abstract: Farmers in countries such as the Philippines and Australia face a high degree of climate variability. One of the reasons that the climate is variable is because of the El Nino Southern Oscillation (ENSO). Regions that are affected by ENSO tend to have a higher degree of variability, but there is also promise in using ENSO as a slow moving variable which offers some prediction and guidance for the coming season. This guidance from ENSO has been described by Glantz as Science's gift to the 20th Century. In a report to the American Academy of Science, Easterling argued that seasonal climate forecasting based on the interaction of the ocean and atmosphere was one of the premier advances in atmospheric sciences in the 20th century. He went on to say that probabilistic seasonal climate forecasts were ill-suited for decision makers and decision making was ill-suited to probabilistic seasonal climate forecasts. It is clear that when forecasts are presented as a probability it is difficult for users to comprehend what is meant and even harder to know how to use them. It is common for the media and intermediaries to ignore the probabilities and to let a forecast for an El Nino become a forecast for drought rather than an increased chance of drought. There is little difficulty in knowing what to do with a very accurate categorical forecast, as it fits the easy logic of IF, THEN, ELSE. IF the season ahead is going to be a drought, THEN reduce inputs, ELSE continue as normal. The challenge is how to communicate and use in decision making skilful, but uncertain forecasts that are best represented as shifts in climatological probability distributions. It is also common for intermediaries such as agronomists to state that farmers need a categorical forecast because in the end they need to make a decision. Implicit in this statement is the notion that probabilistic forecasts can't be used in decision making. In this paper we report on frameworks whereby information for probabilistic forecasts can be used in decision making. These are normative frameworks and they may not fit how decision makers currently make decisions. However they do provide useful ways of thinking about uncertainty and distinguishing between lucky and unlucky decisions.

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Frameworks for using seasonal climate forecasts for decision making

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Abstract

Farmers in countries such as the Philippines and Australia face a high degree of climate variability. One of the reasons that the climate is variable is because of the El Nino Southern Oscillation (ENSO). Regions that are affected by ENSO tend to have a higher degree of variability, but there is also promise in using ENSO as a slow moving variable which offers some prediction and guidance for the coming season. This guidance from ENSO has been described by Glantz as Science’s gift to the 20th Century.

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In this paper we report on frameworks whereby information for probabilistic forecasts
can be used in decision making. These are normative frameworks and they may not fit
how decision makers currently make decisions. However they do provide useful ways
of thinking about uncertainty and distinguishing between lucky and unlucky
decisions.

Introduction

All decisions have some degree of uncertainty, yet most decisions are made
with a minimum of effort. Hard decisions usually involve high levels of uncertainty
and have consequences that are significant to the decision-maker. In other words they
are risky decisions. Climate is a major source of uncertainty often with significant
consequences for agricultural decision-makers.

There are two related items of information that agrometeorologists have to
offer agricultural decision makers dealing with an uncertain climate. First, making
available the historical climatological data allows a decision maker to answer the
“what if” questions along the lines of “ If I were to apply this amount of fertiliser,
how often would I have made a profit over the historic record?” and the related “what’s best” question “What was the optimum rate of fertiliser to apply over the historic record”. In many cases these historic databases can be used in a simulation model or a simple statistical relationship between yield and rainfall.

The second source of information is a forecast of the coming season. Although this can be presented as categorical – “the coming season will be drier than normal”, this information is best presented as a shift in probabilities from the historical climatological odds of 50:50 - “there is a 70% chance that the coming season will be drier than normal and 30% chance that it will be wetter”.

Sivakumar (2002) argued that meteorologists faced an unprecedented urgency and challenge to communicate with agricultural decision makers. He based the urgency on the global demand for food, the declining resources from which food must be produced and the vulnerability of food production to climate variability and climate change. Likewise Thysen and Hocevar (2004) drew attention to the need for agrometeorology as a discipline to engage with agricultural decision makers to strive for the multiple goals of environmental protection, ensuring the quality and safety of food and the profitability of farming.

An underlying assumption is that as a discipline, agrometeorology has information that is useful to agricultural decision makers and more effort is required in communication and dialogue. This assumption is reasonable and can be supported by individual success stories ranging from smallholder farmers in developing countries to large commercial farms in the US, Europe, South America and Australia (Hansen 2002, Meinke and Howden 2004). However, mixed with the success stories is a recognition that the task of communicating information to improve the

**Being Clear about Communication**

The simplest interpretation of the challenge is to develop a better pipeline between the information provider (agrometeorological services) and information user (agricultural decision makers) by building software, using smarter hardware or writing clearer bulletins. This interpretation is based on a notion that knowledge is created by research, communicated by intermediaries and used by farmers. It also implies that knowledge can be transferred as an unambiguous signal. While this may be appropriate for some technologies, we argue that it is inappropriate for communicating climate risk. Firstly because of the complexity of dealing with risk and decision making and second because the knowledge on managing climate risk lies as much with the farming community as it does with the discipline of agrometeorology.

Rolling (1988) provides a poignant criticism by citing a western agricultural expert in a developing country who stated that the extension project could not proceed because the loud hailers had not arrived. While the inappropriateness of agricultural extension officers yelling at farmers through loud hailers is obvious, it is easy for a discussion on communication of agrometeorology to be caught up in discussion of the latest developments in the internet, mobile phones, hand held computers and mass media. It is foolish to ignore the developments in communication technology and the exciting potential benefits of getting information to both wealthy and poor farmers. However, the content of what is communicated remains a challenge. The sociologically naive faith in developments of computer technology some of us held in the related field of decision support systems is discussed in McCown (2002) and
Hayman (2004). As a brief summary, from the late-1980s to the mid-1990s a strongly held view was that farmers would use computers in routine management decisions when computer hardware costs reduced, software improved and farmer computer ownership increased. A decade on the ownership of computers by farmers in the US, Europe and Australia is as high as the rest of the population, yet the use of decision support systems for routine decision making is disappointing. As pointed out by McCown (2002), the reason for a failure of implementation was rarely the technical correctness of the Decision Support System, but usually because it did not fit into the farm manager’s way of doing things.

In this paper we adopt the definition of communication as “the reciprocal construction and clarification of meaning by interacting people”. This is in contrast to a one-way flow of information and recognises the need for dialogue. The need for dialogue is important for any new technology, but we are arguing that the need is greater when discussing risk management. Risk can only be understood in the social and psychological context of the decision maker.

**Defining Risk**

Although the notion of risk and managing risk is so commonplace nowadays as to become a cliché, it is a relatively recent phenomenon. Giddens (2002) maintains that the idea of risk only took hold in Europe in the 16th and 17th century where the term came to the English language through Spanish or Portuguese where it referred to sailing into unchartered waters, with the chance of great gain weighed against the chance of loss. Risk is more than the age-old notion that hazards or dangers occur; rather it refers to outcomes (both good and bad) that are actively assessed in terms of future possibilities. Bernstein (1999) linked risk and modernity: “The revolutionary idea that defines the boundary between modern times and the past is the mastery of
Risk: the notion that the future is more than a whim of the gods and that men and women are not passive before nature. Until human beings discovered a way across that boundary, the future was a mirror of the past or the murky domain of oracles and soothsayers who held a monopoly over knowledge of anticipated events.”

Risk may be part of modernity but the discussion of risk regarding pollution, food safety and climate change is seldom free from emotion. Psychological studies have identified various issues that influence the perception of risk including the subject’s sense of control and worldview, whether a risk is voluntary, and the distribution of costs and benefits. The matter is further complicated by the way society finds some risks acceptable while holds other risks as special (eg the very different treatment of equal probabilities in car accidents vs aeroplane accidents). Rural and urban societies in Australia seem to hold drought risk as special and deserving particular government attention by rural societies compared to other risks such as variations in price or interest rates (Hayman and Cox 2004).

Apart from the social context of risk, communication is further hampered because few of us are intuitive statisticians. When faced with uncertainty we rely on mental shortcuts that can be efficient but sometimes lead to biases that impair the decision-making process. As noted by Slovic (1984) “it is extremely hard for people to think about uncertainty probability and risk.” The roles these biases play in dealing with climate information are discussed in Nicholls 1999 and White 2000.

The Particular Challenge of Communicating Skilful but Uncertain Forecasts for Risky Decisions

In a report to the American Academy of Science, Easterling argued that seasonal climate forecasting based on the interaction of the ocean and atmosphere was one of the premier advances in atmospheric sciences in the 20th century. He went on
to say that SCF were ill-suited for decision makers and decision makers were ill-suited for probabilistic SCF.

There is ample evidence from survey work in Australia and elsewhere that there is a mismatch between the level of accuracy decision makers would prefer from SCF and the level that climate science is able to deliver. There is little difficulty in knowing what to do with a very accurate categorical forecast, as it fits the easy logic of IF, THEN, ELSE. IF the season ahead is going to be a drought, THEN destock heavily, ELSE continue as normal. The challenge is how to communicate and use in decision making skilful but uncertain forecasts that are best represented as shifts in climatological probability distributions. The challenges of conveying probabilities are substantial, however there are examples where gaming has been used to improve understanding (Seal and Przasnyski 2002), or simple but clever use of graphics have been used to explain probabilities without referring to mathematics (Bordley 2007).

Although they present difficulties for communication, it is essential to present forecasts as probabilities first and foremost because it is honest. Laplace (1749-1827) stated that probability has reference partly to our ignorance, and partly to our knowledge. The atmosphere is a complex chaotic fluid, and although patterns of ocean temperatures ‘nudge’ this chaos in certain directions there will always be a significant proportion of unexplained variation. Indeed along with increased understanding of the climate-atmosphere system has come a better understanding of theoretical and practical limits to prediction. As a means of conveying this we have used a spinning probability disc divided into thirds to represent the chance of falling into each tercile. Seasonal climate forecasts are shown as shifts in the three sections of the pie chart. The idea is to convey the combination of knowledge (change pattern on disk) and ignorance (exactly where the disk will stop spinning) (Hayman 2000).
Coventry (2000) suggested that some of the problems communicating probabilities could be overcome by expressing the probability as a frequency (for example, out of 10 times that the sea surface temperatures were in this pattern, 7 of them were wetter than median and 3 drier). The reasoning being that when hearing 70% probability of being wetter, people are less likely to appreciate the 30% chance of being drier. Both the Australian Bureau of Meteorology and the Queensland centre for climate applications word their forecasts as probabilities and frequencies.

The second reason why we need probabilistic forecasts is to ensure that they improve rather than hinder risk management. The perversity of seasonal climate forecasts is that if they are misunderstood as categorical forecasts, they can lead to poorer risk management than if the farmer had never heard of the forecast. In the absence of a forecast, a farmer may plan for a wide range of outcomes. However, if this is adjusted to one outcome in the mind of the decision maker the forecast has clearly been misleading in terms of risk management.

**Decision Analysis – Does it have a Place?**

In our experience the probability disk has been one of a number of ways to convey the uncertainty in the forecast. In some cases when farmers appreciate the level of uncertainty they decide not to use the forecast and concentrate on those aspects of the farming system that they can control. Others pose the challenge: how do you use uncertain information for decision-making?

One approach, decision analysis, provides a logical framework for a decision-maker to formulate preferences, assess uncertainty and make judgements. Although agricultural economists have long used decision analysis (Anderson et al 1977), its use by agrometeorologists and agricultural scientists has been limited. There has been a tradition in agricultural science to talk the language of choice-consequence. For
example, if you put on \(x\) units of nitrogen, you will get a yield of \(y\). This is fine for reviewing experiments, however, looking forward we need to consider the language of **choice-chance-consequences**. In other words, if you put on \(x\) units of nitrogen, depending on the season type you will get a yield of \(y_1, y_2\) or \(y_3\).

Identifying decision-making as an activity that can be separated from the wider context of acting and learning in the world is problematic. The way that management science has isolated, categorised and dissected decisions has been criticised by psychologists and the newer interpretivist (“softer”) schools of management science. For example Ackoff (1981) maintained that rather than solve a series of unrelated problems, managers manage messes. There is ample evidence that decision analysis does not describe how farmers make decisions, however it is a structure which can be used, and is being used, to offer guidance to decision-makers about parts of their wider management “messes”. (Clemen 1998). An example is Gaffney (1996), a farm management economist in Queensland Australia, who promoted decision analysis with farmers in Queensland with the confident slogan “**Decision Analysis - it's what you do when you don’t know what to do**”.

**An Example of Nitrogen Management on Wheat**

A farmer deciding on the rate of nitrogen fertiliser has to balance potential demand from the crop with the supply from the soil and fertiliser. This balancing act is made more difficult when dealing with uncertain crop demand. What is the best rate of fertiliser to use in the absence of seasonal climate forecasts? How can uncertain seasonal climate forecasts be used to change the decision?

Step 1: Define the choices with single consequences: Although there is an infinite range of fertiliser rates, the options can be simplified as fertilising for a low demand in a poor season (20 kg of N per hectare in the bottom third of years) an
average season (60 kg of N per hectare in the middle third of years) or a good season (100 kg of N in the best third of years). Figure 1 is a simplified decision tree that shows the outcome as gross margin per hectare for 20, 60 and 100 kg of N. As we shall show, this tree is an over simplification. However, it shows what we would do with perfect seasonal climate forecasts or what would have been best in hindsight. It also shows that the payoff for nitrogen is asymmetrical, and there are very good returns in the good seasons.

Step 2: Define a range of consequences for each choice: While Figure 1 shows a single consequence for each choice, it avoids the point that any fertiliser rate is likely to over fertilise or under fertilise the crop, depending on what type of season actually eventuates. Rather than looking at the three branches of Figure 1, a more complete picture is shown by the nine branches, as shown in Figure 2. When a farmer aims low the result will either be a balanced budget in a poor season or a nitrogen limit in an average or good season. The other extreme of aiming high will result in a balanced budget in a good season and water limited but excess nitrogen in average or poor seasons.
When the gross margins for each of the 9 outcomes are considered as shown in Figure 3, it is clear that fertilising for a poor season is the low-risk, low-return option while fertilising for a good season has high potential returns but also a chance of a negative gross margin. We have made the initial assumption that the chance of a poor, average or good season are equal (as indicated by the pie chart), and the probability weighted average reflects this. The probability weighted average or Expected Value,
never actually occurs, rather it is a summary statistic. Farmers must choose one of the strategies: “fertilise for poor season”, “fertilise for average season” or “fertilise for good season” before the season unfolds. A risk averse farmer could quite rationally select the first of these in order to avoid the risk of poor outcomes which is a component of the other strategies. In a less risk averse manner another farmer could select the average fertiliser rate and be prepared to sacrifice the difference in the probability weighted average ($100 minus $87) to avoid the 33% chance of making a loss which is contained in the “fertilise for good season” strategy.

**Figure 3:** Gross margins for each fertiliser rate and season type, probability weighted value for each of the three fertiliser rates

<table>
<thead>
<tr>
<th>Fertilise for Poor Season</th>
<th>GM</th>
<th>Chance</th>
<th>Prob weighted average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Season Poor</td>
<td>$60</td>
<td>33%</td>
<td></td>
</tr>
<tr>
<td>Season Avg</td>
<td>$60</td>
<td>34%</td>
<td>$60</td>
</tr>
<tr>
<td>Season Good</td>
<td>$60</td>
<td>33%</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Fertilise for Avg Season</th>
</tr>
</thead>
<tbody>
<tr>
<td>Season Poor</td>
</tr>
<tr>
<td>Season Avg</td>
</tr>
<tr>
<td>Season Good</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Fertilise for Good Season</th>
</tr>
</thead>
<tbody>
<tr>
<td>Season Poor</td>
</tr>
<tr>
<td>Season Avg</td>
</tr>
<tr>
<td>Season Good</td>
</tr>
</tbody>
</table>

What N rate to use?

Shown in Figure 4 is a seasonal forecast in which there is an increased probability of a poor season. Seasonal forecasts do not change the outcomes, they just change the chances of the outcomes and therefore the probability weighted average. In this case even though there is a 55% chance of a poor season, because of the asymmetry of payoffs for nitrogen, the expected value is still maximised by fertilising for an average season. The impact of such a forecast across the farming community should be to shift farmers towards lower fertiliser application rates as the riskiness of poor outcomes at higher rates of fertiliser application has increased.
Figure 4: Gross margins for each fertiliser rate and season type under a forecast for 55% chance of a poor season and 15% chance of a good season.

In our experience, presenting this as a spreadsheet to farmers and agronomists is an effective way to start a dialogue on how uncertain forecasts might be used to change fertiliser decisions. It also reinforces the need to consider the minority outcome (poor season when forecast is for good season). In the case of nitrogen, due to the good payoffs in the good seasons it indicates that the forecast has to be quite negative to reduce rates.

Example of crop choice – Wonderbean

Based in part on the use of a game to think about farm management developed in Western Australia (Stewart et. al. 2000), we developed a simple Excel ® based spreadsheet whereby the key decision is the area of a farm to plant to a higher return but higher risk crop relative to the area to leave with a lower return but lower risk crop. In many cases new technologies offered by agricultural science have better mean returns, but come at an increased cost and hence increase the risk. This is the
case in the game situation presented to participants. The current cereal crop is the low risk and Wonderbean offers higher returns, but higher risk. The game and screens are set out in Appendix 1.

There are three stages to the game. In the first round teams are told that there is a new variety which has performed better in trials than the old variety, and are encouraged to use some in their farming operation. Teams then choose a proportion of their farm to plant to the new variety. To simulate the weather, a random number generator ‘spins’ the probability wheel and a percentile outcome occurs. Depending on whether it is a good season (higher percentile) or poor season (lower percentile) the return from the stable cereal and wonder bean is shown. This stage is run for a few ‘seasons’ and participants start to get a sense of the relative outcomes for the two crops.

In the second stage of the game participants are shown a probability distribution of gross margin returns from each crop. This is equivalent to the output from simulation modelling where the risk and returns for each of the two crops is now known. In the third stage, the notion of seasonal climate forecasting is introduced by revising the probability distribution that is randomly sampled. Participants are shown the revised probability distribution before making their choice. This game illustrates the nature of a good and lucky decision and the fact that even a revised probability distribution does not make the decision obvious. Variations of the game have been used in Australia and the Philippines.

Concluding remarks

Tools such as the spinning probability disk, decision trees and crop choice games are not intended as tools of trade or regular decision support systems. However they are a useful way for climate science to organise its ideas and engage decision
makers. It is a small but useful step in the gap between climate science and decision making.

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McCown RL, Hochman Z and Carberry PS (2002). Probing the enigma of the decision support system for farmers: learning from experience and from theory. Agricultural Systems 74, 1-10.


Appendix 1: **Wonderbean game**

This Excel based game is designed to be played in a workshop setting, with a minimum of two groups. The learning objectives of this game are to experience decision making under uncertainty, and to understand that seasonal climate forecasts may influence decision making and reduce the uncertainty, but don’t eliminate the risks.

The groups are asked to take on the role of a cereal grain farmer who has the option to plant either their usual stable cereal variety, or a new “Wonderbean” variety recommended by their agronomist but with little information on its performance. The groups can choose what percent of their land to sow with each variety. Then, given the rainfall outcome for the season, the groups find out how their chosen crops performed. Each following round represents a new year where, again, groups are asked to decide how much of each variety to plant. As the years go by, the groups are not only armed with knowledge of how the crops have performed for them, but are also given more information about the new Wonderbean variety, and a seasonal forecast for the growing season rainfall.

The following pages explain how to run the Wonderbean game, where instructions specific to navigating through the spreadsheet are highlighted in blue.
**How to run the game**

**Part 1**

1.1 Participants are split into 2-4 groups and are told that each group represents a grain farmer. The following is then read out to everyone:

“I am an agronomist and have a new crop for you. We have examined your current stable cereal and realise that yields are not high enough for you to produce a good surplus in the good years. This new crop, Wonderbean, has consistently out-yielded stable cereal. Oh yes, there was a drought year when it didn't do very well, but nothing does very well in a drought. Our economists have had a look at the results and shown that although Wonderbean is more expensive to grow it is more profitable. We didn't bother analysing the drought year because we thought the results were unreliable.”

Based only on what the agronomist has said, the groups are now asked to decide what percent area of their farm they want to plant with Wonderbean, and the rest will be planted with the stable cereal. This area is entered into the spreadsheet under the “Enter decision here” tab, as per Figure 1.

<table>
<thead>
<tr>
<th>Enter the area of Wonderbean to plant (remainder will be stable crop)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yr 1</td>
</tr>
<tr>
<td>Group 1</td>
</tr>
<tr>
<td>Group 2</td>
</tr>
<tr>
<td>Group 3</td>
</tr>
<tr>
<td>Group 4</td>
</tr>
</tbody>
</table>

**Figure 1**: Example entry of round 1 in the Wonderbean game, where Group 1 has opted to plant 20% of their farm with Wonderbean, and Group 2 with 60% Wonderbean (leaving 40% of their farm area to be planted with the stable cereal crop).
1.2 Go to the “Spinner” tab in the spreadsheet. Participants are shown the chocolate wheel representing the coming season’s rainfall. It is given in terms of terciles where red is the lowest tercile and green is the highest tercile, and begins by showing that there are equal chances of rainfall falling in each tercile. **Press the yellow “Spin” button** – this spins the wheel and generates a random number between 1-100, which represents the percentile of rainfall for that season. For example, a percentile of one means the driest 1% of all years, and a percentile of 55 would mean the 55th driest year in 100, or rather the middle tercile of all years and just above the median (50%) rainfall. This is explained to participants.

1.3 Now that the coming season’s rainfall is known in terms of percentile, we can then calculate how both the Wonderbean crop and the stable cereal crop compared in terms of profit or loss. **Press the yellow “Calc” button.** This gives a bar chart showing the comparison, based on the seasonal rainfall outcome (Figure 2).

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**Figure 2:** The “Spinner” section of Wonderbean, showing the Spin and Calc buttons, the chocolate wheel of the probability of the coming season rainfall in terms of terciles, and the bar chart corresponding to the profit made from Wonderbean in blue ($283; see bottom left) and the Stable crop in pink ($174) given the seasonal rainfall outcome of the 90th percentile (top 10% of historical rainfall).
Finally, participants see how much profit or loss they made on the farm for that year, given the percent of land they chose to sow with the Wonderbean and the stable variety (Figure 3). They also see the results of the other groups, which tends to add some competitiveness to the game!

**Figure 3:** The overall farm profit made in Year 1 given the outcome of sowing a particular area of farm with Wonderbean (as related to Figures 1 and 2). Group 2 has made a greater profit, as they sowed more area with the Wonderbean which performed better than the stable crop with the good seasonal rainfall (90th percentile).

A couple more rounds (years) of the game may be played before moving onto the next part. Each year, the groups can choose whatever area of Wonderbean they’d like to sow (Part 1.1), with the knowledge of recent outcomes likely to influence their choices.

**Part 2**

Part 2 introduces the participants to some formal level of risk associated with the profit of the Wonderbean crop.

The participants are shown the risk profiles of the two crops (Figure 4). This figure is found on the “Risk Profiles” tab. The risk is due to the outcome of seasonal rainfall alone, therefore a probability of say 23% corresponds to the seasonal rainfall being the 23rd percentile, or the 23rd driest year in 100. So we see that for the driest
23% of years, the stable variety makes more of a profit (or less of a loss) than the Wonderbean variety. However once the seasonal rainfall goes beyond the 23\textsuperscript{rd} percentile, the Wonderbean makes more profit, with a higher rainfall percentile resulting in a bigger profit margin for Wonderbean compared to the stable variety.

![Risk profile - $ of Wonderbean crop (closed circles) and stable crop (open triangles)](image)

**Figure 4:** Risk profile of the Wonderbean (closed circles) and stable crop (open triangles), showing the probability of getting a particular profit from sowing either variety in any year.

2.2 Now, aided by the risk profiles of the two crop varieties, repeat steps in Part 1 and play the game for another couple of years.

**Part 3**

Finally, we introduce participants to a seasonal climate forecast which gives some probability on the rainfall outcome for the coming season.

3.1 Go to the “Spinner” tab and show participants the chocolate wheel (Figure 5a). Remind them that up until now, the seasonal rainfall has had equal chances of landing in any tercile, either the lowest tercile (lowest third of rainfall years including rainfall
percentiles up to 33%), the middle tercile (percentile 33 to 66) and the highest tercile (above the 66th percentile), as shown by the chocolate wheel in Figure 5a. Now change the chances of each tercile by using the slide bars to the left of the chocolate wheel. The top bar labelled “good season” will increase the proportion of the highest tercile at the expense of the middle and lowest tercile. The “poor season” will increase the lowest tercile probability.

3.2 Change the forecast to increased chances of a high tercile rainfall season. For example, change the “good season” bar to, say, 60% and the “poor season” to 15%, leaving a 25% chance that the rainfall will be in the middle tercile. The resulting chocolate wheel should look like Figure 5b. Show and explain this to participants before repeating Part 1 of the game where they are now asked what area of each crop to sow given the current forecast. Make sure to note that there are now increased chances of getting in the higher tercile category and hence making more profit if Wonderbean was sown in preference to the stable variety, but there is still a chance (15%) that rainfall will be in the lowest tercile and hence still possible that Wonderbean will cause more of a loss in profit than the stable crop.

3.3 Now change the forecast to a negative one, perhaps with a 10% chance of a good season (highest tercile), and a 70% chance of a poor season (Figure 5c). Again run the game for another year, factoring in the current seasonal forecast. The game can be played for as many years, and as many seasonal forecast combinations, as desired. Be sure to continue to show participants the outcomes of each year and how they are tracking against rival groups (the bar chart in Figure 3). At the conclusion of the game, press the yellow “clear” button on the “Spinner” tab to clear the entire
spreadsheet ready for a new game. Be cautious not to press this during the game as you will lose all the outcomes so far.

![Figure 5a](image1.png) ![Figure 5b](image2.png) ![Figure 5c](image3.png)

**Figure 5:** Chocolate wheels representing a rainfall tercile forecast for the coming season, with the lowest tercile in red, middle tercile in yellow, and highest tercile indicating the top third of rainfall in green. Shown are cases for a “climatology” forecast (equal chances of each tercile) (5a), a good season forecast with a 60% chance of rainfall being in the highest tercile (5b) and a poor season forecast with 70% chance of rainfall being in the lowest tercile.

**Summary**

The Wonderbean game is trying to show:

a) In Part 1, that decisions have to be made with uncertain outcomes and limited information.

b) In Part 2, that it is difficult to capture the risk just by living through 2 or 3 years of a new crop. At their best, modelling and decision support systems quantify some of the uncertainty as risk profiles and this can be a valuable contribution to decision making under uncertainty.

c) In Part 3, that probabilistic forecasts may influence the decision making but they don't eliminate the risk. Seasonal climate forecasts can reduce the uncertainty, but should indicate which way to lean, not jump.
Acknowledgments: The idea for this game came to the creator while playing Risky Business, a game developed by a group of farm management economists in Western Australia. (See V. Stewart, S. Marsh, R. Kingwell, D. Panell, A. Abadi and S. Schizelli. 2000. Journal of Agricultural Education and Extension 7(2):117-128). There is a high probability that these economists would be dismayed at how an agronomist has simplified their whole farm approach and added spinning wheels. The game was first used at a course Peter Hayman ran at IRI Columbia University and has been further developed for the ACIAR project "Bridging the Gap between SCFs and Decision Makers".