Risk management strategies using seasonal climate forecasting in irrigated cotton production: a tale of stochastic dominance*

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Decision-making in agriculture is carried out in an uncertain environment with farmers often seeking information to reduce risk. As a result of the extreme variability of rainfall and stream-flows in north-eastern Australia, water supplies for irrigated agriculture are a limiting factor and a source of risk. The present study examined the use of seasonal climate forecasting (SCF) when calculating planting areas for irrigated cotton in the northern Murray Darling Basin. Results show that minimising risk by adjusting plant areas in response to SCF can lead to significant gains in gross margin returns. However, how farmers respond to SCF is dependent on several other factors including irrigators' attitude towards risk.

1. Introduction

The Murray-Darling Basin (MDB) is the most productive agricultural area in Australia accounting for approximately 25–30 per cent of the gross value of agricultural production and 90 per cent of irrigated agriculture (MDBC 2001). This equates to approximately A\$7.2 billion, or in excess of 1 per cent of Australia's GDP (ABS 2001).

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Similarly to the rest of Australia, the MDB is subject to high climatic variability resulting in high variability in the frequency and magnitude of rainfall and stream-flow. Finlayson and McMahon (1991) reported an interannual stream-flow coefficient of variation of more than 75 per cent as evidence of this variability. The development of irrigated agriculture has come about through a policy by successive governments of building large-scale water-storage infrastructure to alleviate the impact of high climate variability on water resources and assist in regional development (Godden 1997). For example, in the Border Rivers catchment of the northern MDB, the increase in storage and irrigation infrastructure has lead to a 71 per cent increase in water diversions from 212 gigaltires (GL) to 363 GL for the period 1988–1994 (MDBMC 1995).

Despite the considerable increase in both public and private water-storage infrastructure, the high climatic variability ensures that irrigators face uncertain water supplies. This is particularly the case in catchments where a considerable amount of water used in any year for irrigation comes from flows received during that cropping year. Therefore, overestimation of expected water supply can lead to crop and income losses and underestimation represents an opportunity forgone. Uncertainty in knowledge of water supplies in the coming irrigation season is an important factor to be considered by irrigators in making farming decisions, particularly how much area to plant to irrigated crops. Advances in the ability to forecast stream-flow (Chiew *et al*. 2000; Abawi *et al*. 2001) and hence the ability to make inferences about likely water supply has the potential to impact on both the returns and risk management for irrigated agriculture.

The aim of the present study is to explore both how seasonal forecasting of stream-flow can be used in making cropping decisions and the impact of these decisions on the farming enterprise. The present study was conducted in the Border Rivers catchment (BRC) in the northern part of the MDB. The catchment stretches from the western side of the Great Dividing Range to Mungindi and has a total area of 44 000 km^2. Average annual rainfall varies from 800 mm in the east to 550 mm in the west. Cotton is the primary irrigated crop accounting for 83 per cent of the 53 900 ha of the area developed for irrigation in 1997/1998. The production of irrigated cotton in this catchment has grown rapidly in the last decade from approximately 150 000 bales in 1989/1990 to in excess of 460 000 bales in 1999/2000 (Beeston 2000). Specifically, we examined the use of seasonal climate forecasting (SCF) of water supply to calculate irrigated cotton-planting areas. Outcomes from this strategy were compared on the basis of expected income and its variance to a set of planting strategies that ignore SCF to determine whether forecasting is of use to irrigators. Generalised stochastic dominance techniques are then used to compare the impact

on outcomes of decision-makers preferences under different levels of risk aversion.

2. Decision analysis

2.1 Risk management and seasonal forecasting

Seasonal climate forecasting is used in agriculture as an aid to deal with climatic uncertainty and has been the subject of a number of studies in the last decade (Muchow and Bellamy 1991; Abawi *et al.* 1995; Parton and Carberry 1995; Hammer *et al.* 2000; Abawi *et al.* 2001). In general, studies aimed at assessing the value of additional information from a predictor have simulated strategies over long periods of time and compared the outcomes in terms of changes to gross margins, farm profit and/or utility. Abawi *et al.* (1995) investigated the value of seasonal forecasts based on the Southern Oscillation Index (SOI) in wheat harvest management. The SOI was found to be a useful predictor of spring and summer rainfall allowing wheat farmers to gain higher returns from harvesting wheat at higher grain moisture and artificially drying in forecast wet years to reduce the incidence of grain-quality losses associated with a wet harvest. Hammer *et al.* (1996) found that seasonal forecasting was useful in the tactical management of nitrogen fertiliser and crop-cultivar decisions for a wheat crop through the attainment of higher profits and/or reduction in the number of years a profit less than zero was made. Carberry *et al.* (2000) examined the potential value of seasonal forecasting in the management of cropping systems using a simulation case study. This case study demonstrated that the SOI could be used beneficially in the selection of crop rotations over a two-year period to give higher average gross margins, lower soil loss, but an increase in risk of financial loss.

These studies generally focused on rainfall and dry land agriculture with information for irrigated agriculture limited to rainfall effects. In recent years the ability to forecast stream-flow has progressed (Chiew *et al.* 2000; Abawi *et al.* 2001). However, research on the usefulness of stream-flow forecasting as a decision aid to irrigated production systems remains limited.

2.2 Choice among risky decisions

Procedures for decision analysis in risky environments and methods of valuing additional information have been around for decades (Halter and Dean 1971; Meyer 1977; King and Robison 1981; Byerlee and Anderson 1982; Carberry *et al.* 1993; Hardaker *et al.* 1997). Similarly to Klemme (1985), examination of the efficacy of SCF in irrigated cropping decisions entails comparing a new technology against methods currently used. The findings of higher returns

accompanied by higher variability in returns through the use of SCF in dry land cropping by Carberry *et al.* (2000) highlighted that an irrigator's attitude to risk is important in choosing among risky prospects.

Choice amongst risky alternatives can be achieved in a number of ways. Possibly, the simplest is to assume farmers are indifferent to risk and use monetary goals, for example profit, where the objective is to maximise expected monetary value. In practice, maximisation of expected monetary values has proven to be a poor predictor of actual decisions made, suggesting other factors affect the decision making process (Barry 1984). A decision-maker's own beliefs and values about a decision and its outcome particularly with respect to the variability of income also influence decisions. The expected utility (EU) model is a tool used to deal with these other factors, particularly the decision-maker's attitude to higher returns and risk. A thorough explanation of EU analysis can be found in Anderson *et al.* (1977), Hardaker *et al.* (1997) and Barry (1984).

In practical terms, a utility function is an ordering of the decision-maker's preferences between choices that take into account a person's attitude towards additional income and risk where choices resulting in higher utility are preferred. While EU analysis could be considered as one of the mainstays of the methods agricultural economists have used in considering risk in decision-making, it is not without its critics. Buschena and Zilberman (1994) found deviations between optimal decisions identified by the EU approach and actual decisions made under risk. They accepted that the EU methodology is an appropriate normative tool for risk management, but needs to be carried out in an understanding of its shortcomings.

Stochastic dominance analysis (SDA) is a useful technique to identify whether outcomes from a decision process using SCF information are preferred over outcomes from decisions ignoring any SCF information. While SDA is grounded in EU theory (Dias *et al.* 1999), it has the advantage of permitting the ranking of outcomes without the need for detailed knowledge of decision-maker's risk preferences therefore negating the need to directly elicit utility functions from decision-makers (Maynard *et al.* 1997). The use of SDA facilitates the segregation of probability distributions of outcomes into efficient and inefficient sets for different groupings of risk attitudes. Outcomes contained in the efficient set are those that maximise EU for those decision-makers whose preferences are consistent with the admissible class of utility functions in the subset (Mjelde and Cochran 1988; Dias *et al.* 1999).

Stochastic dominance analysis is typically divided into three types, first and second degree stochastic dominance (FSD and SSD, respectively) and generalised stochastic dominance (GSD), that are segregated by different classes of utility functions. FSD assumes that the utility function has a positive first derivative or positive marginal utility; that is, more is always preferred to less. This makes

no assumption about risk preferences, and hence has little discriminatory power to enable choices amongst options. SSD assumes that decision-makers are risk averse. However, it also results in large efficient sets as no account is taken for varying levels of risk aversion (Pandey 1990). To overcome this discriminatory problem, Meyer (1977) examined risky outcomes for decision-makers whose risk attitude falls into intervals defined by the absolute risk aversion coefficient r_s (Pratt 1964). The use of intervals defined by selecting an upper and lower bound of r_x as defined by Meyer (1977) permits the analyst to improve the discriminatory power of the analysis by excluding 'maniacally risk averse' decision-makers (Parton and Carberry 1995, p. 1489). While placing fewer restrictions on the utility function improves the generality of results for decision-makers, it commonly results in poorer discriminatory power between alternatives (Hardaker *et al.* 1997; Maynard *et al.* 1997).

2.3 Stream-flow forecasting

The Southern Oscillation (SO) is the seesaw in the atmospheric pressure over the central and eastern equatorial Pacific Ocean. It is coupled with changes in the Pacific sea-surface temperatures and is a major cause of terrestrial climate variability, especially in the tropics and mid-latitudes. The SO is conveniently measured by the monthly SOI, which incorporates the sea-level-pressure difference between Papeete (Tahiti) and Darwin. There is a positive correlation between monthly rainfall and monthly SOI values in most of eastern Australia (Abawi *et al.* 1995) that justifies its use as a predictor of rainfall.[1] As mentioned, research into the use of the SOI as a predictor of rainfall and stream-flow, and as a decision aid in managing crop production, have shown useful results (Stone and Auliciems 1992; Chiew *et al.* 1994; Hammer *et al.* 1996; Marshall *et al.* 1996; Abawi and Dutta 1998).

The behaviour of the SOI has been grouped by principal component and cluster analysis to identify five phases for use in forecasting of rainfall. These are termed SOI phases and are labelled: consistently negative, consistently positive, rapidly falling, rapidly rising and near-zero phases (Stone and Auliciems 1992). Each phase reflects the magnitude of the SOI value during a given month and the change in the SOI value from the previous month. For example, a consistently negative SOI phase for August has a mean SOI value of −12.2 over the 2-month period (July and August) and a mean difference of 2.3 between the 2 months (Abawi *et al.* 1995). A forecast is obtained by calculating probability distributions of cumulative rainfall (or stream-flow) for a period (e.g., October to January) by breaking up the historical record into subsets of monthly SOI phases. Abawi and

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[1] Monthly SOI values range from about −40 to +40.

Dutta (1998) showed a noticeable shift in the distributions of natural stream-flows, particularly, when comparing opposite phases of the SOI, such as rapidly falling versus rapidly rising, or consistently positive versus consistently negative. For example, a forecast of pre-irrigation development stream-flow volume from October to January based on the SOI phase in May at Goondiwindi displays a shift in median from 134 000 ML when the phase is consistently negative to 358 000 ML when consistently positive. These shifts in volumes provide the justification for the scenario analysis used in the present study.

3. Methodology

To assess the value of seasonal climate forecasts, we have employed scenario analysis to examine outcomes from plant-area decisions made using SCF information with those ignoring any additional information on water-supply availability. This analysis requires a systems approach combining a number of different models covering hydrologic, agronomic and economic components of the farming system. These models were run decoupled for 100 years. The hydrologic model was run to obtain water supply data and the agronomic model was run to determine cotton yield for various water supply options. These data sets were input to the economic model to calculate the outcome from each scenario. Outcome distributions were then input to a computer program examining the impact of decision-makers' risk aversion on scenario preferences. The use of a 100-year time-frame increases the robustness of the results as it tests the outcomes over a large range of climatic conditions.

3.1 Models

3.1.1 Water supply data

The Integrated Quantity Quality Model (IQQM) developed by the New South Wales Department of Land and Water Conservation was used as the core hydrological model in the present study (NSW DLWC 1998). IQQM is the hydrologic model underpinning the current water-reform process in Queensland and New South Wales as part of the Council of Australian Government agreement (ARMCANZ 1995).

IQQM is a daily time step model, which can be applied to regulated and unregulated streams and was run to simulate 100-years of water supply data for irrigators in the BRC using recorded historical rainfall and stream-flow data. The model is configured to simulate the hydrologic system in the BRC using the river-operation rules in 1997/1998. These include State and private dam operations, water-access rules, area irrigated and water used in irrigated cropping. In modelling river flow and water use, the IQQM program

segregates the river into a number of nodes, or points where processes occur. These nodes set out the rules or parameters controlling the processes that occur at each point. For example, an irrigation node specifies the rules for ordering and diversion of water for general security water-licences. An irrigation node is an amalgamation of two or more adjoining farms with similar characteristics and can represent areas between 145 and 11 000 ha. In the BRC IQQM, there are 27 irrigation nodes of which 17 grow irrigated cotton. The model simulates the operation of an irrigation enterprise by determining water supply at each node, calculating plant areas for irrigated crops and simulating crop water demand and irrigation (DNR and DLWC 1999).

Because of inflexibilities in the method IQQM uses to determine plant areas for irrigated crops, the model was configured to plant the maximum area to irrigated cotton each year of the simulation and the resulting water supply data exported to the economic model. The intention was to obtain the maximum water supply available to irrigators in each year and use this in the economic model where a flexible plant-area decision method was used.

3.1.2 Crop water use and crop yield

To calculate cotton yield and crop water use, we used the agronomic model OZCOT developed by the Commonwealth Scientific and Industrial Research Organisation Division of Plant Industry at Narrabri (Hearn 1994). The output of this model gives a yield prediction in response to available water allocation that is similar to the classical production function. A daily balance of plant available water content (PAWC) of the soil controls the irrigation routine in OZCOT. When PAWC reaches a set limit, irrigation takes place subject to the requirement that sufficient water is available for irrigation. In practical terms, this meant that usually between four and five irrigations occurred each year of the simulation, including prewatering in mid-September. Providing sufficient water is available in the allocation, irrigation in any year will continue on demand. However, if there is insufficient water to continue irrigation the crop continues to grow under rain-fed conditions.

For different water allocation levels the average yield attained from the 100-year simulation from 1894 to 1994 is presented in figure 1. Essentially, this is a quasi-production function where crop yield will theoretically respond to increases in water availability until a limit is reached when the yield will decrease as a result of waterlogging. The allocation level is the amount of water available for use on the crop on a per hectare basis, but it is not a measure of the amount of water actually used, as the model does not continue irrigation above plant requirements. Therefore, the graph does not display diminishing marginal productivity beyond the point of maximum
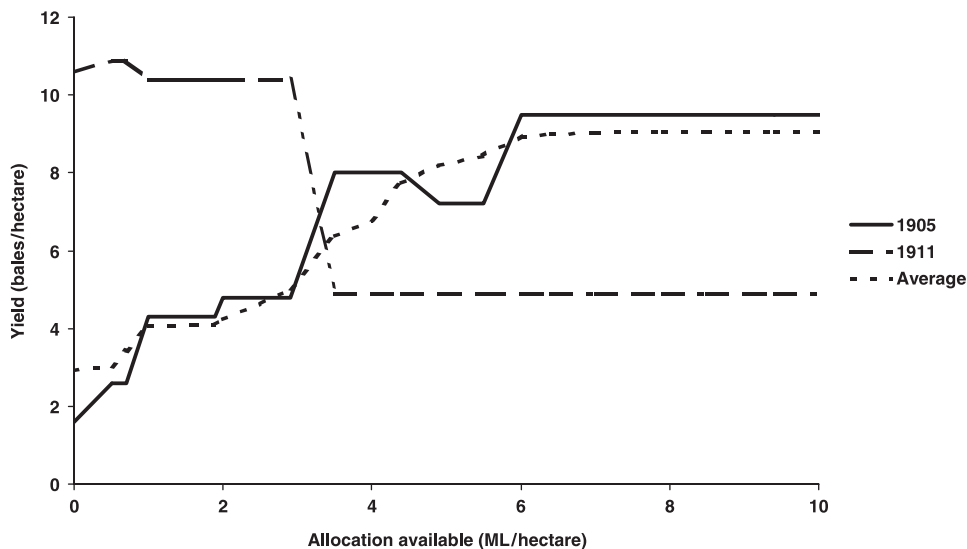
Figure 1 Quasi-production function, yield versus water allocation.

yield. The implication of this process is that the use of the OZCOT model in this analysis is attempting to maximise yield rather than maximise returns.

The advent of cropping simulation models such as OZCOT provides the opportunity to determine yields of crops each year over a simulation and enhance the outcomes of economic modelling by incorporating yield responses to climate variability and changes in crop-management practices. The use of average yields or regression analysis in irrigated systems tend to produce yields that increase with the volume of water applied similarly to the average line in figure 1. In reality however, this pattern is not always accurate and in some years yields may actually decrease as more water is applied. This could be a result of receiving rainfall soon after irrigation producing waterlogging and lower yields. The OZCOT model has no knowledge of the expected or likely rainfall in the short term and may irrigate immediately prior to a rainfall event, therefore producing waterlogging. For example, also displayed in figure 1 is the quasi-production function for two years in the simulation period, 1905 and 1911. The curve for 1905 is close to expectation with yield generally increasing as water supply increases. However, at around the 4.5 ML allocation level a dip and recovery in yield occurs. The dip in yield is a result of a water logging rainfall event immediately after the fourth irrigation. If there was no further water supply available for subsequent irrigations the final yield would remain at 7.2 bales per hectare. However, if water was available for further irrigations yield potential recovers up to a maximum in that year of 9.5 bales per hectare. In 1911 the yield curve

drops dramatically when water supply exceeds approximately 3 ML per hectare. This yield decline is a result of waterlogging and is confirmed by perusal of the rainfall record for that cropping year which showed rainfall considerably in excess of average was received in the December to February period in addition to water applied through irrigation. The same situation can happen to irrigators who are not confident of, or don't use short-term forecasts rainfall. Failure to account for this variability in yield in response to climatic variability has the potential to lead to overestimation of yields and hence financial outcomes. The use of individual year yields brings more realism into the analysis, but these yields are still somewhat artificially high, as the OZCOT model does not account for yield losses resulting from pests and diseases.

The OZCOT model run for this analysis was configured for Goondiwindi using Goondiwindi rainfall records (1894–1994), cotton variety S189, solid plant, soil water holding capacity of 300 mm, starting soil water level of 100 mm and planting on the first of October The cotton variety used is kept the same for the 100-year simulation as the analysis is examining what the outcomes would be for an irrigator who used forecast information over a large sample of climatic conditions as opposed to a time series study with implications for genetic improvement of cotton varieties.

3.1.3 Economic model

Gross margin returns are used to compare outcomes from different scenarios. The model is built in Microsoft Excel using water supply, crop water requirements and yield data as inputs. A monthly rather than seasonal time-step is used to ensure some of the effects of timeliness of water supply and crop water demand are taken into account. One decision rule using a seasonal forecast and several without the forecast are used to determine planting areas for irrigated cotton over the 100-year simulation period, 1894–1994. We have assumed that the cost of obtaining forecast information to be zero as it is likely the purchase of a decision-support system or access to forecast information will involve little cost. There is an issue of time to become familiar with the software or forecast information, but this is not taken into account by the present study.

The gross margin model was developed using variable costs of crop production from QDPI (1998) and a crop price of \$A400 per bale. In the model the water-supply data from IQQM, crop water requirements from OZCOT and plant areas were combined to give the volume of water applied per hectare to the crop and resulting cotton crop yield for each year of the simulation. While most of the costs in the gross margin model are fixed each year, it is responsive to changes in irrigation volumes and field handling of cotton bales as a result of changes in yield. A combined

water-purchase and pumping cost of $A40 per megalitre was used in the gross margin calculation.

The use of gross margins to compare different scenarios is justified by two factors. Makeham and Malcolm (1993) stated that changes to farm operations involving overheads have whole farm implications therefore the use of gross margin analysis is not appropriate. However, in this case we have assumed that there are no implications for overheads and total gross margin (gross margin per hectare multiplied by area planted) was adopted as the key comparison variable. The second factor relates to the scale of the water supply modelling. In modelling catchment operations IQQM amalgamates several adjoining farms with similar characteristics to form irrigation nodes. This results in irrigation nodes that are considerably larger than normal farm sizes in the catchment. The development of a case study or representative farm is not possible without scaling back node sizes, which is likely to introduce errors in how IQQM determines crop irrigation requirements.

The final key assumption in the decision model is that no alternative dry land crop is planted in the area left vacant by a reduction in area planted to irrigated cotton. Discussions with farmers in the catchment revealed a range of actions in this regard. These actions vary from planting a dry land crop in the vacant area to leaving the area fallow and storing the soil moisture until the following season. Others planted a number of irrigated crops as a disease break from cotton. The assumption to fallow the vacant area simplifies the analysis.

3.2 Irrigation water supply

The water supply equation faced by irrigators in the BRC comprises five components:

$$\text{Water Supply} = \text{Announced allocation} + \text{Carryover} + \text{On-farm storage} \\ + \text{Increase in announced allocation} + \text{Off-allocation} \quad (1)$$

Announced allocation refers to the volume of water an irrigator is licensed to draw from the State-owned dams. Licences are specified in terms of a nominal allocation that represents the maximum volume (in megalitres) of water a licence holder may have access to in any given water year, which runs from 1 October to 30 September. The proportion of their allocation received in any one year is dependent on the availability of water in the system. Each year on the first of October the relevant State water authority releases an announced allocation specifying the percentage of nominal allocation available for the water year. This represents a guaranteed minimum

volume of water irrigators can access in the coming water year. While this volume may increase during the water year as inflows enter the system it is not decreased. Such increases are referred to as an increase in announced allocation. Carryover water refers to the volume of licensed allocation not used in a year that is carried over into the next water year. The volume of carryover water is restricted to a maximum of the difference between licensed volume and the allocation announced in the current year (Abawi *et al.* 2001).

In addition to water from State-owned dams, irrigators may also have access to off-allocation water when dams spill or high flows enter the river system. State authorities announce the access only when all other user needs (including environmental) have been met and off-allocation water is independent of their annual volume of announced allocation. Proportionally, supply from off-allocation is crucial as it accounts for the majority of water used for irrigation in the BRC. For example, in the Queensland part of the catchment, an average of 70 per cent of the water diverted for irrigation in the period 1991–1999 came from off-allocation. The corresponding figure in New South Wales was 56 per cent (Abawi *et al.* 2001).

The heavy reliance on off-allocation water is at least partly driven by the small size of State-owned dams in the Border Rivers that ensures the water supply per hectare is relatively low. Based on the 1997/98 area developed for irrigated cotton, the Queensland portion of the BRC had 3.5 ML of licensed allocation per hectare with NSW having 6.8 ML per hectare if the entitlement is fully available (Border Rivers System File 1997/1998 Level of Development; G. Podger, pers. comm., 1999). This has at least partly lead to the substantial development of private on-farm water-storage infrastructure. In 1997/1998 the potential storage of on-farm dams was a total of 165 450 ML in Queensland and 139 660 ML in New South Wales, equivalent to 47 per cent of total storage capacity of the three State-owned dams (DNR and DLWC 1999).

As off-allocation supply is reliant on high flow events during the season, the likely volumes available are unknown when the cotton crop is planted. This is therefore a significant source of uncertainty. However, by linking seasonal climate forecast information with catchment modelling, we are able to provide a probabilistic forecast of likely access to off-allocation with the aim of reducing this uncertainty.

3.3 Use of GSD in defining efficient sets

While GSD has been widely used in researching choices amongst risky decisions (for example, Kramer and Pope 1981; Rister *et al.* 1984; Klemme 1985; Pandey 1990; Williams *et al.* 1993; Harrison *et al.* 1996; Maynard

et al. 1997; Harrison 1998), there have been several methods of determining the risk aversion coefficients (RAC) used as bounds to calculate efficient sets. These methods include the direct elicitation of utility functions and calculation of RAC, use of RAC from other studies and the selection of somewhat arbitrary RAC intervals. A somewhat dated list of RAC used in other studies can be found in Raskin and Cochran (1986). McCarl (1990, p. 53) criticised the use of 'arbitrarily chosen non-overlapping intervals'. He proposed that in the absence of information on the risk aversion coefficient of the decision-maker(s) this method is suboptimal, as it does not identify points at which decision-makers change their preferences between options. To deal with this shortcoming, McCarl (1988) used the findings of Hammond (1974) to develop a methodology for finding the values of the absolute risk aversion coefficient r_x where decision-makers preferences amongst risky choices change. Under the assumptions of a constant absolute risk aversion utility function, finite number of mutually exclusive prospects, discrete distributions and data-free sampling error, McCarl (1988) developed a procedure to calculate ranges of the risk-aversion parameter where individuals prefer one risky outcome above others. These values, called breakeven risk-aversion coefficients (BRAC), allow more useful conclusions on the likely choices amongst risky decisions to be made. A computer program, RISK-ROOT, developed by McCarl (1988) was used in the present study to calculate BRAC.

McCarl and Bessler (1989) raised concerns about the size of the RAC bounds used to define efficient sets in the absence of knowledge about the utility function of the particular decision-makers under study. They developed a procedure to calculate an upper bound of r_x in the form of a confidence interval based on the risk premium. This upper bound is used to ensure that the RAC bounds used in the GSD analysis are not too large or small, thereby leading to meaningful rankings.

3.4 Plant area decision-making

The decision by irrigators in the BRC of how much irrigated cotton to plant in any year is partially a function of their known water supply at the time of the decision, and their approach to managing the variability of supply of off-allocation water they use in making the plant-area decision (i.e., the expected off-allocation volume). Irrigated cotton in the BRC is typically planted from mid-September at which time the first three components of the water supply equation (announced allocation, on-farm storage and carryover) are known. Water supply from off-allocation, any potential increases in announced allocation and in-crop rainfall remain unknown. In the event of known water supply falling short of the volume an irrigator

requires to plant all the area developed for irrigated cotton, two options are possible. The first option is to plant an area based on known water supply and either fallow or plant a dry land crop in the remaining area. The second option is to make an estimate of the amount of off-allocation water that will be received during the cropping season and determine an area to plant based on the addition of known water supply and expected off-allocation. The scenarios tested in this research are based on option two, where estimates of off-allocation are determined using a seasonal forecast and compared with estimates made using a probability distribution of the modelled historical record only. This approach is justified by the historically high use of off-allocation water received during the crop growth cycle for irrigation, which suggests that a considerable number of irrigators use some estimate of expected off-allocation water supply in their area-planting decisions. Furthermore, a survey of 45 irrigators in the Border Rivers by the Queensland Centre for Climate Applications into forecasting climate and water supply found that 51 per cent of irrigators rated off-allocation opportunities as very important and 26 per cent rated them of some importance when deciding planting areas.

3.4.1 Decision strategy without a seasonal forecast

Fixed strategy. An irrigator adopting the second decision option faces the question of how much off-allocation water to expect. The percentiles of off-allocation volume available between October and January for an irrigation node in the Queensland portion of the BRC for the IQQM simulation period 1894–1994 are displayed in figure 2. While the median volume of off-allocation available over this period was 7938 ML, there was a large range from 0 to 60 000 ML. In the absence of a forecast, an irrigator may adopt a risk position and select a value from this All Years line to use in the water-supply equation. For example, if the decision-maker wants to be 70 per cent sure of the volume of off-allocation, the corresponding 30 percentile volume of 2097 ML would be selected. In a sense the irrigator would have taken a 30 per cent risk because in 30 per cent of years in the simulation, the amount of off-allocation received was less than 2097 ML.

   The without-forecast scenario, referred to as the fixed strategy, is based on the decision-maker adopting a certain level of risk by choosing a particular level of risk (percentile) of off-allocation water supply with which they are comfortable. The amount of off-allocation water pertaining to this risk level is obtained from the All Years line (figure 2). For each year of the simulation this volume (constant for the simulation) is added to the known water supply at the time of planting (which varies each year) to give expected water supply. For example, if the 30 per cent risk level was chosen, 2097 ML (30 per cent, figure 2) would be added to the known water supply at the
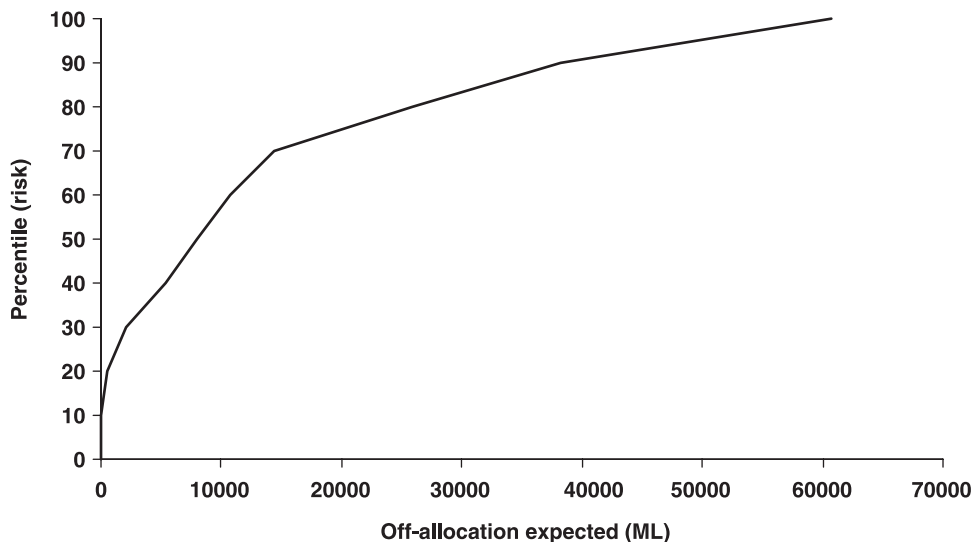
Figure 2 Percentile of simulated off-allocation water (October–January) available for 1894–1994 (All years).

start of each planting season. The total volume expected is then divided by the amount of water per hectare an irrigator expects to need to meet crop water requirements to calculate the area to plant in that year.

The expected volume of water required to meet crop water requirements used in this analysis is based on the results of a non-statistically significant survey of 16 cotton irrigators in the BRC. Irrigators were asked how much water per hectare was required to grow a good crop of cotton in an average year. The mean answer of 6.5 ML was used for the analysis, although, the responses displayed a considerable range from 4 to 9 ML per hectare. While the yield data from the OZCOT model could have been used to determine what volume of water is required to maximise yield, this would have represented peak-picking rather than basing the decision on information actually used by irrigators in the study region.

The final process of the without-forecast decision is to determine what level of risk to take when deciding how much off-allocation water to expect. As part of a sensitivity analysis process, the model was run at all decile levels from 10 to 90 per cent. Examination of results across the full range of deciles provides information on the consistency of the forecast as well as identifying any switch over points where one strategy may be preferred over another.

Other fixed strategies. Three other without-forecast strategies were examined to provide further comparisons of differing risk positions and the value of

a forecast relative to a perfect forecast. The maximum area strategy assumes an irrigator will plant all the irrigable area to cotton each year independent of known water supply or forecast (herein referred to as max area). The zero risk strategy simply means the irrigator ignores the prospect of using off-allocation water received during the growing season when making the decision to plant. It is included as a lower bound for comparison. While not applicable for the GSD analysis, a perfect knowledge strategy that assumes all the water supply variables are known when the planting area decision is made. It is useful to provide an indication of the upper possibility of forecast outcomes.

3.4.2 Decision strategy with a seasonal forecast

SCF can be used to identify years when a decision-maker can expect the pattern of off-allocation supply to be different from that shown in figure 2, and therefore lead to a change in decisions. The percentiles of off-allocation water supply for the peak irrigation period, October to January, partitioned by the SOI phase in August are illustrated in figure 3. Similarly to stream-flow, there are shifts in distributions away from the All Years distribution, particularly for the consistently positive and consistently negative SOI phases. While the September SOI phases show stronger separation shifts amongst different phases, the August SOI phase was used in the analysis when calculating
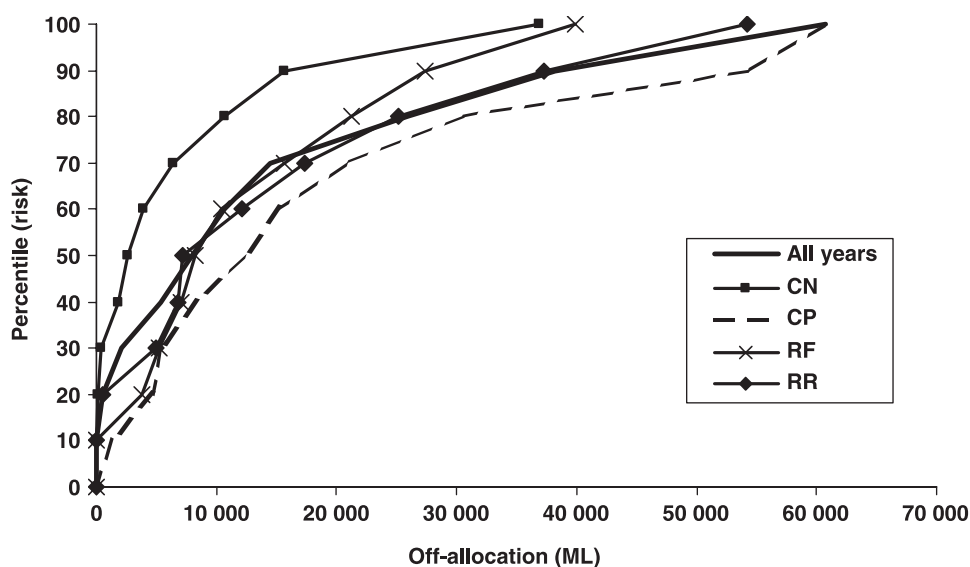

Figure 3 Percentile of simulated off-allocation water supply using SOI (Southern Oscillation Index) phases in August for 1894–1994.
CN, consistently negative; CP, consistently positive; RF, rapidly falling; RR, rapidly rising.

Table 1 Number of years for each SOI phase in August for the period 1895–1994

SOI phase	Occurrences (years)
Consistently negative	19
Consistently positive	20
Near zero	32
Rapidly falling	10
Rapidly rising	19
Total	100

SOI, Southern Oscillation Index.

the SOI strategy. The two reasons for this are first, the September phase is not always known on the first of October (the planting date for this analysis) and second, the irrigated cotton planting window can be as early as mid-September at which point the September SOI phase is unknown.

The with-forecast decision on planting area, referred to as the SOI strategy, was made in a process analogous to that of the without-forecast decision. In this case, for a given level of risk the volume of expected off-allocation water to use in the water-supply equation was determined by the SOI phase in August of the year in which the decision was being made. For example, in 1910 the August SOI phase was consistently positive, therefore, the volume of off-allocation water to be used in the water-supply equation (6900 ML for the 30 per cent risk level) was selected from the consistently positive percentile line from figure 3. In table 1 the number of times that each SOI phase occurred in August for the period 1894–1994 is listed. To ensure comparability of results the same volume of 6.5 ML was used as the divisor for determining plant areas.

3.4.3 Cross validated SOI decision strategy

Robinson and Butler (2001) criticised the methodology used in determining the with-forecast strategy for possibly over-estimating the value of a forecast. They proposed that the inclusion of off-allocation data for the decision year in the calculation of probabilities or percentiles might lead to bias. In dealing with this issue Robinson and Butler (2001) adopted a leave-one-out cross validation when determining crop-management strategies. Operationally, this entails leaving out the off-allocation data for the decision year when calculating percentiles for the water-supply equation. For example, when making the plant area decision for the year 1900, the off-allocation water supply data for that year is excluded from the calculation of the percentiles that are the basis for the planting decision in this year. This strategy, referred to as 'Xvalidated SOI', was included in the analysis to guard against possible over-estimation of the with-forecast strategy outcomes.

4. Results

In this section comparisons between the scenario using a seasonal forecast (with-forecast scenario) and those not using a seasonal forecast (without) are presented. In order to examine the consistency of the efficacy of the with-forecast scenario, comparisons were carried out for six irrigation nodes in the Queensland part of the BRC. These nodes had 15 203 ha of land developed for irrigated cotton in the 1997/1998 water year, which is 69 per cent of the total land developed for irrigated cotton (in that year). The development statistics for the irrigation nodes used in the analysis are summarised in table 2. Both pump capacity and size of on-farm storages (OFS) are reported, as the ratio of these is important in determining how much off-allocation water can be pumped compared to the volume available for pumping. Irrigation efficiency accounts for transmission losses between the OFS and the plant-root zone. An irrigation efficiency of 66 per cent means that of every megalitre of water released from the OFS only 66 per cent actually gets to the root zone. Therefore if 1 ML is needed by the crop 1.5 ML needs to be released from the OFS.

The structure of the analysis where six irrigation nodes were tested for a range of nine off-allocation expectations creates a considerable problem in reporting results through the large number of permutations. Therefore, when reporting results, in some cases one node only will be reported.

When comparing risky outcomes from the point of view of decision-makers, a comparison between the SOI and the Xvalidated SOI strategies is meaningless. The choice between these two strategies is a methodological issue to minimise possible bias. The summary statistics for the two strategies when the 50-percentile off-allocation input is used for Node 2 (table 3) show very little difference between the two outcomes. As this pattern is consistent across all nodes tested, results reported below will only use the SOI strategy to compare with the remaining strategies.

In figure 4 a summary of the 100-year gross margins from the scenario analysis for Node 2 for varying levels of expected off-allocation water is

Table 2 Development statistics for the irrigation nodes used in the analysis

Irrigation node	Pump capacity (ML/day)	On-farm storage capacity (ML)	Licensed volume (ML)	Cotton irrigation area (ha)	Irrigation efficiency
Node 1	550	28 300	9035	3300	0.66
Node 2	803	10 100	4970	1951	0.66
Node 3	720	10 350	4270	1540	0.69
Node 4	675	14 500	3900	1317	0.69
Node 5	850	44 900	9100	4440	0.64
Node 6	937	14 700	8570	2655	0.64

Table 3 Summary statistics for SOI and SOI Xvalidated outcomes ($A total gross margin).

	SOI	SOI Xvalidated
Mean	3 101 874	3 091 775
Median	3 381 275	3 350 501
Standard deviation	1 538 879	1 554 908
Minimum	−893 523	−1 064 232
Maximum	6 168 919	6 168 919
Skewness	−0.52	−0.52

SOI, Southern Oscillation Index.
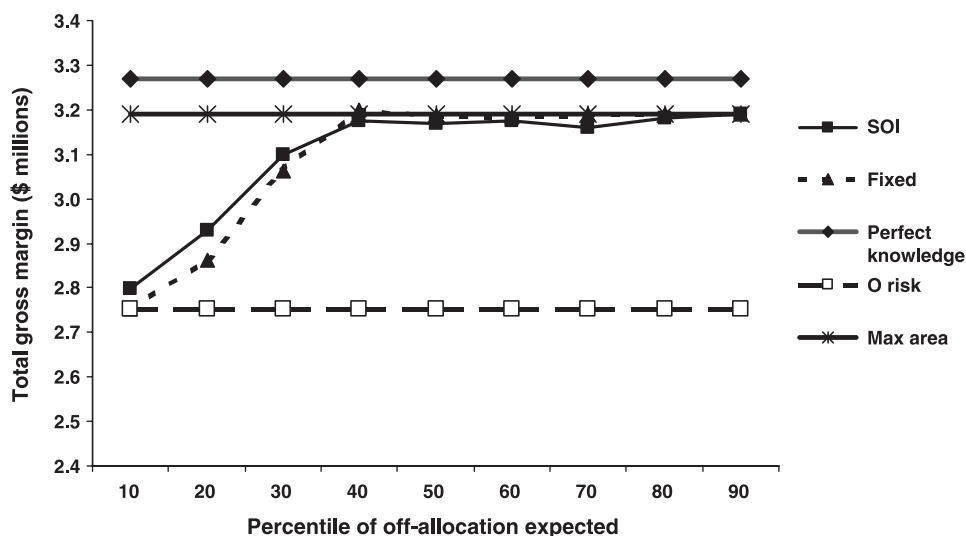
Figure 4 Mean gross margin results for Node 2 at off-allocation expectation of 10–90%.

presented. These results were obtained by running IQQM to determine the components of the water supply equation on the planting date (1 October) for Node 2 for each year of the simulation. The volume of off-allocation water expected for the upcoming cropping season depending on whether the strategy is with or without the forecast (as explained previously), is added to the known water supply. This summation represents the total water supply the irrigator expects to have at their disposal for that year, and is converted to a plant area by dividing by 6.5 ML. The gross margin estimated for each year is calculated in a stepwise process where the actual volume of water applied each year on a per hectare basis of the simulation is used to determine a per hectare yield. While 6.5 ML was used in determining the area to plant, the final yield is calculated using the actual water supply available in

each crop year. The irrigation water use and yield data for each year are then input to the gross margin model resulting in a 100-year data set of gross margin that is multiplied by the area planted each year for each strategy.

The comparative response of the mean gross margin to an increasing level of water-supply risk (defined as increasing percentile of off-allocation expected), is reported in figure 4. At the lower levels of risk (10–30 per cent) the value of the SOI strategy is greater than the value of the fixed strategy. However, in excess of 30 per cent risk, the value of the fixed strategy becomes larger than the value of the SOI strategy. The ultimate cause of this switch in average gross margin is the pattern of the off-allocation percentiles shown in figure 3. This pattern predicts more water on average using the SOI phases than the All Years line for the 0–30 percentiles and results in the SOI strategy planted area being greater than the fixed strategy. In the higher risk 40–90-percentile range of off-allocation expectation, the SOI phases predict less water on average than the fixed strategy which results in larger plant areas for the fixed strategy than the SOI strategy. The larger areas for the fixed strategy in the 40–90-percentile range of off-allocation expectation results in a higher mean gross margin than the SOI strategy.

At all levels of risk the mean return for zero-risk is less than other strategies. Over the complete decile range the value of the maximum strategy is greater than the fixed, SOI and zero-risk strategies. The perfect-knowledge strategy, which simply assumes the complete water-supply equation is known at planting, produces returns above the other strategies tested.

In terms of the sensitivity of expected returns to changes in expected off-allocation, figure 4 is useful. However, it fails to account for the impact of different strategies on the variability of returns. The mean-standard deviation of the 100 years data set of gross margin results for each strategy for Node 2 at the 3rd decile (30 per cent risk) off-allocation is presented in figure 5. While perfect knowledge dominates the remaining strategies (with the exception of zero-risk), this figure highlights the trade-off between mean and variability of gross margin returns. In the absence of perfect knowledge the choice between the remaining strategies is dependent upon the attitude to risk of the individual decision-makers.

Generalised stochastic dominance analysis as described by McCarl (1988) was used to define risk aversion parameter ranges amongst the strategies examined, and identify which outcomes would be preferred for each RAC range. By comparing outcome distributions and their associated probabilities RISKROOT determines the RAC ranges where one strategy is dominant over the others examined under the assumption of constant absolute risk aversion. Using GSD in this situation is effectively examining the trade-off between the mean and standard deviation shown in figure 5 and identifying levels of risk aversion where preferences change. It should be noted that the perfect
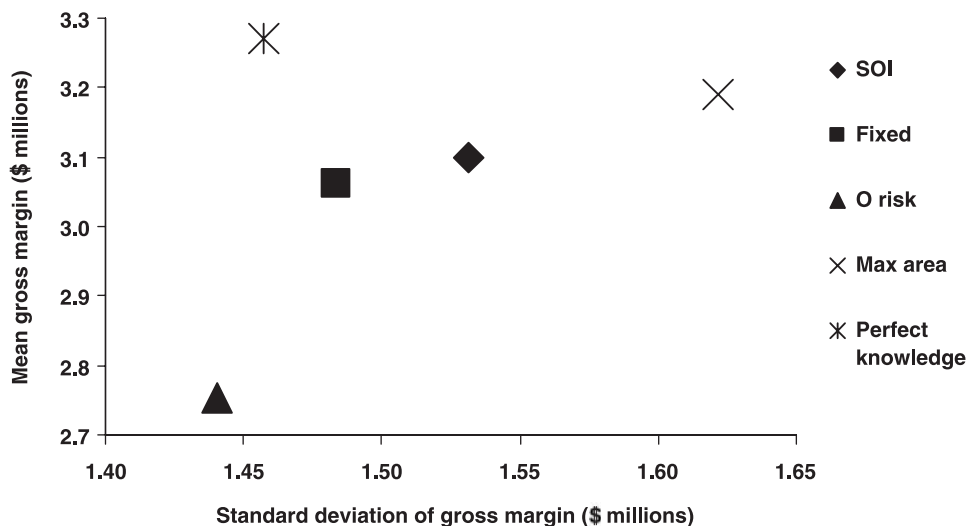
Figure 5 Mean-standard deviation results for Node 2 at off-allocation expectation of 30%.

knowledge strategy is excluded from the GSD analysis as it is already the dominant strategy that would be selected by rational decision-makers because of its highest mean gross margin and low standard deviation.

The results of the GSD rankings for the six nodes again present the problem of a large number of permutations of results (six nodes for nine off-allocation percentile expectations). Therefore, results presented in table 4 are for all nodes however, only one risk level (3rd decile). The results in table 4 are restricted by bounds as described in McCarl and Bessler (1989) using their confidence-interval approach to set the upper bound for r_x:

$$r_x \leq D/\sigma_y \qquad (2)$$

where D is the number of standard deviations in the confidence interval and σ_y is the standard deviation of the without-forecast strategy, in this case the fixed strategy. Under the assumption that the outcomes are normally distributed, the value of D is equivalent to the Z value in the standard normal distribution. Using $\infty = 0.005$ the formula for r_x becomes $r_x \leq 2 * 2.57/\sigma_y$. By restricting the upper bound in this manner we are ensuring the scale of r_x is relevant and that the decision-makers whose preferences are in the range $0 \leq r_x \leq 2 * 2.57/\sigma_y$ will accept some risk-return trade-off.[2] This confidence interval represents an upper bound for BRAC outside of which most rational

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[2] In this context risk is defined as increased variability of income.

Table 4 Ranking of strategies based on BRAC for the six nodes

| Node | Absolute risk aversion coefficient | | Efficient set |
	Lower	Upper	
Node 1		<0.0000001595	Max area
	0.0000001595	0.000000721	SOI
	>0.0000007212		Fixed
Node 2		<0.0000003167	Max area
	0.000000317	0.000000384	SOI
	>0.0000003844		Fixed
Node 3		<0.0000004838	Max area
	>0.0000004838		Fixed
Node 4		<0.0000006720	Max area
	>0.0000006720		Fixed
Node 5		<0.0000001017	Max area
	>0.0000001017		Fixed
Node 6		<0.0000002005	Max area
	>0.0000002005		Fixed

BRAC, breakeven risk-aversion coefficients.

decision-makers would not be expected to operate. For example equation (2) can be rearranged to be

$$z = r_x \sigma_y / 2. \tag{3}$$

If $r_x = 0.0000033955$ and $\sigma_y = 1476303$, $z = 2.506$ which corresponds to a 99 per cent confidence interval. Therefore, outcomes falling into risk aversion coefficient ranges above 0.0000033955 would only be preferred by decision-makers who are extremely risk-averse and interested in outcomes above the 99 per cent confidence interval. In practical terms the confidence interval approach ensures the breadth of the overall RAC bound remains realistic and outcomes outside this bound are excluded from reporting in results.

The results shown in table 4 identify that, for Nodes 1 and 2, as the level of risk aversion increases (i.e., RAC becomes increasingly positive), decision-makers switch their preferences from the maximum strategy to the SOI strategy. Those decision-makers who display even higher levels of risk aversion would prefer the fixed strategy. Decision-makers whose preferences fall within the upper bound set for r_x do not prefer the zero-risk strategy. For Nodes 3–6 decision-makers do not prefer the SOI strategy. It is important to note that the RAC for each node are different which is a result of the divergent outcome distributions. RISKROOT calculates BRAC for each set of distributions under the overall assumptions listed previously and does not assume particular

BRAC for different scenarios. In effect the analysis has the same assumptions from a decision-maker point of view, however, there are differences in irrigation infrastructure development between nodes examined. These differences result in slightly divergent outcome distributions for each node. The findings in this table demonstrate that at least some decision-makers who are risk averse will prefer the SOI strategy. However, by examining preferences for all six nodes (under the same assumptions) we find that this preference is not consistent across farms with different irrigation infrastructure characteristics. This finding does not diminish the fact that the SOI is useful to some decision-makers, but indicates that this set of decision-makers may not be large.

If we assume the choice is restricted to the fixed and SOI strategies, an indication of likely choices based on mean gross margin only through an examination of the percentage difference between these strategies at all off-allocation water risk levels for the six nodes tested is shown in table 5. This table highlights two points in particular, firstly the differences between the outcomes for the two strategies are relatively small. Secondly, outcomes for the SOI strategy are less than that of the fixed strategy for the majority (37) of scenarios tested. The picture presented by table 5 is potentially misleading, as we would expect very few if any decision-makers to be willingly adopting the higher risk 50–90 decile forecast positions. Restricting the results to the 10–40 decile range increases the positive results for the SOI strategy to 14 out of 24 cases tested. Nevertheless, the overall finding of the results thus far is that the SOI strategy is useful but not in all cases examined.

The results presented in table 4 relate to the water supply variables as modelled by IQQM. A further sensitivity analysis was carried out to examine any changes in preferences when water supply at the start of the season is restricted. The water supply data from IQQM show that the median on-farm storage (OFS) level at planting time is in the range of 94–97 per cent for Nodes 2–6 and 65 per cent for Node 1. When the OFS is at 100 per cent

Table 5 Differences (%) between SOI and fixed strategy average gross margin for off-allocation expectation 10–90%.

	10%	20%	30%	40%	50%	60%	70%	80%	90%
Node 1	0.26[†]	0.47	1.66	0.80	−0.92	−0.96	−0.45	−0.66	0.77
Node 2	1.58	2.34	1.19	−0.76	−0.56	−0.27	−0.93	−0.26	0.00
Node 3	0.01	−0.10	−0.31	−0.86	−1.22	−1.11	−0.31	0.25	0.00
Node 4	0.18	−0.28	−0.15	0.31	−0.13	−0.94	−0.53	0.00	0.00
Node 5	−0.04	0.06	−0.54	0.79	0.12	−0.18	−0.50	−1.03	−0.42
Node 6	0.63	1.18	−0.86	−0.34	−1.20	−1.46	−0.34	−0.72	0.00

[†] Positive percentage indicates SOI strategy returns are higher than fixed strategy. SOI, Southern Oscillation Index.
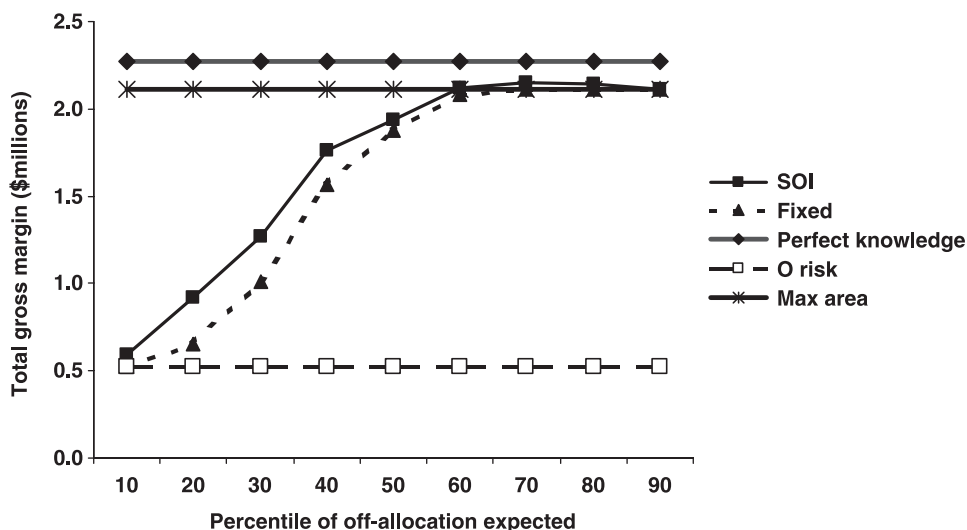
Figure 6 Mean gross margin results for Node 2 at off-allocation expectation of 10–90% when water supply is limited.

Table 6 Differences (%) between SOI and fixed strategy average gross margin for off-allocation expectation 10–90% when starting water supply is restricted.

	10%	20%	30%	40%	50%	60%	70%	80%	90%
Node 1	2.51†	12.03	16.04	8.37	7.16	2.61	7.96	4.21	1.51
Node 2	12.06	28.42	20.64	11.18	3.10	1.94	1.53	1.34	0.00
Node 3	9.89	27.52	18.34	5.57	0.25	−1.77	−1.01	0.71	0.00
Node 4	9.31	10.87	15.61	4.88	1.02	−2.32	−0.39	0.00	0.00
Node 5	1.85	5.45	7.02	11.95	5.88	12.03	3.88	−1.83	−0.67
Node 6	5.10	10.31	12.89	18.96	8.81	7.17	−3.01	−1.29	0.00

† Positive percentage indicates SOI strategy returns are higher than fixed strategy. SOI, Southern Oscillation Index.

at the start of the season we can conclude from table 2 that very little off-allocation water is required to meet an expected crop water demand of 6.5 ML. Therefore, the OFS level at the start of the season was set to zero to ensure a higher importance is placed on the water supply received from off-allocation during the cropping season.

The percentage difference in mean gross margin between the SOI and fixed strategies for each node tested under conditions of increased water scarcity are detailed in figure 6 and table 6. In comparison to table 5 the SOI strategy is now much better performed with differences between the strategies increased in both proportional and numerical terms. For all permutations in the 10–40 decile range the SOI strategy outperforms the fixed strategy.

Table 7 Ranking of strategies based on BRAC for the six nodes when water supply is restricted.

Node	Absolute risk aversion coefficient		Efficient set
	Lower	Upper	
Node 1		<0.0000002042	Max area
	0.0000002042	0.0000017199	SOI
	>0.0000017199		Fixed
Node 2		<0.0000004142	Max area
	0.0000004142	0.000001027	SOI
	>0.000001027		Fixed
Node 3		<0.0000007112	Max area
	0.0000007112	0.0000010406	SOI
	>0.0000010406		Fixed
Node 4		<0.0000008173	Max area
	0.0000008173	0.0000014832	SOI
	>0.0000014832		Fixed
Node 5		<0.0000001972	Max area
	0.0000001972	0.0000005973	SOI
	>0.0000005973		Fixed
Node 6		<0.0000003239	Max area
	0.0000003239	0.0000007912	SOI
	>0.0000007912		Fixed

BRAC, breakeven risk-aversion coefficients; SOI, Southern Oscillation Index.

The GSD results of this scenario (table 7) show that the SOI strategy becomes preferred more often across all nodes tested. However, it is noteworthy that as risk aversion increases the fixed strategy becomes preferred. This result is a consequence of the removal of a bottleneck inherent in the farming system. When starting OFS are close to full, the ability to physically pump the off-allocation available into storage is reduced. Hence the usefulness of the forecast is reduced. Restriction of the starting water supply diminishes the effect of the OFS bottleneck and causes the farming system to be more reliant on off-allocation water supply. The implication from tables 6 and 7 is that increased water-scarcity is likely to enhance the numbers of decision-makers that find the SOI information useful in their crop area decisions.

The results presented are from the Queensland irrigation nodes only, as the analysis showed no response of forecast for New South Wales irrigation nodes. Probable reasons for this include the lower reliance by New South Wales irrigators on off-allocation water and the relatively high ratio of licensed volume of water to area developed for irrigation. These factors reduce the number of years when water supply is a limiting factor. Increases in plant area available or restrictions on access to water through the water reform process would be expected to increase the number of years when water is limited, and therefore increase the value of a seasonal forecast.

5. Conclusions

The present study examined the use of SCF on stream-flows as a decision aid for irrigated-cotton growers in the Border Rivers catchment of the northern Murray–Darling Basin. The results of the unrestricted water supply analysis indicate that some decision-makers who adopt a slight risk averse approach will prefer the use of forecast information over a fixed approach which ignores any seasonal forecast. This can be considered as akin to a lower bound estimate of the usefulness of the SCF information. While the definition slight is tenuous, the use of the confidence interval approach of McCarl and Bessler (1989) ensures the tested RAC bounds are reasonable and produces the conclusion that the SOI strategy will be preferred by at least some decision-makers. This finding is similar to that of Mjelde *et al.* (1997) who found that SO forecasts were useful to some crop producers, but not all.

It is important to note that the results presented in the GSD analysis relate to a situation where the 30 percentile forecast of off-allocation water was used as an input to the water supply equation for determining area to plant. It is arguable that this in fact assumes a certain level of risk aversion and may raise some inconsistencies at high levels of risk aversion where decision-makers would possibly chose a lower percentile input to increase certainty of outcomes.

The restriction of water supply to examine the usefulness of the SOI phases in decision-making indicates its potential as water supplies become more limited and moves towards an upper bound estimate of the usefulness of SCF information. Reasons for a progressive tightening of water supply may include government policy through the water-reform process or continued expansion of area available to plant by irrigators. A Forecasting Climate and Water Supply survey in the Border Rivers catchment found that 16 cotton growers who planted 10 500 ha of cotton in 1999 advised they had access to 6800 ha of additional irrigable land (Keogh *et al.* 2000). Increases in available irrigable land would add to the value of the forecast by increasing the number of years where water would become a limiting factor in crop production. It should be noted that the exercise of restriction of water supply is indicative only as the actual restrictions stemming from policy or development may impact on different components of the water-supply equation and result in different effects on actual water supply.

Results presented here raise an important issue regarding irrigators' intentions when utilising forecast information. The intended use of additional information in decision-making is often as a risk-management exercise (Mjelde and Cochran 1988). If risk is defined as variability of returns, then the results from the present study indicate that the use of forecast information

in the form of the phases of the SOI may not reduce risk. The trade-off between mean income and variability of income is illustrated in figure 5. As a risk-management tool when comparing the max and SOI strategies, the SOI strategy certainly reduces risk. However, if the comparison was between the fixed and SOI strategy, we could conclude that adoption of the SOI strategy would not necessarily be as a risk management tool. Further examination of the outcomes for Node 2 shows that when plant areas are reduced in either consistently negative or rapidly falling SOI phase years, the variability of returns for the SOI strategy is less than that of the fixed strategy. In contrast, when plant areas are increased in consistently positive SOI phase years, the return variability for the SOI strategy is higher than the fixed strategy.

The importance of these results is highlighted by findings from a survey, now admittedly quite old, of 201 farmers throughout Australia that suggested that, although risk aversion was the predominant risk attitude among those surveyed, the average degree of risk aversion was relatively small (Bond and Wonder 1980). While acknowledging the tentative nature of the results, they suggested an aggregate risk-neutral behaviour among farmers. If we take this preliminary finding to be at least partly true, this research suggests at least some decision-makers would benefit by altering decisions on areas to plant based on the SOI.

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