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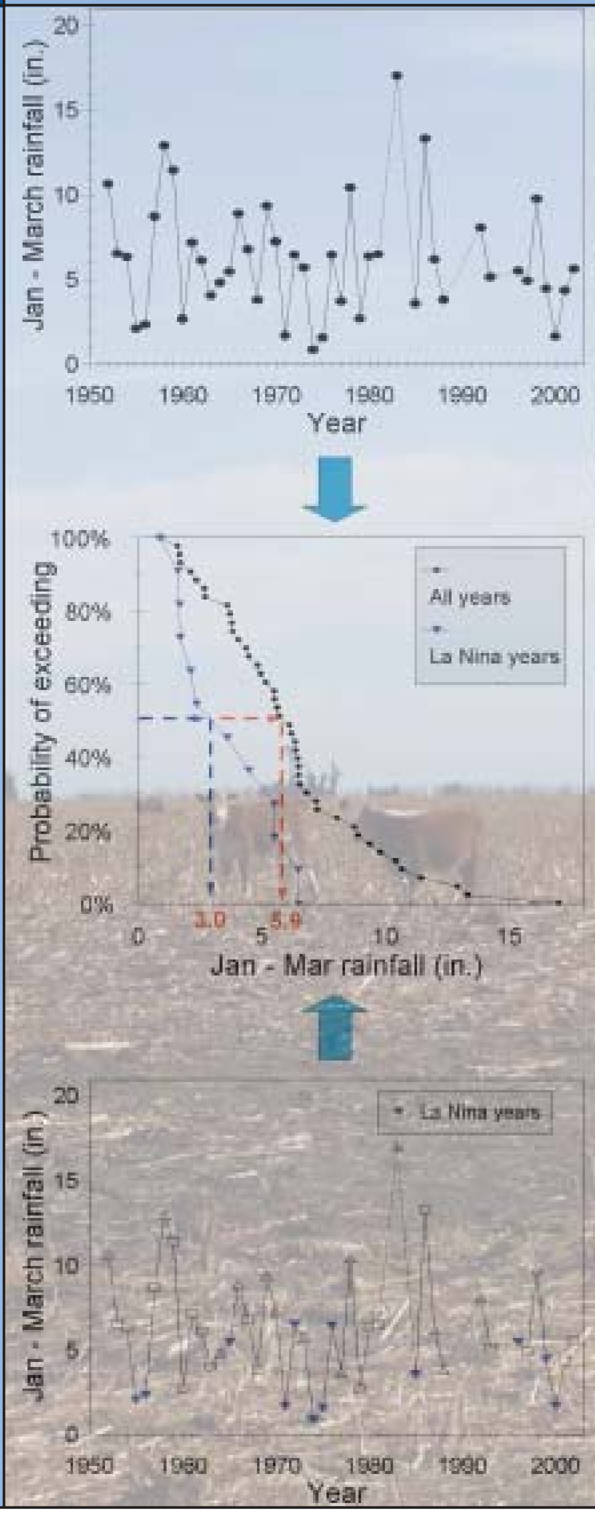

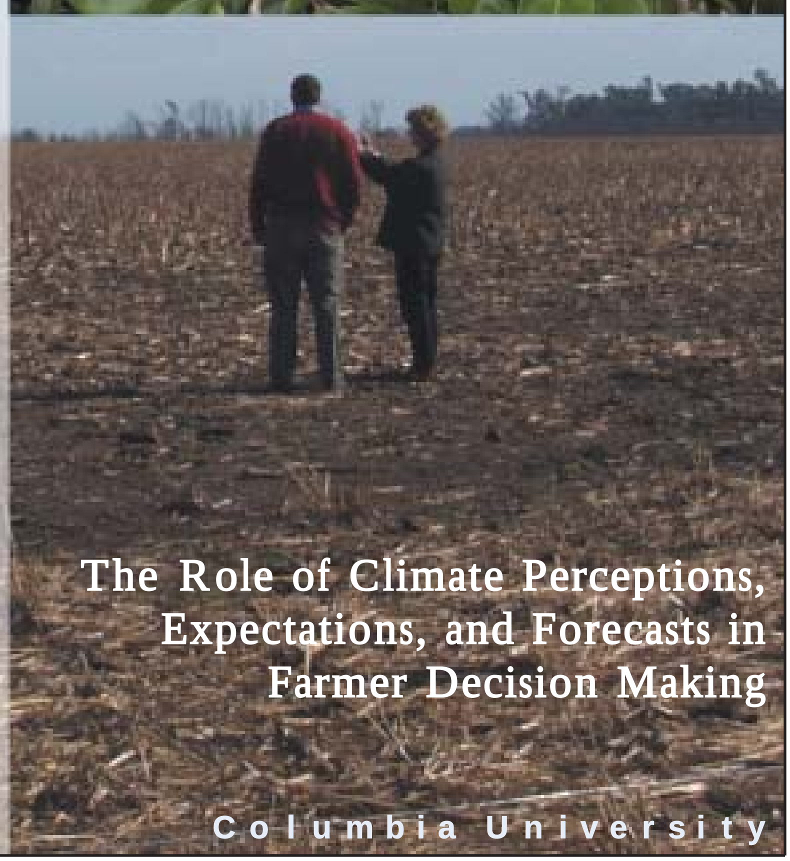

The Role of Climate Perceptions, Expectations, and Forecasts in Farmer Decision Making

Columbia University

About the front cover: Upper right: Lychee grown in Miami-Dade County Florida.
Bottom: Project investigator E. Weber talks with an Argentine farmer during winter fallow (photo by J. Hansen).
Left: Rainfall time series and corresponding probability graphs from a forecast presentation module.

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The Role of Climate Perceptions, Expectations, and Forecasts in Farmer Decision Making

THE ARGENTINE PAMPAS AND SOUTH FLORIDA

Final Report of an IRI Seed Grant Project

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I. Executive Summary

Skillful seasonal climate forecasts reduce climatic uncertainty, but reduce livelihood risk to farmers only if the uncertainty associated with the forecast is accurately communicated and understood, and integrated into the decision process. Of the various determinants of application of seasonal forecast and resulting benefit to farmers, those related to content, communication and understanding are most under the influence of the forecast provider. Improved understanding of how target decision makers perceive and apply probabilistic climate information can inform the design of climate forecast information products and presentation protocols.

This project sought to extend previous research efforts with both a "front end" – mental models that influence climatic expectations and forecast applications – and a "back end" – the decision processes in response to climate expectations derived from farmers' mental models and externally-provided information. Research in this report was motivated by three lines of social science inquiry: (a) the importance of subjective perception of risk, (b) differences in the impact of small-probability events when information about them is learned by personal experience over time as opposed to being provided as a statistical summary, and (c) the role of both material and non-material (including cognitive and affective) goals and processes in risky decision making. Specific objectives of the research were to:

- Characterize mental models of climate expectations and variability and their influence on seasonal forecast use.
- Develop and test forecast presentation materials, with focus on fit to farmers' mental models.
- Identify climate risks and responses that farmers and advisors consider.
- Plan and pilot test a farmer climate risk communication and decision analysis component for a larger NSF Biocomplexity in the Environment project proposal.

We addressed these objectives through review of literature; focus groups, questionnaires and a decision experiment with Argentine farmers; mental model interviews with climate scientists and Florida farmers; and questionnaire-based evaluation of prototype forecast presentation modules. The project originally targeted a farmer association, AACREA (Asociación Argentina de Consorcios Regionales de Experimentación Agrícola), in the Pampas region of Argentina. Circumstances later also favored working with farmers in South Florida through the Florida Agricultural Extension Service.

Insights from Literature

Seasonal forecast products targeting farmers must address requirements for location specificity, temporal specificity, accuracy, and information about impacts and management implications within the agricultural systems. Modest but well-characterized skill may be more valuable than high but uncharacterized skill. Understanding the probabilistic nature of a forecast is crucial for farmers to make appropriate use of it. Although some have argued that farmers are unable to understand probabilistic forecasts or incorporate them into their decisions, other evidence shows that farmers across cultures and socio-economic statuses do understand the probabilistic nature of climate variability and seasonal forecasts, and its implications for livelihood decisions.

Recent research suggests that information from personal experience and information from external description can yield drastically different choice behavior under conditions of risk or uncertainty. The difference in how people process information that is either externally provided (i.e., is description-based) or derived from personal experience (i.e., is experience-based) has important implications for the communication of climate information to farmers. On the positive side, because of their extensive personal exposure to climate variability by personal experience acquired over successive years and its effect on production and income, farmers may be better able to process probabilistic climate information than students or professionals who lack such personal experience, especially if such information is provided in a format conducive to integration into their personal knowledge base. Much of the research on shortcomings in probabilistic reasoning and risky decision making may have been conducted with people who lack personal experience with risk and uncertainty. On the negative side, the mismatch in format and substance between farmers' personal experience with climate from which naï ve forecasts are derived and professional, description-based climate forecasts is likely to present a difficult challenge. We hypothesize that interventions that help farmers map description-based forecast information onto their own knowledge base derived from personal experience will increase the utility of the externally-provided information.

Previous research reveals several difficulties that farmers have with interpreting the categorical climate forecast formats that have become standard. This project examined the potential of continuous probability forecast formats that have not received much research attention.

Results Argentina

Research for this project included several focus groups, a farm decision exercise comparing production decisions made with and without availability of a climate forecast, several questionnaires eliciting farmers' perception of climate, farm decisions and practices, socioeconomic background, and personality characteristics.

Personality Characteristics

One questionnaire assessed personality characteristics known to influence decision-making. These include two regulatory states – *assessment* orientation which values analysis, and *locomotion* orientation which values action –and two regulatory foci – *promotion* which concentrates on promoting ideal states, and *prevention* which concentrates on preventing deviations from norms. Individuals with a *promotion* focus use "approach means" while individuals with a *prevention* focus use "avoidance means" to attain goals. Participating farmers were, on average, more *assessment oriented* than *locomotion oriented*. Farmers scored higher on the *promotion-focus* scale than on the *prevention-focus* scale. This suggests that this group of farmers is more likely to prefer rational and safekeeping modes of thinking rather than to think and act in emotional and experimental modes.

Decision Goals

Farmers and technical advisors differed significantly in their expressed decision goals. Farmers had a wider range of decision goals than technical advisors. Farmers saw maximization of gross receipts and minimization of input costs as important but separate, goals. To minimize decision regret and the impact of political uncertainty, farmers were more likely than advisors to seek a satisfactory rather than an optimal decision. Technical advisors placed more emphasis on maximizing profits (combining the two goals of maximization of receipts and minimization of costs), and on minimizing climate risk. Knowing about expected La Niña conditions did not appear to influence the goals underlying crop selection and crop management production decisions.

Personality, Affect, and Goals

Farmers perceived climate as a greater risk after they had been shown a climate forecast for following spring. As the concern about climatic risk increased, concern about political uncertainty diminished, suggesting a "finite pool of worry."

Farmers' perception of past rainfall amounts showed some evidence of wishful thinking. Expressed belief that more precipitation was seen as beneficial or detrimental was associated with the amount of December rainfall that farmers recalled over the past 10 years.

There was a clear relationship between personality and decision goals. *Assessment-oriented* farmers focused more on the goal of maximizing farm profitability than on subgoals such as maximizing crop prices and minimizing political risks. Farmers who were more *prevention focused* ranked individual subgoals such as maximizing yields higher than the making the best possible decision. Regret minimization played a larger role for *prevention-focused* than for *promotion-focused* personalities.

Farmers' decision goals were related to their perceptions of long-term climate change. Farmers who focused on optimizing decisions were more likely than farmers who focused on satisficing, to believe that climate in their region has changed over the past several years. Personality and with perceptions of climate are related. The number of flooding events that farmers indicated affected them was greater for *prevention-focused* than for *promotion-focused* farmers.

Determinants of Farming Decisions

Farm characteristics, personality, climate perceptions, and decision goals influenced farm decisions in several ways. Farmers who had been in farming or members of AACREA longer, or who were *prevention oriented* were less likely to purchase crop insurance. Farmers with higher incomes were more likely to use insurance.

Obtaining a La Niña forecast did not lead to major differences in crop selection or crop management decisions. Most farmers stayed with the crop-rotation cycle recommended by AACREA. There was no relationship between demographic or personality characteristics adjustment of decisions in response to a La Niña forecast. Farm size and the degree of *prevention* vs. *promotion orientation* did have some influence on some farm decisions. Farm size played a role in selection of planting dates independent of climate forecast information. Risk perception led to action and changes in perceived risk led to changes in production decisions.

Results Florida

We developed two forecast presentation modules which (a) provided climate information for target locations familiar to farmers, (b) presented and explained continuous probability distributions of winter rainfall in Homestead, Florida, (c) related the true historic recorded time series of weather events to personal experience by starting with the time series data, sorting them by climate events, converting those to relative frequencies, and then to probability of exceedance graphs, (e) expressed a seasonal forecast as a shifted probability distribution, and (f) provided explanation and repetition to ensure understanding. The first module we developed and tested presents shifted distributions associated with ENSO phase. The second module, not yet tested with farmers, presents and explains the error (or deviation) distribution of a continuous climate forecast.

In South Florida, we interviewed a convenience sample of 15 farmers and 1 technical advisor, and evaluated a forecast presentation module with a subset of 10 of the same 15 farmers and 3 employees of one farmer. The 15 farms covered represent about 1% of the farms but 11% of Miami-Dade County's farmland. The sample included fruit, vegetable and foliage (ornamental and herb) growers. In addition, we interviewed 8 climate scientists at the International Research Institute for Climate Prediction, allowing us to compare expert and lay concepts of climate variability.

Perceptions of Climate Variability

Because farmers are more exposed to the impacts of climate variability than the general public we hypothesized that they might have a better understanding of it. Yet most farmers in our sample admitted they knew little about the causes of climate variability. The farmers tended to focus on day-to-day weather events, even when specifically asked about seasonal climate variations. When asked about causal factors, they often mentioned El Niño and La Niña, and understood that those occur in the tropical Pacific Ocean and have an impact around the globe, but tended to look for explanations for local climate variations closer to home. Only three farmers cited randomness or natural variability. In contrast, the climate experts placed more emphasis on global-scale influences, and showed more interest in relationship between primary and secondary causal factors, whereas farmers were more interested in relationship between secondary factors and impacts. Some of the differences between farmers' and scientists' responses may reflect the lack of geographic specificity in the interviews with the climate scientists.

Florida farmers' recollections of past climate variability seem to involve climatic events and time scales that affect them most, and that they are accustomed to managing through tactical departures from routine practices. Low temperature extremes, heavy rainfall, and hurricanes stand out in farmers' memory of past climate variations. None mentioned drought or high temperature extremes, presumably because they can protect their crops against heat and drought.

We found some inconsistencies between farmers' memory of years with extremely cold temperatures and available local meteorological data. Since 1970, farmers identified more climatic extremes (primarily freezes) than the data indicate, with a subset identifying every year since 1992 as extreme. Roughly two-thirds of the farmers saw some periodic pattern in climate variability, with freezes or hurricanes occurring every eight to ten years. Some mentioned a winter cooling trend, while others mentioned an overall warming trend. Only one perceived a trend toward more extreme conditions. Several farmers saw a connection between hurricanes and freezes.

Climate-Related Terminology

As other studies have shown, the distinction between *weather* and *climate* is a source of confusion. Ambiguities and inconsistencies associated with the term, *climate variability*, relate to both temporal and spatial scale. For example, one farmer defined climate variability temperature fluctuations on a time scale of one month, while others defined it as fluctuation over several decades. Few farmers equated climate variability with interannual variability, as climate scientists do. Other farmers interpreted *climate variability* as variations in space. In general, farmers were more aware of El Niño than La Niña. Although most regarded El Niño and La Niña as opposites, some saw El Niño as a milder version of La Niña, or vice versa.

Use and Value of Forecast Information

Most farmers saw short-term forecasts as important for decisions but initially saw little relevance for seasonal forecasts. For some, the perceived relevance of seasonal forecasts increased during the interview. For example, one who was initially not interested in seasonal forecasts later considered that they could be a basis for purchasing fabric for freeze protection, or for the timing of greenhouse construction. The type of commodity produced on the farm influenced the perceived relevance of seasonal forecasts. Those growing tree crops saw fewer ways to respond to forecasts than vegetable, herb, and ornamental growers, who have the flexibility to change crops with a lead-time of a few months.

The hesitance to use long-term climate forecast apparent in the interviews was not apparent in answers to questions asked before and after the forecast module. On the forecast module assessment questionnaire, two-thirds of the farmers indicated that climate influences their farming decisions. Most of these decisions relate more to winter temperatures than winter rainfall. When asked specifically about winter precipitation forecasts, anticipation of wetter conditions would influence decisions for more farmers than anticipation of drier conditions. The forecast module, discussed in the next section, increased the number of farmers willing to modify decisions in response to forecasts under both El Niño and La Niña conditions. Results from the questionnaires suggest that many farmers do make climate-sensitive decisions. The apparent contradiction may suggest that the respondents misinterpreted *climate* as *weather* when asked about it in the questionnaires.

Some farmers expressed optimism that both short-term and long-term forecasts would eventually improve. The roughly one-third who expressed skepticism about the prospects of seasonal prediction tended to show a deterministic expectation of forecasts; seasonal prediction to them implies understanding all causal factors well enough to predict all of the variability at a seasonal time scale.

Forecast Presentation Module

The forecast presentation tutorial module met with very positive response. Most farmers agreed that it improved their understanding of the influence of El Niño and La Niña. They saw the degree of difficulty as appropriate. Most were interested in more tutorials, particularly in some addressing predictions of temperature extremes or hurricanes.

Respondents' answers to questions designed to actively engage farmers' thinking also gave an indication of their comprehension of module components. Farmers generally answered these questions correctly. They had no problem identifying the driest and wettest years in a time series. Introducing probability of exceedance graphs by first showing time series of winter precipitation was quite successful. A few farmers needed some explanation of percentiles, but then answered questions related to percentiles correctly.

Judgments of the utility of forecast information for management decisions were negatively associated with age, years in farming and education level. Farm type and size were not associated with judged utility, contradicting statements during the interviews indicating that tree farmers saw fewer ways to respond to a climate forecast than vegetable and foliage growers did.

Conclusions

This study provided multiple insights into determinants of use of climate information related to perception and communication, and some evidence that improved presentation may overcome some of the barriers and enhance utility. Even though we have a wealth of results, as summarized in the remainder of this section, we see several avenues for extending results and addressing limitations of the project's scope and study design.

Mental model interviews and influence diagrams proved useful for obtaining unbiased information about farmers' perceptions and understanding of climate variability, and facilitated comparisons between providers and users of climate forecasts. We anticipate that mental model results can inform the design of climate application educational materials, and more efficient survey instruments for future studies.

Inconsistent use of terminology between climate forecasters and users – in particular the distinction between weather vs. climate time scales, and variability in time vs. space – creates a barrier to understanding and use of forecasts. The tendency to reduce climate forecasts – a statistical abstraction – to weather events that are more in line with personal experience, can be used to advantage in the design of forecast information products. Our forecast presentation modules enhanced farmer understanding and the perceived value of climate information, at least in part because they progressed from the concrete (time series of weather events) to the abstract (probability of exceedance graphs). Based on farmers' response, we expect that other interactive modules and educational materials will generally enhance understanding and use of seasonal forecast information.

We found evidence of challenges imposed by cognitive limitations. Farmers' memory of past climate may be distorted in systematic ways shaped by wishful thinking, personality characteristics and preexisting beliefs. These distortions may need to be remedied before farmers' experience can be used to enhance their understanding of the probabilistic nature of forecasts. Farmers' tendency to compartmentalize overarching goals (e.g., maximizing farm profits) into sub-goals (e.g., maximizing income vs. minimizing costs) is understandable, and potentially beneficial if competing demands of sub-goals can be kept in mind simultaneously (doubtful given cognitive limitations). Decision aids might help farmers with this task. We found evidence that regret avoidance influences the decisions of farmers but not their advisors. We also found evidence for single-worry bias and (in actual farm management records) single-action bias.

Our results have implications for the types of farmers who are most likely to benefit from improved forecasts. The heteorogeneity of farmers with respect to age, education, personality, characteristics of their production systems, resulting perceptions, beliefs and actions related to climate risk suggests a need for a variety of forecast information products and other forms of decision support tailored to the characteristics of particular sub-groups of decision makers.

Results from this study have contributed interesting additional research hypotheses, and have influenced the development of several research larger proposals.

II. Introduction

Farmers must contend with risk regularly, and employ a range of strategies to manage risk from multiple sources, including climate. By definition, skillful seasonal climate forecasts represent a decrease of climatic uncertainty. This however translates into a reduction of production and price risk only if the uncertainty associated with the forecast is assessed, communicated, accurately understood, and successfully integrated into the decision process.

Research has shed light on the determinants of benefit from application of seasonal climate forecasts to farm decision making, and has highlighted a number of constraints to beneficial application. The inherent probabilistic nature of seasonal climate forecasts presents particular challenges. Underestimating (or understating) the accuracy of a forecast system leads to lost opportunity to prepare for adverse conditions and take advantage of favorable conditions. Overestimating (or overstating) the accuracy of a forecast system can lead to excessive responses that are inconsistent with decision makers' risk tolerance, and can damage the credibility of the forecast provider. Methods of communicating probabilistic seasonal climate forecasts in ways that improve their comprehension and usage are an important area of recent research (Fischhoff, 1994; Nicholls and Kestin, 1998; Krantz and Phillips, 2000). Better understanding of how target decision makers perceive and communicate probabilistic information is needed to design climate forecast information products and presentation protocols that move forecast providers, end-users such as farmers, and various intermediaries toward a common language, and overcome the inherent difficulties of understanding and wisely applying probabilistic forecast information.

This project sought to complement and extend previous research efforts by providing it with both a "front end" and a "back end." New "front end" information refers to mental models about climate and weather held by potential users of forecasts, which characterize the factors that influence their expectations about seasonal climate – both expectations of "normal" climate and unusual climate events. Stern and Easterling argued that climate forecast users will likely understand new information better and accept it more fully if they can interpret it in a causal model of climate variability that they understand and with which they agree (Stern and Easterling 1999b). The reported research provides a methodology for identifying farmers' causal theories ("mental models") of climate variability that can be visualized in the form of influence diagrams. We provide examples of several such mental models, elicited in individual interviews with farmers in Florida, and compare those with an expert mental model that represents the composite of answers from mental model interviews conducted with IRI climate researchers. We also explore effective communication of probabilistic climate information (historic and forecast) with farmers and their advisors in the Pampas region of Argentina and in South Florida. New "back end" information refers to the decision processes; to which climate expectations derived from farmers' own mental models and externally-provided forecasts are inputs. New information will only be sought out or used if it allows decision makers to achieve one or more of their decision objectives. Knowledge about the nature of those objectives (and possible individual differences in objectives as the function of demographics or personality) is therefore important.

Theoretical Contributions

Research in this report was motivated by three lines of social science inquiry: (1) the importance of subjective perception of variability, risk, or change, (2) differences in the impact of small probability events when information about them is learned by personal experience over time as opposed to being provided as a statistical summary, and (3) the role of material and non-material and, in particular, affective goals and processes in risky decision making. The described work attempted (a) to apply recent basic social science insights in these areas to an important societal problem, namely the provision of climate forecast information in ways that make them more user-friendly, in the sense of providing information that decision makers can integrate into their existing decision representation and decision processes and (b) to extend basic social science research by testing theoretical hypotheses in field settings that involve experienced decision makers and real stakes, thus satisfying the methodological requirements of experimental economics (Hertwig 2001).

Importance of Subjective Perception of Risk and Uncertainty

Experimental economics and behavioral decision research have made great strides in recent years towards their goal of predicting behavior, especially in those cases where it deviates from the predictions of conventional economic rationality. Many, if not most of these advances assign a causal role to decision makers' subjective perception of the decision situation, including their construal of the uncertainties and risks as a function of reference points, aspiration levels, and other personal circumstances

(Loewenstein 2001a; Weber 2003 a, in press; Weber 2003 b, in press). Economics is virtually alone among the social sciences in the assumption that risk or uncertainty is a stable, objective, inherent characteristic of decisions that will be perceived veridically, and thus identically (or at least similarly) by all individuals. In contrast, the pioneering work of Douglas and Wildavsky (1982) in anthropology hypothesized that risk perception is a collective phenomenon of social construction, by which members of a given culture attend to risks that threaten their interests and way of life (summarized in (Weber 2001b). Palmer found support for this socio-cultural theory of risk perception in the form of systematic differences in the judgments of financial and health/safety risks posed by a set of activities among respondents who came from subcultures with different worldviews (hierarchical, individualist, egalitarian) in Southern California (Palmer 1996). Managerial decision research has shown that aspiration levels will affect the risk perceptions and thus choices of managers (March 1987) and firms (Cyert 1963). Psychology has also contributed to the literature on subjective risk perception. Parametric models of perceived risk can account for both individual and group differences (Yates and Stone 1992; Holtgrave and Weber 1993; Bontempo, Bottom et al. 1997; Weber 1997; Brachinger and Weber 1997b). This literature shows that, while individual differences in risk perception exist, group differences are even larger and sufficiently systematic to result in predictable group differences in risk perception as a function of gender, income, and cultural origin. It also shows that many individual or group differences in risky decision making are mediated by differences in risk perception rather than attitudes towards (perceived) risk (Weber and Milliman 1997; Weber and Hsee 1998a; Weber, Hsee et al. 1998b). In other words, most people dislike risk and will take steps to avoid it or minimize it, if possible. However, people differ in the extent to which they try to manage or avoid risk, because they differ in how risky they perceive a given situation. In the context of climate variability and its consequences, lay people's mental models of how variability arises and what it affects can provide a window onto subjective perceptions of this risk.

Evaluating Rare Events from Description or Experience

When people study pharmaceutical drug package inserts, mutual fund brochures, newspaper weather forecasts, or climate forecasts provided by the IRI or other groups, they enjoy convenient descriptions of risky prospects, i.e., they get a statistical summary description of the different values the random variable of interest in the given decision may take. In these cases, people make *decisions from description*. When people decide whether to back up their computer's hard drive, cross a busy street, or invest in a system to irrigate their crops, they typically base their action on their own past experience with such situations. Recent research has shown that *decisions from experience* and decisions from description can yield drastically different choice behavior (Weber, Shafir et al. 2003 d, in press; Hertwig 2003a, in press; Hertwig 2003b, in press). In decisions from description, people overweight the probability of rare events, as described by prospect theory (Kahnemann 1979). In decisions from experience, in contrast, people make choices as if they underweight the probability of rare events. Other differences exist, typically in the direction that decisions and judgments are more in line with prescriptive models. For example, repeated decisions with experienced outcome feedback can eliminate preference reversals (Chu 1990), and direct experience of base rates can strongly improve Bayesian reasoning (Koehler 1996; Hertwig 2001). For instance, doctors use base rates acquired through personal experience in a normative fashion, which is not true for numerically described base rates (Weber 1993).

This research suggests that the two sources of climate forecasts that are now available to farmers may be at odds with each other: intuitive forecasts are based on their direct experience with weather events over many years; expert forecasts come in the format of statistical summary information. Finding ways in which expert forecasts can be expressed or reexpressed in ways that allows farmers to tie this information to their existing, experience-based representations of climate variability should help in making expert climate forecasts more attractive and more useful.

Material and Non-Material (Cognitive and Affective) Goals in Risky Decision Making

The goals and objectives of decision makers affect whether and how climate information (both historical data and forecasts) is being sought out and is used. This in turn has implications for how climate information should be presented and communicated, i.e., has implications for the design of climate forecasts and for climate information use tutorials. Current decisions about which climate information is forecast and about the formats in which forecasts are presented make implicit assumptions about what farmers are trying to achieve and how climate information will thus be used. To examine the validity of these assumptions, they need to be made explicit and put to test. Objectives frequently include more than just the optimization of material outcome dimensions; people also have non-material needs (including social needs or self-image needs) that often find expression in affective goals (Weber 2003, in press). We want to feel good about ourselves and our decisions, even (or especially) when they turn out to have bad outcomes that needs to be explained to others.

Emotions and affective processes have been shown to play an important and often decisive role in many decision situations (Damasio 1994; Loewenstein 2001a) . One important affective reaction, that probably has important learning functions, is the feeling of regret upon obtaining an outcome in a risky choice situation that is worse than the outcome that one would have obtained, had one chosen a different choice or action alternative. Minimization of anticipated decision regret is a goal frequently observed, even if it results in lower material profitability of the chosen path of action (Markman and . 1993). Regret theory (Loomes 1982; Bell 1985) formalizes the following process: Decision makers compare their obtained outcome to the outcome they could have obtained had they taken another action. They experience regret about their action, if their obtained outcome is worse than the counterfactual outcome, and they rejoice if their obtained outcome is better. Paralleling the phenomenon of loss aversion (Kahnemann 1979), where a loss of a given magnitude elicits greater disutility than the utility of a gain of the same magnitude, the negative feeling of regret is stronger than the positive feeling of rejoicement. Since people anticipate those affective experiences, they choose a course of action that minimizes their anticipated post-decisional net regret. Farmers, for example, may be reluctant to take actions based on probabilistic climate forecasts, which may turn out to be "wrong" after the fact. The anticipation of regretting their decision because it makes them look "foolish" (in their own eyes or those of others) or get questioned about their decisions (by a spouse, neighbor, or technical advisor) may make them reluctant to act on probabilistic climate forecasts, even if the expected value of such action can be shown to be positive. The presence of anticipated post-decision regret in farmers' production decision objective function would have ramifications for the way in which climate information ought to be communicated. While the probabilistic nature of climate forecasts needs more emphasis and explanation for all users (probabilistic thinking is a relatively recent evolutionary accomplishment (Hacking 1975), and not something that comes natural to even highly trained professionals (Eddy 1982), the expectation of a forecast that will turn out to be either "correct" or "false" is especially damaging in those situations where the decision maker will experience post-decisional regret after believing that she acted on a "false" forecast. Bounded rationality constraints in the form of limited attention and limited working memory also predict that farmers may focus less on abstract, higher-order material goals such as profit maximization and concentrate instead more on concrete, operational subgoals (such as the maximization of crop yields and crop prices and the minimization of input costs) that contribute to the higher-order goals. Failure to pay concurrent attention to all of these subgoals could result in less than optimal performance on realization of the higher-order goal.

Study Regions

The project was designed to build on past climate applications experience, and capitalize on complementary activities by the University of Miami in collaboration with the University of Buenos Aires, a social and ecological research group (CENTRO) and a farmer association (AACREA) within Argentina. Unforeseen events, including failure to obtain anticipated funds for farmer focus groups, made it difficult to accomplish all project objectives within Argentina. An ongoing relationship with the Southeast Climate Consortium, and the Florida Agricultural Extension Service administered by the University of Florida provided an opportunity to engage farmers and extension personnel in project activities. The opportunity to work within two contrasting locations and cultures added to the richness and robustness of project outcomes.

Argentina

The temperate Pampas region of Argentina is an important contributor to the world supply of wheat and oilseed crops. The region is characterized by extensive rainfed production of field crops under variable annual rainfall (Hall 1992). The El Niño-Southern Oscillation (ENSO) is the major single influence on climate variability on a seasonal time scale in the Pampas (Ropelewski 1987; Ropelewski 1989; Grimm 2000; Montecinos 2000; Podestá, Letson et al. 2000). During November-December, a critical period for important summer crops, El Niño events are associated with increased median precipitation and likelihood of high rainfall extremes, whereas La Niña events show markedly lower median rainfall and a narrower range of anomalies (Podestá, Messina et al. 1999 ; Rusticucci 2002; Vargas 2002). ENSO influences crop yields in the region through its influence on precipitation, temperatures and solar irradiance (Magrin 1998; Podestá, Letson et al. 2000). Maize, soybean and sorghum yields tend to be lower than normal during La Niña events. Sunflower yield shows a weaker and opposite response. Maize is clearly the most responsive of the major field crops to increases in rainfall during El Niño events.

The project sought to capitalize on a network of Argentine farmers through partnership with the Asociación Argentina de Consorcios Regionales de Experimentación Agrícola (AACREA), a non-profit farmers' organization with a strong focus on dissemination of new technologies. Farmers belong to groups (called "CREA groups") of 7-12 producers, each with a technical advisor who provides information and advice to group members and coordinates exchanges among groups. The AACREA movement has about 1500 member farmers supported by about 140 technical advisors. Dissemination of technological innovations takes place (a) among members of a CREA group during monthly meetings, (b) at "open farmgate" meetings open to non-members, (c) at regional or national meetings and (d) through AACREA's magazine and technical publications. As a result, for each AACREA member, information reaches about 40 non-AACREA farmers (i.e., a total of about 60,000 farmers in Argentina). AACREA's dissemination role has become increasingly important, as budgetary problems have weakened the government agricultural extension system. AACREA's database for each member includes demographic information about each farmer and statistical information about each farm, as well as farm performance over all years of membership. There is also recent information about farmers' scores on several personality traits, potentially related to information processing and farm management decisions. Access to this information (with the informed consent of participating farmers) provides a unique opportunity to explain observed differences in perceptions of climatic and other risks and in farm management objectives and actions, including actions taken to minimize climate risks.

To assess perceptions of ENSO and climate prediction, Letson et al. conducted extended interviews with farmers, focus groups, and a formal survey of about 200 farmers in Pergamino, the top agricultural production region of Argentina (Letson, Llovet et al. 2001). The 1997-98 El Niño event had an important influence on respondents' attitudes towards climate forecasts, because of the magnitude of its climatic effects and the perceived success in predicting its occurrence and climatic effects, Despite the importance of the 1997-98 El Niño for stakeholders' awareness, most survey respondents did not change their management decisions in response to forecasts during the 1997-98 El Niño or the subsequent La Niña of 1998-99. Although agricultural stakeholders revealed widespread interest in climate information, lack of knowledge and thus mistrust remained about the capabilities and limitations of climate forecasting. Two positive findings of the Letson et al. study are that increased exposure to climate forecasts and increased knowledge about regional ENSO effects each appeared to encourage forecast use. Therefore, educating potential users about ENSO and how it affects local climate may help promote greater use of climate forecasts.

Florida

Agriculture is of major economic importance for the state of Florida. South Florida is the United States' most important supplier of fresh vegetables and ornamental foliage in the winter. Florida ranks fifth in the nation and first in the Southeast in the value of crops produced ($5.0 billion in 1997) (NASS). It is second only to California in the categories of fruits and nuts, and commercial vegetables. The region is diverse in terms of its climate and agriculture due in part to the transition from a temperate climate in the north to a subtropical climate in the south. Agricultural production systems are highly diverse in terms of enterprises, scale, and resource endowment in Florida.

ENSO exerts a substantial influence on both climate and agriculture in this region. In the winter and early spring, El Niño is associated with lower temperatures and enhanced precipitation in most of the region (Green 1997). Regional climate anomalies associated with very strong El Niño events are not simply amplifications of normal El Niño conditions (Rosenberg et al., 1997). With some exceptions, La Niña shows effects that are opposite those of El Niño, which include above-average temperatures east of the Mississippi River in the winter and, in northern Florida, in the spring. Effects in the subsequent summer are weaker and spatially more variable. El Niño conditions significantly reduce Atlantic hurricane landfall frequency in the US whereas La Niña conditions have a smaller, positive influence (Bove et al., 1998). Florida's highly profitable citrus and fresh winter vegetable industries are particularly vulnerable to low temperature extremes. ENSO apparently does not influence the probability of low temperature extremes (Hansen, Kiker et al. 1999) or agriculturally important freezes (Dowton) in Florida in a consistent or predictable manner, possibly reducing farmers' interest in ENSO forecasts.

ENSO significantly influenced the success of maize, wheat, cotton, tomato, rice, sugarcane and hay crops in the southeastern states (Hansen 2001). Field crop yield response in the Southeast to the two strongest El Niño events analyzed (1982-83 and 1997-98) was generally opposite in direction to response to weak-to-moderate events (Hansen 2001). The Florida Department of Agriculture attributed $165 million of agriculture and forestry losses in Florida to the strong 1997-98 El Niño event. ENSO influences yields of high-value crops such as some citrus species and winter vegetables (tomato, bell pepper, snap beans and sweet corn), and prices of bell pepper and snap bean in Florida (Hansen 1998b; Hansen, Kiker et al. 1999).

Vulnerability of the region's agriculture and economy to climate fluctuations and weather extremes prompted formation of a consortium of Florida universities (Florida State University, University of Florida and University of Miami; now known as the Southeast Climate Consortium) to seek to capitalize on the potential predictability of climate impacts associated with ENSO. The goal of the research effort is to reduce economic risks and improve social and economic well-being by facilitating the routine and effective use of climate forecasts for agricultural decision making (Jones 2000a; Jagtab 2002).

The Consortium's interactions with agricultural stakeholders have included weather and climate workshops with Florida farmers; farmer surveys in northern Florida, southern Georgia, and Alabama; open-ended surveys of Florida Agricultural Extension service personnel; District Extension meetings; contributing to training workshops; and interactions with agri-business (input and information suppliers, marketing, and commodity organizations). Surveys of extension personnel, who daily interact with and advise farmers, have proven to be a particularly effective means of obtaining information about farmers' perspectives and opportunities for using climate prediction within agricultural production. These past interactions with farmers reveal consistent concern about short-term weather events, particularly hurricanes, freezes, floods and abnormally high temperatures. Weather and climate risks invariably appear on farmers' list of concerns, but climate is never at the top of the list for any commodity. Thus, when commodity groups lobby for research and extension programs, programs related to climate garner little support unless major droughts, freezes, or other events have occurred in the recent past. Attitudes toward seasonal prediction range from strong skepticism to moderate optimism, with skepticism being more common. Reasons for skepticism include lack of understanding of how ENSO influences the region's climate, as well as the long lead time and coarse spatial resolution of forecasts. Farmers often take their perceptions of daily weather forecasts as a starting place for discussing seasonal forecasts. They seem to evaluate seasonal forecasts in deterministic terms, much as they do daily weather forecasts. Some skepticism can be attributed to perceived inaccuracy of weather forecasts, and a sense that longer-lead forecasts will be even less skillful. Awareness of spatial variability of local weather translates into desire for climate forecasts for farmers' specific locations. However, farmers often also ask about forecasts for competitors' regions (e.g., South America), where spatial resolution is not a concern. While rainfed field crop producers are concerned about climate fluctuations, market price variations tend to dominate decisions for high-value crops. Perceived ability to flexibly adjust management in response to climate expectations, and the type (i.e., relevant climatic variables and timing) of information that farmers desire are highly dependent on the production system. The desire for forecast information, concern about location specificity, and concern about the uncertainty of forecasts are more consistent across the state. Florida farmers tend to evaluate the credibility of information and advice based on its source. While they tend to be skeptical or at least cautious about "experts" from outside the community, they generally trust the state extension service and their county agents. In combination, these characteristics make Florida a good setting for field tests of the mental models interview methodology described in this report

Context Within Related Activities and Projects

This project complements several projects and activities related to risk communication and decision analysis and decision making under climate uncertainty. It was initially one of three closely coordinated projects targeting climate risk management in farming systems of the Argentine Pampas. The others were:

- *Climate information and forecasts in agricultural production systems of the Argentine Pampas: planning for their effective use in decision-making* (Podestá, Hansen, Broad, Satorre). Funded by National Science Foundation, Biocomplexity in the Environment. This one-year seed project sought to (a) improve understanding of how climate information can enhance agricultural decision making within given cultural, economic, and institutional contexts, (b) assemble a multidisciplinary team of researchers and agricultural stakeholders, and (c) develop a research plan and proposal for a larger Biocomplexity in the Environment project.

- *Use of climate prediction to support decision making in Argentine agriculture* (Podestá). This project, submitted to NOAA-OGP but not funded, targeted the information requirements, opportunities and impediments to using climate information for agricultural decision-making. The current project intended to leverage anticipated OGP project funds that would have supported a series of farmer focus groups.

It builds on a history of climate applications research activities in Argentina by the Florida Consortium (Univ. Florida, Univ. Miami, Florida State Univ., now known as the Southeast Climate Consortium):

- *Regional application of ENSO-based climate forecasts to agriculture in the Americas* (Jones, Podestá, O'Brien, Hansen, Kiker, Waylen, Letson, Legler). Funded by NOAA Office of Global Programs, 1997-1999. The project sought to promote the effective use of seasonal climate forecasts in agriculture to improve social and economic well being in the southeast US and Argentina. It supported core activities of the Florida Consortium during this period.

- *Comparative assessment of agricultural uses of ENSO-based climate forecasts in Argentina, Mexico, and Costa Rica* (Jones, Magrin, Collado, Ramirez). Funded by Inter-American Institute for Global Change, 1997-1999. The project was designed to promote effective and credible applications of ENSO-based climate forecasts to agriculture in Latin America. Project funds supported training visits and the research activities of collaborators in the three Latin American countries.

- *Regional assessment of the effects of ENSO-related climate variability on the agricultural sector of Argentina and Uruguay: Implications for adoption of climate forecasts* (Jones, Podestá, Letson, O'Brien). Funded by National Science Foundation, Methods and Models for Integrated Assessment, 1997-1998. This project targeted the development of system tools and methodology for analyzing agricultural impacts and crop managenet responses to ENSO-related climate variability in Argentina and Uruguay.

It also builds on and complements past IRI activities on perception and communication of probabilistic climate information:

- *Assessing current and potential use of seasonal climate forecasts for communal farm management in Zimbabwe* (Phillips, Makaudze, Unganai, Makadho, Cane). Funded by NOAA Office of Global Programs, 1997-2000. This project addressed several issues related to the application of seasonal forecasts by farmers, including communication and dissemination. Experience highlighted both the effectiveness and the potential hazards of forecast dissemination by commercial radio. The project supported the *Communication of Climate Forecast Information Workshop* at the IRI.

- I*mproving climate forecast communications for farm management in Uganda* (Phillips, Orlove). Funded by NOAA Office of Global Programs, 2000-2003. This project developed and evaluated a series of radio programs that provided climate forecast information in local languages, targeting rural populations in Uganda. The project sponsored a *Workshop on Media and Climate Information* in Uganda. It was designed to follow up on the previous project, but was forced to relocated due to the political and security situation in Zimbabwe.

- *Improving Comprehension and application of seasonal climate forecasts: Workshop curricula for intermediary users* (Phillips, Krantz). IRI Seed Grant.

- *Responding to climate forecasts using scenarios in the planning process* (Phillips). Columbia Center for New Media Teaching and Learning, 2002. This online course presents a number of decision scenarios to teach principles of decision making under probabilistic climate forecast information.

The project has contributed to several new project proposals:

- *Modeling and aiding farm-level agricultural decision making in Argentina: an integrated systems model of reactions and adaptations to climatic and other sources of risk* (Podestá, Letson, Broad, Easterling, Weber, Hansen, Goddard, Robertson, Herzer, Caputo, Celis, Rodríguez, Bartolomé, Satorre, Menéndez, Penalba, Rabiolo, Villanueva, Núñez). National Science Foundation, Biocomplexity in the Environment. Not funded.

- *Center for individual and group decision making under uncertainty* ((Broad, Krantz, Miller, Weber). National Science Foundation, submitted.

- *Building capacity to use climate information and forecasts to enhance decision-making in agriculture: An application to the Argentine Pampas* (Broad, Podestá, Herzer). NOAA Office of Global Programs, submitted.

- *Understanding decision-making in agricultural production in the Argentine Pampas in the face of interannual climate variability and other risk factors* (Weber, Podestá, Letson). NOAA Office of Global Programs, submitted.

- *Understanding and modeling the scope for adaptive management in agroecosystems in the Pampas in response to interannual and decadal climate variability and other risk factors* (Podestá, Rajagopalan, Easterling, Katz, Weber). National Science Foundation, Biocomplexity in the Environment, submitted.

Research Objectives

This project sought to contribute to improved communication and application of seasonal forecast information, and extend previous research efforts with both a "front end" – mental models that influence climatic expectations and forecast applications – and a "back end" – the decision processes in response to climate expectations derived from farmers' mental models and externally-provided information. Research in this report was motivated by three lines of social science inquiry: (a) the importance of subjective perception of risk, (b) differences in the impact of small-probability events when information about them is learned by personal experience over time as opposed to being provided as a statistical summary, and (c) the role of material and nonmaterial (cognitive and affective) goals and processes in risky decision making. Specific objectives of the research were to:

- Characterize mental models of climate expectations and variability and their influence on seasonal forecast use.

- Develop and test forecast presentation materials, with focus on fit to farmers' mental models.

- Identify climate risks and responses that farmers and advisors consider.

- Plan and pilot test a farmer climate risk communication and decision analysis component for a larger NSF Biocomplexity in the Environment project proposal.

III. Review of Literature

Determinants of Forecast Value

Research has shed considerable light on the determinants of benefits from the agricultural application of seasonal climate forecasts (Lamb 1981; Sonka, Lamb et al. 1986; Easterling and Mjelde 1987; Sonka, Mjelde et al. 1987; Barrett 1998; Stern and Easterling 1999; Nicholls 2000; Hansen 2002), and has highlighted a number of constraints that operate in particular contexts. The potential for farmers to benefit from seasonal forecasts depends on factors that include the sensitivity of farming systems and vulnerability of human populations to climate variations, the predictability of relevant components of climate variability, the ability and willingness to change climate-sensitive decisions in response to forecast information, the appropriateness of information content and effectiveness of the communication process, and the effectiveness of the institutional systems that communicate forecast information and support its application (Hansen 2002). Constraints include the limited predictability of relevant components of climate variability and the farming decision environment (e.g., sensitivity of the system to climate, match between decisions and predictable climate variations and severe resource constraints). Citing work by Kahneman and Tversky (1972), Bar-Hillel (1980), and Gigerenzer and Hoffrange (1995), Stern and Easterling (Stern and Easterling 1999) suggest that people are likely to have rather fundamental difficulties in applying probabilistic climate forecasts because they do not naturally think probabilistically or estimate probabilities accurately. Barrett emphasizes that forecasts will only have value if they lead decision makers to update their prior subjective distributions of outcomes in an appropriate manner (Barrett 1998).

Of the various determinants of climate forecast benefit to farmers, those related to the perception and understanding of the forecast are perhaps most under the control of those who design and communicate forecast information products. The inherent probabilistic nature of seasonal climate forecasts presents particular challenges. Underestimating (or understating) the accuracy of a forecast system leads to lost opportunity to prepare for adverse conditions and take advantage of favorable conditions. Overestimating (or overstating) the accuracy of a forecast system can lead to excessive responses that are inconsistent with decision makers' risk tolerance, and can damage the credibility of the forecast provider. Methods of communicating probabilistic seasonal climate forecasts in ways that improve their comprehension and application are an important area of recent research (Fischhoff 1994 ; Nicholls and Kestin 1998 ; Krantz and Phillips 2000). Better understanding of how target decision makers perceive and communicate probabilistic information is needed for designing information products and presentation protocols to move farmers, researchers and various intermediaries in the communication process toward a common probabilistic language, and overcome the inherent difficulties of understanding and wisely applying probabilistic forecast information. Users of climate forecasts will likely understand new information better and accept it more fully if they can interpret it in a causal model of climate variability that they understand and with which they agree (Stern and Easterling 1999b). Letson et al. found a significant correlation between the accuracy of Argentine farmers' understanding of climate and their acceptance of mitigation responses (Letson, Llovet et al. 2001). Research on climate change has shown a similar relationship between understanding and willingness to act (Kempton 1995; Bord 1998).

Farmers' Climate Information Needs

Several important characteristics arise from previous research on farmers' climate information needs. The first is *location specificity*. Farmers are generally aware of the spatial variability of weather, recognize scale mismatches between available forecast information and decisions, and want to know what to expect on their own farms (Madden and Hayes 2000 ; O'Brien, Sygna et al. 2000 ; Jochec, Mjelde et al. 2001 ; Ingram, Roncoli et al. 2002). Interestingly, they often also ask about price implications of conditions predicted in competitors' regions (Chagnon 1992). The second is *temporal specificity*. Farmers need information beyond the three-month average climate anomalies typically forecast, including season characteristics such as rainy season onset, dry spell distributions and harvest conditions (Phillips and McIntyre 2000; Nelson and Finan 2000 ; O'Brien, Sygna et al. 2000 ; Ingram, Roncoli et al. 2002). Third, farmers are concerned with the *accuracy* of forecasts. They sometimes cite thresholds of accuracy before they will modify decisions based on forecasts. However, farmers seem to be consistent in their need for a clear and honest presentation of the degree of uncertainty of forecasts (Ziervogel 2001a; Childs, Hastings et al. 1991; Madden and Hayes 2000 ; O'Brien, Sygna et al. 2000). For farmers who are concerned with managing risk, modest but well-characterized skill (i.e., accuracy relative to a baseline such as climatology) may be more valuable than high but uncharacterized skill. Fourth, farmers are concerned with *impacts and management implications* within the agricultural systems that they manage. However, preference for including forecasts of agricultural responses and management recommendations is not consistent.

If farmers are to apply seasonal climate forecasts to improve crop management, they must first interpret forecast information at the spatial scale of impacts and decisions, translate forecasts into production and economic outcomes associated with alternative management strategies, and clearly understand forecast uncertainty with respect to those outcomes. By paying attention to these requirements, providers of climate information can do much to enhance the usefulness of the information.

Importance of Understanding the Probabilistic Nature of Forecasts

For the risk-averse farmer, understanding the uncertainty of a forecast in probabilistic terms is crucial to making appropriate use of the forecasts. Communicating forecast uncertainty in probabilistic terms without distortion is increasingly recognized as a crucial challenge (Barrett 1998; Mjelde, Hill et al. 1998; Dilley 2000; O'Brien, Sygna et al. 2000 ; Jones 2000a; Hammer, Hansen et al. 2001; Patt 2001; Phillips, Unganai et al. 2001; Phillips and Hansen 2001; Hansen 2002). Distortion can easily occur anywhere in the forecast generation, distribution, interpretation, and application process.

Simple economic models of the value of optimal responses to probabilistic forecasts can illustrate the dangers of incorporating distorted information about forecast uncertainty into decisions. Within an expected utility framework, we can define the value of an uncertain forecast to the user (with his or her specified, and typically risk-averse utility function) as the difference in the expected utility of outcomes realized with optimal use of the forecast and the expected utility of outcome realized with optimal use of prior information – typically assumed to be climatology. Hansen (Hansen 2001) extended a study of optimal farm land allocation in the Pampas region of Argentina (Messina, Hansen et al. 1999) to consider the economic implications of ignoring the uncertainty of ENSO-based forecasts. To mimic failure to communicate or consider the uncertainty of a forecast, Hansen replaced the probability distributions of yield response in El Niño and La Niña years with unbiased point (i.e., deterministic) estimates of yields. In simulations that preserved forecast uncertainty, use of ENSO information increased both the expected value of farm income and the expected utility of farm income for risk-averse farmers. However, in simulations that replaced the uncertain forecasts of outcomes in El Niño and La Niña years with unbiased, deterministic point estimates, optimal use of the forecast decreased the expected utility of farm incomes for risk-averse farmers. In a similar analysis of optimal farm land allocation among cropping systems for smallholder farmers in Avinashi, Tamil Nadu, India, Hansen and Selvaraju showed that the value of a forecast in expected utility terms decreases to zero and quickly becomes negative as the standard deviation of predicted economic outcomes in El Niño and La Niña years is reduced with a mean-preserving transformation (Hansen and Selvaraju 2001). These analyses illustrate how overconfidence due to miscommunication of uncertainty or due to distorted perception of uncertainty may negate the value of forecast use. Although there are some anecdotes about hesitation on the part of farmers to use climate forecasts because forecast uncertainty is overstated (e.g., Hammer et al. (Hammer, Hansen et al. 2001)) there are few well-documented studies of the effect of perceived forecast certainty (Chagnon 2002). There is evidence that overstating forecast certainty can damage the credibility of forecast providers (Nicholls and Kestin 1998 ; Orlove and Tosteson 1999; Stern and Easterling 1999; Chagnon 2002). Patt and Gwata (2002) suggest that "...the credibility of a probabilistic forecast likely is more resilient than that of a deterministic prediction" (Patt 2002). On the other hand, under-confidence in forecasts due to inflated perception of forecast uncertainty will reduce the value of a forecast through under-response and missed opportunity. The costs of such missed opportunity have not received adequate attention relative to the costs of misinterpretation and misuse of forecasts.

Description-Based vs. Experience-Based Information

Recent research suggests that decisions from experience and decisions from description can yield drastically different choice behavior under conditions of risk or uncertainty (Weber, Shafir et al. 2003 d, in press; Hertwig 2003a, in press; Hertwig 2003b, in press). Those studies asked undergraduate students to choose between two decks of cards (e.g., a blue deck and a green deck), which offered different amounts to win or lose, with different probabilities. In the description-based condition, decision makers were given the different outcome amounts that could be found in each deck, together with their probabilities (e.g., Green Deck: 10% of cards (5 out of 50): you win $10; 90% of cards (45 out of 50): you win nothing. Blue Deck: 100% of cards (all 50): you win $1), and then could choose from which deck they preferred to draw one card for a "real" draw (i.e., whatever amount was shown on that card, was a real win or loss, paid in US dollars). In the experience-based condition, decision makers initially knew nothing about the payoffs of cards in the two decks, but were allowed to sample from the two decks (with replacement) until they felt that they knew which of the two decks they would prefer to draw one card for the "real" (consequential) draw. When choosing based on personal experience, decision makers were strongly influenced by recent events. Since low-probability (or rare) events are, by definition, less likely to have occurred recently than high-probability events, choices on average reflected preferences that underweighted low-probability events. On those rare occasions where a low-probability event did occur on a recent trial, it had more impact on the decision than warranted by its likelihood of occurrence. In description-based decisions, choices reflected preferences in which low-probability events were overweighted, a pattern formalized by the decision weighting function of prospect theory (Kahnemann 1979).

Use of probabilistic information has been shown to differ as a function of how it was acquired (by personal experience over time vs. vicariously as a summary statistic) in other contexts, e.g., in medical diagnosis and the use of disease base rates. While disorders differ in their frequency of occurrence in a population (i.e., in their base rates), physicians have often been observed to fail to appreciate the significance of base rates when presented with questions that require the incorporation of base rates provided as numerical summary estimates (Casscells 1978; Wallsten 1986; Eddy 1982). However, base rate knowledge about diseases acquired through direct experience has been found to affect diagnostic judgments (Medin 1988), presumably by processes other than explicit calculation, and yet in accordance with Bayesian updating rules (Beyth-Marom 1993). Memory-based heuristics that use ease or strength of recall to make relative likelihood judgments work well when memory is a veridical reflection of actual frequencies in the population (Tversky 1973). Weber, Böckenholt, Hilton, and Wallace found that physicians who used personally-experienced base rate information to make diagnostic judgments used them on average quite normatively, and that older physicians (who had more representative knowledge bases, especially for low base rate diseases) were more normatively sensitive to base rates than younger physicians. (Weber 1993)

The fact that repeated, direct experience of probabilistically occurring events is a key to a better of their probabilistic nature may also explain why probabilistic sophistication is often domain specific. Physicians whose experience base allows them to incorporate disease base rates quite accurately into their diagnostic decisions, will be as helpless as any other respondent in other domains (e.g., professional sports) or when questions (even medical problems) are posed to them in a format that does not allow them to connect to their experiential knowledge base.

The difference in how people process description-based vs. experience-based information has several implications for the challenge of communicating climate information to farmers. First, farmers are exposed to repeated direct experience with weather and climate events, as well as outcomes on other dimensions (e.g., the prices of fertilizer, obtained prices for their crops). Farm livelihoods depend on many variables and events that are inherently probabilistic. As a result, they may be better able to process experience-based probabilistic information in domains connected to their livelihood decisions than students or professionals with secure incomes, who have been the subject of much of the research on shortcomings in probabilistic reasoning and risky decision making. Second, inconsistency in how farmers process their own experience with climate variability vs. description-based climate information provided by experts is likely to be a key challenge. Below, we test the hypothesis that interventions (e.g., discussion of the association between climatic time-series and their memory (Childs, Hastings et al. 1991; Clewett, Cliffe et al. 2000)), that help farmers map description-based summary information or forecasts onto their own experience base will increase the utility of the externally provided information.

Affective Processing in Experience-Based Decisions

Analytic, description-based decisions are made by evaluating decision outcomes and their likelihood for all possible actions. The process often involves the optimization of specific outcome dimensions (e.g., maximization of profits, minimization of costs). In contrast, affective-mode decisions involve much simpler (and evolutionarily older) processes that result in selection when an action "feels right", or avoidance when the action seems "risky" or feels "wrong" in some (usually vague) way (Weber 2002), even among sophisticated decision makers (Loewenstein 2001a) and results in some biases. The "single action" bias (Weber 1997) refers to the observation that decision makers are very likely to take one action to reduce a risk, but are much less likely to take additional steps for further risk reduction. The "finite-worry" bias describes the tendency to worry less about other risks when concern about one particular risk rises, because of a finite pool of emotional resources (Linville 1991). Worry and concern direct farmers' attention and thus shape action. For information processors with limited cognitive resources such direction can be beneficial, but may also result in suboptimal responses.

Farmers' Probabilistic Understanding of Climate Variability

Some have argued that farmers are unable to either understand probabilistic forecasts (Ridge and Wylie 1996 ; Austen, Sale et al. 2001) or incorporate them into their decisions (Madden and Hayes 2000). However, other evidence suggests that farmers across cultures and socio-economic status do understand the probabilistic nature of climate variability and seasonal forecasts, and its implications for livelihood decisions, albeit with some biases. For example, three recent studies on the potential application of seasonal forecasts in West, East, and Southern Africa provide evidence that vulnerable smallholder farmers with limited formal education may indeed understand climatic risk in probabilistic terms and appreciate its significance. What these studies seem to have in common is some effort to translate statistical summary information into concrete terms which allows farmers to connect it to their experiential knowledge base.

In the first study in Burkina Faso, researchers met with farmer groups who had not previously been exposed to seasonal forecasts (Ingram, Roncoli et al. 2002). The tercile format of seasonal forecasts from the regional outlook forum was explained to farmers by having them randomly draw squares that were colored according to tercile category and numbered in proportion to the forecast probabilities. Based on subsequent discussions, the researchers concluded that the farmers interpreted forecast probabilities and their implications correctly.

In the second study in Zimbabwe, groups of farmers were introduced to a series of five games that involved betting on categorical outcomes of spinners (Patt 2001). A small monetary payoff provided a real incentive. Participants' choices responded to changing probabilities and payoffs, and improved with experience. Early in the experiment, participants tended to shift bets among outcomes in proportion to their probabilities rather than consistently selecting outcomes with the highest expected payoff. This strategy reflects a common, but inappropriate heuristic called probability matching. By the fifth game however, many had learned to bet consistently on the outcome with the highest expected value.

In the third study, Luseno et al. asked pastoralists in northern Kenya and southern Ethiopia to express their assessment of upcoming seasonal rainfall by allocating 12 stones into piles representing "below-normal," "normal" and "above-normal" in proportion to their probabilistic expectations (Luseno, McPeak et al. 2003). This is consistent with the way the Drought Monitoring Center (DMC) in Nairobi expresses seasonal forecasts. Ninety percent of respondents divided the stones among more than one category. Although the majority had not received the DMC forecasts, elicited forecast distributions agreed qualitatively with the DMC forecasts. The researchers concluded that the pastoralists, most of whom have little or no formal education, "clearly comprehend and can communicate a probabilistic forecast, even if they would not employ such terminology." The research team also demonstrated that those pastoralists who received and expressed confidence in modern (i.e., DMC) forecasts significantly updated their subjective distributions in response to the forecasts, despite the prevalence of indigenous forecasts and their relative unfamiliarity with modern forecasts (Lybbert, Barrett et al. 2002). Contrary to most other studies of similar situations, which tend to find a negativity bias (see (Weber 1994) and next paragraph), Luseno et al. found that the pastoralists tended update their beliefs asymmetrically, with a bias toward favorable forecasts.

Sherrick et al. examined farmers' memory of climate variability (Sherrick, Sonka et al. 2000). They elicited subjective probability distributions of climate events from 54 large-scale grain producers near Urbana, Illinois, and compared those to the objective (true) distributions. Although the elicited distributions varied among farmers, the group showed a tendency to overestimate probabilities associated with conditions adverse for production, and underestimate probabilities associated with favorable conditions. These distortions in probability estimates are consistent with the negativity bias observed in many contexts (Weber 1994). As tested and confirmed in an experimental context by Weber and Hilton (Weber 1990) for verbal probability expressions and by Windschitl and Weber (Windschitl 1999) for numerical probability expressions, people's interpretation of the magnitude of a probability value provided by an expert incorporates the magnitude of positive or negative consequences, should the stated probability turn out to be an overestimate or an underestimate. Often these consequences (also referred to as "loss functions") are asymmetric, e.g., underestimates in situations with adverse conditions turn out to have more serious consequences than overestimates, and in those cases, people will inflate the forecast probability estimate either implicitly or explicitly.

Probabilistic Forecast Formats

Probabilistic climate forecasts can be presented as either categorical (or discrete) or continuous. Categorical probabilistic formats are now standard for forecasts produced and distributed by international forecast centers such as the IRI, regional climate outlook forums in Africa and Latin America, and many farmer-oriented climate application programs such as in eastern Australia. Probability shifts of above and below median or tercile categories are simple to present in maps. Tercile forecasts can be presented by colors on a map. The use of tercile categories eliminates the need to deal with fine-scale spatial variability of climatological quantities within a homogeneous forecast region. Other arguments in favor of categorical over continuous probabilistic forecast formats relate to user perception and interpretation. Clewett et al. proposed that cumulative distributions are good for scientist-scientist communication (Clewett, Cliffe et al. 2000), but simple categorical probabilistic formats are preferred for communicating with farmers, including probability of above-median outcome and tercile shifts. Hayman argued, "The broad categories of good, average, and poor seasons are a useful place to start a discussion of risk (Hayman 2000). When a box plot or cumulative probability graph shows the extreme events these are most noticeable and tend to dominate the discussion."

There is evidence that many people have difficulty interpreting existing categorical probabilistic formats. In southern Africa, O'Brien et al. found that "the presentation of probabilistic forecasts in terciles was considered to be somewhat esoteric for many" (O'Brien, Sygna et al. 2000). Within unstructured interviews with eighteen North Florida cattle farmers, Breuer et al. showed probability shifts of local rainfall associated with El Niño and La Niña in several formats: stacked bar graphs (tercile probability shifts), box plots, smoothed histograms, probability of exceedance graphs and coded time series (Breuer, Church et al. 2000). Those respondents who expressed interest in seasonal climate forecasts preferred probability of exceedance and time-series graphs to the two categorical formats (terciles and box plots).

Research by Dalgleish et al. (Univ. of Queensland, personal communication) reveals some of the difficulties with interpreting categorical probabilistic forecasts. Participants at an agricultural trade show were given three statements of probability of either exceeding or falling below median rainfall, and asked whether the statements imply that rainfall will be higher or lower than normal. Respondents took longest and had the highest (50%) rate of misinterpretation from the statement, "the probability of getting below median rainfall ... is 30%." In another study, many farmers misinterpreted the phrase "30% probability of getting above the median rainfall" as a tendency toward increased rainfall, apparently interpreted it to mean that rainfall would exceed the median by 30%. The authors concluded that farmers have difficulty distinguishing between the probability of climatic event and the direction of the event, and have particular trouble when changes in the probability (reduced from normal) and the event (exceeding the median) are in opposite directions. Expressing forecast probabilities in terms of categories requires the decision maker to process several quantities: probability, categories that are defined by probability ranges, and climatic thresholds at category boundaries. The work of Dalgleish and his colleagues identifies confusion between the direction of the probability shift and the direction of the category with respect to "normal." Ambiguous or inconsistent interpretations of forecast categories can contribute further to misunderstanding of categorical probabilistic forecasts (Fischhoff 1994 ; Gigerenzer, Hertwig et al. 2003 submitted). For example, communal farmers in Zimbabwe considered most years as "dry" and very few as "normal" (Patt 2003a). Likewise, O'Brien et al. reported that Namibian farmers tended to interpret "normal" in a manner that can include unusually good rainfall years (O'Brien, Sygna et al. 2000). From surveys of farmers in Namibia and Tanzania, they concluded that farmers couldn't relate to tercile forecast categories in the absence of the 30-year climatology records on which the probabilities are based.

Finally, when qualitative expressions of probabilities (e.g., "likely," "extremely unlikely") are used by convention or required by text-based communication media, ambiguous or inconsistent interpretation of qualitative expressions of probabilities can be another source of misinterpretation of categorical probabilistic forecasts. Patt and Schrag discuss this in the context of climate change risk and provide evidence that communicators and recipients (university students in this case) incorporate the magnitudes of events into their use of probability descriptors (Patt 2003). Their work is consistent with previous results by Weber and Hilton (1990) which shows that the magnitude of an event influences the interpretation of vague, verbal labels designed to denote the probability of the event because event magnitude influences the costs of misestimating the probability directionally. People provide a larger numerical interpretation for the expression "a small chance of skin cancer" than for the expression "a small chance of indigestion" because the downside of underestimating the chance of skin cancer is more severe than those of underestimating the chance of indigestion (and also larger than the costs of overestimating either condition).

Recent research has reconfirmed the salutary effect that the representation of probabilities as (relative) frequencies have on many quantitative reasoning or estimation tasks (Gigerenzer and Hoffrage 1995), partly because frequency formats correspond to the sequential way in which information is acquired in experience-based decision making (E.U. Weber, Shafir, & Blais, 2004). Requiring forecast users to personally derive the (relative) frequency of experiencing an event that is of particular interest to them (i.e., a category of their own design) in this fashion will make the derived probability information personally relevant and interpretable, for having been derived by processes that correspond to natural experience.

The loss of information that results from categorizing a cumulative distribution, the arbitrary nature of thresholds embodied in category boundaries and the evidence of difficulties in interpreting categorical probabilistic presentations of forecast information can be regarded as arguments for presenting seasonal forecasts as continuous distributions. Unfortunately, because most studies have focused on categorical probability formats, we know far less about how farmers and other decision makers perceive and interpret continuous probability formats.

Perception of Climate Variability and Mental Models

Perceptions of risks are part of larger "mental models" that guide the decisions people make to protect themselves and others from climate-related damages to crops. Extensive work in cognitive psychology has demonstrated that when people receive new information they process it in the context of existing beliefs – or mental models (Stern and Easterling 1999). In broad terms, mental models are mental representations of how the world works (Markmann and Gentner 2001). They are not models in a formal sense. Yet they help people to figure out which things are worthy of attention in a complicated situation and provide general principles for judging how the elements of their model interact with one another. They are often shaped by previous experience and allow people to interpret past, present, and future events (Rogers 1992; Doyle and Ford 1997). As Weber suggests in the case of Illinois cash-crop farmers, perceptions and expectations – or mental models -- of climate change affected farmers' adaptation of production and pricing practices (Weber 1997).

The method of mental model interviews has been mainly used in risk communication studies (BOSTROM 1994; READ 1994; Lazo 1999; Morgan, Fischhoff et al. 2002) for it can make lay perceptions accessible to policy makers, scientists, and educators. Various studies (as discussed in the previous section) have looked at elements of lay perceptions and concepts of climate variability among farmers. Yet they have generally not done so within a mental model framework. The mental model approach found application in other domains, such as public understanding of risks of global climate change, radon, nuclear energy, and PCE use in dry cleaning (Kempton 1991; Maharik and Fischhoff 1993; BOSTROM 1994; READ 1994; Lazo 1999; Lazo 2000; Kovacs 2001; Morgan, Fischhoff et al. 2002). While most research has focused on lay concepts of scientific phenomena, few have compared lay and expert mental models (Lazo 1999; Lazo 2000; Slovic, Kraus et al. 2000). Influenced by these studies, ours is the first to apply a mental models framework to lay (farmers') and expert (climate scientists') perceptions of climate variability.

IV. Methods

Argentine Pampas Focus Groups, Questionnaires, and Farm Decision Exercise

Research conducted for this project in Argentina took place in the context of several focus groups (Morgan 1997), and included a farm decision-making exercise that compared production decisions made with and without the benefit of a climate forecast and several questionnaires answered by the participants in the focus groups. These survey instruments served to elicit farmers' perceptions of climate variability, agricultural decisions and practices, socioeconomic background, and personality.

Focus groups participants were recruited among AACREA (Asociación Argentina de Consorcios Regionales de Experimentación Agrícola) members. The topics discussed in the second set of focus groups described here (FG2) built on earlier work with the same set of Argentine farmers (FG1) which had addressed climate characterization, i.e., perception and memory of climate conditions, events, and variability; perceptions of climate related risks in farming; risk strategies; use of sources of climatic information; farmers' needs and expectations. Some of these themes were repeated in FG2. In addition, FG2 explored farmers' perceptions of forecasts and their farm management decisions and practices with and without the benefit of seasonal forecasts. Twenty-four farmers participated in the first set of focus groups. Of those, 14 farmers (as well as three AACREA technical advisors) participated in the second set of focus groups.

Focus group discussions were supplemented by several questionnaires that were answered by between 15 and 27 respondents, including farmers and advisors who had participated in the first or second set of focus groups. The questionnaires collected information about socioeconomic variables (farmers' age, gender, education, income, AACREA membership), farm characteristics (farm size, locations, farm equipment, crops, farming practices, farming costs and profits) and farmers' climate perceptions (climate characterization, perception of seasonal, interannual, and long-term changes in precipitation and temperature).

One questionnaire assessed farmers' scores on four personality characteristics that have been documented to be associated with differences in decision making (Weber 2003, in press). Self-regulation theory (Higgins 1999; Kruglanski et al. 2002) distinguishes between two regulatory states (assessment orientation, which puts emphasis and value on careful analysis, and locomotion orientation, which values rapid action) and two regulatory foci (promotion focus, which involves promoting the achievement of ideal states, and prevention focus, which concentrates on preventing deviations from oughts and obligations). The promotion and the prevention system each serve distinct survival functions. The human promotion system is concerned with obtaining nurturance (e.g., nourishing food) and underlies higher-level concerns with accomplishment and advancement. The promotion system responds to the pleasurable presence of positive outcomes (i.e., gains) and to the painful absence of positive outcomes (i.e., non-gains). In contrast, the human prevention system is concerned with obtaining security and underlies higher-level concerns with safety and fulfillment of responsibilities. The prevention system responds to the pleasurable absence of negative outcomes (e.g., non-losses) and to the painful presence of negative outcomes (e.g., losses). The promotion and prevention systems have been shown to employ qualitatively distinct means towards desired end-states. Individuals with a chronic or situationally induced promotion focus are inclined to utilize "approach means" in order to attain their goals. For instance, a promotion-focused student seeking a high exam score might study extra material or organize a study group with fellow classmates. Conversely, individuals with a prevention focus tend to use "avoidance means" in order to attain their goals. For example, a prevention-focused student seeking a high exam score (or rather, trying to avoid a low exam score) might ensure that he or she knows the required material and will avoid distractions prior to the exam. A chronic promotion or prevention focus is assumed to derive from a subjective history of past success in promotion and prevention goal attainment, respectively.

AACREA also provided us with farmer scores on four components of the Hermann Brain Dominance Instrument, a standardized test to examine personality profiles. The Herrmann Brain Dominance Instrument (HBDI) is a 120-question survey that measures thinking style preferences and provides a profile of mental preferences. Knowing one's preferred thinking style can be helpful in understanding how someone learns, makes decisions, solves problems, and communicates. It is a survey that measures preferences rather than skills. The instrument classifies mental preferences in four different modes, or quadrants, based on the specialized functioning of the physical brain:

- Left brain, cerebral: logical, analytical, quantitative, factual, critical
- Left brain, limbic: sequential, organized, planned, detailed, structured

- Right brain, limbic: emotional, interpersonal, sensory, symbolic

- Right brain, cerebral: visual, holistic, innovative, experimental

These constructs are a set of ideas or concepts in the quadrant model about how people prefer to use different brain processes, or avoid them. It is important to note that constructs represent separate clusters of brain functions, not different ends of a single process. The HBDI reveals which mode of thinking is used predominantly, which one is a fall-back style of thinking that is available for situational use, and which mode one avoids. Research has shown that members of the same profession often show similar HBDI profiles. For instance, people in engineering have on average a strong A-quadrant dominance. Information about farmers' profiles can enhance the communication with farmers by tailoring climate information such as tutorials to preferred styles of thinking, because preferred constructs translate into preferred learning styles and strategies.

To gain further insight into the specifics of farmers' climate sensitive decisions and farmers' strategies to adapt to climate variability, we designed a farm decision scenario that occurred in September of 2002. In the first part of this exercise (Scenario 1), farmers received detailed descriptions and maps of two pieces of farm land ("Don Albino" and "La Josefa"), consisting of six lots each. For a specified decision date (May 2003) and a specified prehistory of the types of crops that had been planted in each lot in previous years and specified information about estimated crop prices for the 2003/04-crop season respondents were asked to indicate which crop they would grow in each lot in the coming growing season. If they indicated that they chose to plant corn in a given lot, they were asked to specify the particular hybrid, planting date, and quantity and density of fertilizer they would apply. After completion of the exercise, respondents received a seasonal climate forecast (predicting La Nina conditions) in two different formats. From the formats received, farmers selected their preferred one. (Different farmers received different formats, out of a total of five, which included a narrative paragraph, two tercile format category forecasts, one histogram, and one probability of exceedance graph; see Appendix B). They were then asked to repeat the farm decision exercise in light of the additional climate information (i.e., the forecast) they had just received (Scenario 2). Responses to both scenarios of the exercise were collected in a structured questionnaire. In addition to the farm management decisions, the questionnaire asked farmers to state their concern or worry about four types of risks (political risk, climate risk, and two types of price risk, one related to the prices of production inputs such as seed corn or fertilizer, the other related to the price of crops at harvest). The questionnaire also asked them to rate how much attention they expected to allocate during the growing season described in each scenario to each of four factors (land allocation to crops, additional decisions regarding production details of maize and other crops, the ways in which crops would be sold [e.g., by future contracts, at harvest, or after storing them for some period of time], and all other farm management decisions). Finally, the questionnaires asked farmers about the role that ten different goals would play in the decisions made under each scenario (see Table 2 below for a list of goals).

Expert and Farmer Mental Models Interviews and Florida Questionnaires

Mental model interviews have served as a valuable tool in this study. This approach offers several advantages over other survey forms such as questionnaires: An open-ended interview procedure minimizes the problem of assuming that one knows in advance the full set of potentially relevant expert and lay beliefs (and misconceptions), as well as the terms in which they are intuitively phrased. This allows the interviewee to talk about a wide range of representations of reality used to understand specific phenomena. This approach permits insight into incomplete and contradicting explanations of a complex phenomenon and measures of uncertainty about their validity – ingredients that can be found among experts and laypeople. It avoids questions that give cues in cases where respondents are unsure of the answer; cues that would change the interviewee's mental model during the interview. The method is based on ethnographic interviews (Spradley 1979; Kempton 1991).

There are a number of methods of investigating perceptions, yet semi-structured interviews conducted in face-to-face situations combined with structured questionnaires appear to measure perceptions quite well. There is no best interview technique and approaches such as the *sondeo* method developed by Peter Hildebrand or the associative interview advanced by Paul Slovic and Anthony Leiserowitz certainly have their merits. While each of these methods brings with it various strengths and weaknesses (in particular, interviews and their analysis are much more time consuming than large scale surveys yet sample sizes must be kept rather small), we chose the mental model approach, for it is best suited for both expert and lay participants and because it bears reliable results even with small sample sizes.

Our study is the first to apply a mental models approach to climate variability. Our interviews started with a very broad question. We asked experts to tell us about climate variability. Each aspect raised by the interviewee was followed up by "can you elaborate on this issue?" For interviews with farmers, we had to modify this initial question because pretests had shown that lay people are not familiar with the term climate variability. Instead, we first asked, "What is the climate like here?" followed by "How likely is it that the climate follows this pattern?" After setting the stage in such a manner, we were able talk about reasons for climate variability and how the factors involved might relate do each other. The complete interview protocol can be found in Appendix B.

The rationale behind the two-way approach of expert and farmer interview was to elicit the mental models of forecast producers and users, which allows for a reciprocal flow of information. Farmers are presented with scientific information from experts' models and forecasts of climate variability and, in turn, the understanding of farmers' needs – if reported back to scientists – can lead to modification of forecast components and forecast formats. The protocol is designed to

- Elicit mental model(s) of climate expectations and variability that identifies current types and sources of information used to make intuitive climate predictions
- Characterize perceptions of climate-related risks and determinants of the use of forecast information
- Determine range of climate risks and action alternatives considered by farmers and advisors, and
- Examine differences in mental models between farmers and scientists.

It is essential to compare the scientists' and lay people's mental models if we are to improve the communication about climate variability with laypeople/farmers, to improve forecasts, to provide more adequate training for farmers to better understand forecast and to better respond to them. We conducted mental model interviews with eight scientists at the International Research Institute for Climate Prediction and 16 with farmers in Miami-Dade County. Our sample size, while small, compares well with other mental model studies. Kempton interviewed 14 people (Kempton 1991). Bostrom et al. based their work on 7 preliminary interviews, 51 written responses to definitions of climate change related concepts, and 37 mental model interviews. The latter differed from the preliminary interviews by two added tasks (ranking of causes and policy questions) (BOSTROM 1994; READ 1994). Lazo carried out 58 interviews (Lazo 1999). Another study by Lazo et al. is based on 26 expert interviews, 30 phone interviews with the general public (plus 64 questionnaires) (Lazo 2000).

Our sample was selected with the help of the University of Florida extension service. Extension agents (Dr. Jonathon Crane and Dr. Teresa Olczyk) contacted farmers who they thought would be interested in our study. Because our contacts were not randomly selected, participants are more likely to be more informed and more receptive of new information (tutorials) than farmers at large.

The taped and transcribed interviews were analyzed with NVivo (content analysis). The program Data 3.0 TreeAge aided in the development of influence diagrams.

Questionnaires, one filled out prior to interview and one accompanying the tutorial were developed to elicit information about socioeconomic background, perceptions of climate variability, attitudes toward climate forecasts, climate sensitive farming decisions. The questionnaire about perceptions, attitudes, and decisions was repeated after farmers had learned about the influence of climate variability precipitation in Southern Florida (see tutorial description below).

Forecast Presentation Modules

The original project objectives included, "test and refine the training materials developed by Krantz and Phillips (Krantz and Phillips 2000) with a different sample of users in a different region (Argentine farmers) and with a focus on their fit to the mental models identified in the first research objective ("perception matters"). Upon examining the materials that Krantz and Phillips developed for two workshops in East Africa, and considering what we learned from literature on forecast presentation, we chose to develop new prototype forecast presentation modules. The two modules were designed to meet the following criteria:

Target familiar locations and climatic (or impact) variables. Farmers are interested in particular climatic features at a local scale (Madden and Hayes 2000 ; O'Brien, Sygna et al. 2000 ; Letson, Llovet et al. 2001; Jochec, Mjelde et al. 2001 ; Ingram, Roncoli et al. 2002). Our modules can be developed for any climatic or impact variable at any spatial scale.

In the absence of express interest in specific climatic or probability thresholds, start with continuous climatic variables. The loss of information that results from categorizing a cumulative distribution, the arbitrary nature of thresholds embodied in category boundaries and the evidence (discussed above) of difficulties in interpreting categorical probabilistic presentations of forecast information (Fischhoff 1994; Gigerenzer, Hertwig et al. 2003 submitted; Patt 2003a; Patt 2003b; Dalgleish personal conversation) can be regarded as arguments for presenting seasonal forecasts as continuous distributions. Unfortunately, because most studies have focused on categorical probability formats, we know far less about how farmers and other decision makers perceive and interpret continuous probability formats.

Relate objective time series to farmer experience. Evidence suggests that the way people process description-based information is fundamentally different from the way they process experience-based information. We hypothesize that starting with a time-series representation will help the decision maker relate climate variability to memory of personal experience. Clewett et al. suggest that, "The fullest understanding of climate risk often occurs where people have been able to view all of the historical rainfall (e.g., 100 years) as a time series histogram (Clewett, Cliffe et al. 2000). Time series can be particularly useful because they give an analogue representation (rather than digital) of people's chronological memory pattern." According to Childs et al., allowing farmers to compare their own experience with time series of ENSO events was highly valuable (Childs, Hastings et al. 1991). The modules include questions designed to help farmers relate time series graphs to their own experience.
Convert time series to frequencies. Presenting information as (relative) frequencies rather than equivalent probabilities has a positive effect on many quantitative reasoning or estimation tasks. The frequency of experiencing any climatic category or exceeding any climatic quantity is easily derived from a time series sorted by climatic outcome. The first module illustrates sorting the time series graph and using the rank of climatic observations to derive frequencies.

Convert frequencies to probabilities within a probability-of-exceedance format. A cumulative distribution can be presented mathematically or graphically either as a cumulative distribution function (CDF) or a probability density function (PDF). The histograms associated with a PDF may be more familiar to many. However, we favor the CDF over the PDF. First, a CDF graph explicitly relates probabilities and climatic thresholds. Either may be of interest to farm decision making. Second, it is relatively easy to show how a CDF is derived from a time series. Probability of exceedance (POE) is simply the inverse of a cumulative distribution function (POE = 1-CDF). There is some evidence that suggests that POE might be easier to understand than CDF. "Participants took longer and were more inaccurate in answering the 'probability of getting below median rainfall' statements compared to the 'probability of exceeding median rainfall' statements, irrespective of the probability values" (Dalgleish, personal communication)

Provide the minimum explanation and repetition to ensure understanding. Some training is clearly needed in order for a person to understand an unfamiliar graphic format. The appropriate amount of explanation may depend on the audience. We provided what we considered a minimum set of explanations and examples to illustrate derivation and interpretation of the probability of exceedance graph.

Repeat the procedure for hindcast time series to communicate the forecast as a shifted probability distribution. Details differ for categorical (module 1) and continuous (module 2) prediction systems. The first module highlights La Niña years in the time series graph, and uses them to build a second, conditional probability of exceedance graph. Comparing the climatological and conditional distributions represents the predictability associated with La Niña events as a shifted probability distribution. We also developed a second module for continuous predictions. Module 2 uses the concept of prediction error (i.e., deviation between predictions and observations) to build an error distribution and center it on a particular forecast. We did not give module 2 as much attention as module 1, or test it with farmers.

Thirteen farmers agreed to do the tutorial, 10 of them had also participated in a mental model interview and 3 farmers did only the tutorial.

Content analysis was done with NVivo and statistical analysis with SPSS.

V. Results

Argentine Pampas

Farmer and Farm Characteristics

Most of the farmers (93%) and all of the AACREA technical advisors were male. The average age of farmers was 41.5 years, with a range from 25 to 57 years. They had spent 22.6 years, on average, in farming (with a range from 3 to 53 years) and had been AACREA members for 9.0 years (with a range from 1 to 25 years). Eighty-four percent of them farmed full time. Education was assessed on a ranked category scale from 1 (“less than 9 years of schooling”) to 8 (“university degree”). Level of schooling ranged from 4 (“secondary school, 10 years) to 8, with an average level of 7.23, with 7 corresponding to “some university education, but no degree.” Income was assessed on a ranked category scale from 1 ($0-50,000)) to 6 (more than $200,000) and ranged from 1 to 6, with an average level of 4.04 ($100,000-150,000).

Farm size ranged from 670 to 6,500 ha, with a mean of 2402 ha. For 54% of farms, all land was contiguous; the other 46% of farm operations had land holdings in more than one location. The predominant crops are grains (mostly soy, corn, and wheat). The farms employed between one and ten workers, with an average of 5.4 employees. Not surprisingly, farm income was positively related to farm size ($r = 0.60$, $p < 0.005$).

Personality characteristics varied within the sample of farmers. On the two regulatory states, farmers scored between 19 and 37 on the locomotion scale (which has a range from 12 to 72) and between 25 and 49 on the assessment scale (which has a range from 11 to 66). Farmers were, on average, more assessment oriented (with a mean score of 37.5) than locomotion or action oriented (with a mean score of 26.6). On the two regulatory foci, farmers scored between 17 and 26 (with a mean of 21.3) on the promotion-focus scale (which has a range from 5 to 25) and between 17 and 22 (with a mean of 18.9) on the prevention-focus scale (which has range from 6 to 30). Both sets of characteristics (promotion and prevention focus, and assessment and locomotion orientation) should not be conceptualized as end points on a single continuum. Instead, they are independent dimensions, and a given individual could be both highly promotion and prevention focused, or score low on both dimensions, or high on one and low on the other. There was a significant correlation between level of schooling and degree of promotion focus ($r = 0.62$, $p < 0.02$), such that farmers with higher levels of schooling were more promotion focused. Table 1 shows means and the observed ranges of scores for the Herrmann Brain Dominance Instrument (HBDI) preferred thinking styles which are measured in two ways, as preference codes and as profile scores. The four modes or quadrants for which scores are calculated and to whom codes are assigned are “A” for logical, analytical, quanti-

Table 1. Mean scores, observed range of scores, and theoretical range of score for preferred thinking style.

Scales	Mean	Observed Min	Observed Max	Theoretical Min	Theoretical Max
HBDI Preference Code					
A	1.1	1	2	1	3
B	1.3	1	2	1	3
C	1.8	1	3	1	3
D	1.6	1	3	1	3
HBDI Profile Scores					
A	88.1	54	120	10	150
B	83.6	51	120	10	150
C	56.9	26	95	10	150
D	63.5	32	105	10	150

A=rational thinking style
B=safekeeping thinking style
C=feeling thinking style
D=experimental thinking style

1=primary/dominant preference for point score of 67 and higher
2=secondary/intermediate preference for point score of 34 – 66
3=tertiary preference/avoided thinking style for point score lower than 34

tative, factual, and critical thinking (the rational self); “B” for sequential, organized, planned, detailed, and structured thinking (the safekeeping self); “C” for emotional, interpersonal, sensory, and symbolic thinking (the feeling self); and “D” for visual, holistic, and innovative thinking (the experimental self). For the profile scores, each quadrant score can range from 10 to over 150. The higher someone scores in a quadrant, the stronger the preference of thinking in that mode. Preference codes are derived from profile scores and group profile scores into a family of similar profiles. “1” or “primary” refers to profile scores 67 and higher and indicates a strong preference in a particular thinking style, often visible to others. “2” or “secondary” describes thinking styles that are relatively easily accessible. Preference codes are labeled “3” or “tertiary” for thinking preferences that are used more rarely and which a person finds less comfortable or which they try to avoid. Mode A (rational thinking style) and Mode B (safekeeping thinking style) seem to measure a related construct, by virtue of correlating positively across respondents (r = 0.48, p < 0.02), as do Mode C (emotional/interpersonal thinking style) and Mode D (experimental/discovering thinking style) (r = 0.60, p < 0. 001). AB and CD pairs are found together and are more compatible, most likely because of the location of A and B in the left hemisphere of the brain and C and D in the right hemisphere. In general, it is less common to find an individual to be both a “thinker” and a “feeler” (AC) or both a “risk seeker” and “risk avoider” (BD). In our sample of Argentine farmers, the two construct pairs correlated indeed negatively with each other (e.g., preference code A with preference code C, r = -0.38, p < 0.06; preference code B with preference code C, r = -0.51, p < 0.01).

The preference codes and the profile points obviously measure related constructs, with highly significant negative correlations in all cases (preference code to profile score correlations were -0.50 (for A), -0.69 (B), -0.87 (C), -0.90 (D)), but were not identical. Preference codes and profile score measures often predicted different behaviors as described below.

The only significant relationship between the HBDI measures and the measures from self-regulation theory was between assessment orientation and profile scores. In particular, farmers with higher scores on profile scores A and B and lower scores on profile scores C and D were more assessment oriented (r = 0. 52 between Assessment and profile score A, p < 0.05; r = 0.43 between Assessment and profile score B, p < 0.10; r = -0.45 between Assessment and profile score C, p < 0.10; r = -0.55 between Assessment and profile score D, p < 0.05), meaning that rational and safekeeping types are more assessment oriented, which is plausible and validates both scales.

Decision Goals

People often have decision goals that differ from those of economic models. While the maximization of profits as a goal entails equal attention to the maximization of prices and of yields and to minimization of input costs, farmers in a study in the American Midwest were found to differ in the attention paid to these two sub-objectives (Weber 1997).

During the focus group in which we conducted the decision experiment that involved the allocation of farm plots to different crops and cultivation regimes, we also surveyed the decision goals or objectives underlying the stated production decisions. In particular, respondents indicated (on a numeric rating scale from 0 = “no role at all” to 10 = “a very important role”) the extent to which each of the goals shown in Table 2 played a role in the production decisions made by them in the two scenarios of the farm decision making exercise. As described above, farmers were presented with a detailed description of a typical farm in the region and were asked to make a series of crop selection and crop management decisions under two different scenarios. In the first scenario, only historical climate information (provided to farmers) was available. The second scenario was identical on all dimensions (political risk, crop prices, etc.) except for the expected climate conditions (farmers were given a forecast for a very dry spring, typical of a La Niña year).

Ratings provided for the role played by each of the ten goals in the production decisions made under the two scenarios were highly correlated with each other, i.e., the importance of goals was very similar in the scenario without the climate forecast than in the scenario that added the climate forecast. (Correlations of ratings across respondents between the two scenarios ranged from 0.44 [maximization of crop prices] to 0.91 [maximization of farm profitability]). Thus, we present the combined (average) importance ratings across both scenarios in Table 2. There were significant differences in goal importance, however, as a function of respondent. 14 participating farmers and 3 AACREA technical advisors completed the farm decision exercise and the associated goals survey. Even with our small sample size, we found strong and systematic differences in the role that different decision objectives played for farmers versus technical advisors. As shown in Table 2, farmers gave significantly greater importance ratings than technical advisors to the following decision objectives: maximization of crop yields and crop prices, and minimization of input costs, as separate concerns. The technical advisors were more likely to subsume the two into maximization of profits. Given that farmers have to take many more actions than technical advisors to accomplish these sub-objectives and

Table 2. Mean responses (on a 10-point scale) by farmers (n=14) and AACREA technical advisors (n=3) about the degree to which indicated goals played in role in farm management decisions made during the farm decision making exercise.

Goals	Farmers	Technical Advisors	F(1, 16)	*p-value*
Maximize Crop Yields	**7.75**	5.67	*4.72*	.05
Maximize Crop Prices	**6.54**	3.17	*5.73*	.03
Maximize Farm Profitability	7.92	7.17		
Satisfice Farm Profitability and Insure against Worst-Case Scenario	8.11	8.17		
Minimize Cost of Production Inputs	**6.25**	2.66	*4.07*	.06
Minimize Impact of Drought, Floods on Crop Yields	8.92	8.17		
Minimize Impact of Political Uncertainty	**6.43**	3.00	*4.11*	.06
Make Best Possible Decisions Given Circumstances	9.14	9.00		
Make Reasonable Decisions Given Circumstances	**6.82**	3.00	*6.06*	.03
Minimize Possible Regret about Decisions After the Fact	***6.89***	*3.83*	5.12	.04

Responses are averaged across both scenarios (Scenario 1 without climate forecast; Scenario 2 with a forecast of La Niña conditions). Boldfaced entries indicate the larger of the two means in those cases where responses by farmers and technical advisors differed significantly, at alpha levels of at least 0.10.

that they have to take different sets of actions to accomplish the separate sub-objectives, it is understandable and probably quite useful for them to pay separate attention to each one, as long as the fact that profit maximization ought to be the final goal is not forgotten. (Farm profit maximization as a stated goal was, in fact, significantly correlated with maximization of crop yields ($r = 0.70$) and of crop prices ($r = 0.62$)).

Table 2 also shows that farmers had a broader set of decision goals. They were significantly more likely than the technical advisors to endorse the importance of the minimization of post-decision regret, of making a satisfactory (rather than the best possible) decision, and of minimizing the impact of political uncertainty. Technical advisors, on the other hand, were largely focused on maximizing farm profitability and minimizing climate risks.

Affective Goals and Affect-Based Processing

Minimization of decision regret (i.e., of the unpleasant feeling that one made the "wrong" decision upon experiencing an unfavorable outcome) is an affective goal frequently observed, even though regret minimization often results in decisions that have lower objective profit. That is, people often prefer a choice alternative that offers a certain amount of profit and a minimal chance that they will regret their decision over other alternatives that offer higher profitability at the cost of a greater chance to experience regret (Loomes 1987). The farmers in our sample confirmed that the minimization of post-decision regret played some role in their production decisions (6.89), more important in fact than the minimization of input costs (6.25) and the maximization of crop prices (6.54).

People have been shown to use affect, i.e., their emotional reactions to possible decision options and their consequences as guides to action, either in addition to or instead of using analytic evaluations. Such affective or intuitive reactions have many advantages. They are often the result of years of personal experience, and incorporate lessons learned the hard way, i.e., by trial and error. They also are fast and thus enable us to react in situations where a timely response is of essence. Unlike analytic reactions and models, they require no computers, spreadsheets, or calculations. They are part of our evolutionary heritage and come either hardwired or are learned automatically. As a result, they are hard to turn off, i.e., occur even if we do not want to use them. However, research has also identified some downsides to affective processing of information. We examined whether some of those previously identified negative consequences were present in the judgments and decisions made by AACREA farmers in the focus group and the decision experiment where farmers were presented with a detailed description of a typical farm in the region and were asked to go through a series of land allocation and crop management decisions under two different scenarios. In the first scenario, only historical climate information (provided to farmers) was available. The second scenario was identical on all dimensions (political risk, crop prices, etc.) except for the expected climate conditions (farmers were given a forecast for a very dry spring, typical of a La Niña year).

One phenomenon we investigated was the "finite pool of worry" bias, which refers to the fact that as worry increases about one type of risk, concern about other risks oftentimes goes down, as if people had only so much worry to spend (Linville 1991). We found some evidence of this tendency in our decision experiment. In each of the two scenarios of the decision exercise, respondents

Table 3. Mean ratings of concern or worry (on a 11-point scale) provided by farmers (n=14) for each of four categories of risk in Scenarios 1 and 2 of the Farm Decision Making Exercise.

Category of Risk	Scenario 1	Scenario 2	p-value of Test of Difference
Political Risk	**8.6**	8.1	*.10*
Climate Risk	7.5	**8.4**	*.05*
Input Price Risk	4.7	**6.5**	*.05*
Crop Price Risk	8.1	8.3	

P-values for ratings that were significant at least the 0.10 level are also shown.

rated the extent that they were worried about (a) the political situation and its effects on taxes, etc., (b) weather and climate, (c) prices of input variables, and (d) prices of crops at harvest, with ratings on a scale from 0 ("not at all worried") to 10 ("extremely worried"). As shown in Table 3, stated concern about climate risks among the 14 farmers in our sample went up from the first to the second scenario (from mean rating of 7.5 to a mean rating of 8.4 on a ten-point scale, where larger numbers indicated greater perceived riskiness, $p < 0.05$), suggesting that our manipulation of climate information was understood correctly and resulted in appropriately greater concern. At the same time, however, concern with political risk decreased between scenarios (from a mean rating of 8.6 to a mean rating of 8.1, $p < 0.10$), even though the objective political risk had not changed at all (it was stated to be the same as the actual conditions at the time of the focus group). There was some indication that concern and worry (and as the result of an affective evaluation, perceived risk) was a finite resource even *within* each scenario. In both climate scenarios, those farmers who worried more about political risk tended to worry less about climate risk. The correlation between ratings of political risk and climate risk was -0.50 in Scenario 1 and -0.47 in Scenario 2. In addition, differences in farmers' perceptions of the degree of risk posed by political, climate, input costs and crop price variables were associated with differences in subsequent actions taken.

Contrary to expectations, the decision experiment showed no evidence of another suboptimal consequence of affective processing, the "single-action" bias (Weber 1997). It refers to the tendency to take only a single action to solve a problem or manage some risk in situations where a portfolio of responses would be more appropriate. This suboptimal behavior is thought to result from the fact that the first action taken to respond to the risk or problem at hand reduces or removes the feeling of worry or concern previously experienced. With the removal of the affective marker, motivation for further action has been reduced. The participants in our decision experiment did not show any evidence of the single-action bias, at least not for the four classes of actions we examined, namely land allocation, fine tuning of production decisions regarding choice of corn hybrids and fertilization levels, strategy to price crops, and other operational decisions. As shown in Table 4, projected attention to three of the four classes of actions did not differ between the two scenarios. Only crop pricing decisions were projected to receive greater attention in Scenario 2, with its forecast of La Niña climate conditions. Regarding the single-action bias, a greater projected likelihood to engage in one of these actions did not result in a smaller likelihood of engaging in any of the other actions (i.e., there were no significant negative pairwise correlations between stated engagement likelihoods for the four types of action) either for the first scenario and, more importantly, nor for the second scenario which

Table 4. Mean ratings of attention (on a 11-point scale) provided by farmers (n=14) projected to be allocated to each of four types of action in Scenarios 1 and 2 of the Farm Decision Making Exercise.

Category of Action	Scenario 1	Scenario 2	p-value of Test of Difference
Land Allocation to Crops	6.5	6.6	
Fine Tune Maize Plantings	6.9	6.9	
Crop Pricing	7.8	**8.4**	*.05*
Other Farm Management	7.7	7.7	

P-values for ratings that were significant at least the 0.10 level are also shown.

had alerted farmers to the presence of a climate risk. It is possible that it is the hypothetical and simultaneous elicitation of likely attention to different classes of action that is responsible for our failure to find evidence for the single-action bias. After all, the prediction for the bias is based on the fact that the *execution* of some protective action takes down the affective marker that warns of some impending danger. Evidence to support this interpretation comes from the fact that we did find evidence for the single-action bias in the actual farm practices reported by our respondents that can be interpreted as protective actions against climate change (see Table 7). Thus farmers who indicated that they had the capacity to store grain on their farms were significantly less likely to indicate that they used irrigation (r = -0.52, $p < 0.01$) and that they had signed up for crop insurance at some point (r = -0.47, $p < 0.02$).

There was some evidence of wishful thinking in farmers' recollections of the maximum and minimum amount of December rainfall experienced in their region over the past 10 years (see Table 7). There were strong correlations between the remembered amounts of rainfall and their expressed belief that more rainfall was either desirable or undesirable. In particular, farmers who thought more December rain desirable recalled larger maximum and minimum rainfalls; farmers who thought more December rainfall undesirable, on the other hand, recalled smaller maximum and minimum rainfalls (r = 0.61 and 0.73, respectively, $p < 0.05$).

Relationships between Personality and Decision Goals

Farmers' scores on assessment orientation, prevention focus, profile score B (Safekeeping), and profile score D (Experimenting) were found to be associated with differences in the stated importance of the different decision goals shown in Table 2. In particular, farmers who were more assessment oriented were less likely to indicate that sub-goals to the overall goal of maximizing farm profitability played a significant role in their decision making. Specifically, there was a negative correlation between assessment orientation and the importance rating of the sub-goal "maximize crop prices" (r = -0.93, $p < 0.001$) and of the sub-goal "minimize political risks" (r = -0.73, $p < 0.05$). In contrast, farmers who were more prevention focused indicated that the goal of "making the best possible decision under the circumstances" played a smaller role in their farm management decisions (r = -0.81, $p < 0.01$) and that the goal of "maximizing yields" played a larger role (r = 0.72, $p < 0.05$). Finally, the stated importance of the affective goal of "minimizing possible regret about farm management decisions after the fact" was positively related to farmers' score on profile score B (Safekeeping) (r = 0.60, $p < 0.04$) and negatively to their score on profile score D (Experimenting) (r = -0.61, $p < 0.04$).

Climate Change Perceptions

Responses to a variety of questions related to perceptions and beliefs about climate variability and climate change are shown in Table 7. Not surprisingly, farmers who had larger farms (both in terms of area and number of employees) reported a larger number of instances over the past 12 years during which floods affected their farm operation (r = 0.44 and 0.60, $p < 0.05$).

Relationships between Decision Goals and Climate Change Perceptions

Farmers who gave less importance to the goal of satisficing, i.e., making a "just reasonable" rather than the "best possible decision" under the circumstances, were more likely to believe that the climate in their region had changed over the last several years (r = -0.68, $p < 0.01$). Farmers who assigned more importance to the goal of minimizing possible post-decision regret (especially for farm management decisions made in Scenario 2, with its La Niña climate forecast) were less likely to believe that spring rainfall had increased in quantity and intensity (r = -0.58 and -0.57, $p <. 03$), that fall, winter, and spring temperatures had increased (r = -0.57, -0.58, and -0.57, $p <. 03$), and that fall, winter, and spring frost periods had become more frequent (r = -0.58, -0.58, and -0.57, $p < 0.03$), possibly related to the issue of wishful thinking discussed above. Finally, those farmers who gave greater importance to the subgoal of maximizing crop prices provided larger estimates from memory of the minimum level of December rainfall over the past 10 years (r = 0. 97, $p < 0.005$), possibly another wishful thinking or wishful memory effect.

Effects of Personality and Demographics on Climate Related Perceptions and Beliefs

Farmers who were more promotion focused were more likely to express the belief that the climate in their region had changed over the last few years (r = 0.51, $p < 0.05$) and were more likely to have come by that belief by personal observation (r = 0.50, $p < 0.05$). Farmers who were more prevention focused, on the other hand, were more likely to have arrived at their belief in climate change as the result of information received from other farmers (r = 0.59, $p < 0.02$). Promotion-focused farmers were also more likely to believe that summer and fall rainfall had increased in quantity and in intensity (i.e., more rain in shorter periods of time), and that fall, winter, and

Table 5. Actual Production and Management Decisions of Farmers.

Action or Behavior	Mean or Proportion	Minimum	Maximum
Plants ….			
Soybean	1.0		
Maize	.96		
Wheat	.96		
Sorghum	.08		
Other Crop	.08		
Changes in ha of Crop Planted between 2001/02 and 1997/98 …..			
Maize	235	-50	500
Wheat	290	32	500
Soybean_1	351	160	500
Soybean_2	515	32	1500
Uses Own Cultivation Equipment	.73		
Leases Cultivation Equipment	.63		
Has Storage Facilities for Grain	.74		
Uses Irrigation	.08		
Uses Crop Insurance	.83		
Used Futures Contracts in 2001/02 to Price Crops	1.0		
Annual Farm Expenses (in thousands of dollars) Related to……			
Labor	20.3	18	25
Input (Seed Corn, Fertilizer, etc.)	27.5	17	41
Administration	22.5	5	30
Infrastructure	24.8	10	45
Taxes	10.8	5	33
Debt Repayment	6.9	5	12
Other	10.0	10	10

Table 6. Hypothetical Crop Choices and Cultivation Decisions in Farm Decision Making Exercise made for Scenario 1 (Climatology) and Scenario 2 (La Niña Forecast).

	Scen 1			Scen 2			Difference Between Scen 1 and 2
Action	Mean/Prop	Min	Max	Mean/Prop	Min	Max	
Number of Don Albino Plots Planted With……							
Maize	2.1	0	4	2.1	0	4	
Soybean	2.2	0	4	2.2	0	4	
Wheat	0	0	0	0	0	0	
Wheat-Soybean Combination	1.7	0	4	1.7	0	4	
Number of La Josefa Plots Planted With……							
Maize	1.9	1	3	1.5	0	2	t(13)=2,97, $p < 0.01$
Soybean	2.4	1	4	2.9	1	5	
Wheat	0	0	0	0	0	0	
Wheat-Soybean Combination	1.7	0	4	1.6	0	3	
Proportion of Farmers Using a Mix of Maize Hybrids	.21			.14			
Cycle of Maize Hybrid (larger numbers denote larger cycle)	2.10	0	2.75	2.40	1.25	3.00	
Date of Maize Planting (larger numbers denote later date)	3.73	0	5.5	4.34	2.50	6.00	t(13)=1.90, $p < 0.05$
Density of Maize Planting (#plants/ha)	72,116	66,375	78,333	71,192	66,400	79,000	
Quantity of Maize Fertilizer (kg/ha)	138.2	17.4	110.2	140.3	100.5	189.2	

spring temperatures had increased over the past few years, (with correlations significant at the 0.05 level between each of these perceptions and farmers' promotion-focus score). Prevention-focused farmers, on the other hand, were more likely to report more intense frosts during winter and less frequent frosts during the spring season, i.e., seemed to be more attentive to specific adverse events (presumably in an effort to guard or protect against them).

Farmers who had been in farming longer and had been more longstanding AACREA members (the two variables were strongly correlated with each other) were more likely to report more continuous rainfall during the winter season (r = 0.56, $p < 0.01$) and less frequent hail storms during the spring (r = 0.56, $p < 0.01$). Older farmers were also more likely to rank climate risks highly on a list of threats to their farm operation (r = -0.60, $p < 0.03$). Farmers who operated larger farms were more likely to report an increased frequency of hailstorms during the summer and fall season (r = 0.51 and 0.54, respectively, $p < 0.01$). More safekeeping farmers (those scoring higher on profile score B) reported being affected by a larger number of flood episodes (r = 0.79, $p < 0.0001$) and more emotional and experiential farmers (those scoring higher on profile score C and profile score D) reported being affected by a smaller number of flood episodes (r = -0.50 and -0.61, $p <$. 03). This was particularly true for the years 2001 and 2002.

Farm Decisions

We had information both about farmers' actual farm decisions from databases at AACREA and about their self-reported practices from various questionnaires. Means and ranges on those variables are shown in Table 5.

We also had their planting and cultivation decisions in the farm decision making exercise, which – while hypothetical – have the advantage of exposing every farmer to the same decision environment: same described farm with multiple plots with same prior crop planting history and same information about time period and climate conditions (with climatology, farmers' typical climate "forecast" in Scenario 1, and a professional forecast of La Niña conditions in Scenario 2). Those responses are shown in Table 6. Since all farmers responded to both scenarios, this allows us to identify changes in farm management decisions (crop choices, fertilization and other cultivation decisions) that are the result of the additional climate forecast information as the *only* variable that has changed in the scenario. The variables in the table were computed from the responses provided by farmers about crop choices and cultivation decisions (for maize plantings) for six plots each in two different locations. Table 8 presents the crop selection decision that the 3-year crop rotation cycle advocated by AACREA (maize, followed by soybean, followed by wheat/soybean) would suggest for each plot, together with the number of farmers who selected the thus-recommended crop, as well as the number of farmers who selected other crops, both in Scenario 1 and in Scenario 2. As Table 8 shows, farmers' selection of crops did not differ very much between scenarios, i.e., as the result of receiving the La Niña forecast under Scenario 2. In both scenarios, a strong majority of farmers selected the crop-cycle-appropriate crop. For Plot 5 in the La Josefa location there is some question about which crop farmers thought to be the cycle-recommended one. Perhaps due to a clerical error, the history of the plot provided a deviation from the 3-year rotational pattern, such that soybean was followed by wheat/soybean, followed by soybean again (rather than maize). The data show that farmers thought that wheat/soybean was the next appropriate crop, rather than catching up to the cycle by planting maize. Table 8 also shows that, for some reason, farmers adhered slightly more strictly to the crop-cycle recommendation in Scenario 2 (with its La Niña forecast) than in Scenario 1 for the six plots in the Don Albino location, whereas the opposite was true for the La Josefa location.

Table 7 presents summary indices about cultivation decision details for those plots in which farmers decided to grow maize. There were few differences in those decisions as a function of obtaining a climate forecast of La Niña conditions. However, the number of La Josefa plots in which maize was grown increased significantly, as did the date at which maize planting was started, i.e., it started significantly earlier as the result of the La Niña climate forecast.

Effect of Farm and Farmer Characteristics, Personality, Perceptions, and Decision Goals on Farm Decisions

The greater the reported farm income, the more land was converted to maize, wheat, and soybean from the 1997/98 to the 2001/02 growing season (r = 0.99, 0.98, and 0.98, respectively, all $p < 0.001$). Farmers with larger farm incomes were more likely to report the use of crop insurance (r = 0.43, $p < 0.05$). Farmers who had been in operation longer and had been AACREA members longer, however, were less likely to use crop insurance (r = -0.41 and -0.42, $p < 0.05$).

Farmers who had more employees and farmers who were more prevention focused were significantly less likely to have used the Argentine equivalent of FEMA to compensate them for crop damage during the years 2000 (r = -0.44 and -0.53, $p < 0.05$) and 2002 (r = -0.54 and -0.53, $p < 0.05$), perhaps in both cases because they had

Table 7. Perceptions and Beliefs related to Climate Change expressed by Farmers in Questionnaires Before and During Focus Group 1.

Beliefs or Statement of Facts	Proportion of Farmers Endorsing Belief or Statement or Mean Judgment (and Range)
Climate in Region Has Changed Over Last Several Years	.38
Source of Belief in Climate Change:	
Personal Memory	.29
Other Farmers	.18
Press	.11
Television	.04
Other	.11
More December Rainfall is Desirable	.45
More December Rainfall is Undesirable	.55
Climate Change Has Affected Farm Management Decisions	.36
Lowest Amount of December Rainfall (in mm) Remembered Over Last 10 Years	28 (0 to 50)
Lowest Amount of December Rainfall (in mm) Remembered Over Last 10 Years	159 (100 to 300)
Number of Times over last 10 Years that Government Insurance Fund similar to FEMA was Approached as the Result of Crop Damage	1 (0 to 3)
Number of Years (out of last 12) Affected by Flood	1.45 (0 to 4)
Particular Years that Flood Damage was mentioned……..	
1995	.04
1998	.04
1999	.08
2000	.33
2001	.55
Affected by Drought anytime over last 12 years	.33

Table 8. Farmers' crop choices for six plots in Don Albino and six plots in La Josefa location, made under the climatology conditions of Scenario 1 and the La Niña forecast of Scenario 2.

		Scenario 1			Scenario 2		
	AACREA Cycle Recommendation	Maize	Soybean	Wheat/Soybean	Maize	Soybean	Wheat/Soybean
Don Albino							
Plot 1	Maize	**11**	3	0	**13**	1	0
Plot 2	Wheat/Soybean	4	0	**10**	3	0	**11**
Plot 3	Soybean	0	**11**	3	0	2	**12**
Plot 4	Maize	**10**	4	0	**11**	3	0
Plot 5	Wheat/Soybean	4	1	**9**	2	3	**9**
Plot 6	Soybean	0	**12**	2	0	**12**	2
La Josefa							
Plot 1	Wheat/Soybean	2	2	**10**	3	3	**8**
Plot 2	Soybean	0	**12**	2	0	**12**	2
Plot 3	Soybean	0	**14**	0	0	**13**	1
Plot 4	Maize	**10**	2	2	**7**	6	1
Plot 5	?	2	2	**10**	3	2	**9**
Plot 6	Maize	**13**	1	0	**9**	4	1

Boldface cells indicate the choice that coincides with the AACREA crop -cycle recommendation.

the resources (manpower in one case, attentional focus in the other) to prevent such damage. The same (i.e., lower likelihood of having used FEMA during 2000 and 2002) was true for more safekeeping farmers (those scoring higher on profile score B) (r = -0.51 and -0.39, $p < 0.05$), even though there was no significant correlation between profile score B and prevention focus (r = 0.11, p = 0.67).

Interestingly, personality affected the percentage of farm expenses allocated to different expense categories. In particular, farmers who scored higher on profile score B (rationality) and who were more assessment oriented (two personality measures that were positively correlated, r=0. 44, $p < 0.10$) spent more money on farm administration (r = 0.50, $p < 0.05$) and infrastructure (r = 0.68, $p < 0.01$) and less on labor (r = 0 -.82, p < 0 .05) and debt repayment/maintenance (r = -0.70, $p < 0.01$). Those farmers who were less assessment oriented and who scored more highly on profile score D (experimenting) (two personality measures that were negatively correlated, r = -0.55, $p < 0.03$) showed the opposite pattern of expenditures, spending more on labor (r = 0.94, $p < 0.01$) and debt (r = 0.76, $p < 0.005$) and less on administration (r = -0.59, $p < 0.05$) and infrastructure (r = -0.59, $p < 0.05$).

For the production decisions made during the farm decision exercise, we computed the following four summary indices of actions taken by a given farmer (across the 12 plots), for each of the two scenarios: type of hybrid of maize chosen (ranging from 1 for a short cycle hybrid to 3 for a long cycle hybrid), planting date (ranging from 1 for an early August starting date to 8 for a late October starting date), density of planting (as the number of plants per ha), and the quantity of fertilizer applied (kg per ha).

A repeated-measures regression analysis, employing the general linear model procedure of SAS (PROC GLM) analyzed these four decision indices (the type of hybrid of maize chosen, the planting date, the density of planting, and the amount of fertilizer used) for Scenarios 1 and 2, respectively, as a function of demographic characteristics and personality variables identified above as affecting many farm management decisions. In particular, we examined the effect of farm income, years of farming experience, whether the farmer was working full-time or part-time, number of farm employees, the four personality variables defined by self-regulation theory, and the two combined Hermann personality variables AB and CD. The analysis showed no significant repeated-measures effect of scenario, i.e., there was no main effect for scenario (the presence or absence of a La Niña forecast), nor any interaction between the effects of demographic or personality variables and a change in decisions as a function of having the La Niña climate forecast scenario. The size of the farm operation (as measured by land area as well as the number of farm employees) and the degree of promotion and especially prevention focus, on the other hand, affected some of the cultivation decision indices, but not others (i.e., there was a significant interaction between decision type and farm size [$F(7,14)=2.66$, $p < 0.05$], number of employees [$F(3,13)=7.80$, $p < 0.02$], promotion focus [$F(7,14)=3.52$, $p < 0.02$, and prevention focus [$F(7,14)=7.77$, $p < 0.002$]. In both scenarios, farm size (as measured by both size variables) made farmers start planting later. Farmers with larger operations were also more likely (but only marginally, with a 0.10 or 0.15 level of statistical significance) to use a higher-cycle maize hybrid, grow it at higher density, and use more fertilizer. Promotion focus had the same effects (though also at lower degrees of statistical significance) as having a larger farm operation. Having a greater prevention focus, on the other hand, had the opposite effect, making farmers start planting earlier and use a lower cycle hybrid, as well as (though only marginally) using less fertilizer and planting at lower densities.

In summary, there was significant evidence that individual differences in farmers' perceptions of the degree of risk posed by political, climate, input costs and crop price variables affected farm management decisions. In addition, changes in the perceptions of the degree of risk resulted in changes in some management decisions. As predicted, risk perception drove action, and changes in perceived risk resulted in changes in action, including production decisions.

Southern Florida

Farmer and Farm Characteristics

We interviewed 8 climate scientists (2 female, 6 male) at the International Research Institute for Climate Prediction. Participants were selected from researchers in forecasting, monitoring, and modeling. We interviewed a convenience sample of 15 farmers and 1 advisor, and administered the tutorial to 13 farmers (10 farmers and 3 growers employed by one of the farmers), leading to a total of 19 responses. Seventy-five percent of the participants were male, 25% were female. The average age of farmers was 48.5 years, with a range from 31 to 60 years. They had spent, on average, 24.6 years in farming (with a range from 8 to 60 years). Education was assessed on a ranked category scale for highest degree (1 = High school, 2 = Community College, Technical College, or some college, 3 = Univ. Degree, 4 = Graduate degree). The average level of schooling was 2.95. Farm size ranged from 3 to 4000 acres, with a mean of 673 acres. Thirty-one percent of the farmers were engaged in fruit production, 67% were vegetable growers, and 2% grew ornamentals or landscaping plants (with one farmer being engaged in both fruit and vegetable production).

Table 9. Agricultural Production in Miami-Dade County: Comparison of sample with entire county

Farm land use	Sample			Miami-Dade County	
	No. farms	acres	percent	acres	percent
Fruit production	9*	3,322	30.8%	15,611	20.4%
Vegetable production	3*	7,200	66.9%	40,411	52.9%
Ornamental nurseries	4	247	2.3%	12,000	15.7%
Fallow	0	0	0.0%	2,357	3.1%
Livestock	0	0	0.0%	6,000	7.9%
TOTAL	16	10,769	100.0%	76,361	100.0%

Source: http://www.agmarketing.ifas.ufl.edu/dlfiles/Findings_Descriptive.pdf, p. 12
* one farmer grows fruit trees and vegetables.

The amount of acres farmed by the interviewed farmers totals 10,769, which is roughly 11% of the county's acreage used for agricultural production. Yet the study participants represent only roughly 1% of all farms (16 out of 1576 (number for 1997). We interviewed some of the largest farms in the county. While only 1% (19 farms) of Miami-Dade county's farms are larger than 1000 acres, five farmers in our sample cultivate at least this amount of land.[1]

As Table 9 shows, in our study, tropical fruit growers are over-represented, vegetable growers over-represented, nurseries under-represented. Sample selection for follow-up research in Florida should consider this. In regard to the age of farmers, the average age of 48.5 years in our sample matches that of the average Floridian farmer (operator with farming as their occupation) quite well.[2]

Perceptions of Climate Variability

General Observations. Common sense and previous studies have shown that the general public has a very limited understanding of climate variability. Lazo et al. (Lazo 2000) found that people rated all risks that related to climate variability lower on the understandability factor than ecological scientists did. Some of these risks are decreased or increased rainfall, extreme temperatures, frequent flooding events, increased severity of winter storms, and more droughts. Understandability here means observability, predictability, recognition of impacts, timing of effects, and understandability in general. Because farmers are more vulnerable to the impacts of climate variability, we hypothesized that they might have a greater understanding of this phenomenon than the public. Yet, the majority of farmers in our sample admitted during the interviews that they had very little knowledge of the causes and particular effects of climate variability.

Influence Diagrams. Influence diagrams are a good way to illustrate mental models. They can be understood as a snapshot of perceptions of all the factors that influence climate variability.[3] While influence diagrams are often used to describe factors involved in a decision, we have employed them to depict factors influencing the outcome of environmental processes. Following are two examples of farmers' mental models. Appendix D contains influence diagrams for all farmers and climate scientists, and one influence diagram representing the merged mental models of the interviewed climate scientists.

Rectangle (blue) nodes represent the question "what will the conditions be like next season?" or "will there be climate variability?" Oval or round (green) nodes are chance nodes and indicate a variable or event whose value or outcome is uncertain. Double-lined oval (purple) nodes represent deterministic nodes. Diamond-shaped (red) nodes depict some measure or quantity of a final outcome. Arcs denote influence from one node to another and arrows show the direction of such influence.

Table 10 summarizes farmers' mental models and compares them with expert mental models. The table demonstrates that farmers think largely in terms of day-to-day weather, even when specifically asked about inter-annual and seasonal variation of climatic patterns. Other studies have pointed out that when asked about climate variability, farmers tend to easily slide into talking about weather rather than climate, knowingly or not. This is not necessarily a failure on part of farmers. Rather it reflects farmers' concerns with weather events. Yet, as many previous studies have highlighted, an even more important message is that climate scientists have become comfortable with their jargon and need to be conscious of the inconsistency of how climate scientists vs. farmers distinguish and label the different time scales.

Local vs. Global Factors. When it comes to climate variability, farmers think more locally or at least within the frame of North America, and experts explain climate variability globally. While many farmers mention El Niño and La Niña as factors influencing climate variability, and while many of them know that these two phenomena oc-

Table 10. Comparison Farmers and Expert Mental Models of Climate Variability

Factor causing climate variability	Items mentioned by farmers (n=15)	Items mentioned by experts (n=7)
Oceans		
Oceans, general	60%	100%
Pacific Ocean, general	33%	
Atlantic Ocean, general	13%	
Indian Ocean, general	7%	
Ocean temperatures in remote locations	53%	100%
Ocean temperatures locally	13%	0
Pacific Ocean SSTs	0	100%
Atlantic Ocean SSTs	0	57%
Indian Ocean SSTs	0	57%
Ocean currents, general	13%	14%
Gulf stream	7%	0
Sea ice	7%	57%
Atmosphere, large scale	53%	100%
Atmosphere, general	7%	100%
Winds, general	53%	100%
Jet stream, large scale	0	14%
Air temperatures above land in remote areas	40%	Indirectly mentioned by 57%
Atmosphere, local scale		
Jet stream, small scale (Southeast US)	60%	14%
Cloud cover locally	7%	0
Hurricanes locally	13 %	0
Thunderstorms	7%	0
Fronts	20%	0
Ocean-Atmosphere coupled system		100%
El Niño	60% (most only mention term but don't understand it as ocean-atmosphere coupled system)	100%
La Niña	53% (most only mention term but don't understand it as ocean-atmosphere coupled system)	100%
Land surface		
Mountain ranges	0	57%
Land cover/vegetation	0	57%
Land/soil moisture	0	57%
Snow cover	0	57%
Astronomic	20%	43%
Sun	0	43%
Sunspots	7%	0
Moon	20%	0
Tides	7%	0
Anthropogenic	20%	0
Global climate change	60%	0
Randomness/Chaotic nature/noise	13%	71%
Other		
Conditions at beginning of season	0	14%
Seasonal cycle	0	14%
Volcanic activity	7%	0
Rupture in panel ocean bottom	7%	0

cur in the tropical Pacific Ocean and have an impact around the globe, they look for explanations closer to home. For instance, to farmers the variability of winter temperatures in Florida depends on temperatures in Canada. In addition, they see an important role in local cloud cover, wind currents over the US and Mexico, and water conditions in Lake Okeechobee, the Everglades, the Atlantic around Florida, and the Gulf coast.

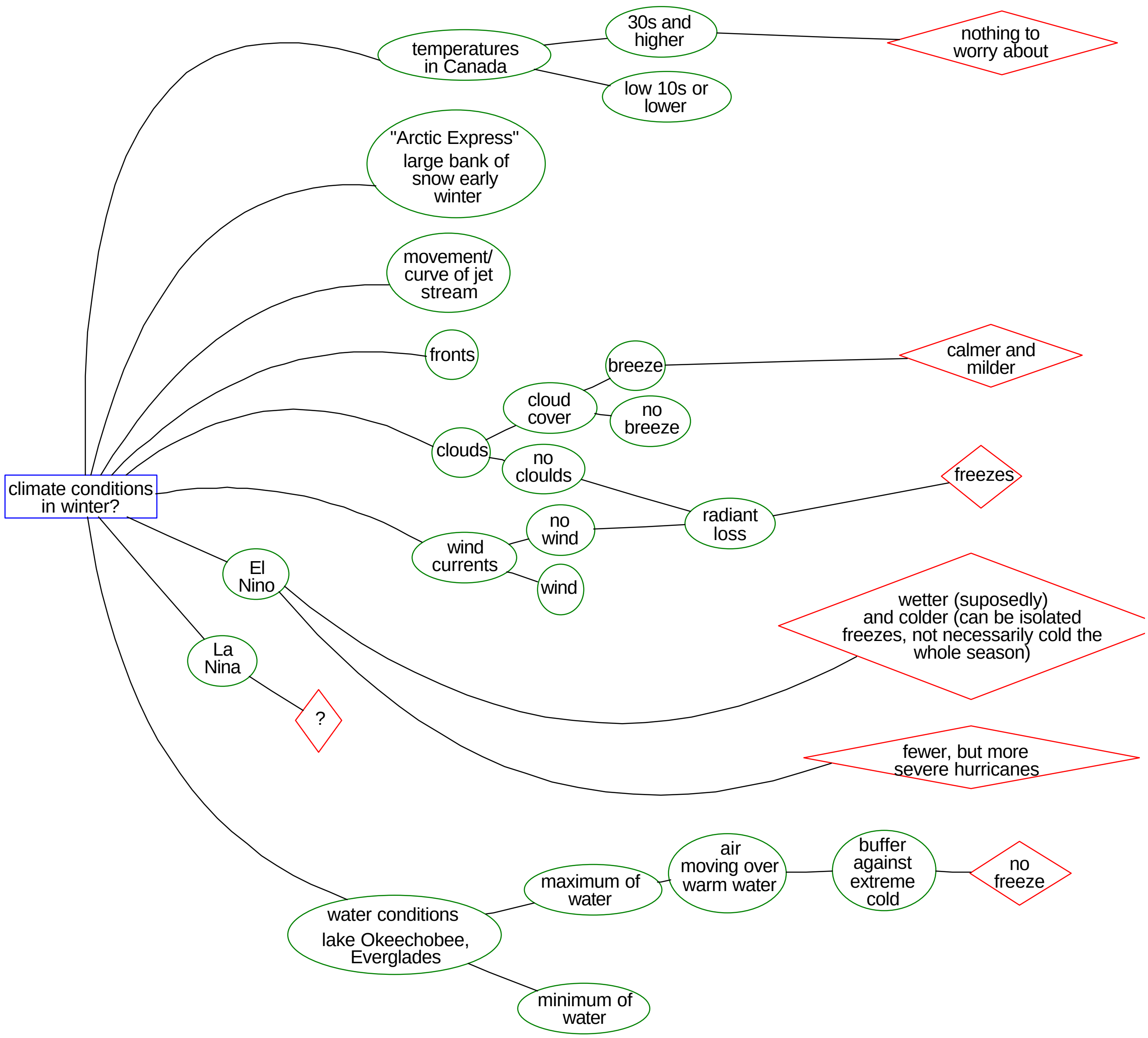
An example of local explanations is the jet stream, which farmers see as one of the most important factor influencing climate variability in Southern Florida. Sixty percent of all farmers mentioned the jet stream, but only 14% of the experts did. It is important to note that experts did not specifically talk about Florida, many concentrated on global phenomena or on other parts of globe. However, few farmers can explain what exact role it plays. Quite a few farmers see a connection between the changes in the jet stream and El Niño, but the majority view El Nino and the jet stream as separate aspects of climate variability. For example, farmer 12 reasons: "Over the last four or five years, we've had a strange occurrence, we've had two jet streams. We've had the southern one. We've had the northern one. The southern one has been keeping us in these mild winters. So long as that's in place, we're in good shape. Once those two become one, then it begins again. Then you have no protection [against] those subtropical winds. That's one thing in particular that we've noticed -- that we've been lucky to have two jet streams throughout our winter season. Now, what causes that? El Niño? La Niña? Who knows? I don't [know] where that all comes from. I do know that those affect us and I don't exactly know how they affect us." Farmer 3 sees the following connection: "I think the ocean temperatures will probably be the most important [factor in causing climate variability], because I think they actually drive the intensity and the location of the jet streams and the trade winds. I think it's the differences in ocean temperature that are actually causing the movements at the location and the speed of the winds. They're sort of, well I mean, it's sort of thermodynamics."

In comparison, the following excerpt from an expert interview represents the scientific view of the relationship between the jet stream and climate variability:

> … from year to year you get very noticeable temperature differences in the sea surface. And on top of that, they happen to be at a latitude in the tropics where it affects the amount of thunderstorms that you get over the water. When the water's warmer, you get a lot more thunderstorms over the water. When it's cooler, you get fewer than normal. And it's such a large region that changes dramatically in temperature from year to year that the differences in the thunderstorms are enough. The area's big enough so that it affects the global heat budget. Because when you have thunderstorms, you're heating the upper atmosphere a lot more than when you don't. You have rising air from the surface; you have condensation and thunderstorm clouds. And condensation involves heating. It's a latent heat. And what this does is, it's enough to change the circulation patterns across the globe. When there's a lot of heating, you get upper air moving away from the equator. Because the air rises at the equator and it has no place to go. When it hits the stratosphere, it can't rise any farther. Because there's an inversion there. The stratosphere's warmer than the troposphere, at least where the ozone is. So it can't keep rising. So it goes away from the equator. And in doing that, it encounters the effects of the Earth's rotation. And that causes it to turn to the right in the Northern Hemisphere and to the left in the Southern Hemisphere, and it increases the jet stream speed when it makes that turn. And also for other reasons, it brings the jet stream farther south than it usually is. It makes it stronger and farther south and that gives rise to lows and highs in the weather that are different from a normal (IRI scientist).

Some farmers try to see a global connection of the causes and impacts of climate variability. A few farmers' statements indicate a tendency to think of a global balance or equilibrium of temperature and rainfall, although they might only reflect reports in the media. For instance, in the context of El Niño, farmer 10 explained: "[El Niño means] typically decreased rainfall, much warmer weather, and temperatures in the Pacific Ocean that influences moisture levels into the United States. But then, I guess, maybe drier conditions in other areas of the world such as Australia. ... As you have extremes in one area of the world, for instance, let's say, maybe wetter than normal El Niño conditions in the US, then you have extremes in the opposite in other parts of the world." While reasoning about the jet stream occupied a considerable amount of time in discussions with farmers, other factors perceived as influencing climate variability were the oceans, in particular the Pacific Ocean, ocean temperatures, El

Figure 1: Influence Diagram Representing Farmer Mental Model of Climate Variability (Farmer 1)



Legend:

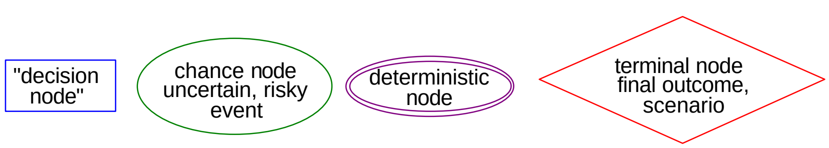
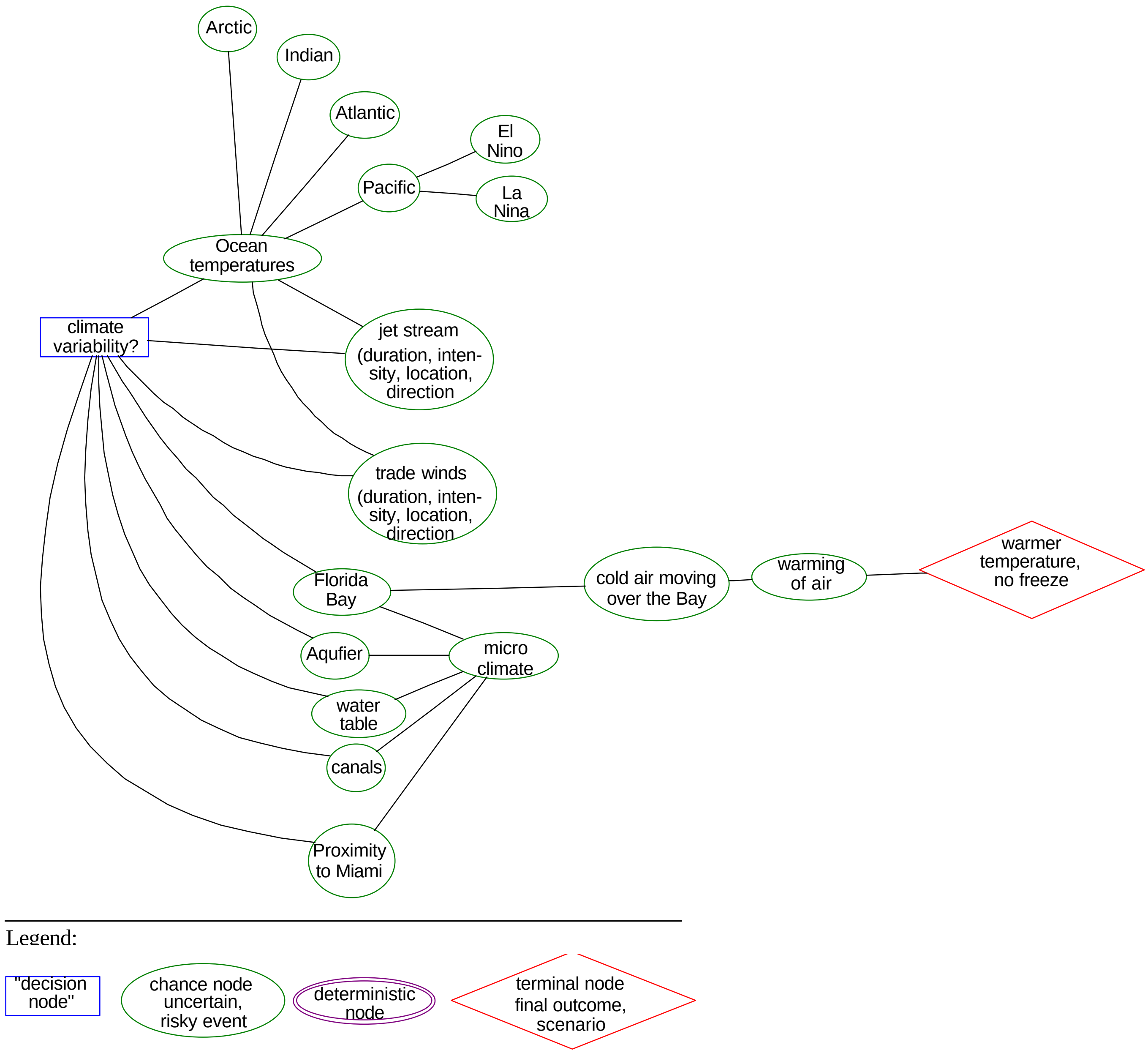


Figure 2: Influence Diagram Representing Farmer Mental Model of Climate Variability (Farmer 3)



Niño, La Niña, global warming, and winds. More than half of the farmers commented on these items.

Many farmers admit that they do not know the specific effects of El Niño and La Niña on local climate. They are uncertain as to whether El Niño or La Niña conditions lead to warmer or cooler temperatures, and to more or less precipitation in Florida. Besides precipitation and temperature variability, some farmers think that some of the above factors have an impact on the development and land-falling capacity of hurricanes.

Among climate scientists, too, there exist areas of uncertainty: One is concerned with the roles of Atlantic Ocean and the Indian Ocean. Scientists were not sure whether they are factors in themselves or mediators that are influenced by the Pacific Ocean. Another question that scientists are debating is: What is the major driving force behind all of the described processes? Three experts mention the sun in this context.

This table reflects mental models, as they existed prior to giving farmers any further information about climate variability. Throughout the interview process, farmers' mental models changed as new information was added by the interviewer that could then be integrated into, or replace, existing knowledge and beliefs.

The following two tables (Table 11 and Table 12) show that farmers initially come up with more factors that could influence climate variability than experts could. Yet, these factors lead to fewer outcomes. Consequentially more branches remain incomplete. For instance, some farmers know that sea surface temperatures play a role in climate variability, however they have difficulty linking SSTs to a particular outcome.

Compared with farmers, climate experts tend to start out with fewer initial factors that they then link with many other factors, branching off in multiple directions. Not all paths lead to one separate outcome however. Branches merge again, several heading to the same outcome, indicating multicausality.

Memory of Extreme Years and Patterns of Variability

In farmers' memory of past weather and climate events, low temperature extremes and below average temperatures, heavy rainfall averages, and hurricanes figure

Table 11. Analysis of Influence Diagrams

	Farmers (n=14)			**Experts (n=6)**		
	Min	**Max**	**Average**	**Min**	**Max**	**Average**
Number of initial branches	1	8	4.43	2	6	3.17
Total number of branches	3	13	9.64	2	31	12.67
Number of outcomes	1	5	4.29	0	13	5.33
Number of incomplete paths	0	14	3.86	1	2	0.56
Number of factors in a chain	1	10	2.61	1	16	7.12

Table 12. Number of outcomes that are weather vs. climate

Farmers						**Experts**	
Climate	**Weather**					**Climate**	**Weather**
9%	91%					100%	0
	Rain	Temp	Freeze	Hurricane	other		
	25%	48%	10%	3%	4%		

Percentages don't add up due to rounding higher than above average temperatures and droughts. Yet, years that were shaped by extreme temperatures stand out mostly in Florida farmers' minds. When asked about extreme years and climatic anomalies, no farmer mentioned years of drought or extremely high temperatures, presumably because they can protect their crops against heat and drought, and in their minds yields are not affected by these conditions. The importance that Florida farmers put on freezes does not compare to Argentine farmers' priorities. The latter are much more interested in rainfall. This difference in results illustrates the fact that climate related observations and decisions are specific to the crops that farmers are producing. Production systems and their differential sensitivity to climate variability influence the importance of different types of climate variable and forecast lead time that users will require. Florida farmers' recollection of extreme years seems to be conditioned on the climatic variables and impacts that their farming system are most sensitive to. In fact, tropical fruit trees can endure droughts moderately well, meaning they can withstand several days of drought, yet tree growth and yields may be diminished. According to farmers' experience, there have so far not been any restrictions on irrigation in Miami-Dade County. Even during times of drought, an extensive system of shallow wells supplies water for irrigation. Tropical fruit have rather low cold and flood tolerances. Exposure to temperatures below 31-32ºF can even in mature trees result in damage to leaves, limbs, and trunk. One or more days of flooded soil can damage or kill a tree. Depending on time of the year, stage of growth, tree size, and genetics, the extent of damage can vary. Most vegetables produced in Miami-Dade County have no drought tolerance, yet farmers can protect their plants by irrigation. Farmers can do less against the devastation from floods, to which hardly any row crop can withstand. Cold temperatures of 40ºF or less cause death of any vegetable plant. Irrigating with water of 60ºF or warmer can prevent some damage, yet continued exposure to freezing air temperatures will result in damage or death. Ornamentals and herbs are equally vulnerable to environmental stresses as row crops are. In addition, their wind tolerance is extremely low. Despite the high damage susceptibility, many nurseries grow their plants in fields. Alternatives are container nurseries and production within structures (shade structures and/or solid-cover greenhouses). Ornamental plants are unable to survive without cold protection, either in form of irrigation or misting water.[4]

Low Temperatures. A comparison of farmers' memory of extreme years with data about actual temperature and precipitation anomalies shows that farmers' memory of years with extremely cold temperatures differs from the years identified in official data. Let us consider the past three decades (a period during which most of the interviewed farmers were alive and many of them active in the farming business; freezing temperatures during the 1950s and 1960s date too far back in time for the younger farmers to recall): Farmers claim to have experienced 13 freeze years whereas official data reports only 7 years. One of the reasons for the lacking overlap might be that official temperatures taken at the Homestead station and Florida in general can vary from temperatures in certain fields by a few degrees. Unfortunately, we don't have data at our disposal that would allow us to look more closely at spatial variation of such detailed degree.[5] We must also note that we cannot be certain as to which winter farmers referred to when reporting, for instance, that the year 2001 was extremely cold. Such statement could imply either January of 2001 or December 2001. Despite these caveat, we might interpret the missing overlap as potential bias in farmers' memory of climate risk. We can explain farmers' overestimation of freeze years as a tendency to overrate probabilities associated with conditions that are adverse for production, and underestimate probabilities associated with favorable conditions, as pointed out by Sherrick et al. (Sherrick, Sonka et al. 2000).

Weber (1997) showed that farmers' memory of climate and weather events is at best imperfect reflection of past events, that is, past events filtered through selective attention, where attention is affected by such things as the need to act on events in ways that deviate from normal farm operation. In our data, this can explain the attention Florida farmers pay to the incidence of freezes. In addition to selective attention, beliefs and expectations can also lead to the faulty reconstruction of memory. In Weber's (1997) case, this meant that farmers who reported a belief in climate change (global warming) were producing memories of July temperatures over the past 7 years that were higher than actual statistics, whereas those farmers who reported that they did not believe in global warming were producing climate temperature memories that were lower than true values. In our Florida sample, farmers were remembering a greater incidence of freezes than had actually occurred. Three farmers see a cooling trend, which goes hand-in-hand with stronger memory of freezes.

We further asked farmers about their perceptions of patterns of climate variability. The following table (Table 13) summarizes their responses:

Roughly two-thirds of the farmers see some pattern in climate variability. Most of them perceive climate variation as cyclical where freezes or hurricanes occur every ten years or every eight to ten years. For instance, farmer 15 states "every 10 years, we have some freezes or a bad hurricane." Similarly, farmer 16: "I know that once every ten years we're going to get a hard freeze." Others reason

Table 13. Farmers' perception of patterns of climate variability

Pattern	Mentioned
See no pattern / random	5 (38.4%)
See some pattern	8 (61.5%)
Cycles (general)	6 (46.1%)
- **10 year cycles**	3 (23.0%)
- **8-10 year pattern**	
- **Cold year followed by warm year**	1 (7.7%)
	2 (15.4%)
Winters getting cooler	3 (23%)
Warming trend	2 (15.4%)
Hurricane years are no freeze years	2 (15.4%)
More extremes	1 (7.7%)
El Niño year no hurricane year	1 (7.7%)

N=13
Multiple answers possible

that after ten cold winters the following ten winters are warm. Others see the alternation of cold and warm winters on an annual basis where each cold winter is usually followed by a warm one, such as farmer 15 who explained: "It is, more or less in my experience, that if we have a really cold year, the next year is not that cold. The next year may come a little colder. That's the pattern that we see." Farmer 6 perceives an alternating of wet and dry years, "[if you have] little rain some years [it] makes up for it the next year."

23% of all farmers claim to notice that winters are getting cooler, while 15% mention a warming trend in temperatures overall. Only one farmer thinks that there are more years with extreme conditions now than there were in the past. Farmer 10 senses "that in the last 10 years it's been a lot more erratic. A lot more extremes. And not just here, I'm talking the whole country. … No doubt you get into patterns, but patterns seem to be a lot more erratic and a lot more extreme than they used to go. And I've realized that weather typically works in cycles. But again, it seems for whatever reason to be going through a lot more extremes."

Several farmers try to make a connection between certain climate variables, especially between hurricanes and freezes. Fifteen percent of the farmers observe that hurricane years and freeze years do not coincide. Farmer 3 mentioned, "that for South Florida … the chances of a hurricane decreased in the year you had freezing weather. And so, you know, you could say ok, if we have a freeze, then we won't [have] a hurricane. If we have hurricanes, we won't have a freeze." Eight percent say they have heard that hurricanes are less likely to hit land during El Niño years. However, based on Andrew occurring during an El Niño year, they question this statement. Farmer 6 sees yet another relationship between the occurrence of cold winter temperatures and hurricanes: "The 80s seemed to be like it was cold more often, we [also] ended up having to work with freeze protection more often in the 90s. Andrew was kind of like a weather change pattern [and our winters got warmer]."

While the majority of farmers tend to see patterns of climate variability or climate change, 38.4% object to such an idea. A good example is farmer 12 who expressed: "It doesn't look like it's on a five-year cycle or a 10-year cycle. I don't see any rhyme or reason in it. I do see that our winters are getting warmer and warmer. That is something that I hope data backs me up, but it just seems that way."

Overall, when farmers talk about patterns, they differentiate by climate variable. The same farmer who perceives an alternating cold/warm pattern may not see any pattern for hurricanes; a farmer who observes warming temperatures may not see any pattern of increased or decreased precipitation. For instance, farmer 3: "Our freezing weather … seemed to be about an 8-to-12 year pattern. That one's pretty pronounced. The hurricane pattern, you know, it's just so random where these hurricanes go. … So far as drought, wet-dry cycles, I don't see any real pattern to the drought cycles." Farmer 9 exemplifies a similar confusedness when trying to make sense of different climatic observations and when trying to frame them within one pattern: "I actually think that the summers are a little more steeper, I have personally noticed. I do think there is a slight global warming … even in the winter … and then you have your extremes, where I see it. I see where it is warmer during the day, and even at nights. Well actually, the days are extremely warmer, the last three years. … This year for a short period in January, we had extremely cold nights. So that kind of contradicts what I said earlier about the days. The days have been extremely warmer."

Climate-Related Terminology

Part of the interviews elicited in a more formal way the comprehension of climate related terminology by asking farmers to give quick definitions. Table 14 contains terms frequently associated with climate forecasts. This set of terms was compiled with input from climate scientist at IRI and includes terms they thought farmers might have find difficult to understand.

El Niño and La Niña. In general, farmers have a somewhat better knowledge of El Niño than of La Niña. The interviews show several gaps in knowledge about both terminology and the mechanisms underlying climate variability. One of the most frequent impressions among farmers is that La Niña is the opposite of El Niño. A comment by farmer 2 summarizes a typical view of El Niño and La Niña: "They're opposite, basically, I just don't know which one is which. I don't know how much it matters." Another common assumption among farmers is that El Niño is a milder version of La Niña, or vice versa, as farmer 9 put it: "El Niño is usually … I believe it's a colder year and not as wet as a La Niña year. I consider La Niña wetter than El Niño and I consider La Niña worse weather than El Niño."

Climate Variability. Ambiguities and inconsistencies associated with the term climate variability include temporal scale and spatial scale. Climate variability is often understood as variability of extremely high and low temperatures on a time scale of one month (e.g., farmer 7). Others think climate variability refers to a variation over several decades. Few farmers perceive the term as relating to interannual variability as it is used in the ENSO discussions. Often, farmers read the term climate variability as spatial variability. A quote by farmer 10 illustrates this: "For different areas of the country, you have different ranges of temperature, moisture levels, humidity levels, rainfall, windy conditions. That to me is climate variability. Different areas of the country will vary with different climates." This common misconception has been highlighted by studies of interpretations of weather forecast. Gigerenzer et al. found that most people interpret a 30% chance of rain tomorrow as "30% of the time tomorrow," a smaller portion as "30% of the area," and only few as "in 30% of days like tomorrow" (Gigerenzer, Hertwig et

Table 14. Farmers' knowledge of climate related terminology

Definition requested	**Answer Correct[1]**	**Partially correct/partially incorrect**	**Answer Incorrect**	**Don't know**	**Question not asked**	**Farmers definition most often mismatched with**
Climate Variability	2	5	7	0	0	Weather change, climate change
El Niño	7	4	3	0	0	La Niña
La Niña	2	8	4	0	0	El Niño
ENSO		0	2	11	1	
Weather	12	1	0	0	1	Climate
Climate	6	3	3	0	1; 1missing	Weather
Climate change	6	1	6	0	0	Weather change, climate variability
SST	2	7	3	0	1; 1 missing	
Probabilistic climate forecast	2	1	0	0	11	

N=14

al. 2003 submitted). Similarly, Fischhoff reports an even distribution of those people who think the probability of rain occurring refers to an area, time, or the chance of at least some rain somewhere (Fischhoff 1994). Argentine farmers demonstrated a similar difficulty in distinguishing spatial and temporal climate variability. Farmers in our focus groups commented on experiencing El Nino and La Niña in different parts of the county or in different fields. In informal discussions, technical advisors in Argentina also referred to La Niña conditions occurring in some parts of the region during an El Niño event.

These results bear important implications for recommendations about how climate forecasts ought to be communicated. One suggestion is to spell out the meaning of a certain probability as "in x% of all winters like the next one, at least some conditions associated with El Nino will be experienced somewhere in the area. "Miscommunication can lead to misconception. While scientist among themselves are very clear about he meaning of their terminology, the public clearly is not.

Weather and Climate. As many other studies have suggested, there exists a confusion of weather and climate, weather change and climate change. Climate is confused with "temperature … atmosphere" (farmer 15). "Climate to me it's more temperature and humidity … Weather is part of it but I think weather to be hot, cold, sunny, rainy" (farmer 9). "Climate to me is a measure of temperature" (farmer 10).

Terminology Perceived as Unclear. Interestingly, farmers did not necessarily think that they misunderstood commonly used terminology. We asked specifically, which terms and phrases that come up in forecasts are unclear to them. The only two terms mentioned frequently are "dew point" and "isobars" both of which refer to weather forecasts rather than seasonal climate forecasts. An important result of our mental model interviews is that farmers are not aware of their misconceptions. Therefore, they are less likely to seek clarifying information.

Use and Value of Forecast Information

Long-term vs. Short-term Forecasts and Decision Making. Most farmers show greater interest in, and claim to base most of their decisions on, short-term forecasts – this is reflected in the sources listed in Table 15 which give short-term forecasts. For example, farmer 13 states:

Table 15. Sources of Climate and Weather Forecasts Used by Farmers

Source	Number of farmers who use this source	Percentage of farmers who use this source	Medium
FAWN*	10	67%	Internet
(Other) internet source	7	47%	Internet
Private meteorologist#	5	30%	Phone/fax/email
Check radar/satellite	4	27%	Internet
Weather Channel	4	27%	TV/Internet
TV other than weather channel	3	20%	TV
National Weather Service	3	20%	Internet/TV
Farmer's Almanac**	4	27%	Print
Local indicators (water table, moisture, fronts)	3	20%	Observations
Full moon	3	20%	Observations
Service provided by Chemical Company	2	13%	
Continental Weather Service	2	13%	TV/Internet
DTM/DTN?+	2	13%	Unknown
Weather radio	2	13%	Radio
Friends	2	13%	Word of mouth
FNGA++	1	7%	Internet
MyCast (via cell phone/internet)	1	7%	Internet/phone
MIPA	1	7%	Internet
Marine radio	1	7%	Radio
Service emailed/faxed	1	7%	Email/fax
Newspaper	1	7%	Print

N=15, multiple answers
* Florida Automated Weather Network
# Meteorologist who started his own company, some mention namely Allan Archer
+ DTM/DTN (=digital terrain models?), gives 30-day precipitation forecasts, temperature forecasts,
++ Florida Nursing and Growers Association
** Farmers Almanac: forecasts are calculated by using a proprietary formula that considers a multitude of factors, such as sunspots, moon phases, and other astronomical and atmospheric signs and conditions. Since 1818, this formula has been passed along from calculator to calculator and has never been revealed.

"Yes, I have thermometers in the field. We monitor those until we put the water on. Once the water is on, it changes the situation, so we cease to monitor that. But I live in [indiscernible city name], which is like 30 miles away, and the weather can be very different where I live compared with what it is down on the farms. It's those kind of variations that are much more important to what I do than whether it's El Niño or La Niña." Farmer 10: "I used to [look at long-tem forecasts], but I don't even look at it. Everything changes, you know, it really does. Very seldom do those forecasts hold true. And most of them are just generalities. They're usually not specific, and again, if they are specific, by the time you get to that time period, it's usually the complete opposite. I don't rely on that, everything changes, there are so many factors in the atmosphere that change the weather patterns. You really can't get a good feel until cold events, I'd say generally 10 days out is probably as far as you want to go. Beyond that, it's hard to predict." Farmer 11 "But again, I don't predicate any of my decisions based on the fact that there is a Niño or there is not a Niño or the Niña or whether there is or is not a Niña. … I just can't do that. You know, I can't say, oh well it's supposed to be a warm winter. It only takes one cold night to completely ruin your entire enterprise. If you're not ready, you're not ready … I think if I was a strategic planner for some big corporation I'd be looking at those things: climatic, long-term effects. But my decisions are based, you know, no more than 2 weeks out."

Some farmers, however, like to get a wider, long-term perspective. Farmer 16 was at first not interested in long-term forecasts, but upon further probing imagined that early knowledge of drought or flood conditions could be useful. "I might up another greenhouse … What I did one time that we had a really hard freeze, I bought the fabric that you cover your crops with, because I had a lot of young material, so I bought enough material to cover pretty much everything I had. I do believe in that. So if I had another advanced warning I would do it, because I do not have enough storage material to store all of that, so I would have to buy it, and then it takes time to put it all up there, too."

A small number (13%) indicated some general interest in seasonal forecasts but would not want to base any decisions on them, unless these sources said something about hurricanes. An equal number of farmers occasionally go to long-term forecasts at the University of Florida's Agricultural Center. Only one farmer (7%) thought that a long-term forecast would matter greatly to him. Overall, farmers are mostly concerned with freezes. Freeze hazard is an issue of extreme temperatures and not one of averages; the response has a short lead-time. Therefore, ENSO information has limited value for freeze management.

One long-term forecast source that farmers do consult is the *Farmers Almanac*. Four farmers (27%) mention the almanac and say they use or trust it to some extent. Farmer 12, for instance said "I do look at *Poor Richard's Almanac* once in a while, just to take a peek. I'm not going to depend solely on *Poor Richard's Almanac,* but I do take a look at it. It was actually through 'Poor Richard's Almanac' -- we were having some problems initiating some flower bloom on a particular variety that we try to trick and it was working quite well and then it quit working. For the life of me, I couldn't figure out what was going on. We were doing everything, and that's when I found out that during the summer we were having 14 hours of daylight. In winter, you only have nine or 10. It was through *Poor Richard's Almanac* [that I found out about this]. I was just sitting there reading it and I go, oh, wait a minute. Fourteen hours of daylight, there it is. So then we came in, we installed blackout curtains and we were right back in business again. You'll get information from the strangest places." Farmer 11 doesn't "know why, but it sure seems that they [*Farmers Almanac*] know, they get the general trends right. I don't know how they do it, but I buy that and I read that, and that's where I get my first understanding." Farmer 13 elaborated: "Well, my father was a farmer, and his father was a farmer up in Michigan, and they actually used the *Farmer's Almanac*, and he heeded it, but there were certain practices, and I was too young and didn't really care, that he would do, like he wouldn't plant certain things until we had a good electrical storm, because it got the frost out of the ground. And it was, it was true, you would see where the water would drain off the land. All of a sudden, overnight, you would have water standing in ice ponds, and then the next morning, you had an electrical storm overnight, and next morning it was gone." Farmer 6 gives the almanac high credit: "I don't know how long has it been since they [scientist] have really been able to predict, other than the *Farmer's Almanac*."

Influence of Farm Type on Forecast Preferences. Tree farmers see fewer ways to respond to a climate forecast than vegetable, herb, and flower/plant growers. One nursery owner stated that he could imagine choosing to grow a different kind of crop if he knew that conditions for a certain season were expected to deviate from the normal. Vegetable growers could respond similarly, whereas tree farmers do not have this option. This hesitance to use long-term climate forecast is not evidenced in answers to the questions asked shortly before and after the tutorial. A comparison of interview answers and answers to the questionnaires shows a discrepancy of attitudes toward climate-based decision making. In contrast to discussions during the interview, results from the questionnaires suggest that many farmers make decisions that are sensitive to climate. One explanation for this contradiction is that respondents misinterpreted the term climate as weather. In the interview, this confusion can be revealed. (This is another good reason for conducting mental model interviews where the interviewer asks follow-up questions).

Farmers' attitudes toward seasonal climate forecasts changed after introduction to more information about climate variability. For a detailed discussion of how farmers' attitudes changed, see section "Utility for farm management decisions" below in this report. If we want to increase the appeal of climate forecasts, information about long-term strategies to protect crops and selection of appropriate varieties should accompany climate information. This is a crucial point that needs further research and extension.

Sources of Climate and Weather Information. The most frequently used medium to access forecasts is the Internet, followed by subscription to a private meteorologist and TV forecasts. Among the internet-based forecasts, the FAWN (Florida Automated Weather Network) website is the most popular. Almost all farmers in our study consult more than one source of information. The following example illustrates this: Farmer 12 stated, "I'm never going to depend solely on one person. I go everywhere. Every time I hear of a new site, I check it out and see what's in it. Because they all have bits and pieces of the puzzle. The National Weather Service has the offshore buoys telling me what the wind trends are doing. You know, I'm always looking way, way out. Every piece of puzzle, every element has a piece that I'm looking for. I don't know of one Web site that has it all. But still, (if that site existed) I still wouldn't trust it. I would still continue to look around."

Climatic Information Requested by Farmers. When asked what additional climate information would be useful, 42% of all farmers would like to know more about the influence of El Niño and La Niña on temperatures, in particular winter temperature lows. Data related to hurricanes are second most valuable to farmers. A small number of farmers request that information be downscaled to the local level (county or, if possible, to fields). Without specifying the kind of detail he would like to receive, one farmer would like to have access to any information that is available. Similarly, another farmer admitted that he was "not knowledgeable enough to determine at present" what would be useful to him but thought that any additional material would be valuable. Twenty-five percent of farmers are satisfied with the information that current seasonal forecasts provide, as it was presented in the tutorial.

Trust and Confidence in Forecasts. Content analysis of interview questions regarding the trust that farmers have in the accuracy of scientific forecasts shows a more or less even split of positive and negative attitudes. However, those who express confidence in scientific forecasts do so more strongly than those who raise doubts, therefore, the overall attitude is slightly more positive. Not all farmers distinguish between long-term and short-term forecasts in their answers, yet those who do, think that scientist are better at forecasting up to a week rather than a whole season. Many have an optimistic outlook though, estimating that both short-term and long-term forecasts will get better and better. Farmers think that the science of forecasting is still in a learning process ("I don't think they have a complete understanding themselves at this point" farmer 7; " I don't think they have scratched the surface as far as learning how to detect weather" farmer 9), yet the majority of farmers' has great confidence in scientists themselves and the technology they utilize.

However, several farmers (roughly one-third) are not certain that scientist will ever be able to understand the many variables that factor into a forecast. Farmer 12, while evaluating forecasts overall as very good, adjusted his opinion depending on whether a prediction was based on hindcasting or on a computer model. "You know, so many things can happen. You can probably lean on them or be pretty confident … me personally, I would probably be comfortable maybe a month out. Because there are so many variations -- you have a volcano eruption in Haiti or in the Philippines -- this is going to change things. So I wouldn't lean too much [on it], but that's out of their [scientists'] control. There are just so many things that can happen that I would be a little leery of going too far out there. But if you were looking for trends, if you were looking to do the averages over a span of let's say 20 years and then base some decisions on those averages that you're finding, I don't have a problem with that. Because then as you get closer, you're going to start to fine-tune what you're going to do. I would never say, ok, according to all weather data for the 20 years, we will not get a frost in March. I'm not ever going to bank on that. But chances are, it's very slim. Then you take those averages and you weigh them out and then you make a decision."

Twenty-five percent of the farmers are very skeptical of scientists ever getting a handle on all the factors influencing weather and climate. They see it as "a gamble" (farmer 13) or as another farmer put it: "It's still a guessing game (farmer 5)."

Two farmers voice explicit mistrust and speculate that information is being withheld from them. Farmer 2 wonders: "they say you have 50% chance of rain today, [but] you don't see a cloud in the sky -- where are they getting this from? Is there pressure out there? … So I don't know how accurate that is per se, but I think that they tend to know more than we do, but we just count on them to take it all in, and make decision based upon what we get." Farmer 15: "With the technology we have today, I think we know exactly what's going on a weekly basis. Farther than that, I think that they're still working on it. Or they know it, but they're staying quiet, until they get more funding … I think the technology is there to do more forecasts. Maybe they're waiting to bring the information out. But us farmers, we really do have to be checking on the weather. If you're in a law office, you don't care if it's raining or not. So, different businesses should have more information than others."

Tutorial Evaluation

Overall Impressions. The tutorial was met with very positive response. As Table 16a and Table 16b demonstrate, most farmers agreed that the tutorial was useful and that it improved their understanding of the influence of El Niño and La Niña on local climate. The degree of difficulty was seen mostly as appropriate. When asked about which graphs were easy to understand, all farmers agreed that all or almost all graphs were easy to understand. When asked specifically if they had problems understanding any graph, one farmer admitted that the probability graphs were hard to understand and one farmer stated that he found all of them somewhat difficult. Farmers thought the tutorial length was more or less appropriate. We conclude that the next incarnation of this tutorial should definitely be neither harder nor longer.

A vast majority of farmers would be interested in doing more tutorials. Themes that they would like to learn more about in particular are the influence of ENSO on temperature and on hurricanes.

Understanding. The tutorial included questions that were designed to stimulate farmers' thinking and active participation throughout the tutorial. The primary purpose was not to assess or test understanding. Overall, farmers answered tutorial questions correctly, as one would expect based on their evaluation of the level of difficulty as appropriate. They had no problems identifying the driest and wettest years in a time series. We introduced probability of exceedance graphs by first showing time series of winter precipitation and then transforming them into probability graphs. This approach turned out to be very successful. The complete tutorial can be found in Appendix C.

Table 16A. Tutorial Assessment

N=12	Agree	Unsure	Disagree	Mean (scale of 1-5)
Tutorial useful	9	1	1	4.18
Tutorial improved understanding of El Niño/La Niña influence on local climate	12	0	1	4.5
Difficulty appropriate	9	n/a	3	3.33
Length appropriate	11	0	2	3.08

Table 16B. Tutorial Assessment

N=12	Agree	Disagree	Mean	Missing cases	Comments
Graphs easy to understand	12	0	1.00	0	1=yes, 0=no Original question asked, "which graphs were easy to understand?" I created new variable based on whether they entered anything or not. "Agree" here means that they entered "all" or "almost all"
Graphs hard to understand	2	10	0.20	0	1=yes, 0=no When asked specifically which graphs were hard to understand, 1 farmer mentioned probability, one farmer found all graphs somewhat difficult; "disagree means none were hard to understand.
Interested in doing more tutorials	11	1	0.92	0	1=yes, 0=no

Table 17. Climate sensitive decisions

N=13	Agree	Unsure	Disagree
Pre-tutorial			
Climate info influences my farming decisions	9	1	1
Change farm management decisions if I knew winter was likely to be *drier* than normal	3	7	3
Change farm management decisions if I knew winter was likely to be *wetter* than normal	7	4	2
Change farm management decisions if I knew *La Niña* conditions would occur over winter	5	4	3
Change farm management decisions if I knew *El Niño* conditions would occur over winter	5	4	3
Post-tutorial			
Change farm management decisions if I knew *La Niña* conditions would occur over winter	8	3	2
Change farm management decisions if I knew *El Niño* conditions would occur over winter	8	3	2
Tutorial increased my willingness to modify farming decisions in response to El Niño and La Niña	7	3	2

Only one question stands out as problematic. "We found earlier that the median rainfall in all winters was 5.9 inches. Without knowing about La Niña, the probability of getting more than median rainfall in a given winter is 50%. What is the probability of getting more than the long-term median in La Niña winter?" (See slide 21). The correct answer is 15%. Even when they were given the answer farmers had difficulty understanding how to arrive at that percentage. In the next version of the tutorial, this question should be rephrased, or we should think about giving a bit more explanation.

Another interesting observation is worth mentioning: The responses to "What range of rainfall do you expect next winter?" – a question asked as part of slide 2 showing a time series of precipitation for 1950 through 2002 – displayed a wide array of "predictions." Estimated winter rainfall ranged from 2 inches to 11 inches; from "will go down" to "normal" to "will go up;" from "not extreme" to "similar to 1975" to "maybe same as this year." While we can't infer too much from these answers, there is a tendency to expect rainfall to be within the normal range of the values presented in the graph (see slide 2).

A few farmers needed some more explanation in order to understand percentiles. It helped to put the terminology into a more familiar context, e.g., a student being within the 90th percentile of its class. Once the terminology was clarified, farmers answered questions related to percentiles correctly. We should note that the set of questions eliciting understanding of La Niña's influence on rainfall amounts appears to be somewhat redundant. Slides 15, 16, and 18 ask the same question four times phrased slightly differently.

Utility for Farm Management Decisions. Roughly two-thirds of all farmers (63%) say climate influences their farming decisions. These farmers see several ways of responding to climatic conditions, including crop selection and cultural practices (21%), irrigation needs (16%), winterization of greenhouses and cold protection (26%), and employee recruitment and movement (5%). Most of these farm management decisions are related to winter temperatures rather than winter rainfall. Only one-third of the participants (37%) indicate that they make decisions that are sensitive to winter precipitation.

Table 17 shows a discrepancy between the high number (69%) of people who say climate information influences their farming decisions and the lower number (23%-53%) of those reacting to forecasts of either wetter, drier, El Niño, or La Niña conditions. This raises the question of what other climate information is important to farmers. Based on the interviews, it is temperature and hurricane information. When asked specifically about winter precipitation forecasts, anticipation of wetter conditions would influence decisions for more farmers than anticipation of dryer conditions.

When repeatedly asked after the tutorial, more farmers indicated a willingness to change farm management based on La Niña and El Niño forecasts than did before the tutorial. Thus, the tutorial increased the value that farmers place on forecasts. In general, the tutorial increased the willingness to modify farming based on climate forecast. The number of farmers who say they would adjust farm management decisions based on a forecast of "El Niño conditions" is lower than that for farmers who would respond to a forecast of "wetter conditions." The reverse is true for a forecast of "drier conditions" compared with

Table 18. Value of climate forecast

N=13	Agree	Unsure	Disagree	Missing
Pre-tutorial				
La Niña forecast valuable	6	3	3	1
El Niño forecast valuable	7	3	3	0
Post-tutorial				
La Niña forecast valuable	9	1	3	0
El Niño forecast valuable	9	1	3	0

"La Niña conditions": more farmers would make changes if La Niña conditions were forecasted than if "drier conditions" are forecasted. While in Florida, the impact of El Niño usually creates wetter winters and La Niña is accompanied by drier conditions, we cannot assume that farmers made this connection when reading these questions. In fact, the inconsistencies in their responses could mean that farmers did not understand the terminology. Yet, it is more likely that this is a reflection of the uncertainty about rainfall if only the ENSO phase is known

We elicited perception of and attitudes towards seasonal climate forecasts before and after farmers went through the tutorial. Table 18 shows a tendency to value both El Niño and La Niña forecasts more highly after learning about the influence of ENSO phase on local climate than before the tutorial.

Willingness to Pay. As indicated in Table 19, of the 10 people who answered that question, 7 are willing to pay something, 3 would not pay anything. After the tutorial, 5 out of 8 who answered the question would pay, 3 would not: only a slight increase of the ones who are willing to pay something, yet the higher non-response rate after the tutorial indicates disinterest in seasonal forecasts. Of those who indicated a willingness to pay for seasonal forecasts prior to doing the tutorial, 43% are tree growers, 43% are in the ornamental business, and only 14% grow vegetable. After the tutorial, these proportions remain roughly the same (40/40/20). The amounts offered ranged from $30 to $4000 per year. The amounts offered pre and post tutorial did not change by much although one farmer increased his amount from $120 to $200**.**

We expected that learning about the influence of EL Niño and La Niña on Florida rainfall patterns would lead to an increased willingness to pay for seasonal climate forecasts. However, this was not the case. The reasons may lie in the mismatch between climate sensitive decisions and the particular climate variable (winter precipitation) in the tutorial prototype. One farmer clearly stated his general willingness to pay but the amount would depend on the forecasted climate variable (farmer 14). The purpose of the tutorial in this study was designed as a template that could later be used with other climate variables and for other locations.

During one interview, farmer 1, who didn't fill out the questionnaire, stated that he would be willing to pay several hundred dollars per month. This farmer subscribes to a weather forecast service and pays "several hundred dollars a month, probably, four, five hundred dollars throughout the month." Asked if he was willing to pay if a long-term forecast was available, he responded: "Yeah, if it was very accurate and had a proven track record."

Determinants of forecast utility

When looking at the correlation of demographics and climate sensitive farming decisions, farm management deci-

Table 19. Change of willingness to pay for seasonal forecast

	Yes	No	N
Willingness to pay for seasonal forecast **(pre-tutorial)**	7	3	10
Willingness to pay for seasonal forecast **(post-tutorial)**	5	3	8*

*Two farmers of those who were initially interested in paying rather high amounts, did not answer that question after the tutorial.

sions appear to be negatively correlated to age, years in farming (age and years in farming are not correlated to each other!), and education level. There was no significant correlation between gender and decision-making. Interestingly, farm management decisions related to climate forecasts are not a function of farm size and farm type. The latter result contradicts farmers' statements during the interviews, where tree farmers saw fewer ways to respond to a climate forecast than vegetable, herb, and flower/plant growers. Repetition of the questionnaire with a larger sample could clarify this issue.

We can create the following farmer profile:

- The younger a farmer the more likely to change farm management decisions if they knew in advance that a given winter was likely to be wetter than normal, to be influenced by La Niña conditions, or to be influenced by El Niño conditions ($r = -0.831$, $p < 0.01$; $r = -0.640$, $p < 0.05$; and $r = -0.664$, $p < 0.05$ respectively).

- The less educated (having completed high school or spent some time in college) the more likely to change farm management decision if they had advance knowledge of a wetter than normal winter or of La Niña conditions occurring over the next winter ($r = -0.753$, $p < 0.05$ and $r = -0.644$, $p < 0.05$ respectively). After the tutorial this correlation was even stronger: the correlation between age and likeliness to change farm management based on a La Niña forecast changed to $r = –0.828$, $p < 0.01$; the correlation between age and likeliness to change farm management based on a forecast of El Niño conditions was $r = -0.869$, $p < 0.01$.

- The more farming experience a farmer had, the less likely he or she was to change farm management based on advance knowledge of either wetter than normal, or El Niño or La Niña conditions ($r = -0.732$, $p < 0.05$; $r = -0.751$, $p < 0.05$ and $r = -0.723$, $p < 0.05$ respectively).

- While education level did not play a significant role in the perceived value of climate forecasts <u>before</u> farmers went through the tutorial, lesser-educated farmers tended to value seasonal forecasts more highly after they had seen the tutorial ($r = -0.645$, $p < 0.05$ for La Niña forecasts and $r = -0.645$, $p < 0.05$ for El Niño forecasts).

One explanation for the low perceived value of climate forecasts by highly-educated farmers is that that they did not think the tutorial raised their level of understanding the influence of ENSO on local climate. Farmers with lower education levels reported that the tutorial improved their understanding of the influence of El Niño and La Niña on local climate, and they found the tutorial more useful in general than their better-educated peers did. Education appears to create skeptics.

The negative correlation between respondent age and climate information importance that we found is similar to Letson's et al. findings ((Letson et al., 2001)(in particular p. 61, 65)). While they found a positive correlation between farm size and climate information importance, there is no evidence for this in our quantitative data. The discrepancy between our results and Letson's study could be related to the different farming types represented in our sample: Fruit tree farmers tend to have considerably larger farms than growers of vegetables and horticulture. While there might be more at stake for an Argentine farmer with a large amount of land than for a farmer with less land, this doesn't hold true for Florida farmers. Farm size is a less meaningful criterion in Florida.

VI. Conclusions

This study provided multiple insights into determinants of use of climate information related to perception and communication, and some evidence that improved presentation may overcome some of the barriers and enhance utility. Although we were able to draw an abundance of conclusions, as summarized below, further research could address limitations of the scope and study design of this seed project that limit the strength of some of the generalizations. It would be useful to obtain data from the same sample of farmers for the farm decision experiment and personality inventories studied in Argentina and the mental model interviews and forecast presentation module evaluation conducted in Florida. Our work with Florida farmers suggested that the modules we developed increased both understanding and willingness to act on seasonal forecasts. More formal experimentation with larger samples would be needed to establish the robustness of the results, and to determine whether the enhanced utility is due to the continuous probability distribution format, relating probabilities to past outcomes in a time-series format, the explanation in the module, or thinking about forecast application through the course of the interview. Replications with other decision makers in other socio-economic, cultural and geographic contexts would add to the generalizability of our results.

Inconsistent use of terminology between climate forecasters and users creates a barrier to understanding and use. There is a need to communicate clearly to users the distinction between the time scales of weather vs. those of climate, and variability in time vs. variability in space. Weather is what people experience on a daily basis. Climate is a statistical abstraction that cannot be experienced, but can only be presented as a summarizing description. Given that vivid, experiential information has been shown to overshadow pallid, statistical information in many situations, it should not come as a surprise that farmers and other potential climate forecast users try to reduce climate forecasts to weather events. Rather than condemn this tendency on the part of users, forecast providers can use it to their advantage by designing forecast presentation modules that capitalize on people's desire for concrete events and use them to build up to summary information, whose probabilistic nature will be better understood because it derives from experienced or (re-) constructed frequency distributions of imaginable weather events. The specific sequence used in our forecast presentation modules enhanced farmer understanding and the perceived value of climate forecast information, at least in part because it provided for such transition from the concrete (time series of weather events) to the abstract (probability of exceedance graphs). Based on farmers' response to the tutorials, we expect that other interactive forecast presentation modules and educational materials can and will generally enhance both the understanding and use of seasonal climate forecast information.

Farmers' emphasis on local causal factors that we found in their mental models of climate variability may also reflect the experiential basis of their understanding of such variability, in contrast with climate scientists' analytic, description-based perspective of causal influences.

The study offers some suggestive evidence that farmers' memory of past climatic variability may be distorted in systematic ways, reflecting wishful thinking by distortions consistent with decision goals as well as being shaped by personality characteristics and preexisting beliefs, all of which may selectively guide attention. Possible distortions in the memory representation of past weather events may need to be addressed or remedied before taking advantage of farmers' personal experience with past variability to enhance their understanding of the probabilistic nature and utility of description-based forecast information.

We found evidence for cognitive capacity limitations in the form of greater attentional focus by farmers (though not technical advisors) on sub-goals (e.g., maximizing crop yields and prices, minimizing input costs) rather than superordinate goals (maximizing farm profitability). Given that the optimization of different sub-goals requires different action steps, such compartmentalization is understandable and potentially beneficial, if the competing demands of all sub-goals can be kept in mind simultaneously (which is doubtful, given cognitive capacity limitations). Decision aids that help farmers with this task seem advisable. We also found evidence for affective processes and resulting biases in farmers' judgments and decisions. Farmers (though not technical advisors) indicated that regret avoidance plays a significant role in their farm management decisions. We also found evidence for the single-worry bias and (in the actual farm management records) for the single-action bias.

The positive evaluation of the forecast presentation modules by Florida farmers demonstrated the value of our approach. The stepwise procedure from time-series to probability of exceedance graphs follows a path that first relates to farmers' experience (time-series) and then becomes more statistical and description-based as the tutorial moves to probability of exceedance graphs. In addition, the mental model interview method allowed us to identify building blocks of farmers' concepts of climate variability and to interpret those into additional tutorial exercises.

Mental model interviews proved to be a valuable first step in a large regional project. The method is very useful to gain insight into the lay concepts of scientific phenomena that is untainted by information that questionnaires and structured interviews provide. Mental model interviews with members of the scientific community educate the researcher about the scientific topic and provide insight that is not necessarily available in textbook materials. The visual summary of mental models in influence diagrams serves as an effective format to compare the models of experts and novices. Results from mental model interviews and influence diagrams can then guide us in the development of subsequent survey tools that are less time consuming to researchers and participants. Future research could sort farmers' influence diagrams into several types and study their relationship to risk perception.

Our results also have something to say about the types of farmers who are most likely to benefit from improved forecasts and educational materials. Older farmers and farmers with more education in our Florida sample indicated that professional climate forecasts had less utility to them, possibly because their own knowledge (based on many years of personal experience or on well-schooled mental models) seemed sufficient in making personal forecasts. The production systems we encountered in Florida are quite diverse. The climatic variables and time scales that are relevant to farm decision making depend strongly on the characteristics of the production system, and may or may not match the variables and time scales that are most predictable. Similarly, our results with Argentine farmers indicate that farmers are not a homogeneous group with respect to perceptions of climate variability and its risks. Perceptions, beliefs, and actions related to climate risks differed systematically as a function of age, personality differences, and farm characteristics. This suggests a need to offer a variety of forecast information products and other forms of decision support tailored to the characteristics of particular sub-groups of decision makers.

The wealth of results from this study has been gratifying. It has contributed to the creation of interesting hypotheses for further research, and has influenced the development of several proposals for research to implement and evaluate project materials and insights, and to follow up on new hypotheses.

[1] USDA National Agricultural Statistics Service, 1997 Census of Agriculture, see http://www.nass.usda.gov/census/census97/county/farms/index.htm; see also http://www.agmarketing.ifas.ufl.edu/dlfiles/Findings_Descriptive.pdf, p.10.

[2] http://ers.usda.gov/StateFacts/FL.HTM

[3] Influence diagrams should not be confused with flowcharts. Influence diagrams do not illustrate deterministic processes, nodes have uncertain outcomes, and more than one node can be involved at the same time, they depict causal and non-causal influences.

[4] For more detail on environmental stress tolerance see Miami-Dade Agricultural Retention Study, Appendix A, vol. 2, pp. 23-27, 34, 41, 53, 55, 57, 61, 65, 69, 71, 75, 77, 81, 83, 96-97.

[5] The majority of farmers in our sample have fields within a radius of roughly 5 miles of Homestead.

VII. References

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Appendix A: Key Outputs

Outreach

Weber E. and H. Herzer, "El Clima en la region pampeana y su importancia en la toma de decision agricola," Revista CREA, Supplement (March 2003): 6-7. (Publication of the Argentine Regional Consortium for Agricultural Experimentation)

Reports

Climate and other risk factors in farming: An interpretation of focus groups in the Wet Pampa, Argentina. First Project Report: "Use of climate forecasts as a tool in agronomic decision making in the Wet Pampa, Buenos Aires, July 2002 (Bartolomé, Caputo, Graciela, Celis, Herzer, Rodríguez).

Input to Project and Grant Proposals

Modeling and aiding farm-level agricultural decision making in Argentina: An integrated systems model of reactions and adaptations to climatic and other sources of risk (Hansen, Weber, Roberts, Goddard). .Subcontract NSF Biocomplexity in the Environment, 2002: (not funded but we used feedback to resubmit and to develop two NOAA grant proposals)

Understanding and modeling the scope for adaptive management in agroecosystems in the Pampas in response to interannual and decadal climate variability and other risk factors (Podestá, Rajagopalan, Easterling, Katz, Weber) NSF Biocomplexity in the Environment, 2003 (submitted).

Proposal for a Center for Individual and Group Decision Making Under Uncertainty (Broad, Krantz, Miller, Weber). NSF DMUU 2003 (submitted).

Building capacity to use climate information and forecasts to enhance decision-making in agriculture: An application to the Argentine Pampas (Broad, Podestá, Herzer). NOAA OGP's Environment, Science, and Development Program 2003 (submitted).

Understanding decision-making in agricultural production in the Argentine Pampas in the face of inter-annual climate variability and other risk factors (Weber, Letson). NOAA OPG's Human Dimensions of Global Change Research Program 2003 (submitted).

Forecast Presentation Modules

Module 1: Seasonal forecast as a shifted probability distribution: January-March, Homestead, Florida

Module 2: Uncertainty of a seasonal climate forecast system: January-March, Homestead, Florida

Publications in Progress

Marx, Hansen, Weber, "Mental models of climate variability and farmers' decision making in Southern Florida [*working title*]" (to be submitted to *Risk Analysis*)

Hansen, Weber, Podestá, Broad, Herzer, Marx, "Decision making in agricultural production in the Argentine Pampas [*working title*]" (to be submitted to *Journal of Applied Meteorology*)

Appendix B: Survey Instruments

SURVEY INSTRUMENTS ARGENTINA

Fecha:

N° de cuestionario:

Código de productor:[1] (MEMO: Colocar pie de página en nota aparte a AACREA)

Esta encuesta es anónima. En la misma se intenta reunir datos que permitan comprender cuáles son sus necesidades respecto a la información climática de su región.
Le rogamos tenga la amabilidad de leer las preguntas con detenimiento y responderlas en su totalidad, a fin de aprovechar al máximo el esfuerzo que significa realizarla.
Para evitar confusiones, queremos aclarar que, cuando hablamos de "clima" nos referimos a los promedios de temperatura, precipitación u otras condiciones climáticas, durante un período aproximado de 1 a 6 meses. Este término no debe confundirse con el "tiempo meteorológico", que se refiere a las condiciones de temperatura, precipitación, vientos, etc. durante un período de 1 a 10 días.

Información personal

Grupo AACREA al que pertenece:..........................

Edad:...............

Sexo: Masculino ☐ Femenino ☐

¿Cuál es su nivel de educación alcanzado? (tilde uno sólo)

Sin estudios ☐
Primaria incompleta ☐
Primaria completa ☐
Secundaria incompleta ☐
Secundaria completa ☐
Terciario incompleta ☐
Terciario completa ☐
Universitario incompleto ☐
Universitario completo ☐

5. Lugar de residencia permanente (indique localidad y provincia):...

[1] Cabe aclarar que este cuestionario es anónimo. Sin embargo, para el trabajo es indispensable poder cotejar las respuestas de este cuestionario con las de la encuesta preliminar y las de la encuesta de evaluación final. Por este motivo, le solicitamos a AACREA que le adjudique a cada productor un dentificación, que se mantendrá vigente para todas las encuestas que se suministrarán a lo largo de esta investigación. Le rogamos a AACREA elegir códigos que nos permitan identificar

Clima

1- ¿Considera que el clima de su región ha cambiado en los últimos años?

SI ☐ NO ☐

1.1. En caso de responder NO: Pasar a pregunta 2.

1.2. En caso de responder SI, por favor, en los siguientes cuadros coloque una cruz en todos los campos en los que reconoce dichos cambios.

1.2.1.

LLUVIAS	**VERANO** Enero-febrero-marzo	**OTOÑO** Abril-mayo-junio	**INVIERNO** Julio-agosto-septiembre	**PRIMAVERA** Octubre-noviembre-diciembre
Menor cantidad				
Mayor cantidad				
Más intensas (llueve más en menos tiempo)				
Más frecuentes				

1.2.2.

Temperaturas	**VERANO** Enero-febrero-marzo	**OTOÑO** Abril-mayo-junio	**INVIERNO** Julio-agosto-septiembre	**PRIMAVERA** Octubre-noviembre-diciembre
Menores				
Mayores				

1.2.3.

HELADAS	**VERANO** Enero-febrero-marzo	**OTOÑO** Abril-mayo-junio	**INVIERNO** Julio-agosto-septiembre	**PRIMAVERA** Octubre-noviembre-diciembre
Menor cantidad				
Mayor cantidad				
Mas intensas				

1.2.4.

GRANIZADAS	**VERANO** Enero-febrero-marzo	**OTOÑO** Abril-mayo-junio	**INVIERNO** Julio-agosto-septiembre	**PRIMAVERA** Octubre-noviembre-diciembre
Más frecuentes				

Menos frecuentes				

1.2.5. Otros cambios que considere importante mencionar:

....

1.3. Indique desde cuándo, aproximadamente, se dio cuenta de los cambios mencionados:

....

2.
¿Cuánto espera que llueva en un año normal:[2]

.... milímetros

Aproximadamente, en cuánto estima el agua caída en el año más lluvioso de la última década:

.... milímetros

Aproximadamente, en cuánto estima el agua caída en el año menos lluvioso de la última década:

.......................milímetros

3. En comparación con épocas anteriores, cómo afecta a su actividad productiva, los cambios en la disponibilidad de agua?

	Lo benefician	Lo perjudican
Más que en otras épocas		
Menos que antes		
Igual que antes		
No lo afectan		

3.1. ¿Qué lo afecta más?

Exceso de agua ☐

Déficit de agua ☐

Ambos ☐

4. ¿Los cambios climáticos modificaron sus decisiones productivas?
SI ☐
NO ☐

4.1. Si responde SI: ¿Qué decisiones modificó?

2 Ver si es necesario reformular; ver los ejemplos que enviará Elke

FUENTE	LA USO	NO LA USO
Clarín Rural		
La Nación Rural		
Servicio Meteorológico Nacional		
INTA		
Otras fuentes (por favor especifíquelas)		

5.1. En caso de utilizar alguna fuente de información climática ¿Cuál es la que utiliza con mayor frecuencia?

5.2.: ¿Considera que la información que le brindan las fuentes mencionadas le es realmente útil en su actividad productiva?

SI ☐ NO ☐

5.2.1. Si responde SI: ¿Porqué sí?

5.2.2. Si responde NO ¿Por qué no?

5.3. En caso de no utilizar las fuentes de información climática: ¿Por qué no las utiliza?

Caracterización de los productores agrícolas que participarán en los grupos focales

Cuestionario

Fecha:

N° de cuestionario:

Código de productor:[3]

Información personal

1. Grupo AACREA al que pertenece:
2. Edad:
3. Sexo: Masculino ☐ Femenino ☐
4. ¿Cuál es su nivel de educación alcanzado: (tilde uno sólo)

Sin estudios ☐
Primaria incompleta ☐
Primaria completa ☐
Secundaria incompleta ☐
Secundaria completa ☐
Terciario incompleta ☐
Terciario completa ☐
Universitario incompleto ☐
Universitario completo ☐

6. ¿Cuál es su lugar de residencia permanente? (indique localidad y provincia):

Información relacionada a su unidad productiva

1. ¿Hace cuántos años que se dedica a actividades productivas, en esta región?
2. ¿Cuál era su actividad anterior?
3. ¿Hace cuánto tiempo es miembro de un grupo AACREA?
4. ¿Dedica su tiempo completo al campo?

   Si ☐ No ☐
5. En caso de responder NO: ¿Qué otra actividad realiza?
6. En caso de responder SI: ¿Qué porcentaje de su tiempo está presente en su campo?

[3] Cabe aclarar que este cuestionario es anónimo. Sin embargo, para el trabajo es indispensable poder cotejar las respuestas de este cuestionario con las de la encuesta preliminar y las de la encuesta de evaluación final. Por este motivo, le solicitamos a AACREA que le adjudique a cada productor un código de identificación, que se mantendrá vigente para todas las encuestas que se suministrarán a lo largo de este proyecto. Le rogamos a

7. ¿Cuál es el tamaño de su explotación?

8. ¿Toda la superficie se encuentra en la misma región?

   Si ☐ No ☐

9. En caso de responder NO, ¿En qué regiones se encuentran sus tierras?

10. Por favor, indique qué porcentaje de su explotación es:

    Arrendada para capitalización:

    Propia:

11. ¿Qué cultivos produce?

12. ¿Cuál es su cultivo principal?

13. Por favor, complete el siguiente cuadro:

	En la actualidad		**Hace 5 años atrás**		**En 1997/1998**	
TIPO DE CULTIVO	Cantidad de lotes cultivados	Porcentaje respecto de la superficie total	Cantidad de lotes cultivados	Porcentaje respecto de la superficie total	Cantidad de lotes cultivados	Porcentaje respecto de la superficie total
Maíz						
Trigo						
Soja 1°						
Soja 2°						

14. ¿Cuántos empleados permanentes tiene?

15. ¿Tiene maquinaria propia? Si ☐ No ☐
16. ¿Contrata maquinaria? Si ☐ No ☐
17. ¿Tiene capacidad de almacenaje de granos? Si ☐ No ☐
18. En caso afirmativo, por favor indique en el siguiente cuadro, cuáles cultivos puede almacenar y por cuánto tiempo:

Tipo de cultivo	**Cantidad que puede almacenar**	**Período de almacenamiento**

19. Respecto a su cosecha, vende a futuro o toma opciones de venta? Por favor especifique:
20. Tiene acceso a:
    - Computadora ☐
    - Correo electrónico ☐
    - Internet ☐
21. Lleva registros climáticos propios? Si ☐ No ☐
22. ¿Qué mide? (por ejemplo, lluvia, temperatura, etc.)
23. ¿Usa riego? Si ☐ No ☐
24. ¿Estuvo alguna vez afectado por una inundación? Si ☐ No ☐
25. En caso afirmativo ¿Cuándo?
26. ¿Estuvo alguna vez afectado por una sequía? Si ☐ No ☐
27. En caso afirmativo ¿Cuándo?
28. ¿Cuántas veces se acogió a la Ley de Emergencia Agropecuaria en los últimos 10 años?
29. Por favor especifique en cuáles años:
30. Tiene seguro agrícola? Si ☐ No ☐
31. En caso afirmativo, ¿De qué tipo?
32. ¿Está endeudado? Si ☐ No ☐
33. En caso afirmativo, ¿a cuánto asciende su deuda?
34. Por favor indique los porcentajes relativos de sus gastos:
    - labores:
    - insumos:
    - impuestos:
    - otros:
35. ¿Cuál fue el promedio de su ganancia, en los últimos 5 años?

Pregunta 1 (al tope de Tarjeta 1 y al tope de tarjeta 4)

Al planear la campaña agrícola 2003/04 en el campo que Ud. ha heredado, por favor indique en qué grado le preocupa o lo inquieta cada una de las fuentes de incertidumbre use un número del 1 al 9, donde 1 indica "no me preocupa en absoluto" y 9 indica "estoy sumamente preocupado por este tema."

Grado de preocupación o inquietud (de 1 a 9)	
	Situación política/macroeconómica y sus efectos sobre impuestos, retenciones, etc.
	Clima
	Precios de insumos
	Precios de granos a la cosecha

Preguntas 2 y 3 (a incluirse al final de las Tarjetas 3 y 7)

Pregunta 2.

Le rogamos que olvide por un momento las decisiones detalladas que Ud. acaba de tomar en el ejercicio y conteste un par de preguntas más generales. Por favor indique cuánto tiempo o atención espera dedicar durante la próxima campaña agrícola en el campo que Ud. ha heredado a cada una de las clases de decisiones listadas abajo. Por favor use una escala numérica de 1 a 5, donde 1 indica "ningún tiempo o atención" y 5 indica "una cantidad importante de tiempo o atención."

Grado de atención o dedicación de tiempo (de 1 a 5)	Clases de decisiones
	Area asignada a cada cultivo
	Decisiones de manejo para cada cultivo
	Decisiones sobre la forma en que comercializará su cosecha (mercado de futuros, venta a cosecha, almacenaje para venta posterior, etc.)
	Otras decisiones relativas a la empresa

Pregunta 3.

Al tomar decisiones para la próxima campaña agrícola en el establecimiento que ha heredado, Ud. obviamente prestó atención a una amplia serie de consideraciones. Abajo encontrará una lista de algunas consideraciones que pueden o no haber pasado por su cabeza en ese momento. Estas consideraciones pueden haber jugado un rol mayor o menor en las decisiones que Ud. tomó durante el ejercicio.

Para cada una de las consideraciones listadas, le rogamos que indique el grado en que tuvieron un rol en las decisiones que Ud. tomó. Por favor utilice una escala numérica de

1 a 7, en la cual 1 indica “esta consideración no jugó ningún rol en mis decisiones” y 7 indica “esta consideración tuvo un rol muy importante en mis decisiones”.

Rol en su toma de decisiones (escala numérica de 1 a 7)	
	Maximizar el rendimiento de los cultivos
	Diseñar estrategias de comercialización para maximizar precios recibidos por los cultivos
	Maximizar la rentabilidad total del establecimiento
	Garantizar un nivel mínimo de rentabilidad ante un escenario sumamente desfavorable
	Minimizar el costo de insumos (semilla, fertilizante, etc.)
	Minimizar los posibles impactos de sequías o inundaciones sobre los rendimientos
	Minimizar el posible impacto de incertidumbre respecto a la situación política/económica
	Tomar la mejor decisión posible para las condiciones planteadas
	Tomar una decisión suficientemente razonable para luego enfocarse en otros temas o decisiones
	Minimizar la posibilidad de tener que lamentar después algunas de las decisiones tomadas

TARJETA N°1

Nombre:	

<u>Consigna</u>: Actualmente estamos en el mes de mayo del 2003. De acuerdo a la información que recibió sobre el campo que ha heredado, le pedimos que arme su planteo productivo para la campaña 2003-04. Por favor, indique en el siguiente esquema qué cultivo hará en cada lote (si lo desea, puede subdividir los lotes indicando la superficie utilizada en cada caso).

NOTA: por favor anote dentro de cada lote, el cultivo que ha decidido sembrar

Los precios de mercado a término para la campaña 03 / 04 son los siguientes:

Maíz (en abril): 83.5 U$/Ton

Trigo (en enero): 123.5 U$/Ton

Soja (en mayo): 146 U$/Ton

<u>La Josefa: esquema</u>

6 lotes de 75 has cada

LJF1 02/03: soja 1°	***LJF2*** 02/03: maíz
LJF3 02/03: maíz	***LJF4*** 02/03: trigo/soja
LJF5 02/03: soja 1°	***LJF6*** 02/03: trigo/soja

<u>Don Albino: esquema</u>

6 lotes de 75 has cada

DA1 02/03: trigo/soja 2°	***DA2*** 02/03: soja 1°	***DA3*** 02/03: maíz Galpones
DA4 02/03: trigo/soja 2°	***DA5*** 02/03: soja 1°	***DA6*** 02/03: maíz

TARJETA N°2

Nombre:

Consigna: para cada uno de los lotes en los que ha escogido sembrar maíz en el campo por favor elija el híbrido que utilizará y la fecha de siembra.

N° LOTE: DA......

HÍBRIDO: ....

Fecha de siembra: en el siguiente esquema señale con un círculo o una cruz la fecha de siembre elegida:

10/8 20/8 30/8 10/9 20/9 30/9 10/10

Por favor, explicite por qué eligió dicho híbrido y dicha fecha de siembra:

....

N° LOTE: DA..............

HÍBRIDO: ....

Fecha de siembra: en el siguiente esquema señale con un círculo la fecha de siembre elegida:

10/8 20/8 30/8 10/9 20/9 30/9 10/10

Por favor, explicite por qué eligió dicho híbrido y dicha fecha de siembra:

....

N° LOTE: DA.................

HÍBRIDO: ....

Fecha de siembra: en el siguiente esquema señale con un círculo la fecha de siembre elegida:

10/8 20/8 30/8 10/9 20/9 30/9 10/10

Por favor, explicite por qué eligió dicho híbrido y dicha fecha de siembra:

....

N° LOTE: DA.............

HÍBRIDO: ....

Fecha de siembra: en el siguiente esquema señale con un círculo la fecha de siembre elegida:

10/8 20/8 30/8 10/9 20/9 30/9 10/10

Por favor, explicite por qué eligió dicho híbrido y dicha fecha de siembra:

....

<u>Consigna:</u> para cada uno de los lotes en los que ha escogido sembrar maíz en el campo , por favor elija el híbrido que utilizará y la fecha de siembra.

N° LOTE: LJF......

HÍBRIDO:..

Fecha de siembra: en el siguiente esquema señale con un círculo o una cruz la fecha de siembre elegida:

10/8 20/8 30/8 10/9 20/9 30/9 10/10

Por favor, explicite por qué eligió dicho híbrido y dicha fecha de siembra:

....

N° LOTE: LJF ....

HÍBRIDO:..

Fecha de siembra: en el siguiente esquema señale con un círculo la fecha de siembre elegida:

10/8 20/8 30/8 10/9 20/9 30/9 10/10

Por favor, explicite por qué eligió dicho híbrido y dicha fecha de siembra:

....

N° LOTE: LJF.........

HÍBRIDO: ....

Fecha de siembra: en el siguiente esquema señale con un círculo la fecha de siembre elegida:

10/8 20/8 30/8 10/9 20/9 30/9 10/10

Por favor, explicite por qué eligió dicho híbrido y dicha fecha de siembra:

....

N° LOTE: LJF

HÍBRIDO:

Fecha de siembra: en el siguiente esquema señale con un círculo la fecha de siembre elegida:

Por favor, explicite por qué eligió dicho híbrido y dicha fecha de siembra:

....

TARJETA n°3

Nombre:

Consigna:

Han pasado 3 meses desde que realizó su planteo productivo. Desde el 1° de mayo hasta el 18 de agosto han caído 108 mm (es decir, las precipitaciones se han mantenido dentro de las condiciones normales). Actualmente es 19 de agosto de 2003 y le pedimos que realice el ajuste fino para el maíz para las variables que se indican a continuación.

CAMPO "DON ALBINO"

De acuerdo a los análisis de suelo y otros datos que maneja, indique la cantidad de e utilizará para fertilizar los lotes en los que sembró maíz.

ANÁLISIS DE SUELO PARA LOS SIGUIENTES 4 LOTES:

INSERTAR GRAFICO QUE PROVEERÁ FRT

1) N° LOTE: DA......

Cantidad (kg) de urea/ha:................................

¿Por qué elige esta dosis de fertilizante?:

....

Densidad de plantas a cosecha: en el siguiente esquema señale con un círculo o una cruz la densidad de plantas/ha que quiere cosechar:

65.000 70.000 75.000 80.000 85.000 90.000

Por favor explicite por qué elige esta densidad:

....

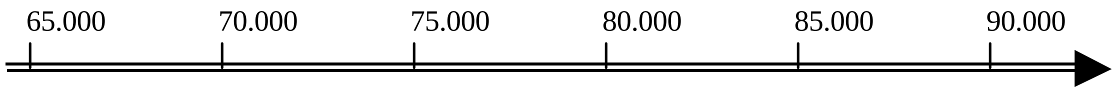
2) N° LOTE: DA......

Cantidad (kg) de urea/ha:................................

¿Por qué elige esta dosis de fertilizante?:

....

Densidad de plantas a cosecha: en el siguiente esquema señale con un círculo o una cruz la densidad de plantas/ha que quiere cosechar:



Por favor explicite por qué elige esta densidad:

....

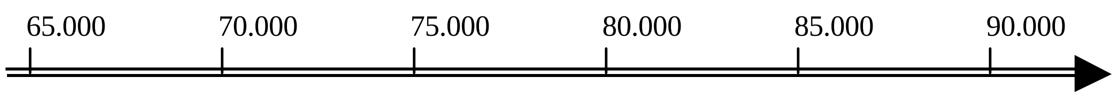
3) N° LOTE: DA......

Cantidad (kg) de urea/ha:................................

¿Por qué elige esta dosis de fertilizante?:

....

Densidad de plantas a cosecha: en el siguiente esquema señale con un círculo o una cruz la densidad de plantas/ha que quiere cosechar:



Por favor explicite por qué elige esta densidad:

....

4) N° LOTE: DA......

Cantidad (kg) de urea/ha:................................

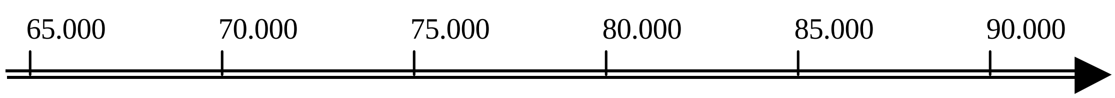
¿Por qué elige esta dosis de fertilizante?:

....

....

....

Densidad de plantas a cosecha: en el siguiente esquema señale con un círculo o una cruz la densidad de plantas/ha que quiere cosechar:



Por favor explicite por qué elige esta densidad:

....

....

....

CAMPO "LA JOSEFA"

De acuerdo a los análisis de suelo y otros datos que maneja, indique la cantidad de urea/ hectárea que utilizará para fertilizar los lotes en los que s

ANÁLISIS DE SUELO PARA EL SIGUIENTE LOTE:

INSERTAR GRAFICO QUE PROVEERÁ FRT

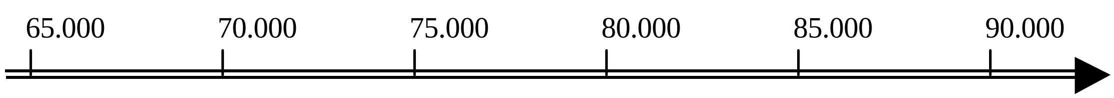
1) N° LOTE: LJF......

Cantidad (kg) de urea/ha:................................

¿Por qué elige esta dosis de fertilizante?:

....

Densidad de plantas a cosecha: en el siguiente esquema señale con un círculo o una cruz la densidad de plantas/ha que quiere cosechar:



Por favor explicite por qué elige esta densidad:

....

ANÁLISIS DE SUELO PARA LOS SIGUIENTES 3 LOTES:

INSERTAR GRAFICO QUE PROVEERÁ FRT

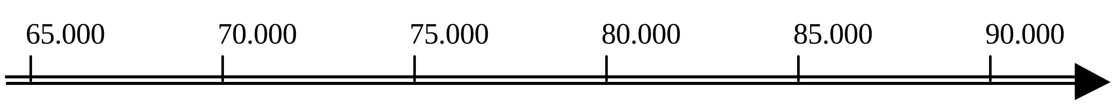
2) N° LOTE: LJF......

Cantidad (kg) de urea/ha:................................

¿Por qué elige esta dosis de fertilizante?:

....

Densidad de plantas a cosecha: en el siguiente esquema señale con un círculo o una cruz la densidad de plantas/ha que quiere cosechar:



Por favor explicite por qué elige esta densidad:

....

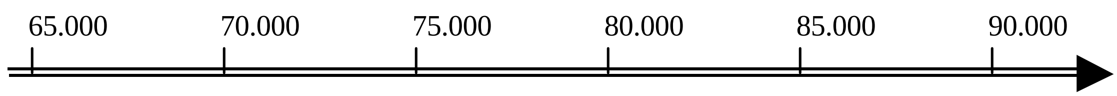
3) N° LOTE: LJF......

Cantidad (kg) de urea/ha:...............................

¿Por qué elige esta dosis de fertilizante?:

....

Densidad de plantas a cosecha: en el siguiente esquema señale con un círculo o una cruz la densidad de plantas/ha que quiere cosechar:



Por favor explicite por qué elige esta densidad:

....

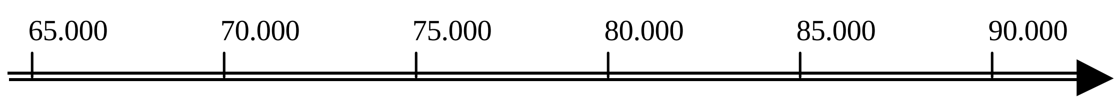
4) N° LOTE: LJF......

Cantidad (kg) de urea/ha:...............................

¿Por qué elige esta dosis de fertilizante?:

....

Densidad de plantas a cosecha: en el siguiente esquema señale con un círculo o una cruz la densidad de plantas/ha que quiere cosechar:



Por favor explicite por qué elige esta densidad:

....

....

....

TARJETA N° 4

Nombre:

Pronósticos recibidos:.........................

¿Por favor, indique algunas diferencias y semejanzas entre los 2 pronósticos recibidos?

....

Elija uno de los pronósticos para realizar un ejercicio que se indicará mas adelante.

Pronóstico elegido:.....................

¿Por qué eligió este pronóstico?

....

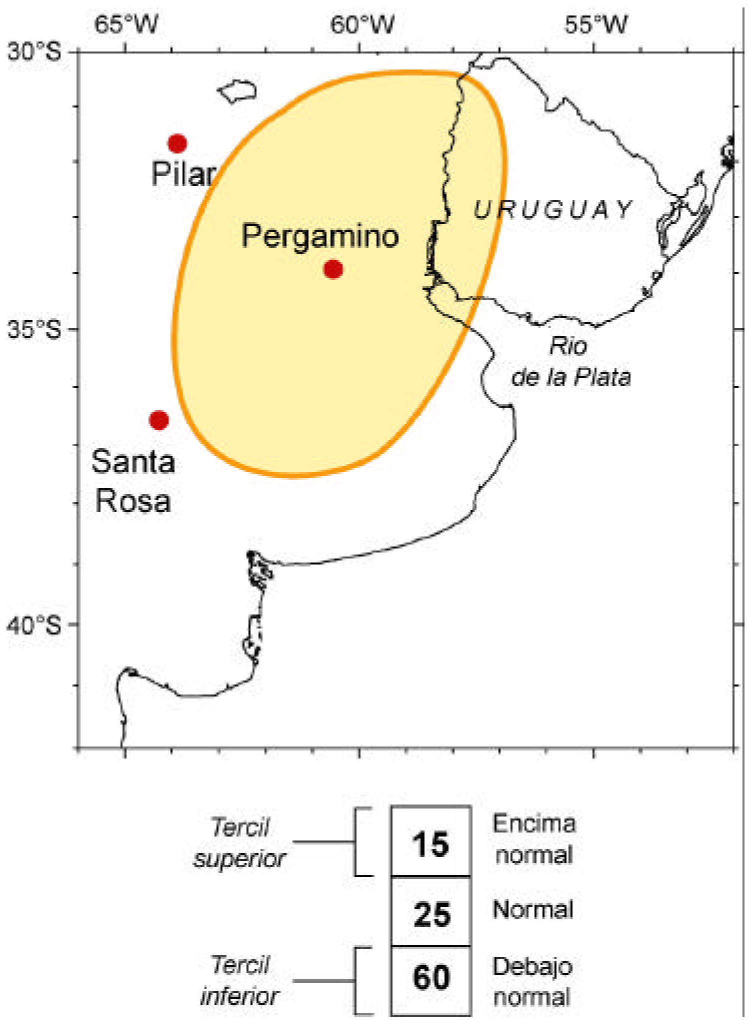
PRONÓSTICO A

Pronóstico de precipitaciones para noviembre/diciembre de 2003 (emitido el 1 de mayo de 2003)

Entre junio y octubre de 2003, los valores esperados para las precipitaciones en el norte de la provincia de Buenos Aires, sur de Santa Fe y oeste de Entre Ríos estarán cerca de los promedios históricos. En cambio, hay una alta probabilidad de que las precipitaciones acumuladas para noviembre y diciembre de 2003 estén debajo de lo normal en esta región. Correspondientemente, la probabilidad de precipitaciones acumuladas por encima de lo normal será baja para los meses de noviembre y diciembre de 2003. Las probabilidades pronosticadas de precipitaciones debajo de lo normal, normales y encima de lo normal serán, respectivamente, 0.60, 0.25 y 0.15. En años recientes, valores de precipitaciones en noviembre/diciembre similares a aquellos con gran probabilidad de ocurrir en 2003 han ocurrido en 1994 y 1999.

PRONÓSTICO B

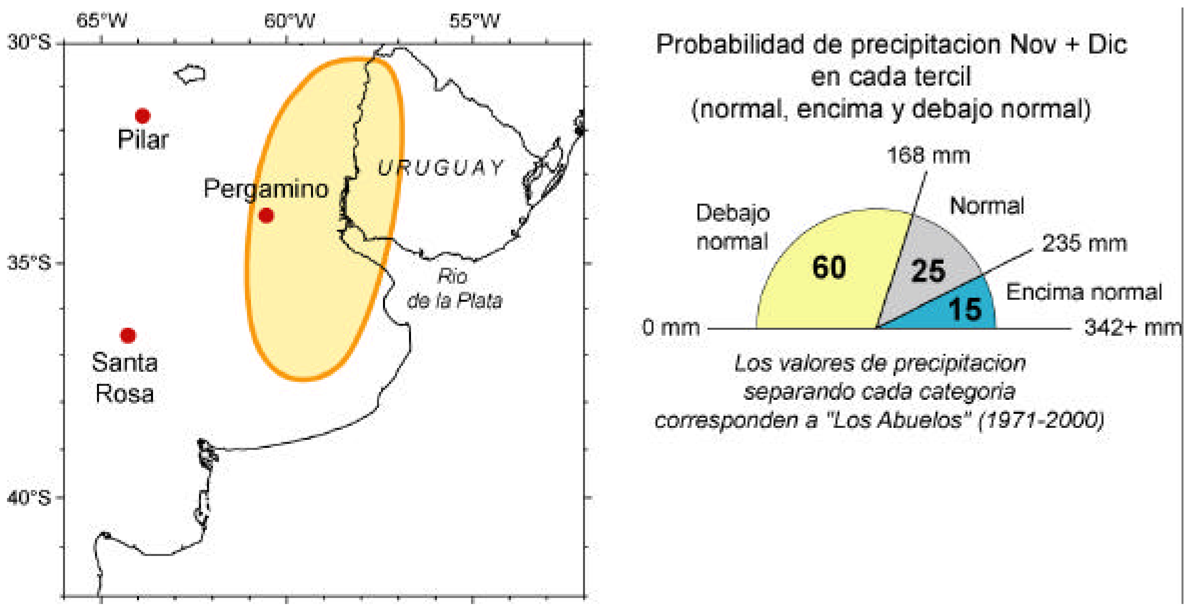
Pronóstico de precipitaciones para noviembre/diciembre de 2003 (emitido el 1 de mayo de 2003)



El mapa muestra el área para la cual se pronostican precipitaciones totales para el período noviembre/diciembre de 2003. Los números en cada casilla debajo del mapa indican la probabilidad de que las lluvias en este período sean "mayores de lo normal", "normales", o "debajo de lo normal."

PRONÓSTICO C

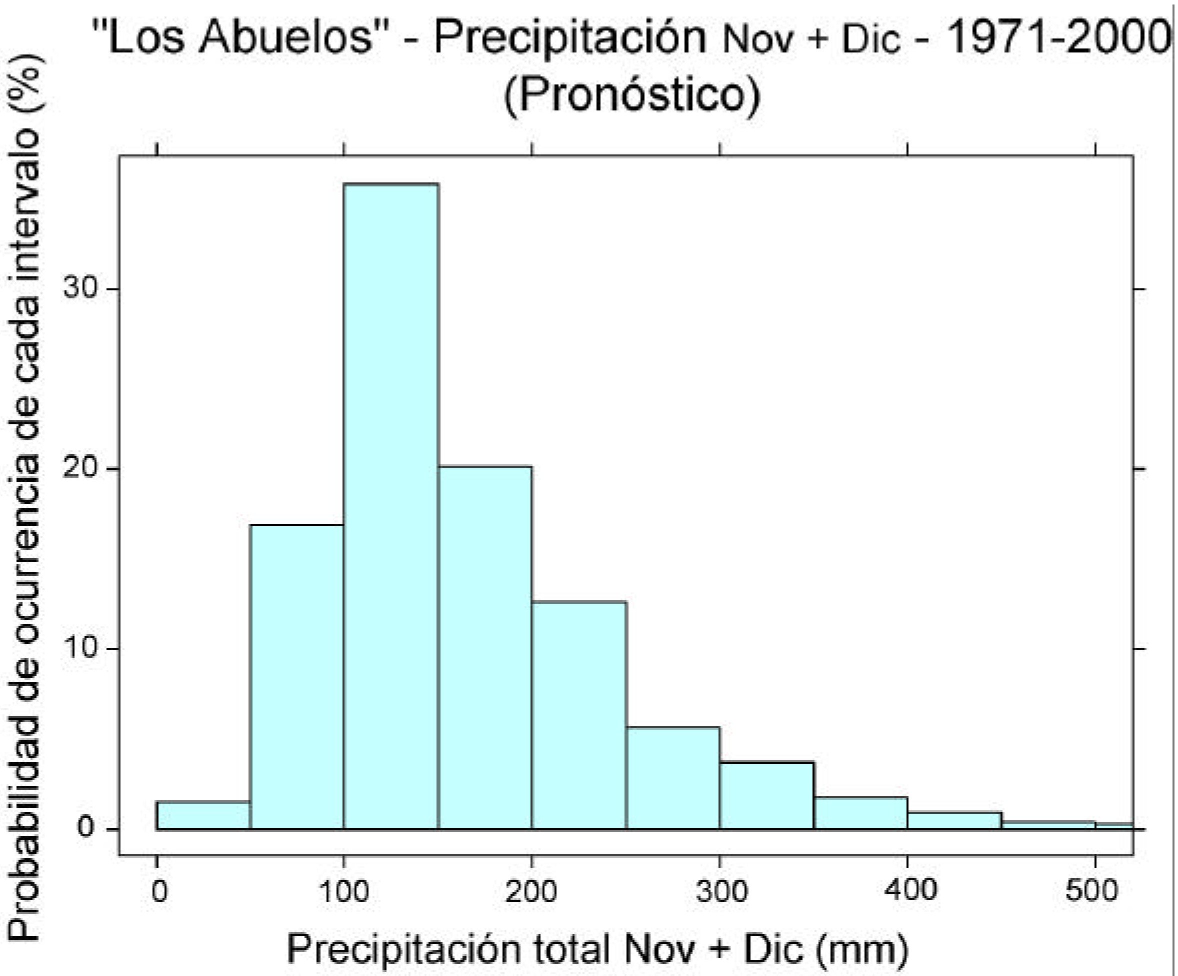
Pronóstico de precipitaciones
para noviembre/diciembre de 2003
(emitido el 1 de mayo de 2003)



El mapa muestra el área para la cual se pronostican precipitaciones totales para el período noviembre/diciembre de 200X. Los números en cada sector del ángulo inferior derecho indican la probabilidad de que las lluvias en este período sean “debajo de lo normal”, “normales”, o “debajo de lo normal.”

PRONÓSTICO D

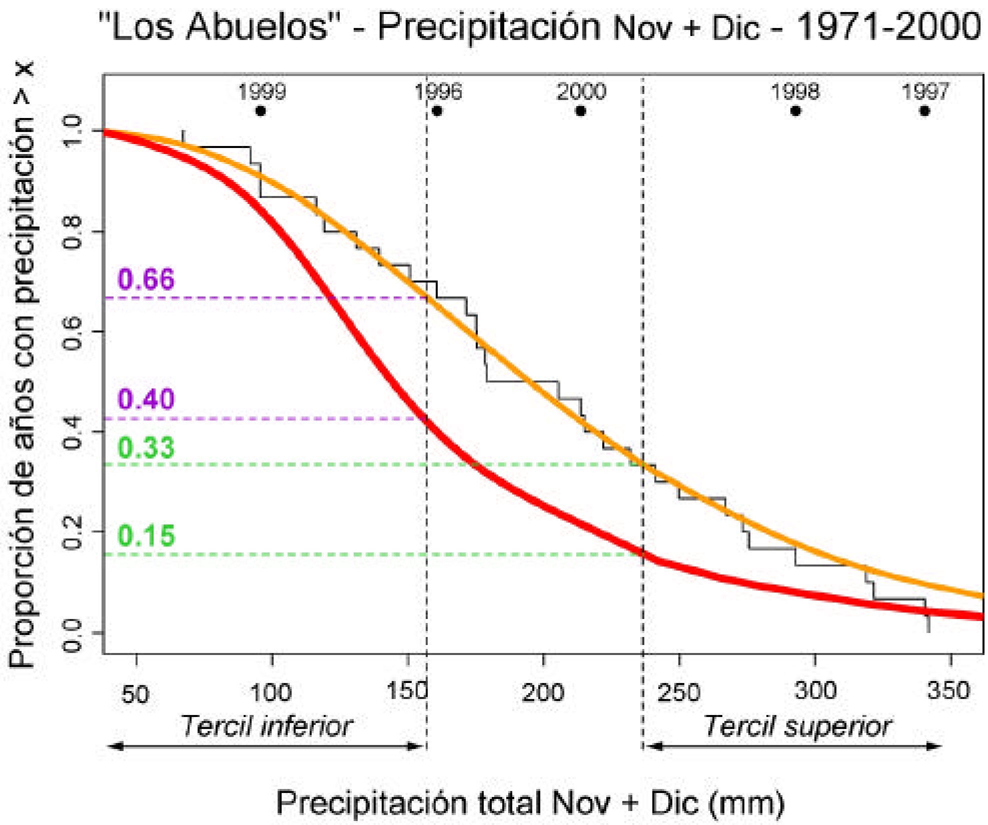
Pronóstico de precipitaciones
para noviembre/diciembre de 2003
(emitido el 1 de mayo de 2003)



El gráfico muestra la distribución pronosticada de valores de precipitación total para noviembre y diciembre de 200X en la zona de "Los Abuelos."

PRONÓSTICO E

Pronóstico de precipitaciones
para noviembre/diciembre de 2003
(emitido el 1 de mayo de 2003)



El gráfico muestra un pronóstico de la probabilidad de exceder un valor determinado de precipitación acumulada durante noviembre/diciembre. El pronóstico corresponde a la

Los valores de precipitación se muestran a lo largo del eje horizontal del gráfico. La línea roja* corresponde a la probabilidad pronosticada de exceder un valor de precipitación determinado (leído a lo largo del eje horizontal).

La línea negra** escalonada corresponde a los valores observados en la serie. La línea naranja*** corresponde a un suavizado de la distribución histórica.

Como referencia, se incluyen en el gráfico (debajo del eje horizontal superior) los valores de precipitación para los últimos cinco años disponibles (1996-2000) en la serie histórica.

* fat grey line
** thin black line
*** light grey line

TARJETA N°5

Nombre:	

1. Por favor indique brevemente en que difieren las condiciones climáticas indicadas en el pronóstico que ha elegido de la información climática histórica (recibida en el ejercicio 1, junto con el campo):
....

2. Actualmente estamos en el mes de mayo del 2003 y las condiciones climáticas esperadas para noviembre y diciembre son las que Ud. tiene en el pronóstico
De acuerdo a la información que posee sobre el campo heredado, le pedimos que arme su planteo productivo para la campaña 2003-04. Por favor, indique en el siguiente esquema qué cultivo hará en cada lote (si lo desea, puede subdividir los lotes indicando la superficie utilizada en cada caso).
NOTA: por favor anote en dentro de cada lote, el cultivo que ha decidido sembrar.

Los precios de mercado a término para la campaña 03 / 04 son los siguientes:
Maíz (en abril): 83.5 U$/Ton
Trigo (en enero): 123.5 U$/Ton
Soja (en mayo): 146.0 U$/Ton

Don Albino: esquema
6 lotes de 75 has cada uno

DA1 02/03: trigo/soja 2°	***DA2*** 02/03: soja 1°	***DA3*** 02/03: maíz Galpones
DA4 02/03: trigo/soja 2°	***DA5*** 02/03: soja 1°	***DA6*** 02/03: maíz

La Josefa: esquema
6 lotes de 75 has cada uno

LJF1 02/03: soja 1°	***LJF2*** 02/03: maíz
LJF3 02/03: maíz	***LJF4*** 02/03: trigo/soja
LJF5 02/03: soja 1°	***LJF6*** 02/03: trigo/soja

Ciclo corto	*ciclo intermedio*	*ciclo largo*
752	682	707
757	696	615
Chalten	664	37P73
	882	
	33Y09	

Fecha de siembra: en el siguiente esquema señale con un círculo o una cruz la fecha de siembre elegida:

10/8 20/8 30/8 10/9 20/9 30/9 10/10

Por favor, explicite por qué eligió dicho híbrido y dicha fecha de siembra:

....

N° LOTE: DA

HÍBRIDO: señale con un circulo la opción que le parece más adecuada.

Ciclo corto	*ciclo intermedio*	*ciclo largo*
752	682	707
757	696	615
Chalten	664	37P73
	882	
	33Y09	

Fecha de siembra: señale con un círculo la fecha de siembre elegida:

10/8 20/8 30/8 10/9 20/9 30/9 10/10

Por favor, explicite por qué eligió dicho híbrido y dicha fecha de siembra:

....

N° LOTE: DA.......

HÍBRIDO: señale con un circulo la opción que le parece más adecuada.

Ciclo corto	***ciclo intermedio***	***ciclo largo***
752	682	707
757	696	615
Chalten	664	37P73
	882	
	33Y09	

Fecha de siembra: señale con un círculo la fecha de siembre elegida:

10/8 20/8 30/8 10/9 20/9 30/9 10/10

¿Por qué eligió dicho híbrido y dicha fecha de siembra?

....

N° LOTE: DA....

HÍBRIDO: señale con un circulo la opción que le parece más adecuada.

Ciclo corto	***ciclo intermedio***	***ciclo largo***
752	682	707
757	696	615
Chalten	664	37P73
	882	
	33Y09	

Fecha de siembra: señale con un círculo la fecha de siembre elegida:

10/8 20/8 30/8 10/9 20/9 30/9 10/10

¿Por qué eligió dicho híbrido y dicha fecha de siembra?

....

<u>Consigna:</u> para cada uno de los lotes en los que ha escogido sembrar maíz en el campo
, por favor elija el híbrido que utilizará y la fecha de siembra. Recuerde que las

Ciclo corto ***ciclo intermedio*** ***ciclo largo***

752 682 707
757 696 615
Chalten 664 37P73
882
33Y09

Fecha de siembra: señale con un círculo o una cruz la fecha de siembre elegida:

10/8 20/8 30/8 10/9 20/9 30/9 10/10

¿Por qué eligió dicho híbrido y dicha fecha de siembra?

....

N° LOTE: LJF

HÍBRIDO: señale con un circulo la opción que le parece más adecuada.

Ciclo corto ***ciclo intermedio*** ***ciclo largo***

752 682 707
757 696 615
Chalten 664 37P73
882
33Y09

Fecha de siembra: señale con un círculo la fecha de siembre elegida:

10/8 20/8 30/8 10/9 20/9 30/9 10/10

¿Por qué eligió dicho híbrido y dicha fecha de

siembra?...

....

N° LOTE: LJF.........

HÍBRIDO: señale con un circulo la opción que le parece más adecuada.

Ciclo corto	*ciclo intermedio*	*ciclo largo*
752	682	707
757	696	615
Chalten	664	37P73
	882	
	33Y09	

Fecha de siembra: señale con un círculo la fecha de siembre elegida:

10/8 20/8 30/8 10/9 20/9 30/9 10/10

¿Por qué eligió dicho híbrido y dicha fecha de siembra?

....

N° LOTE: LJF......

HÍBRIDO: señale con un circulo la opción que le parece más adecuada.

Ciclo corto	*ciclo intermedio*	*ciclo largo*
752	682	707
757	696	615
Chalten	664	37P73
	882	
	33Y09	

Fecha de siembra: señale con un círculo la fecha de siembre elegida:

10/8 20/8 30/8 10/9 20/9 30/9 10/10

¿Por favor qué eligió dicho híbrido y dicha fecha de siembra?

....

Trajeta No. 7

Nombre:

Han pasado 3 meses desde que realizó su planteo productivo. Desde el 1° de mayo hasta el 18 de agosto han caído 108 mm (es decir, las precipitaciones se han mantenido dentro de las condiciones normales). Actualmente es 19 de agosto de 2003 y se ha ratificado que las condiciones climáticas esperadas para noviembre y diciembre de 2003 son las que figuran en su pronóstico. Le pedimos que realice el ajuste fino para el maíz para las variables que se indican a continuación.

CAMPO "DON ALBINO"

De acuerdo a los análisis de suelo y otros datos que maneja, indique la cantidad de urea/ hectárea que utilizará para fertilizar los lotes en los que sembró maíz.

ANÁLISIS DE SUELO PARA LOS SIGUIENTES 4 LOTES:
INSERTAR GRAFICO QUE PROVEERÁ FRT

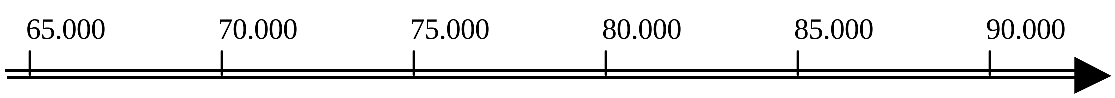
1) N° LOTE: DA......

Cantidad (kg) de urea/ha:...............................

¿Por qué elige esta dosis de fertilizante?:

....

Densidad de plantas a cosecha: en el siguiente esquema señale con un círculo o una cruz la densidad de plantas/ha que quiere cosechar:



Por favor explicite por qué elige esta densidad:

....

2) N° LOTE: DA......

Cantidad (kg) de urea/ha:...............................

¿Por qué elige esta dosis de fertilizante?:

....

....

Densidad de plantas a cosecha: en el siguiente esquema señale con un círculo o una cruz la densidad de plantas/ha que quiere cosechar:

65.000 70.000 75.000 80.000 85.000 90.000

Por favor explicite por qué elige esta densidad:

....

3) N° LOTE: DA......

Cantidad (kg) de urea/ha:................................

¿Por qué elige esta dosis de fertilizante?:

....

Densidad de plantas a cosecha: en el siguiente esquema señale con un círculo o una cruz la densidad de plantas/ha que quiere cosechar:

65.000 70.000 75.000 80.000 85.000 90.000

Por favor explicite por qué elige esta densidad:

....

4) N° LOTE: DA......

Cantidad (kg) de urea/ha:................................

¿Por qué elige esta dosis de fertilizante?:

....

Densidad de plantas a cosecha: en el siguiente esquema señale con un círculo o una cruz la densidad de plantas/ha que quiere cosechar:

65.000 70.000 75.000 80.000 85.000 90.000

Por favor explicite por qué elige esta densidad:

....

CAMPO "LA JOSEFA"

De acuerdo a los análisis de suelo y otros datos que maneja, indique la cantidad de urea/ hectárea que utilizará para fertilizar los lotes en los que sembró maíz.

ANÁLISIS DE SUELO PARA EL SIGUIENTE LOTE:

INSERTAR GRAFICO QUE PROVEERÁ FRT

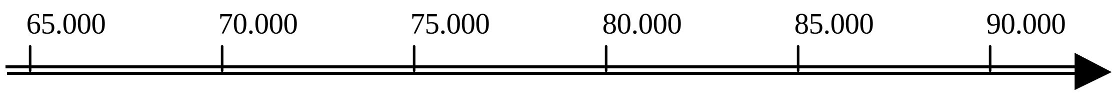
1) N° LOTE: LJF......

Cantidad (kg) de urea/ha:...............................

¿Por qué elige esta dosis de fertilizante?:

....

Densidad de plantas a cosecha: en el siguiente esquema señale con un círculo o una cruz la densidad de plantas/ha que quiere cosechar:



Por favor explicite por qué elige esta densidad:

....

ANÁLISIS DE SUELO PARA LOS SIGUIENTES 3 LOTES:

INSERTAR GRAFICO QUE PROVEERÁ FRT

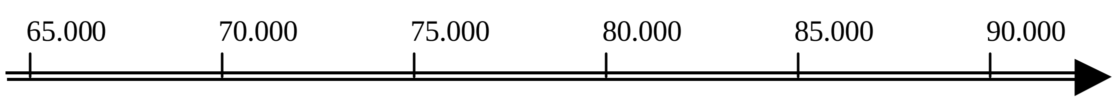
2) N° LOTE: LJF......

Cantidad (kg) de urea/ha:...............................

¿Por qué elige esta dosis de fertilizante?:

....

Densidad de plantas a cosecha: en el siguiente esquema señale con un círculo o una cruz la densidad de plantas/ha que quiere cosechar:



Por favor explicite por qué elige esta densidad:

....

3) N° LOTE: LJF......

Cantidad (kg) de urea/ha:...............................

¿Por qué elige esta dosis de fertilizante?:

....

Densidad de plantas a cosecha: en el siguiente esquema señale con un círculo o una cruz la densidad de plantas/ha que quiere cosechar:

Por favor explicite por qué elige esta densidad:

....

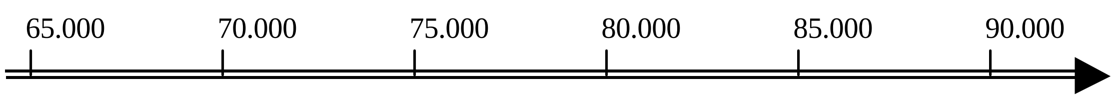
4) N° LOTE: LJF......

Cantidad (kg) de urea/ha:...............................

¿Por qué elige esta dosis de fertilizante?:

....

Densidad de plantas a cosecha: en el siguiente esquema señale con un círculo o una cruz la densidad de plantas/ha que quiere cosechar:



¿Por qué elige esta densidad:?

....

Por favor, en el siguiente espacio, indique si realizaría alguna otra modificación que no haya sido registrada en los anteriores ejercicios, tanto en su planteo productivo como en el ajuste fino para el cultivo de maíz, teniendo en cuenta el pronóstico para noviembre y diciembre de 2003. Por favor, también indique qué tareas adicionales, no relacionadas con el planteo productivo, planificaría teniendo en cuenta ese pronóstico.

Campo “Don Albino”

Historia de lotes

	DA 1	DA 2	DA 3	DA 4	DA 5	DA 6	DA 7	DA 8	DA 9	DA 10
91/92	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz
92/93	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º
93/94	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja
94/95	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz
95/96	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º
96/97	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja
97/98	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz
98/99	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º
99/00	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja
00/01	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz
01/02	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º
02/03	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja

Campo “La Josefa”

Historia de lotes

	LJf 1	LJf 2	LJf 3	LJf 4	LJf 5	LJf 6	LJf 7	LJf 8	LJf 9	LJf 10
91/92	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Maiz
92/93	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Soja 1º
93/94	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Trigo/Soja
94/95	Trigo/Soja	Soja 1º	Soja 1º	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Maiz
95/96	Maiz	Trigo/Soja	Trigo/Soja	Soja 1º	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Soja 1º
96/97	Soja 1º	Maiz	Maiz	Trigo/Soja	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Trigo/Soja
97/98	Trigo/Soja	Soja 1º	Soja 1º	Maiz	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Maiz
98/99	Maiz	Trigo/Soja	Trigo/Soja	Soja 1º	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Soja 1º
99/00	Soja 1º	Maiz	Maiz	Trigo/Soja	Maiz	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Trigo/Soja
00/01	Trigo/Soja	Soja 1º	Soja 1º	Maiz	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Maiz	Maiz
01/02	Maiz	Trigo/Soja	Trigo/Soja	Soja 1º	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Soja 1º	Soja 1º
02/03	Soja 1º	Maiz	Maiz	Trigo/Soja	Soja 1º	Trigo/Soja	Soja 1º	Maiz	Trigo/Soja	Trigo/Soja

SURVEY INSTRUMENTS SOUTHERN FLORIDA

Brief biographical information

Age: ______________________________

Gender: ______________________________

Education/Degree: __________________________________

County: __________________________________

Farm size: __________________________________

How long in farming: __________________________________

What type(s) of farming
do you practice? __________________________________

Mental Model Interview Protocol (Farmers)

Mental Models Climate Variability

What is the climate like here?
[Then move to variability by asking:]
How likely is it that the climate will be like you described it? Is there variability/is it changing?

Do you remember extreme events, years that stand out?

What factors might influence such climate variability?
Tell me all the causes of climate variability you can think of. What causes variability of a season from one year to another year, or from one crop season to the next?

[*For the following question it can work well to w rite items on cards/post-it notes:*]
Can you order these factors according to their importance?
Can you tell me why … is the most important cause of variability?
Do you think these causes that you listed are related to each other?
Any ideas how?

What kinds/what other kinds of climate variability might there be? Any variability that comes to your mind outside of, or in addition to what you discussed earlier?

Let's talk [a bit more] about El Niño/La Niña:
What precursors/signs might there be before you notice the influence of El Niño/La Niña events/before a drought or a flood/before a dry or a wet season?
How well can you observe these signs?

What role does climate variability play in your life and in your decision making?
What are the effects/impacts of El Niño/La Niña here in your region?
Will the effects/impacts of climate variability be the same everywhere?
What potential climate anomalies are expected to accompany the El Niño/La Niña? Do El Niño and La Niña have an effect on the climate here? What effect?

A question about expected climate and climate prediction:
Do you use meteorological forecasts/climate forecasts?
(Do you check seasonal forecasts?)
If yes:
What sources of information on climate prediction do you use?
What types of information impact your decision making? On which of these sources do you base your decisions?
Are there any local indicators, things that you can observe here where you live?

What do you think are the odds that next winter (Dec-Feb) will be an average, warmer (milder) than average, or colder (more severe) than average one?
What do you think are the odds that next winter (Dec-Feb) will be wetter than average, dryer than average, or just average?

What do you think: Is climate variability a naturally occurring phenomenon, or do man-made factors contribute to climate variability? Do we as humans have an influence on the occurrence of floods and droughts, on freezes and heat waves, extreme winds?
Do you think we as inhabitants of the earth can do anything about this?
If yes, what?

In your view, how old do you think is the phenomenon of climate variability?
[Note: if not asked earlier, ask here:]
What years stand out in your memory? Do you remember an extreme climate event?
Do you see any patterns in climate variability? Does one event usually follow another one?

Do you think climate variability is good, bad, or neutral?
[if not covered enough earlier:]
What effect does it have on your life?
Does El Niño raise or lower the yields of your crops? How about La Niña? Which regional crop is mostly influenced by ENSO? Why?
[if necessary, ask here more questions about decisions, management, like "what do you do about it?"]

Definitions:

Climate experts and forecasters would like to know how much of their terminology is understood by/has trickled down to the users of climate forecasts. Therefore, I am going to ask you for several definitions. Some of this may seem repetitive, but please bear with me. Don't worry about how much you know. We are interested in what you think about these things.

What is climate variability?
What is El Niño?
What is La Niña?
What is ENSO?
What is Sea Surface Temperature?

What is weather?
What is climate?
What is climate change?

[*Following definitions are optional, time permitting*]
What is a probabilistic seasonal climate forecast?
What is reliability?
What is normal? What does normal rainfall mean?
What is average?
What is a median?
What does probability mean?
How would you define drought?
How do you interpret scientific uncertainty?
What are terciles?
What is frontal weather?
What is convection?
What is the difference between deterministic and probabilistic?
What is risk?

How well do you understand each of the above? How well do think scientists understand …?
How certain are you/scientists that you/they understand …?

Are there any terms that you come across when reading about climate that you don't know but would like to know more about? Are there any terms that climatologists and forecasters use that you don't understand, or that are confusing?

Would you like to know more about these things? Do you think it is important that you know more about the details behind forecasts?

What are important temperature thresholds that you would like to know about in advance? E.g., is it important to know that the temperature might rise above a certain point, like 45 degrees, or 75 degrees? Any similar thresholds for rainfall?

What would be useful information for you in addition to probabilistic forecasts?

Were any questions too hard or unclear?

Were there any issues related to climate variability that you thought of but didn't get a chance to talk about?

[*Note: Throughout interview, use neutral prompts*:]

Can you tell me more about …?
Can you explain how …?
Can you explain why…?
Does … bring anything else to mind?
If you were going to explain climate variability to someone else, is there anything you would say differently or add to what you have said?

Pre-Tutorial Questionnaire

Before we start with the tutorial, we would like you answer a few quick questions:

1. What decisions do you make that are sensitive to climate?

2. What decisions do you make that are sensitive to winter rainfall?

3. Information about climate influences my farming decisions.

1	2	3	4	5
(strongly disagree)				(strongly agree)

4. I would change farm management decisions if I knew in advance that a given winter was likely to be dryer than normal.

1	2	3	4	5
(strongly disagree)				(strongly agree)

5. I would change farm management decisions if I knew in advance that a given winter was likely to be wetter than normal.

1	2	3	4	5
(strongly disagree)				(strongly agree)

6. I would change farm management decisions if I knew in advance that La Niña conditions would occur over winter.

1	2	3	4	5
(strongly disagree)				(strongly agree)

7. I would change farm management decisions if I knew in advance that El Niño conditions would occur over winter.

1	2	3	4	5
(strongly disagree)				(strongly agree)

8. If you knew in advance that La Niña conditions would occur next winter, what would you do differently?

---

9. If you knew in advance that El Niño conditions would occur next winter, what would you do differently?

---

10. I regard advanced forecasts of La Niña conditions to be valuable.

1	2	3	4	5
(strongly disagree)				(strongly agree)

---

11. I regard advanced forecasts of El Niño conditions to be valuable.

1	2	3	4	5
(strongly disagree)				(strongly agree)

---

12. Assume that information about El Niño, Neutral or La Niña conditions was not publically available. What is the most you would pay each year to know 3 months in advance whether El Niño, Neutral or La Niña conditions would occur over the winter?

$ _________

Please stop here. We will now move on to the TUTORIAL.

Post-Tutorial Questionnaire

Continue here after you have worked through the tutorial:

13. I would change farm management decisions if I knew in advance that La Niña conditions would occur over winter.

1 2 3 4 5
(strongly disagree) (strongly agree)

---

14. I would change farm management decisions if I knew in advance that El Niño conditions would occur over winter.

1 2 3 4 5
(strongly disagree) (strongly agree)

---

15. If you knew in advance that La Niña conditions would occur next winter, what would you do differently?

---

16. If you knew in advance that El Niño conditions would occur next winter, what would you do differently?

---

17. I regard advanced forecasts of La Niña conditions to be valuable.

1 2 3 4 5
(strongly disagree) (strongly agree)

---

18. I regard advanced forecasts of El Niño conditions to be valuable.

1 2 3 4 5
(strongly disagree) (strongly agree)

---

19. Assume that information about El Niño, Neutral or La Niña conditions was not publically available. What is the most you would pay each year to know 3 months in advance whether El Niño, Neutral or tions would occur over the winter?

$ _______

---

1 2 3 4 5
(strongly disagree) (strongly agree)

---

23. The degree of difficulty was:

1 2 3 4 5
(too simple) (appropriate) (too difficult)

23.a. Which graph(s) did you find easy to understand?

24.b. Which graph(s) did you find hard to understand?

---

25. The length was (scale: too short ... appropriate ... too long).

1 2 3 4 5
(Too short) (appropriate) (too long)

---

26. Would you like to do more of such tutorial-based learning?

Yes ___ No ___

---

27. What would you change to improve the tutorial?

---

28. What additional information would you like to see in educational materials related to El Niño and

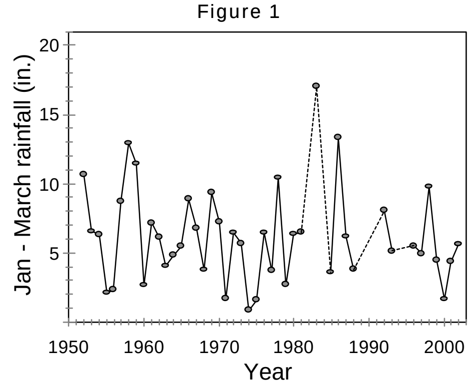
Appendix C: Forecast Presentation Modules

MODULE 1:
SEASONAL FORECAST AS A SHIFTED PROBABILITY DISTRIBUTION

January-March Precipitation

Homestead, Florida

Figure 1



This graph (Figure 1) shows winter (January to March) rainfall recorded at Homestead for 44 previous years. Note the range of variability. Do particular years stand out in your mind? What was the wettest winter? What was the driest winter? What range of rainfall do you expect next winter?

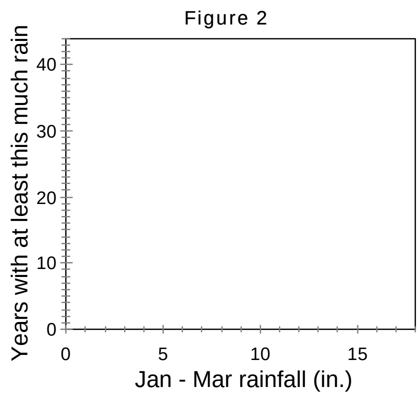
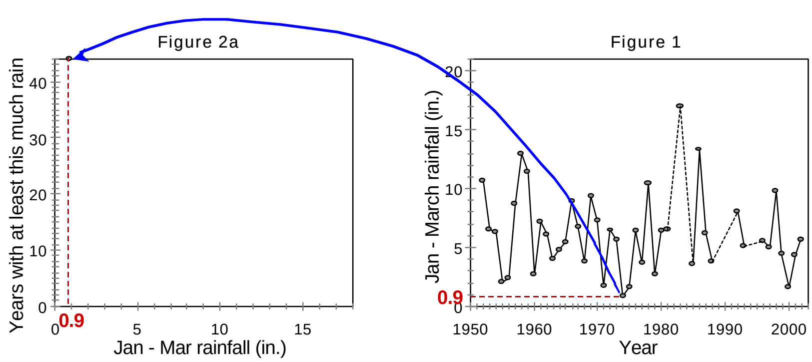
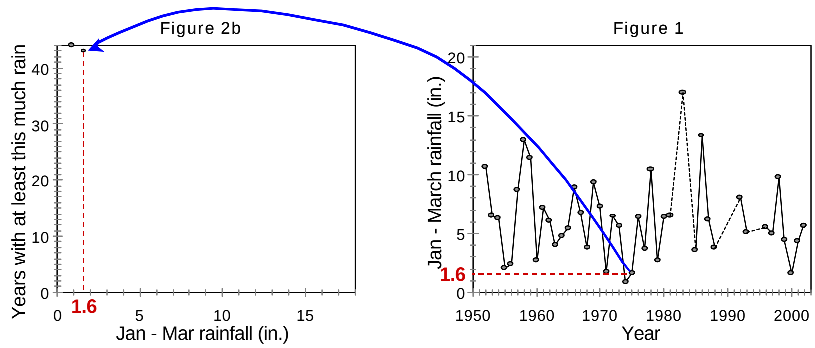


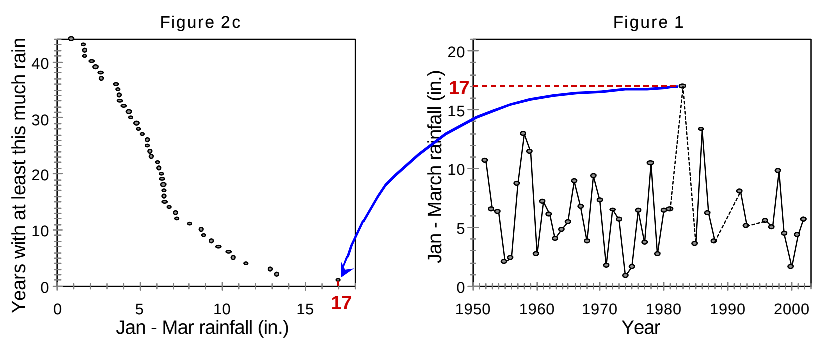
Figure 2 shows an empty graph with amount of winter rainfall on the bottom (x axis), and the number of winters that had at least this much rain on the left (y axis).



We take the rainfall amount (0.9 inches) in the driest winter (1974) from Figure 1, and move it to Figure 2. Note that all 44 winters had at least 0.9 inches of rain.

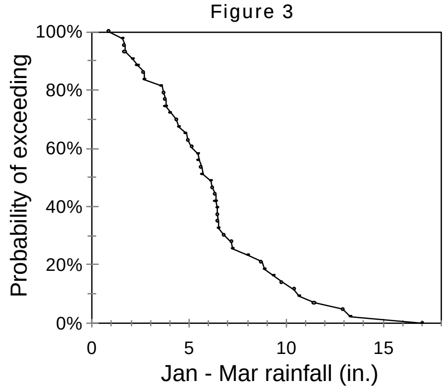


We repeat this for the second driest winter (1975). Forty-three out of 44, or 98%, of the winters, had at least 1.6 inches of rain (i.e., 1.6 or more inches). Another way to think of it is that the probability of getting at least 1.6 inches of rain next winter is 98%. The probability of getting less than 1.6 inches is 2%.



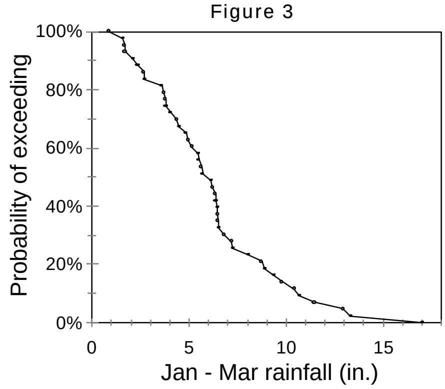
We repeat the process for the third driest winter, and so on, until the graph is complete.

Figure 3

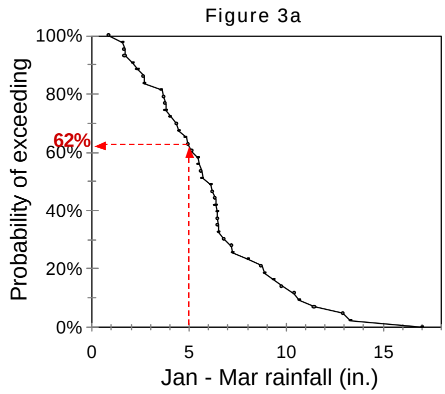


In Figure 3, we replace the **number** of winters with at least a given amount of rain with the **percent probability** of getting at least the given amount. We call this a "*probability of exceedence*" graph. This graph shows the relationship between rainfall amounts and probabilities. It is one way to represent a probability distribution.

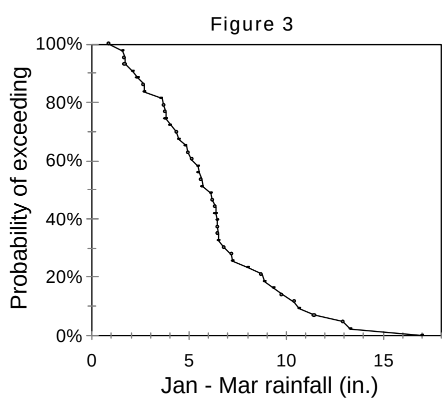
Figure 3



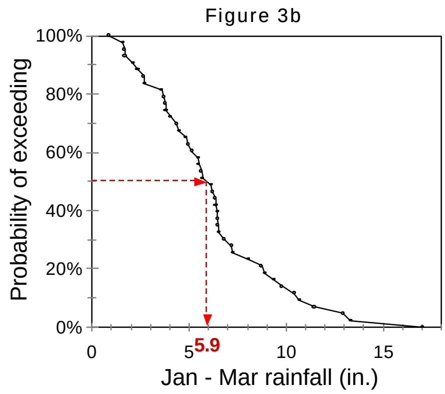
Suppose a farmer needs at least 5 inches of rain in January-March to avoid crop failure (i.e., the value of the harvested crop will not cover variable costs). What is the probability of getting at least 5 inches in a given winter?



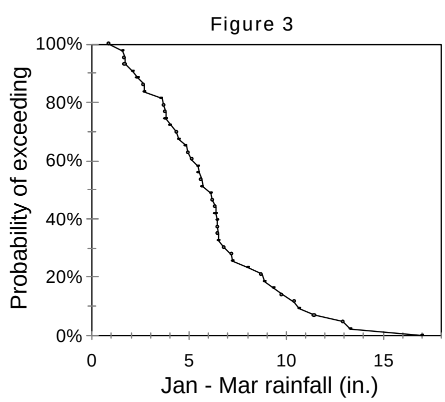
We can find the probability of exceeding 5 inches by drawing a vertical line from 5 inches to where it meets the curve, then extending a horizontal line from that point to the associated probability on the left.



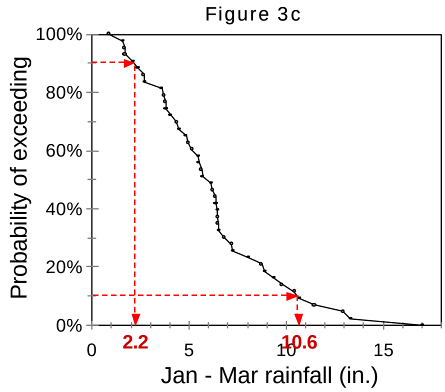
The probability of exceedence graph can also give us rainfall amounts associated with particular probabilities. For example, what winter rainfall amount would you expect to exceed with a probability of 50%, or in half of the winters?



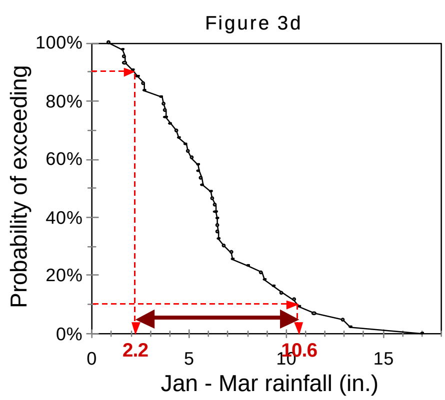
We draw a horizontal line from the 50% probability on the left side of the graph to the curve, then down to the corresponding rainfall amount. The amount of rainfall that you would have a 50% probability of exceeding (5.9 inches) is known as the 50th "*percentile*." It is also known as the "*median*," and is one measure of "*central tendency*." The average is another.



How much winter rainfall would you expect to exceed with a probability of 90%, or in nine out of ten winters? Would this be a wet winter or a dry winter? How much would you expect to exceed with a 10% probability, or in one out of 10 winters?



We can use the same procedure to find these rainfall amounts. The amount exceeded with a 90% probability (2.2 inches) is known as the 10th percentile because 10% of winters have no more than this amount of rain. The amount exceeded with 10% probability (10.6 inches) is known as the 90th percentile.



The difference between the 90th and 10th percentile is one measure of variability, or the uncertainty that one could face in a given winter. In this case, 10.6 – 2.2 = 8.4 inches is the range of winter rainfall that would occur in the middle 80% of winters.

This measure of uncertainty is somewhat arbitrary. We could just as easily use, for example, the 75th – 25th percentile, which would give us the maximum range in the middle 50% of winters. Standard deviation is another common measure of uncertainty.

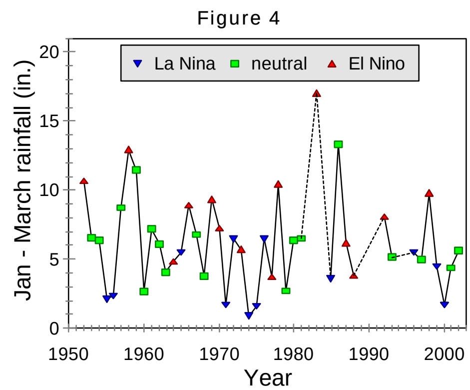
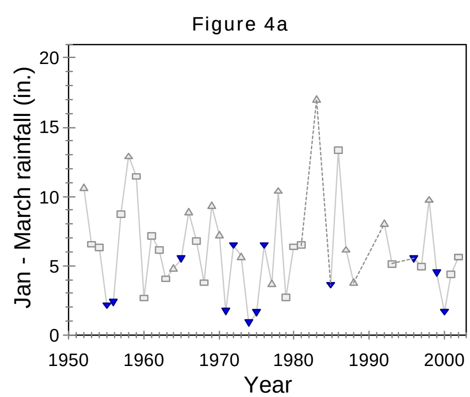
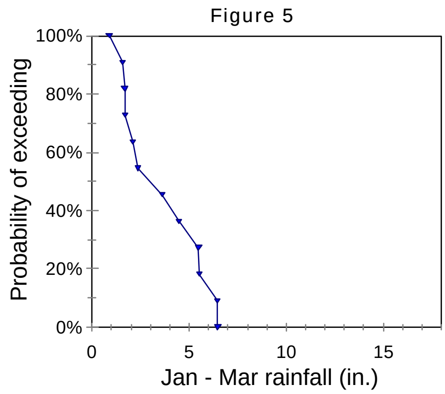


Figure 4 is identical to Figure 1, except that it uses different symbols to show which years were El Niño, La Niña and neutral. If you learned that La Niña conditions are expected for the coming winter, what range of rainfall would you expect? Would the news lead you to expect wetter or dryer conditions than you would normally expect without knowing about the La Niña?



Let us, for a moment, consider only the 12 La Niña years. If you knew that La Niña conditions would occur next winter, how would it affect the amount of rainfall that you would expect?



To help answer that question, we build a probability of exceedence graph for just the La Niña years, just as we did earlier for all 44 years. We can read and interpret Figure 5 in the same way we did Figure 3.

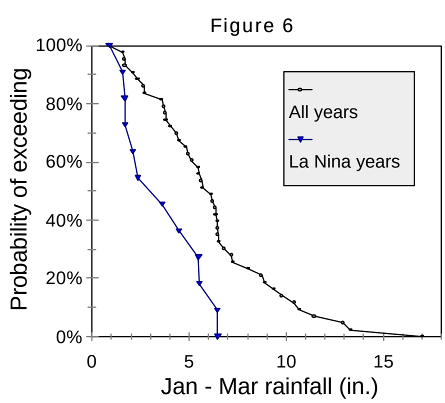
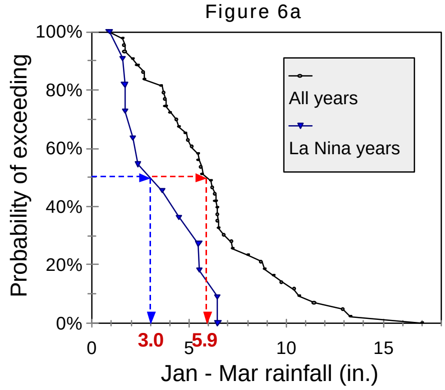


Figure 6 shows the probability of exceedence plots for all winters and for the La Niña winters on the same graph to allow us to compare probability distributions with and without knowing about La Niña. What can we infer from the two curves?

Figure 6a



Note first that the median rainfall in La Niña winters is less than the median for all winters.

Figure 6b

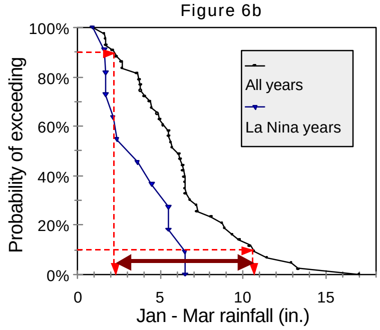
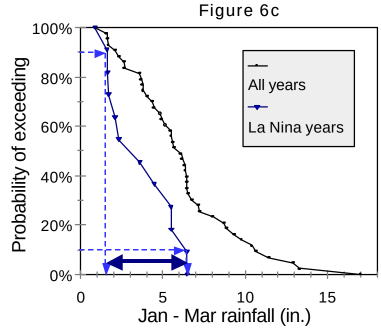
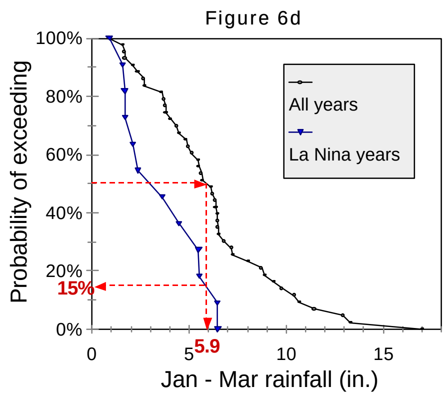


Figure 6c



We also find that the difference between the 90th and 10th percentiles (the range in the middle 80% of winters) is less in La Niña years (4.8 inches, Figure 6c) than in all years (8.4 inches, Figure 6b). Knowing that La Niña conditions will prevail reduces uncertainty.



We found earlier that the median rainfall in all winters was 5.9 inches. Without knowing about La Niña, the probability of getting more than median rainfall in a given winter is 50%. What is the probability of getting more than the long-term median in a La Niña winter? (15%)

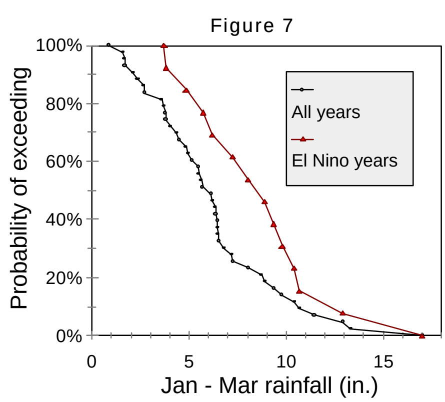
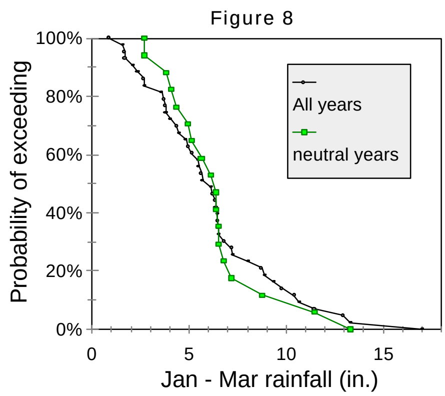


Figure 7 shows the probability of exceedence curves for all years and for El Niño years. How would a forecast of El Niño conditions influence the amount of winter rainfall that you would expect?



Finally, Figure 8 shows the probability of exceedence curves for all years and for neutral years. How would a forecast of neutral conditions influence the amount of winter rainfall that you would expect?

End of Module 1

MODULE 2: UNCERTAINTY OF A SEASONAL CLIMATE FORECAST SYSTEM

January-March Precipitation

Homestead, Florida

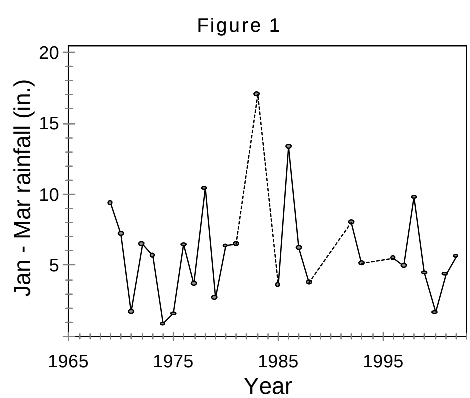
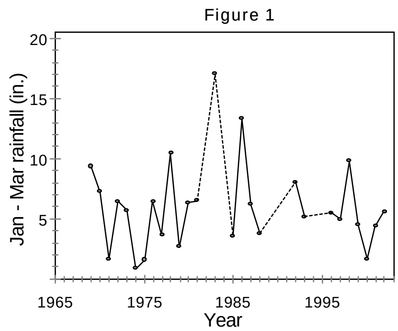


Figure 1 shows winter (January to March) rainfall recorded at Homestead each year since 1969.



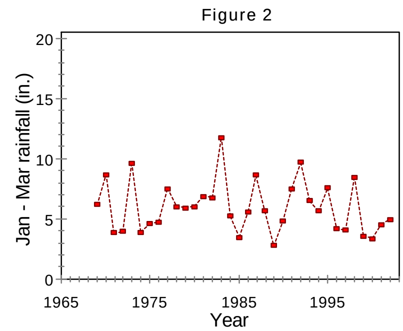
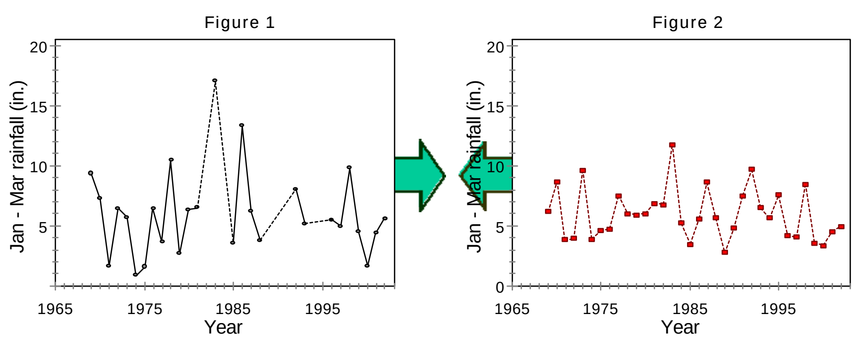
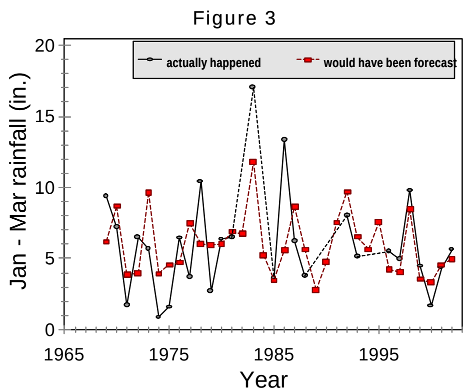


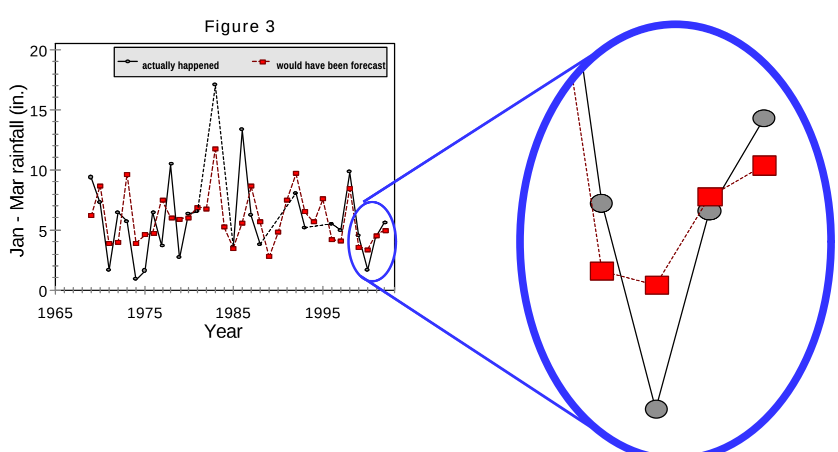
Figure 2 shows how much winter rainfall a forecast system would have predicted for each of the years. We call a forecast made for some past period a "*hindcast*." Although they are not from an operational forecast system, the hindcasts are plausible predictions made from a mathematical model that simulates the physical processes within the atmosphere, and the atmosphere's response to ocean temperatures. Each January-March hindcast used only information that would have been available the previous December.



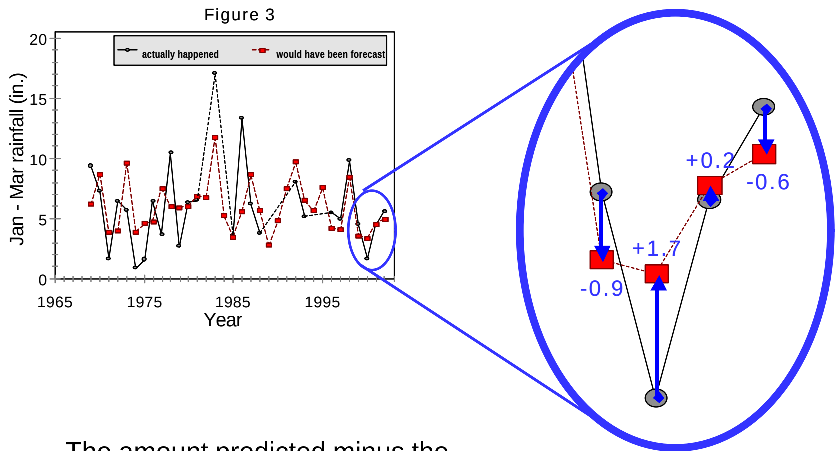
By putting the rainfall that would have been predicted on the same graph as the rainfall that actually occurred, we can get a sense of how well the forecast system performs over time.



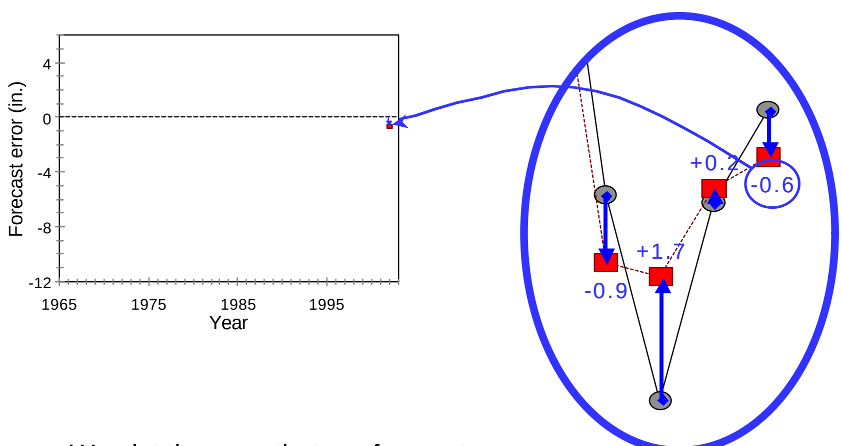
How well do you think the forecast system predicts year-to-year variations in rainfall? Recall from Module 1 that La Niña and El Niño cannot tell us what the weather will be like, but can help us predict shifts in the probability distributions. In the same way, physically-based climate models can predict shifts in probabilities, but generally cannot tell us the exact amount of rainfall that will occur.



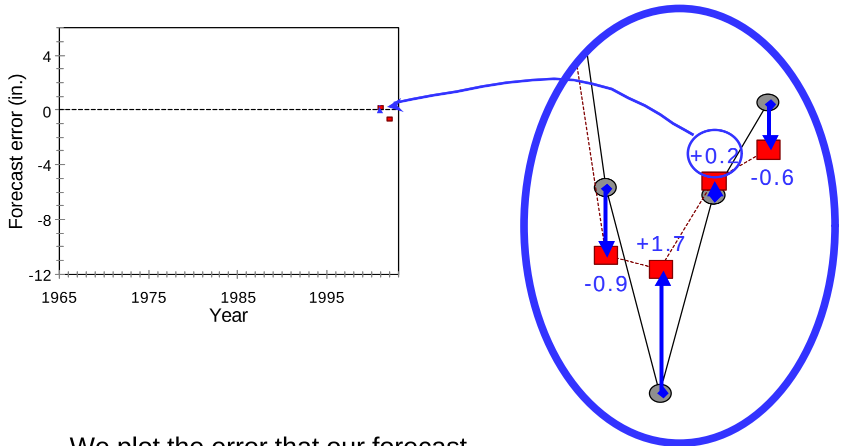
We take a closer look at a few years to see how far off the predictions were.



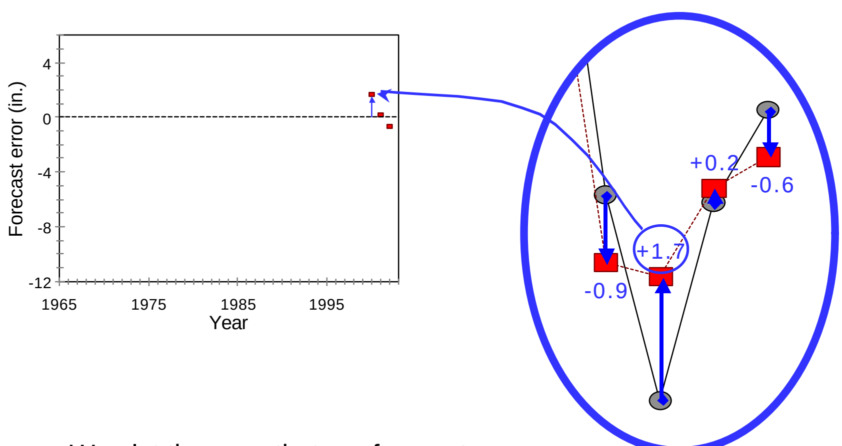
The amount predicted minus the amount that occurred is a measure of the "*forecast error*" in a particular year.



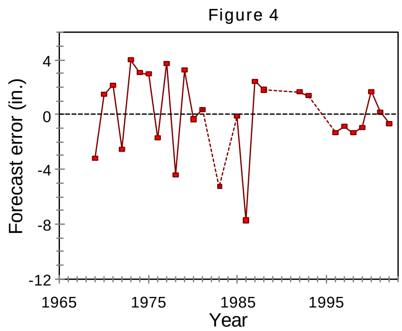
We plot the error that our forecast system would have produced each year.



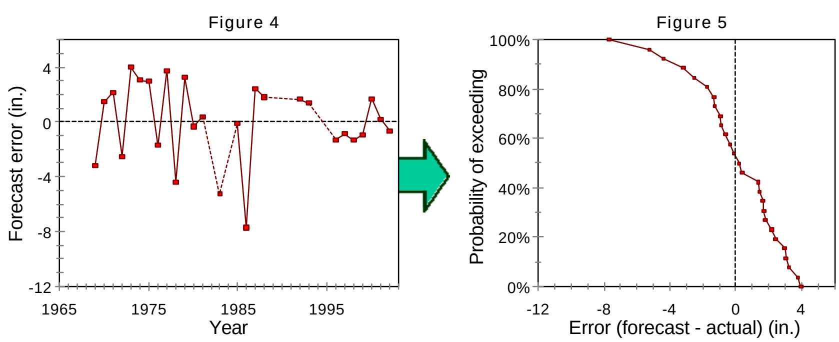
We plot the error that our forecast
system would have produced each year.



We plot the error that our forecast
system would have produced each year.

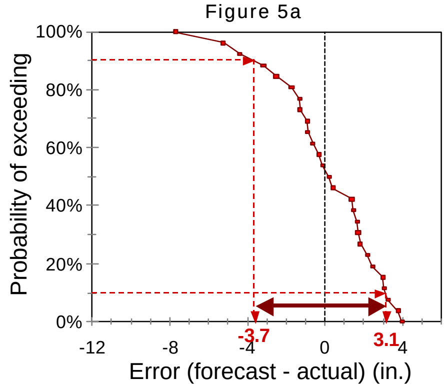


We plot the error that our forecast system would have produced each year (Figure 4).



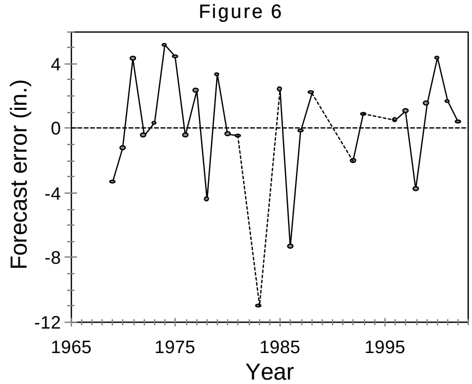
We create a probability of exceedence graph that shows the distribution of errors associated with the forecast system (Figure 5), just as we did earlier with total winter rainfall. The graph expresses the uncertainty of the forecast system as a probability distribution.

Figure 5a

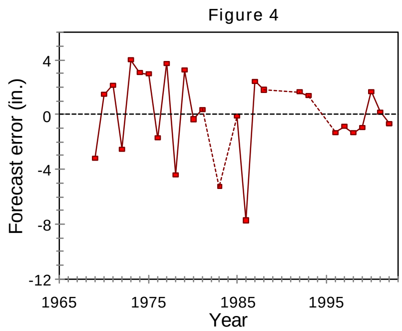


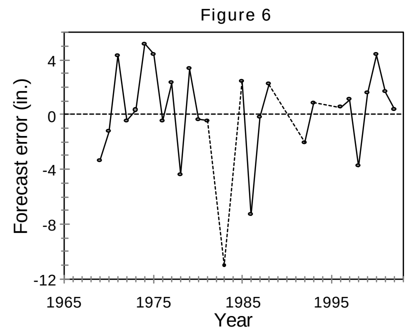
The range between the 90th and 10th percentiles (6.8 in.) give us an measure of the maximum error that we can expect in most (80%) years.

Figure 6

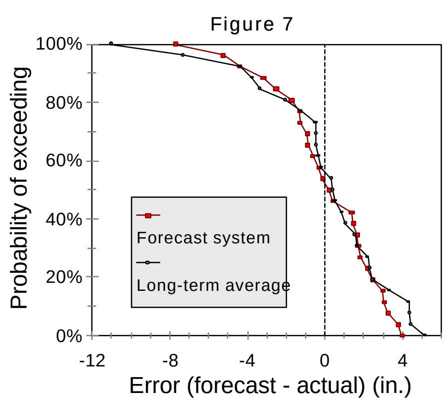


If we did not have access to seasonal forecasts, we might use the long-term average as a naive "forecast" for any given winter. Figure 6 shows error (average minus observed rainfall) that would result each winter from using the long-term average as a forecast.

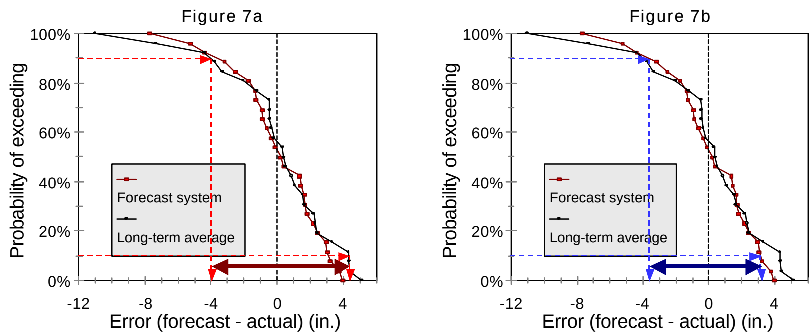




What can you conclude from comparing the error distribution from the climate model (Figure 4) with the error distribution from using the long-term average (Figure 6)?



Another way to compare the errors from the climate model and the long-term average rainfall is to plot probability of exceedence curves for both on one graph (Figure 7).

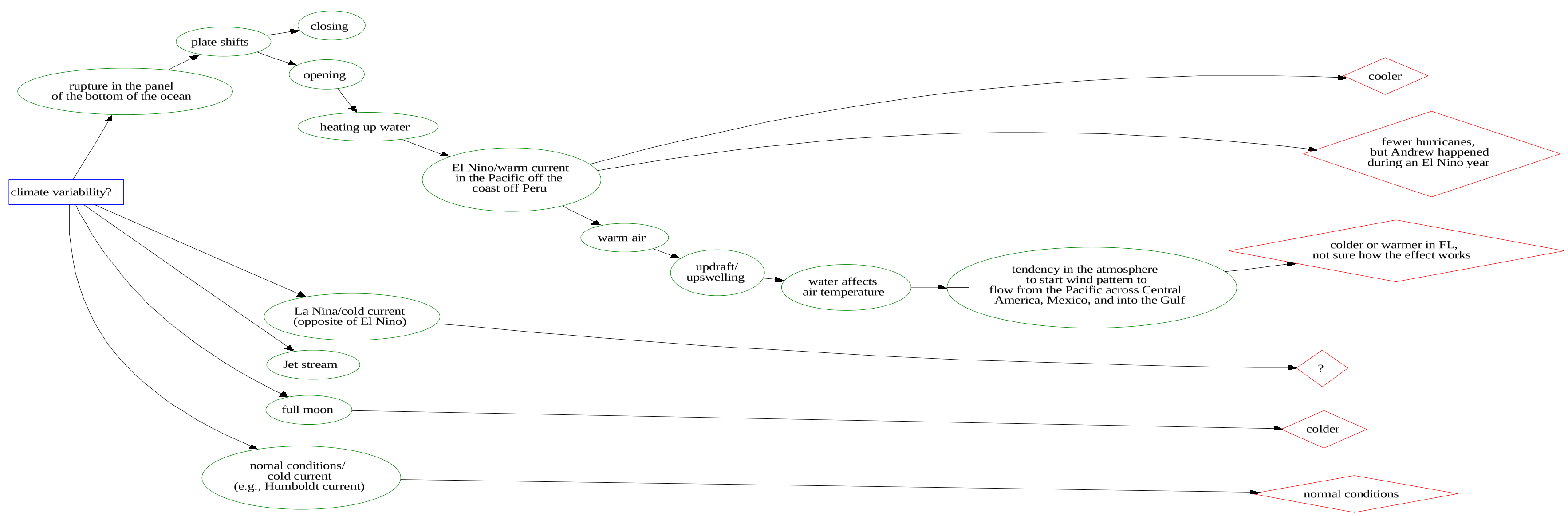


The forecast system reduces the uncertainty of predicted winter rainfall, expressed here as range between the 90th and 10th percentiles, from 8.4 (Figure 7a) to 6.8 inches (Figure 7b).

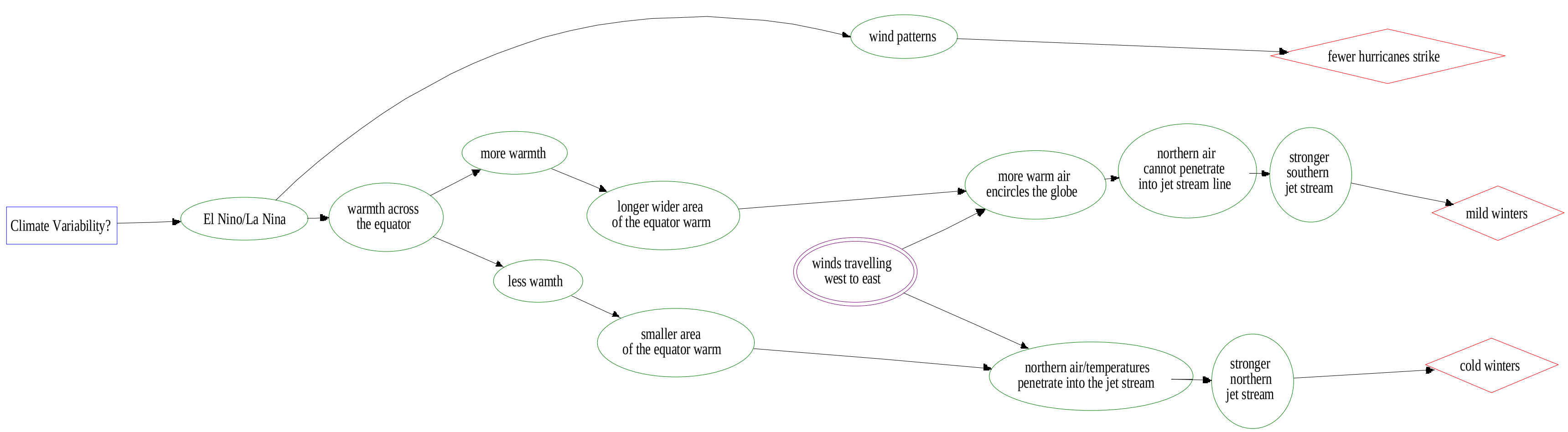
The forecast system reduces the standard deviation of forecast error, another measure of uncertainty, from 3.6 to 2.8 inches.

End of Module 2

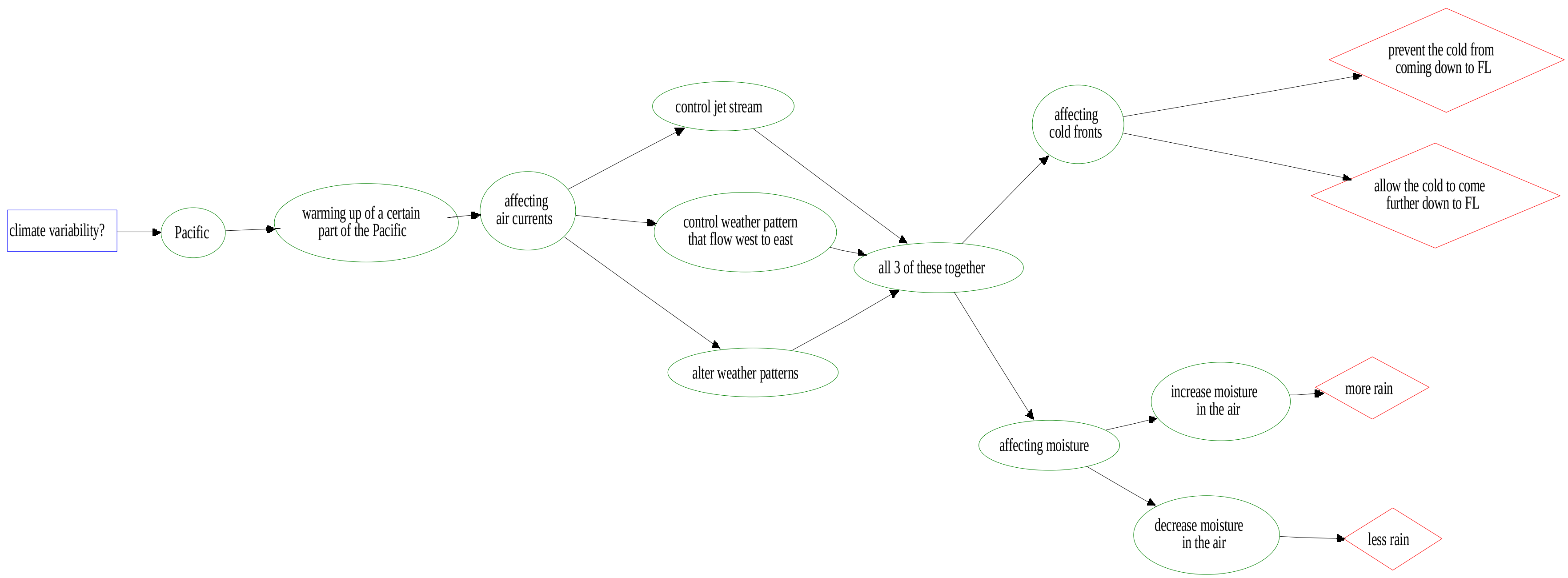
Appendix D: Influence Diagrams



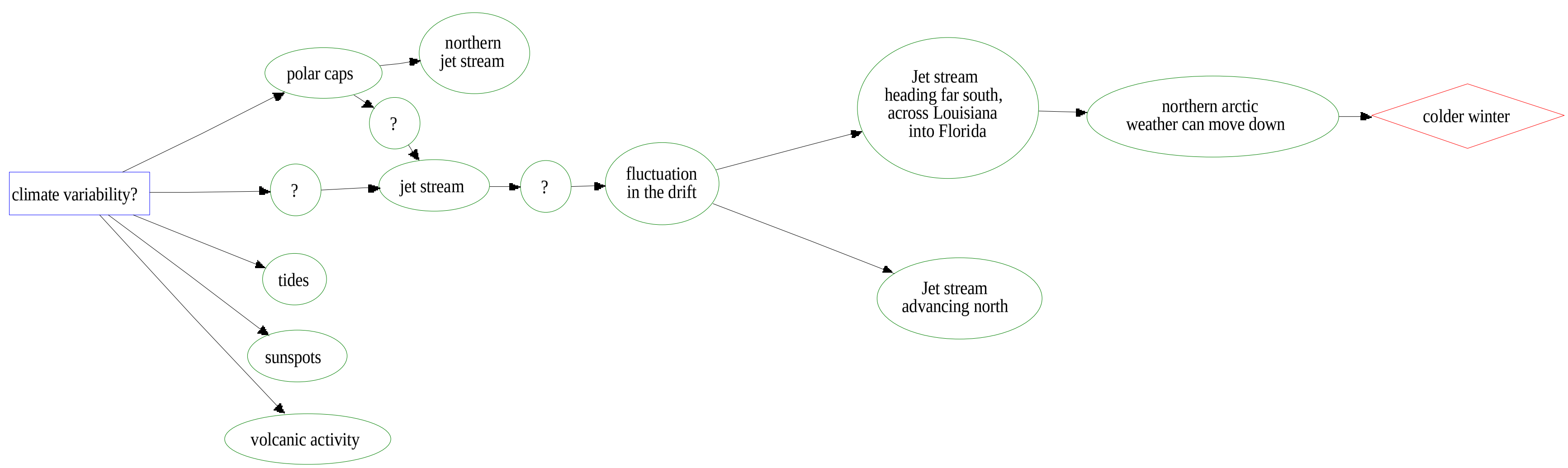
Farmer 11, Mental Model Influence Diagram



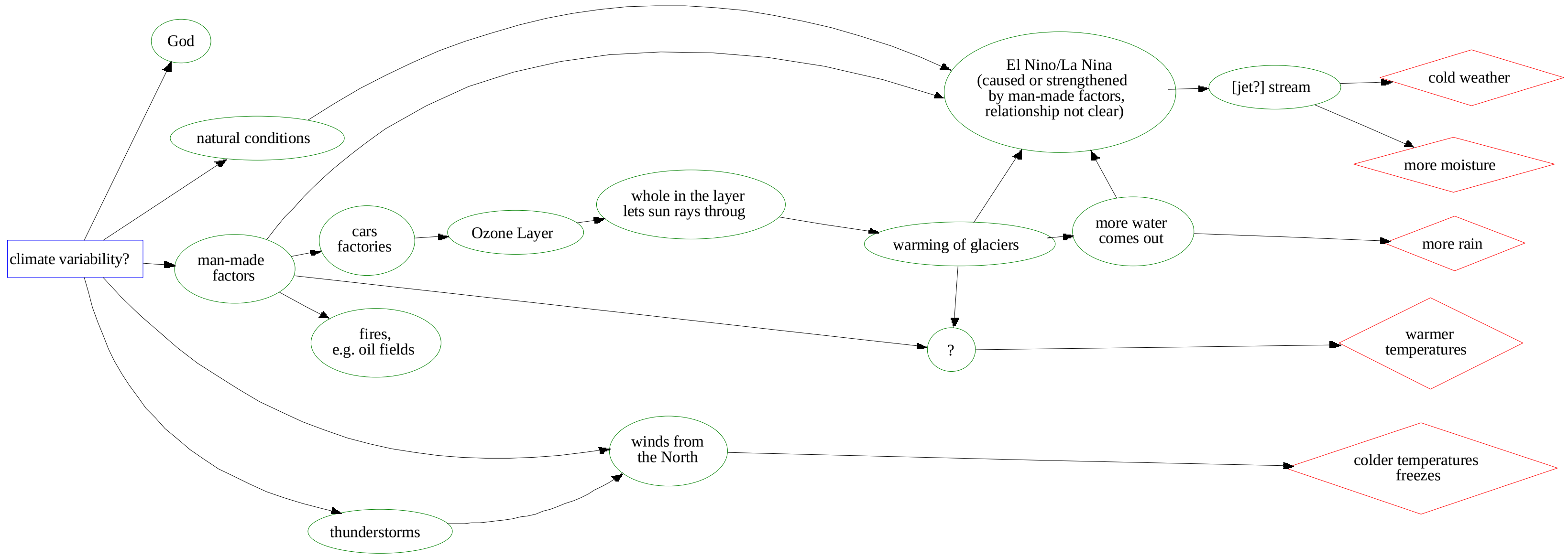
Farmer 12, Mental Model Influence Diagram



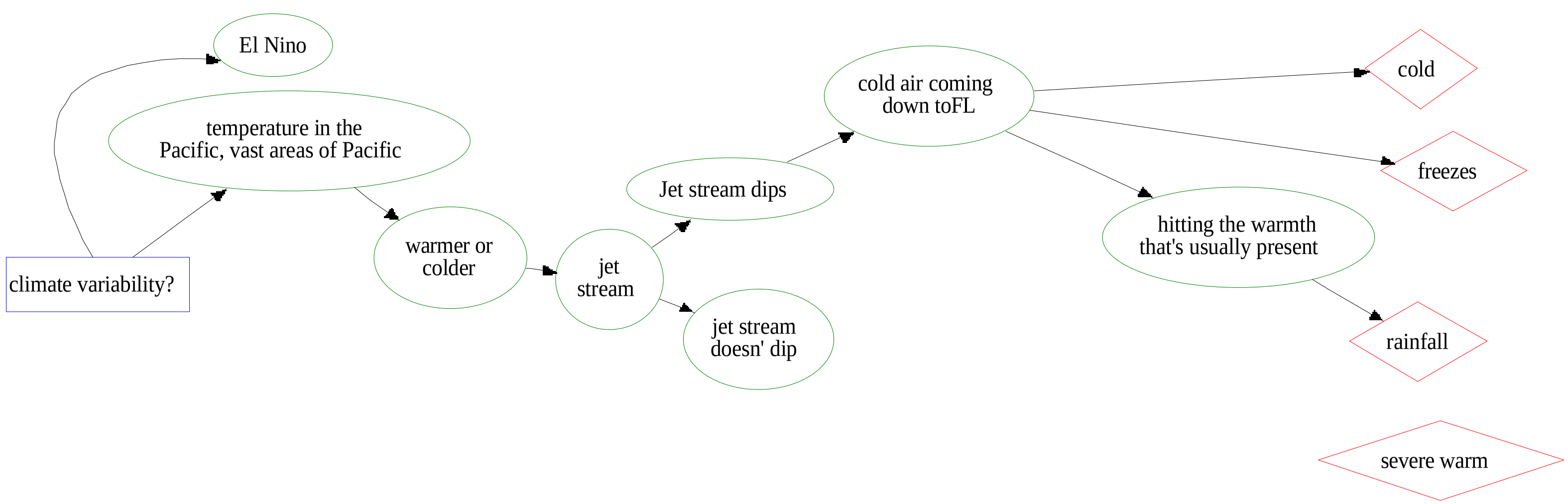
Farmer 4, Mental Model Influence Diagram



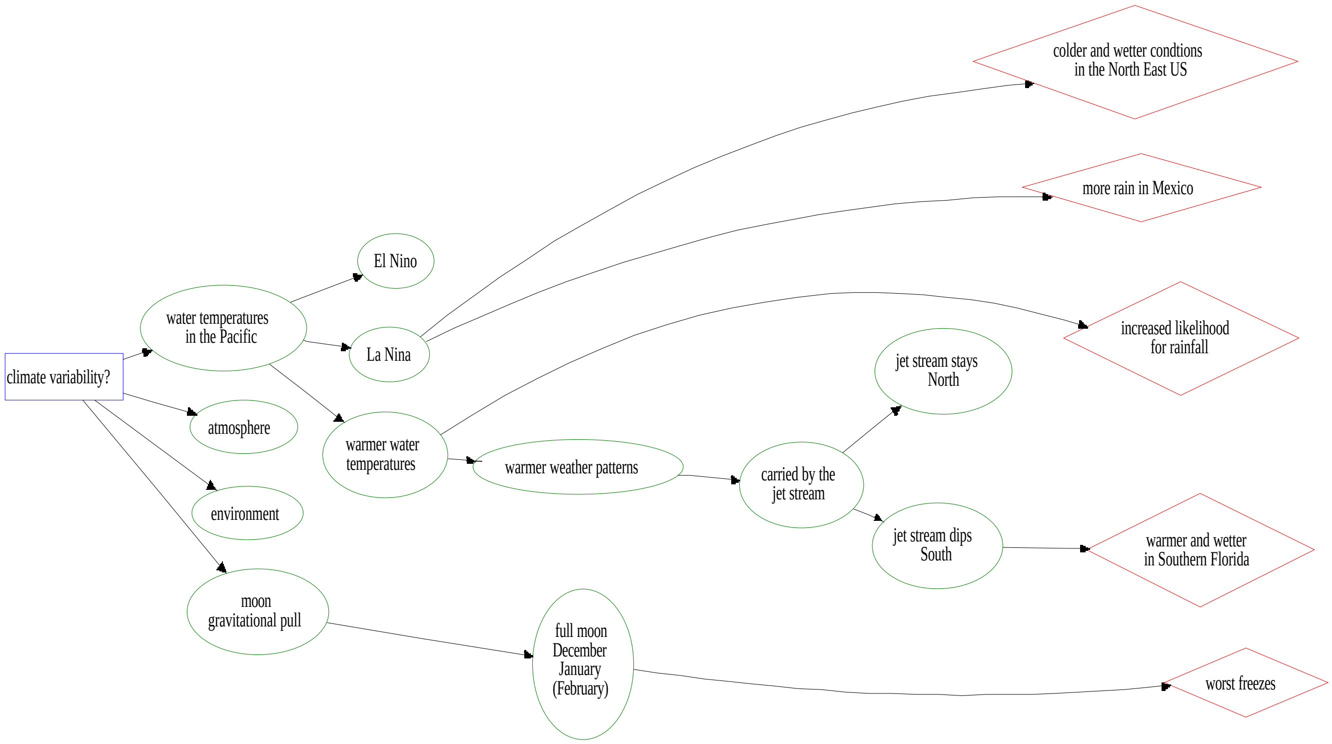
Farmer 16, Mental Model Influence Diagram



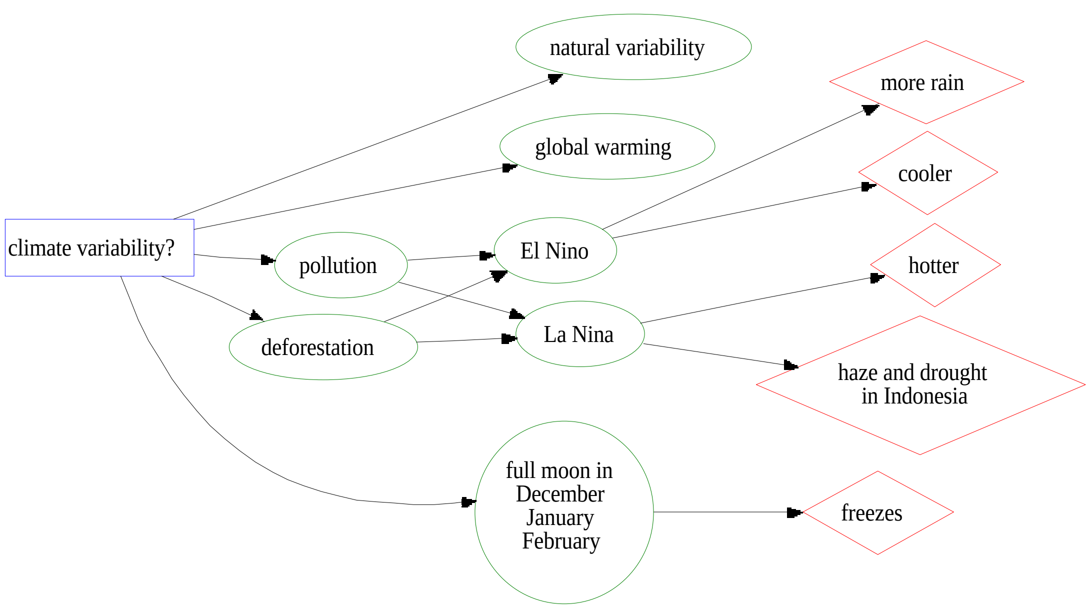
Farmer 15, Mental Model Influence Diagram



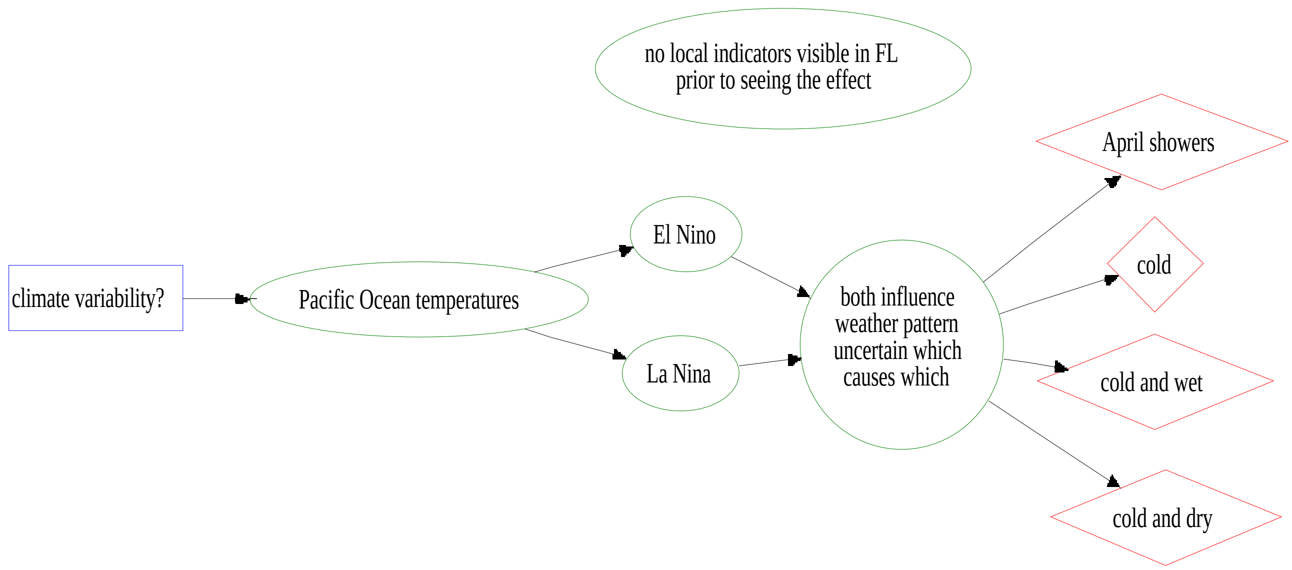
Farmer 5, Mental Model Influence Diagram



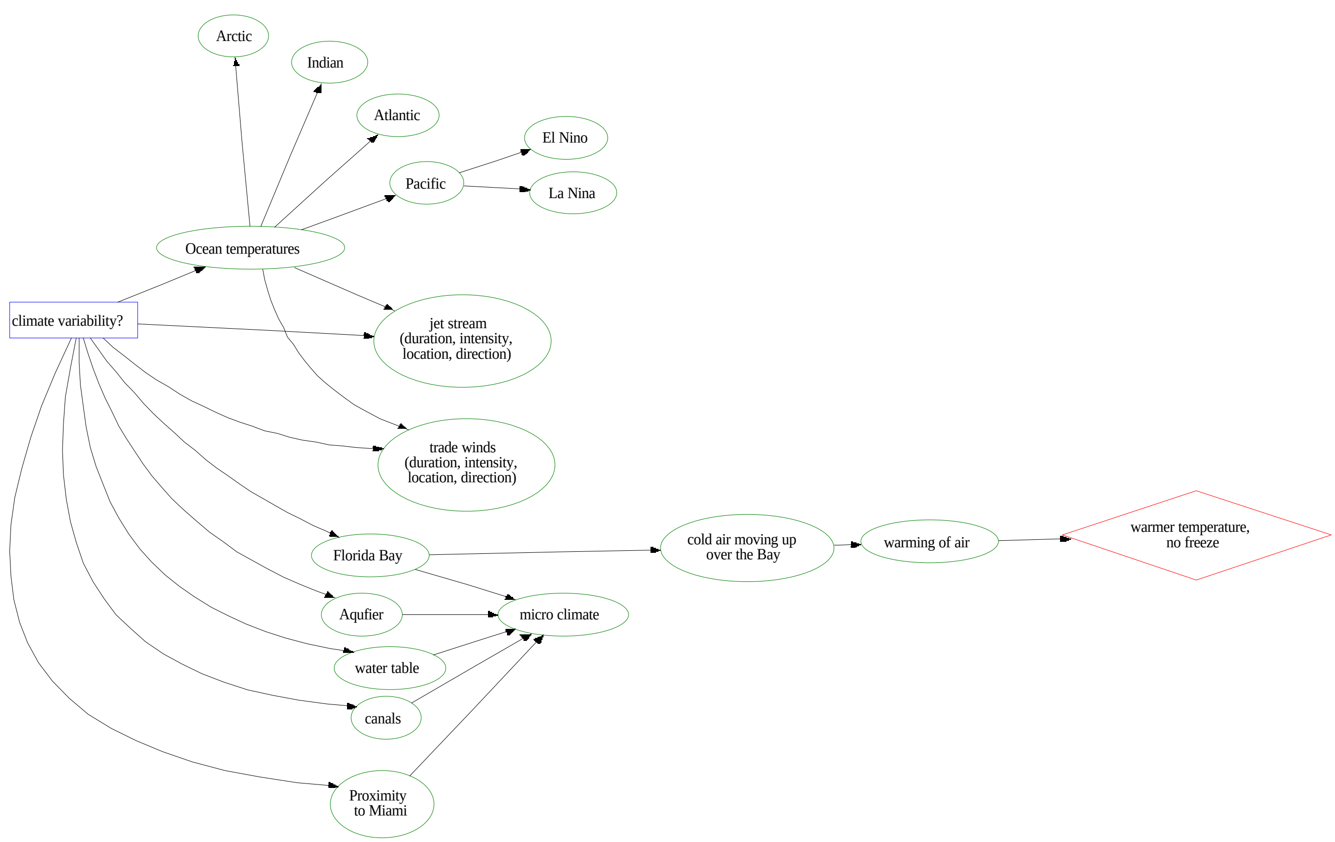
Farmer 10, Mental Model Influence Diagram



Farmer 13, Mental Model Influence Diagram

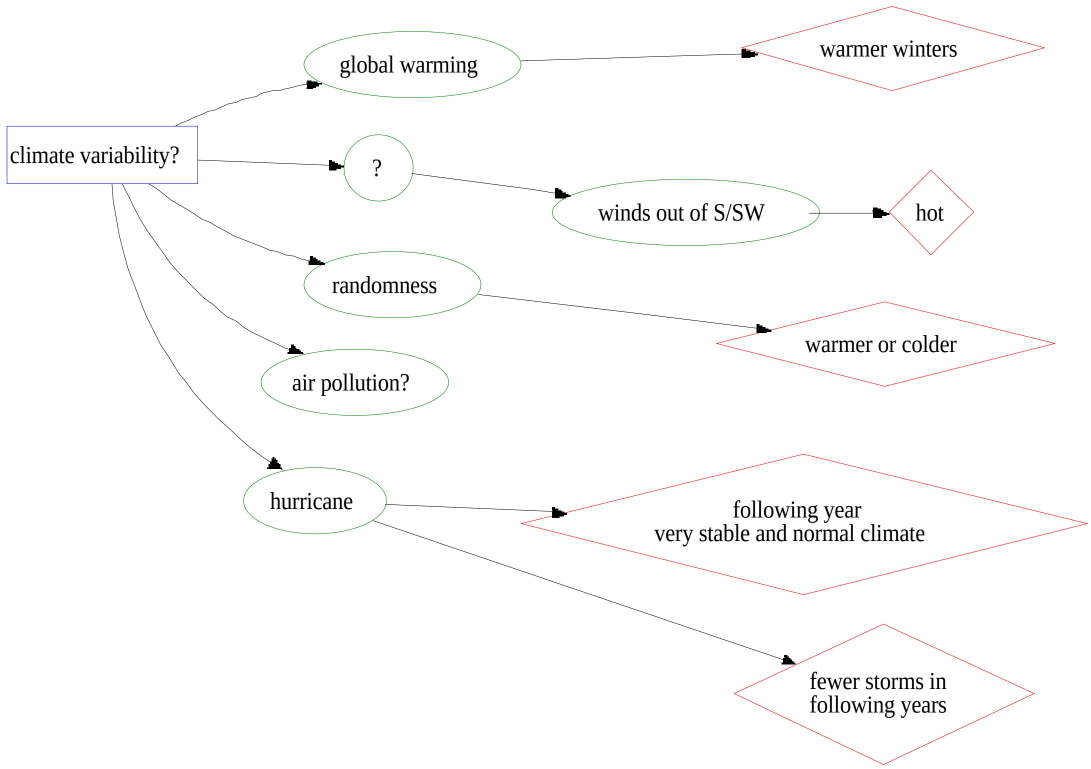


Farmer 2, Mental Model Influence Diagram

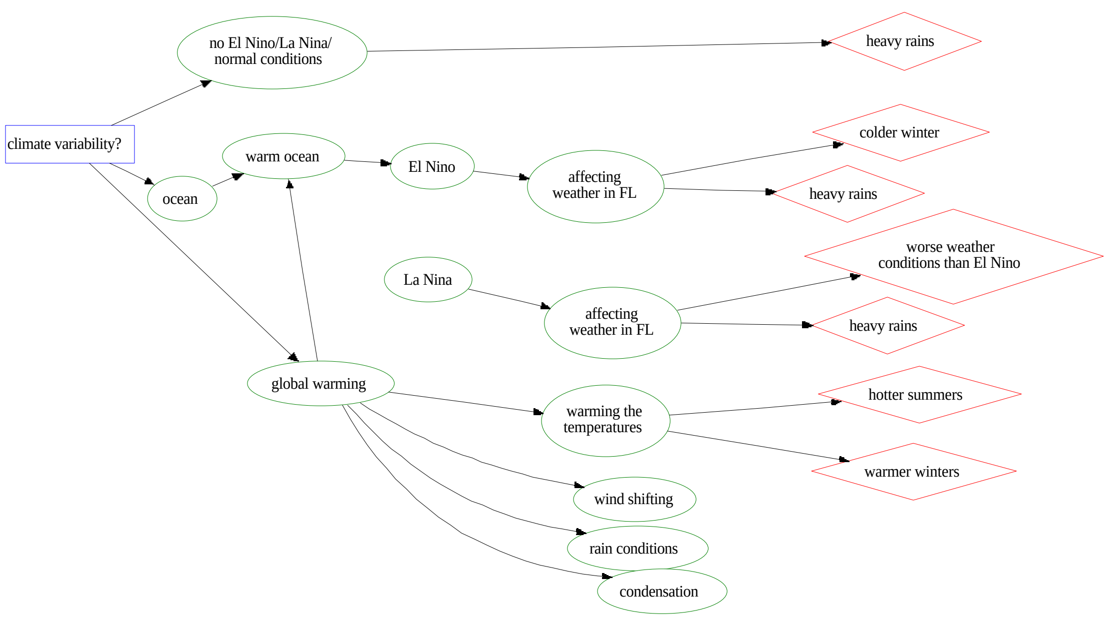


Farmer 3, Mental Model Influence Diagram

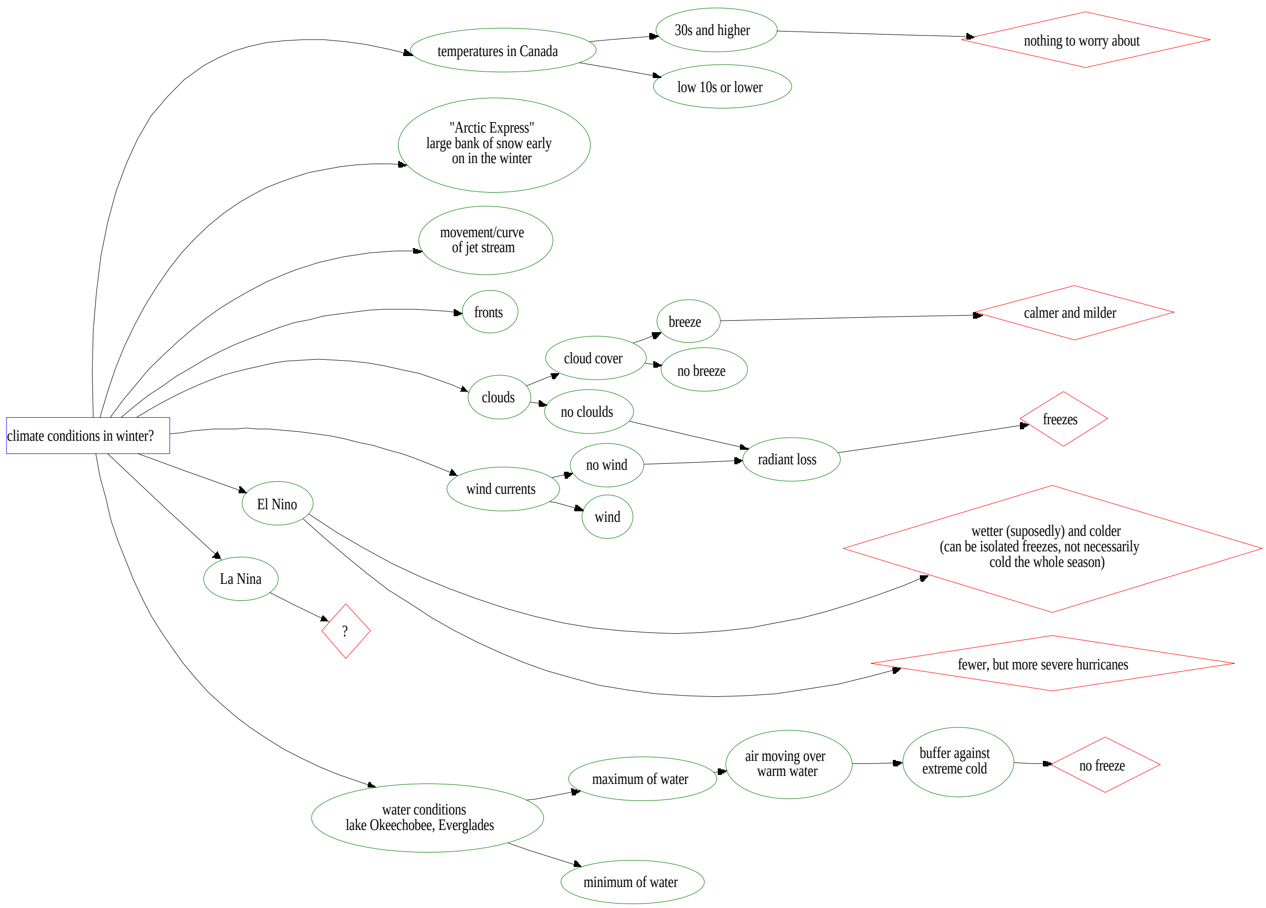
Farmer 6, Mental Model Influence Diagram



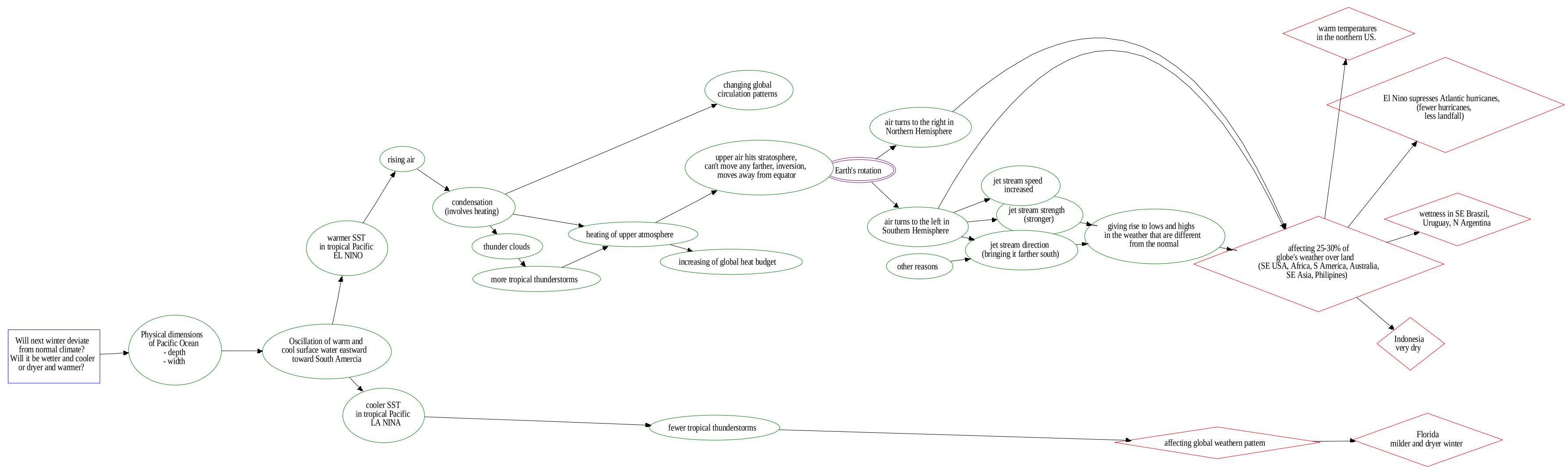
Farmer 7, Mental Model Influence Diagram



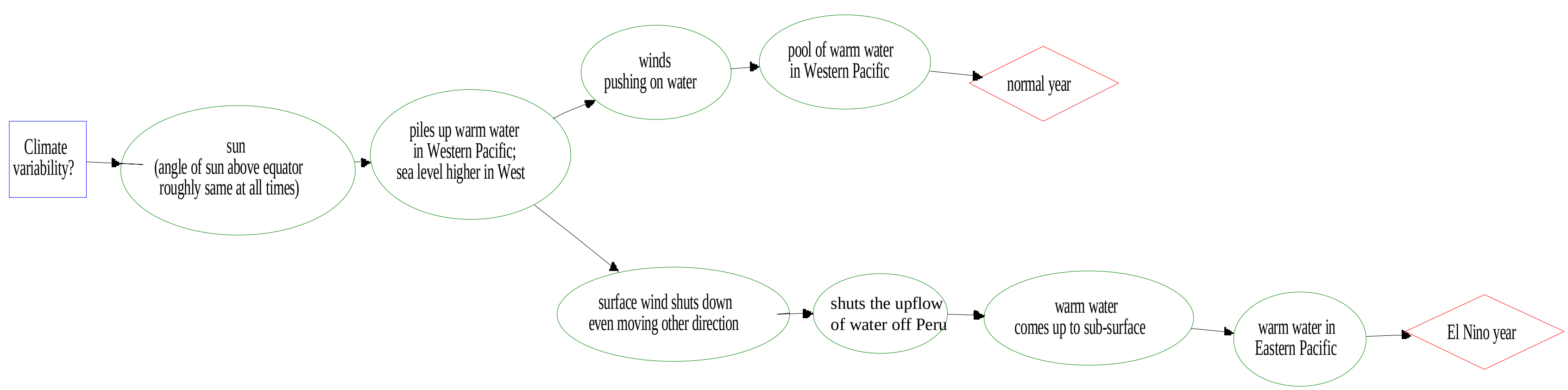
Farmer 9, Mental Model Influence Diagram



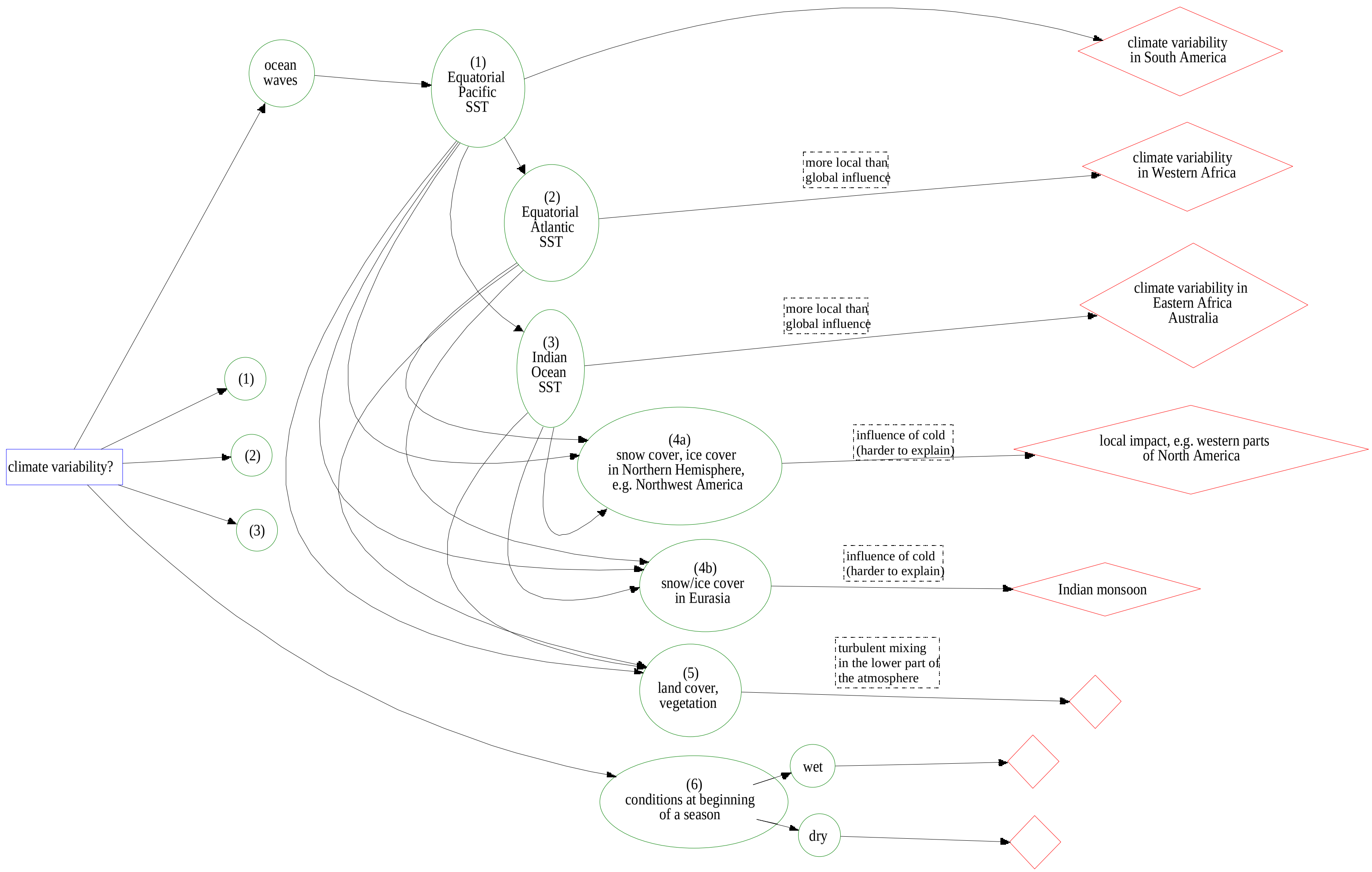
Farmer 1, Mental Model Influence Diagram



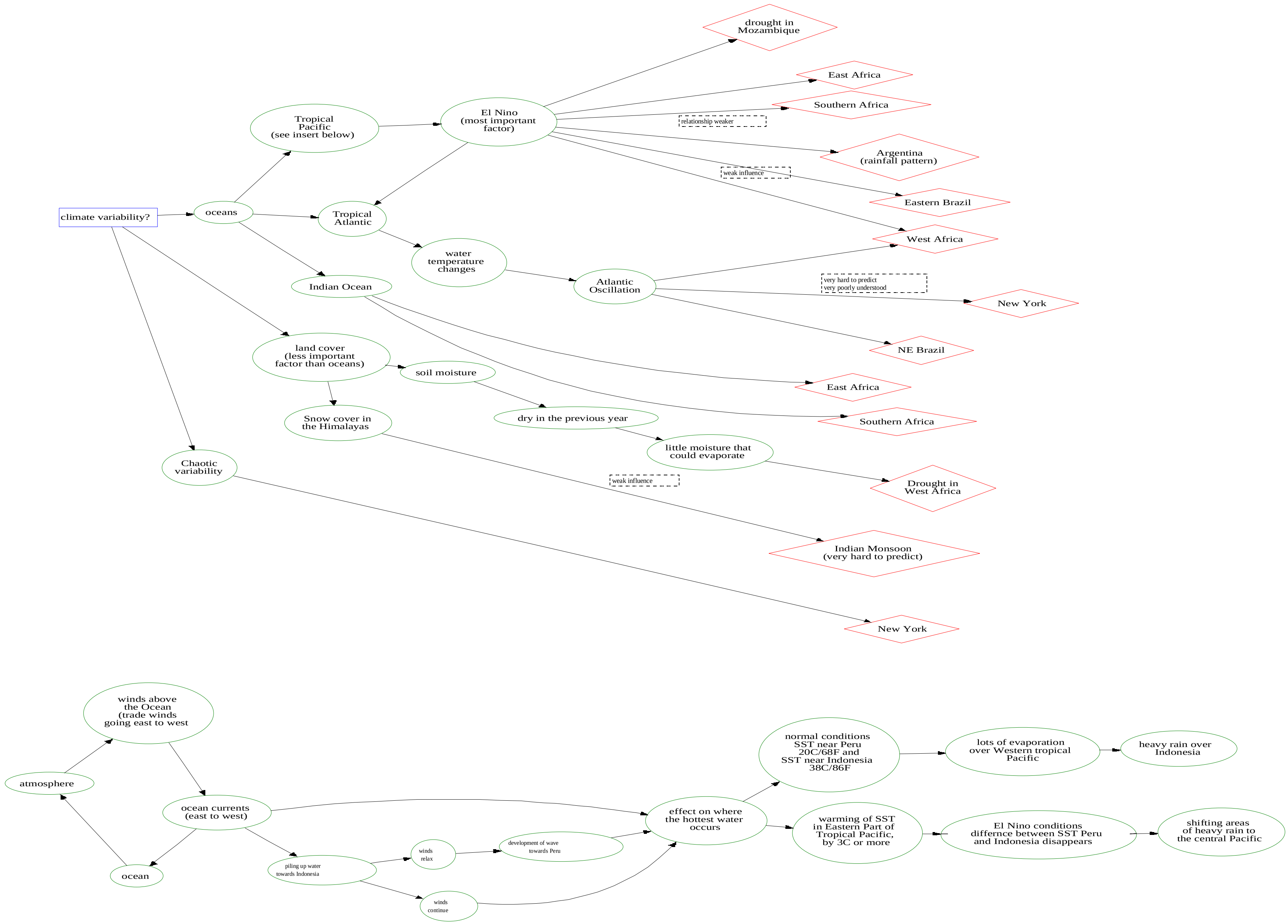
Expert 1, Mental Model Influence Diagram



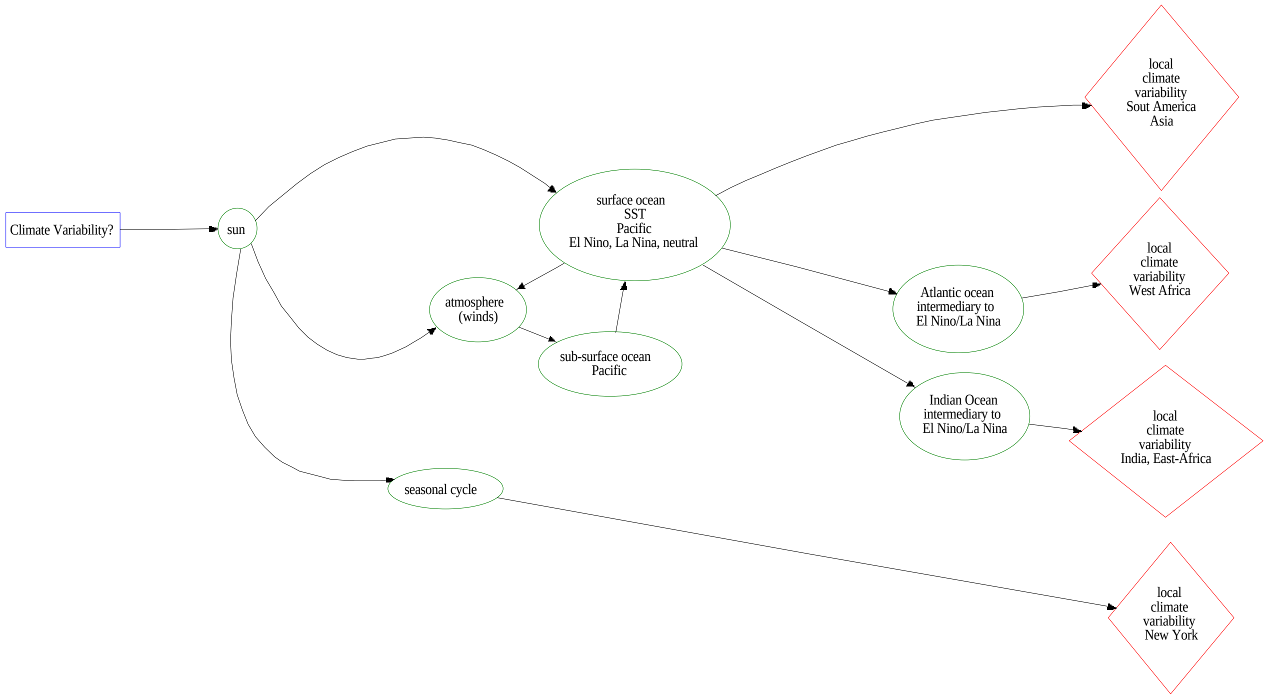
Expert 7, Mental Model Influence Diagram



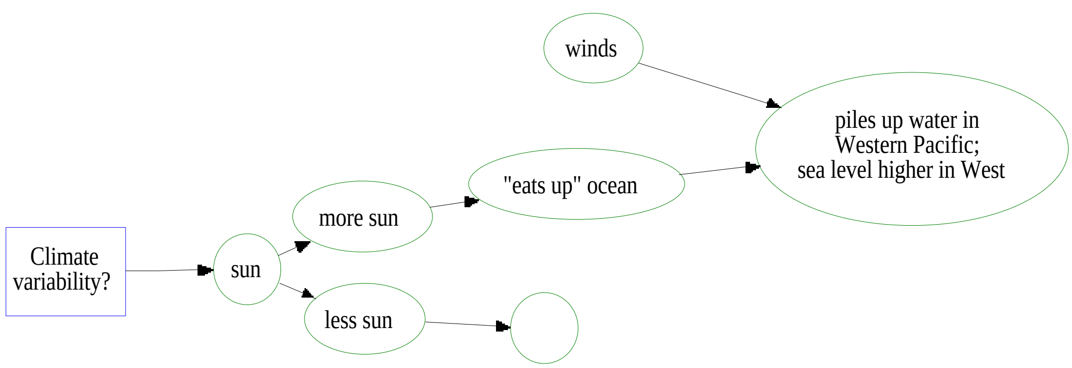
Expert 3, Mental Model Influence Diagram



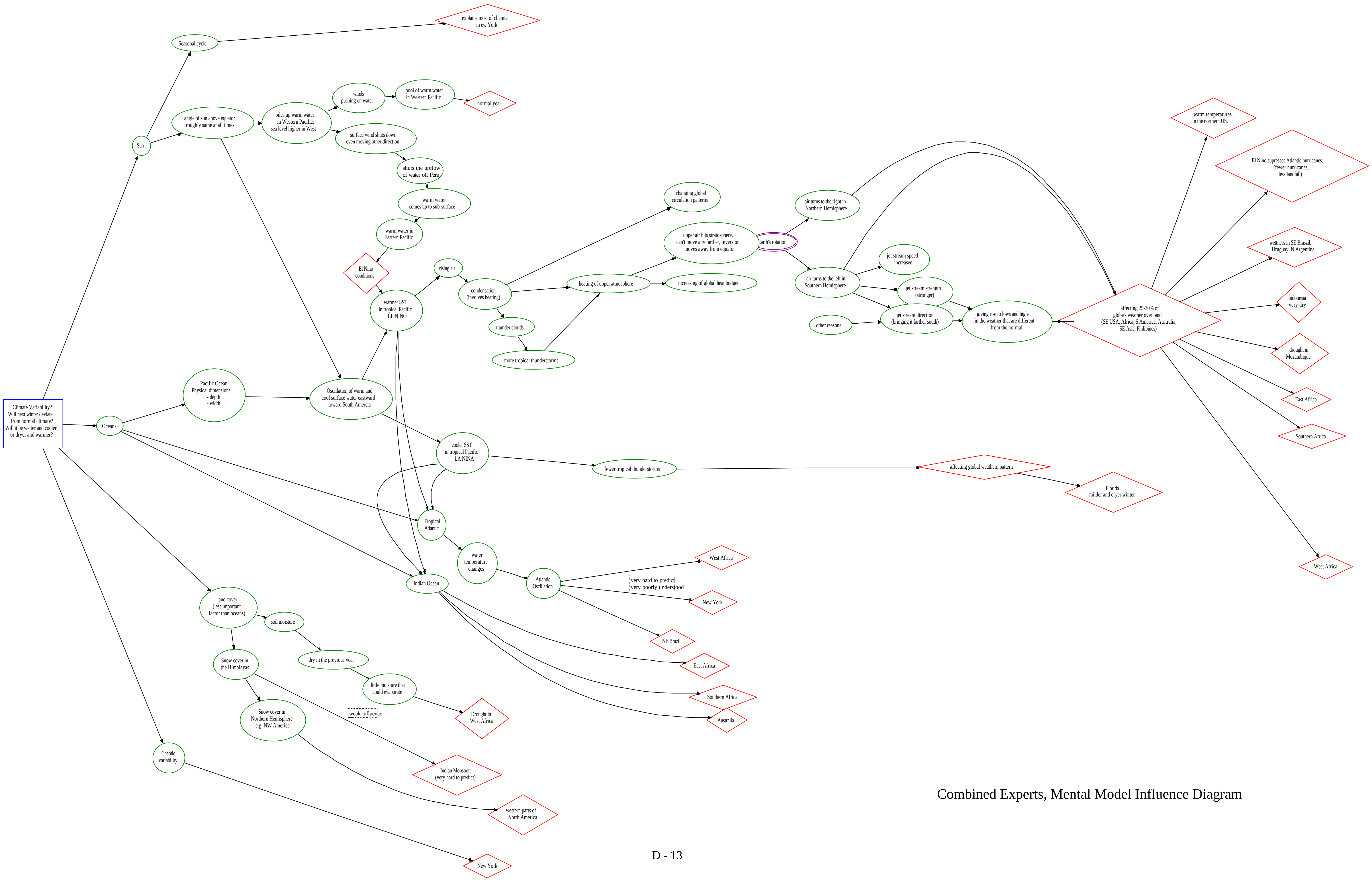
Expert 5, Mental Model Influence Diagram



Expert 4, Mental Model Influence Diagram



Expert 6, Mental Model Influence Diagram



Combined Experts, Mental Model Influence Diagram