can incorporate this evolution through the development of procedures to generate sets of synthetic weather series consistent with forecasted scenarios (e.g., a wet spring).

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Appendix

A Farm model decision variables and objectives, cost calculations and data sources

To select optimal actions, we use a decision model that is a mathematical formulation of the outcomes associated with all combinations of a set of actions and a set of possible states of the world (e.g., Hardaker et al. 2004). The mathematical statement of our model will not be repeated here, as it is quite similar to the decision model in Appendix C in Letson et al. (2005), though here without a labor constraint. Below we describe our decision variables, objective functions, assumptions and data sources.

B Decision variables

Each possible action is given by the vector $\vec{x} = (x_1, \ldots, x_{64})$ that includes the percentage of area of a hypothetical farm allocated to each of the 64 CAs (Tables 1 and 2). For example, a given action $\vec{x}$ may involve an allocation of 25% of the area to CA x_8 (a specific management for maize), 35% to CA x_{27} (a specific wheat–soybean CA) and 40% to CA x_{56} (a specific soybean CA). Values for other components of $\vec{x}$ are 0 (i.e., no land is allocated to them).

C Objective functions

Expected utility optimization The *EU* of a gamble (Eq. 2) may be expressed as a linear combination of the utility of the final wealth w_i outcomes and their associated probabilities:

$$E[U(\vec{x})] = \sum_{i=1}^{n} p_i u[w_i(\vec{x})] \tag{7}$$

where p_i is the probability of a given climate for production cycle i. We assume the climates for all production cycles in the historical record have the same probability (i.e., ignoring any trends in climate), i.e., $p_i = 1/n$, where n is 72 cycles. The optimization selects $\vec{x}^* = \left(x_1^*, \ldots, x_{64}^*\right)$, the proportion of land allocated to each CA that maximizes *EU*.

Prospect theory value optimization Kahneman and Tversky (1979) propose a value function, $v(\cdot)$, that assigns a value to an outcome (Fig. 1). The value function passes through the reference point, w_{ref}, and is s-shaped. Its curvature is given by the parameter $0 \le \alpha \le 1$ (Eq. 5). As its asymmetry implies, given the same variation in absolute value, there is a bigger impact of losses than of gains, where $\lambda > 1$ reflects increasing loss aversion (Eq. 6).

One plausible reference wealth value is the income w_{rent} a farmer could get with minimal effort (e.g., renting his/her land) added to the decision maker's initial wealth, w_0: $w_{\text{ref}} = w_0 + w_{\text{rent}}$. The change in wealth then becomes: $\Delta w_i = \pi_i - w_{\text{rent}}$. The total value function for PT (Eq. 4) then can be rewritten as:

$$V(\vec{x}) = \sum_{i=1}^{n} p_i v[\Delta w_i(\vec{x})]. \tag{8}$$

The optimization selects $\vec{x}^* = \left(x_1^*, \ldots, x_{64}^*\right)$, the proportion of land allocated to each CA that maximizes the value of $V(\cdot)$.

Optimizing the value function with the GAMS software (Gill et al. 2000) was problematic because of the discontinuity of function $h(\cdot)$ (defined in Eq. 6) at $\Delta w_i = 0$ (where the PT 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 $h(\cdot)$:

$$\tilde{h}(x) = 1/2[1 - \lambda + (1 + \lambda)\tan h(\rho x)] \tag{9}$$

where ρ is an arbitrary parameter such that $\rho > 1$; large values of ρ (we used $\rho = 10$) reproduce the function more closely. More information about and justification for this approximation can be found in Podestá et al. (2008).

D Cost calculations and data sources

We computed net economic returns per hectare π_{ij} for year i and CA j as the difference between income and costs:

$$\pi_{ij} = Y_{ij}P_j - (F_j + V_{ij} + S_i + T_i). \tag{10}$$

Gross incomes per hectare $Y_{ij}P_j$ were the product of simulated yield for a year and CA (Y_{ij}) and a constant output price for each crop (P_j). Assumed output prices were in constant US dollars equivalent to 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 US \$78.9, \$166.0, and \$112.0 ton^{-1} for maize, soybean and wheat, respectively. Because some costs applied only to owners or to tenants, we calculated the economic returns for each separately. Four different kinds of costs were involved in the computation of net returns.

Fixed costs F_j for CA j are independent of yield. For land owners, fixed costs included: (a) farmer's salary, health insurance and a fixed fiscal contribution. For land tenants, fixed costs also included (b) land rental (assumed to be \$232.5 ha^{-1}, equal to the value of 1.4 tons of soybean) and (c) management costs (\$12 ha^{-1}).

Variable costs V_{ij} are a function of yield in year i for CA j. These include: (a) input costs (e.g., fertilizer, seed, field labors), (b) harvesting costs, estimated as 8% of gross income ($Y_{ij}P_j$), (c) transportation costs (\$10 ton^{-1}), (d) sales tax and commissions, estimated as 8% of gross income. Variable costs were the same for land owners and tenants.

Structural costs S_i are applicable only to land owners 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 CA 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 hectare after subtracting variable costs ($Y_{ij}P_j - V_{ij}$). Because structural costs are incurred even if part of the farm is idle, we assume that the entire 600-ha area of the hypothetical farm is cultivated.

Income tax T_i applies equally to land owners and tenants and was computed as:

$$T = \begin{cases} b\,(\bar{\pi} - a) + c & if\ \bar{\pi} \geq a \\ c & if\ \bar{\pi} < a \end{cases} \tag{11}$$

where a is a threshold income above which farmers pay an average tax rate $b = 0.32$. Below a, farmers pay a minimum tax c assumed to be \$59.33 ha^{-1}. To simplify calculations, an average annual income $\bar{\pi}$ of \$177.5 ha^{-1} (\$57.6 ha^{-1}) was assumed for owners (tenants). While our assumed average income differs from our simulations in Section 5.2, as a lump sum that deviation influences neither our optimal land allocations nor our EVOI estimates.

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