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Modelling hydroclimatic uncertainty and short-run irrigator decision making: the Goulburn system*

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Australia has an incredibly variable and unpredictable hydroclimate, and while irrigation is designed to reduce risk, significant uncertainty remains in both seasonal water availability ('allocations') and irrigation crop water requirements. This paper explores the nature and impacts of seasonal hydroclimatic uncertainty on irrigator decision making and temporary water markets in the Goulburn system in northern Victoria. Irrigation and water trading plans are modelled for the three seasons of the irrigation year (spring, summer and autumn) via discrete stochastic programming, and contrasted against a perfect information base case. In water-scarce environments, hydroclimatic uncertainty is found to be costly, in terms of both the efficiency of irrigation decisions and the allocation of water via the water market.

Key words: climate variability, decision making under uncertainty, water allocation, water markets.

1. Introduction

Fair, sustainable and efficient water resources management is one of the biggest challenges facing humankind. One of the difficulties in setting policy for water resources is the complexity of the environment, encompassing the underlying hydrological cycle, a wide range of demands and values for water, issues regarding the renewal, pricing and access to storage and distribution infrastructure, and often, a deeply embedded historical and political context. Against this complex background, water allocation models can provide valuable information.

Economic models of water allocation allocate water to optimise some economic criterion, subject to physical and institutional constraints. The overriding assumption is that the variables determining an optimal allocation are

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known. While irrigation is designed to reduce risk, by securing access to water, an otherwise highly uncertain input, significant uncertainty remains in both seasonal water availability ('allocations') and supplementary (irrigation) crop water requirements. This is particularly true in Australia due to a variable and unpredictable hydroclimate.[1]

Not accounting for the stochastic nature of the hydroclimate, and irrigator responses to it, is widely recognised as a limitation in the water allocation modelling literature (Guise and Flinn 1970; Hall *et al.* 1993; Eigenraam *et al.* 2003; Appels *et al.* 2004). This paper aims to address this gap by examining the nature and impacts of seasonal hydroclimatic uncertainty on irrigator decision making and water markets in the Goulburn system in northern Victoria.

The Goulburn system comprises the Goulburn, Campaspe and Loddon Rivers and their storages. The area accounted for over 50 per cent of irrigation water use in Victoria in 2005–2006, and over 10 per cent of total irrigation water use in Australia (ABS 2008). Water allocation within the Goulburn system is managed by Goulburn-Murray Water, a corporatised state government body. This paper models the impacts of uncertainty for 10 regions and the three principal irrigation industries (dairy, mixed farming and horticulture) practiced in the Goulburn system.

Irrigators in the region have been allowed to trade water temporarily (for use within the irrigation season, August–May) for the past 20 years, and trading has emerged as an integral part of farm management. In particular, water markets are an important means of adjusting to incoming information on seasonal water availability and crop demands (Brennan 2006).

Irrigation and water trading plans are modelled for the three seasons of the irrigation year (spring, summer and autumn) via discrete stochastic programming (Cocks 1968). The assumptions regarding irrigator decision making under uncertainty are hypothetical, and hence the modelling is explorative in nature, with the aims of investigating:

- The nature of seasonal hydroclimatic variability and uncertainty.
- A modelling approach to simulate irrigator decision making under uncertainty, including a methodology for forming water market price expectations and the timing of trades throughout the irrigation year.
- The implications and costs of uncertainty, based on a comparison of the discrete stochastic program against a perfect information base case.
- The performance of water markets under uncertainty.

It is worth noting that this is modelling *of* irrigators rather than *for* irrigators: the aim is to better reflect reality with respect to the underlying uncertainties facing irrigators, and hence improve the ability of water allocation models to support policy making.

[1] Hydroclimatology might be defined as the study of the hydrological interactions between the land surface and atmosphere at seasonal or longer timescales.

The outline of the paper is as follows. Section 2 assesses the variability and uncertainty in availability of irrigation water and crop water requirements. Section 3 describes the discrete stochastic program, while Section 4 presents the results of the modelling. Section 5 discusses these results in the context of real-world decision making and Section 6 summarises the paper and offers some conclusions.

2. Uncertainty facing Goulburn system irrigators

The hydroclimate encompasses climatic variables such as precipitation and temperature and hydrologic variables such as soil moisture, evapotranspiration and runoff. Uncertainty arises mainly from the stochastic variation of these climate characteristics both within and between irrigation seasons. Additional uncertainty may arise from a trend component attributable to climate change but this is not considered here. In this paper, the impacts of the hydroclimate on irrigators are limited to the availability of and the need for irrigation water.

Uncertainty in aggregate water availability depends not just on the hydroclimate but on dam management. Australia follows a proportional rights system, whereby irrigators hold entitlements to water (water rights) to which a percentage allocation factor is applied each season based primarily on the volume of water in the associated storages. Victoria has a conservative allocation policy: all water is allocated up to 100 per cent of water right. After that no further water is allocated until next year's water right can also be covered (with high probability), at which point any additional water is also allocated. Allocations of water in excess of 100 per cent of water right are known as 'sales' water. (The modelling in this paper reflects the policy environment prior to 2007, where 'sales' water was tied to water right. This water is now a separate entitlement (DSE 2004).)

An initial allocation is made prior to the start of the irrigation season, and may be revised upward through the season. An increase in allocations from 100 per cent to 120 per cent, for example, means farmers may call on up to 120 per cent of their water right, rather than 100 per cent, before the end of the irrigation season in May. Goulburn-Murray Water announces any increase monthly, or twice-monthly in drought years. Given an initial allocation is made, seasonal uncertainty in allocations relates to the size of the increase that might occur over the remainder of the season. As the wettest part of the year in the catchment is winter/spring, while summer and autumn are fairly dry, final allocations are reached by November approximately 80 per cent of the time (i.e. there are no further increases to the allocation percentage after this time).

Data for supplementary crop water requirements and allocations are taken from 112-year simulations of two other models: the Program for Regional Demand Estimation (PRIDE) and the Goulburn Simulation Model (GSM).

2.1 Program for Regional Irrigation Demand Estimation (PRIDE)

The Program for Regional Irrigation Demand Estimation (PRIDE) (SKM 1998) estimates monthly supplementary crop water demands based mostly on pan evaporation and rainfall data. The model has been calibrated to historical observations, and thus also reflects management practices.

Six crops are modelled: annual and perennial pastures, a horticulture crop, a winter crop (wheat), a summer crop (millet) and lucerne. Seasonal supplementary water requirements show significant variability from year to year. Figure 1 shows this for perennial pastures in the Rodney area, presented in the form of seasonal cumulative distribution functions.

There is little evidence of correlation in supplementary water requirements from year to year. There is however correlation between seasons within the same year, particularly between spring and summer, and this is incorporated into the modelling.

Southern Oscillation Index-based forecasting techniques, which could provide further information about upcoming supplementary crop water requirements, are not considered here, although the model estimates of the costs of uncertainty could be used to derive the potential benefits of these forecasts. (Southern Oscillation refers to shifts in air pressure between Asia and the east Pacific, and is associated with rainfall across northern and eastern Australia: see http://www.bom.gov.au/climate/enso.)

2.2 Goulburn Simulation Model (GSM)

The Goulburn Simulation Model (GSM) is a network allocation model built in the REALM (REsource ALlocation Model) software (Perera *et al.* 2003). Water is allocated (routed) via a linear program which minimises the cost of delivering water given the capacity constraints of carriers. Estimates of supplies are based on rainfall-runoff and evaporation from major storages, while irrigation demands are based in part on PRIDE model output. Cost is imposed by 'penalties' associated with the use of a carrier.

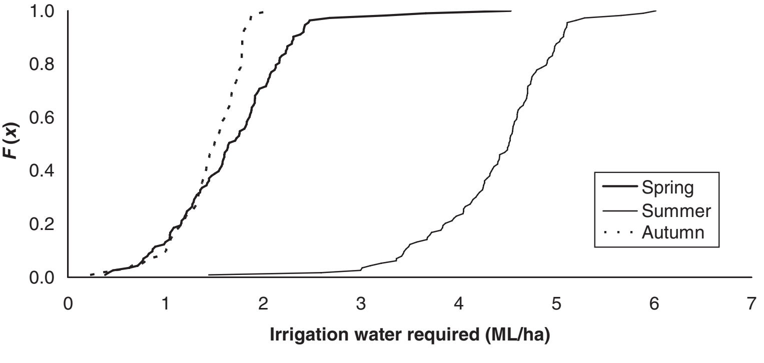

Figure 1 Cumulative distribution functions of supplementary crop water requirements for perennial pastures in the Rodney Irrigation Area.

Initial allocations contain a significant amount of information about final allocations (Figure 2). For example, for initial allocations up to 85 per cent, the highest final allocation is 100 per cent. At the other end of the spectrum, according to the historical series, initial allocations must be at least 134 per cent for final allocations to reach 220 per cent. There is a high degree of uncertainty in the middle, with some years showing no or little increase on initial allocations and other years having large upward revisions.

The ability of allocations to support irrigation throughout the Goulburn system depends on seasonal conditions. That said, at allocations below about 80 per cent, there is very little mixed cropping and grazing irrigation and the dairy industry has to buy in some feed grain. At allocations of around 100 per cent, the dairy industry starts to provide the bulk of feed requirements from pastures and mixed cropping and grazing irrigates some crops. Once allocations are above about 140 per cent, most areas are able to be irrigated.

3. Modelling decision making under hydroclimatic uncertainty

In this paper, horticulture aims to maximise the expected net present value of its fruit trees. Mixed farmers are expected gross margin maximisers (where gross margins are defined as revenues minus costs, with costs other than water held fixed). The dairy industry seeks to provide sufficient energy for their herd (from a mix of annual pastures, perennial pastures and a bought-in feed grain) at least expected cost. The basic decision is on crop areas to irrigate, up to a fixed maximum irrigable area per crop. The complex crop yield-water trade-off is not modelled: as the season progresses, irrigators may only reduce areas previously irrigated. Water trading is conducted to support the irrigation plan (i.e. buying to make up a water deficit or selling a surplus). The problem basically involves weighing the benefits of water use, profits from crops harvested or feed grain avoided, against its opportunity cost, the temporary water market price. Uncertainty in hydroclimatic variables clouds both the benefits and costs of water use.

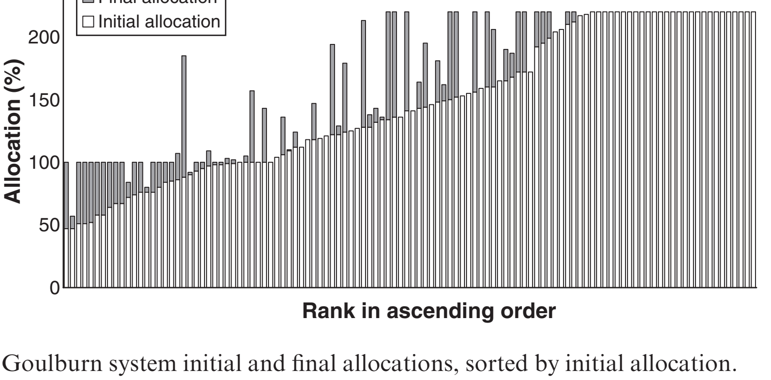

Figure 2 Goulburn system initial and final allocations, sorted by initial allocation.

All trade is assumed to occur through an institution similar to Watermove, the public water exchange run weekly through the irrigation season by Goulburn-Murray Water (see http://www.watermove.com.au).

Discrete stochastic programming is used to choose optimal crop areas to irrigate (up to a predetermined maximum for each crop) when uncertainty pervades the decision making environment. The technique requires the characterisation of uncertain variables into discrete states of nature, along with beliefs regarding probability of occurrence. Given the desirability of parsimony, supplementary crop water requirements for each of the three seasons are limited to a 'wet' (low water requirement) state versus a 'dry' (high water requirement) state, and final allocations (given an initial allocation) are limited to a 'high' versus a 'low' state.

States of nature are based on hydroclimatic data taken from 112-year model runs of PRIDE and GSM. Additional data including maximum crop areas, gross margins, and dairy herd sizes were estimated from Goulburn-Murray Water's Culture Census (Douglass *et al.* 1998) and the Victorian Department of Primary Industries (DPI) Water Policy Model output. Information on cow energy requirements and pastures was estimated based on Armstrong *et al.* (2000) and data provided by the Victorian DPI.

3.1 Discrete stochastic programming

This irrigation problem, as is the case for most agricultural problems (Anderson *et al.* 1977), is sequential or embedded: decisions are spread through time, with later decisions affected by both earlier decisions and uncertain events which have come to pass in the meantime.

Discrete stochastic programming is commonly regarded as the best way to handle embedded risk (Hardaker *et al.* 1991; Torkamani and Hardaker 1996; Dorward 1999). The technique was introduced by Cocks (1968) and extended by Rae (1971b) to cover a variety of assumptions regarding information and utility.

Problems involved with applying the technique include the 'curse of dimensionality' and high costs of model development and data acquisition. Rae (1971a) and Dorward (1999) discuss some preconditions that should apply before developing a discrete stochastic program. Hardaker *et al.* (1997) suggest limiting the number of stages and states of nature at each stage to two or three, while Hardaker *et al.* (1991) and Rae (1971a) provide other methods for overcoming dimensionality problems.

Perceived difficulties notwithstanding, the technique can be used to generate much useful information, including optimal tactical adjustments (Kingwell *et al.* 1993); the benefits of modelling tactical adjustments (versus implementing a fixed plan) (Cocks 1968; Rae 1971a,b; Kingwell *et al.* 1993); and the value of additional information (in particular, the value of perfect information, or the flipside, the cost of uncertainty) (Rae 1971a,b).

Taylor and Young (1995) and Turner and Perry (1997) use discrete stochastic programming to generate demand curves for irrigation water under uncertain water supplies (and also uncertain precipitation in the case of Taylor and Young (1995)).

In Taylor and Young (1995), the water transfers in question had already occurred, and their aim was an *ex post* evaluation of the efficiency of these transfers. Turner and Perry (1997) used the irrigation demand curves to assess the quantity of water that might be released from agriculture to support instream flows. While these two papers are ostensibly concerned with water markets, water markets are not modelled explicitly. Thus, decision making incorporates uncertainty in water supplies but not uncertainty in water market prices.

Calatrava and Garrido (2005) identify a research gap in simulating water markets under uncertainty. They model a water market where irrigators trade with other irrigators in a region in Spain. Binding planting decisions are made early in the year (stage 1) subject to uncertainty in water availability and hence uncertainty in water market prices. Water markets are modelled using the spatial equilibrium approach once uncertainty in water availability is resolved (stage 2). An iterative procedure is followed, with expected market prices in each state of nature progressively refined until the equilibrium water markets prices calculated in stage 2 are equal to the expected water market prices used in stage 1.

This paper also includes explicit consideration of uncertainty in water market prices, and incorporates this into farmer decision making. However here, water markets are staggered in time, with one run at the beginning of each season, while uncertainty still pervades the decision making environment. In addition, no attempt has been made to force them to clear. As in Watermove, irrigators enter the auction without knowing the bids of the other participants, and market imbalances are not 'corrected'. Thus, while irrigators make plans assuming water will be able to be freely traded at expected prices, this may not be borne out.

3.2 Seasonal water use and trading as a discrete stochastic program

3.2.1 Probability model

The first step in constructing a discrete stochastic program is to specify the probability model: a sequence of decisions, events and information (Rae 1971a). Figure 3 shows the probability model for the three-season irrigation and water trading problem. The dashed boxes represent points at which farmers make decisions and a branching represents a change in information. The same probability model applies to each industry.

The season starts with an initial allocation. Based only on this information, farmers have an opportunity to enter the spring water market. This decision is represented by the set X1.

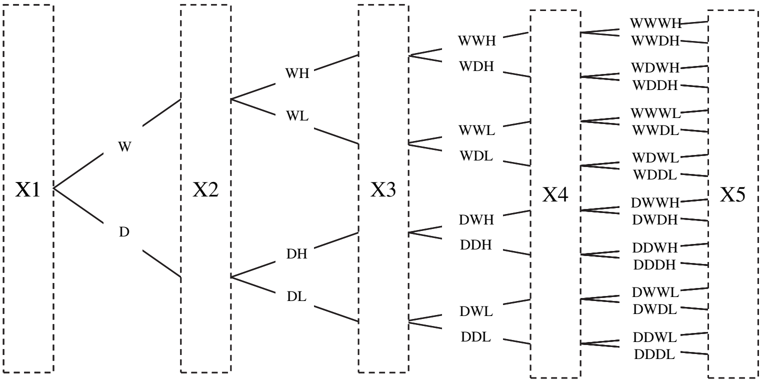

Figure 3 Decision tree representation of the discrete stochastic program.

After the spring water market is run, spring supplementary water requirements are revealed as either wet (W) or dry (D). Irrigators thus know whether spring is wet or dry before they decide which crop areas to irrigate, represented by the set X2. However, they do not know future seasonal conditions or whether allocations will be revised upwards significantly.

It is assumed that the final allocation is revealed as either high (H) or low (L) at the beginning of summer. Irrigators then have the opportunity to enter the summer water market (set X3), however, they do so not knowing summer or autumn supplementary water requirements.

After the summer water market is run, summer supplementary water requirements are revealed as wet or dry, and farmers decide whether to continue irrigating crops. The only source of uncertainty at this stage is autumn supplementary water requirements. This is not revealed before the autumn water market is run, so set X4 includes both summer irrigation decisions and autumn water market decisions.

Autumn supplementary water requirements are assumed known before decisions regarding autumn irrigation, X5, are made. The irrigation year has now revealed itself as one of 16 types, ranging from all seasons wet and allocations high through to all seasons dry and allocations low.

To summarise the information structure: all values for the past are known, values for the present are sometimes known (each season, supplementary water requirements are not known when the water market is run, but are known before irrigation decisions are made), and as discussed below, knowledge of the present can inform future probabilities (a wet summer is relatively likely to follow a wet spring).

3.2.2 Algebraic representation

The algebraic representation of the discrete stochastic program for horticulture is provided below. The structure of the problems for mixed farming and dairy is the same, although their objective functions differ.

In a discrete stochastic program, constraints must hold in each state of nature, and the objective function is formulated as an expected value (Cocks 1968).

The regional horticultural industry's problem is to maximise the expected net present value of its fruit trees.[2] The objective function thus includes revenues or costs from water market transactions, variable costs of water delivery, and the expected net revenue from sales of fruit at the end of the season. These terms enter the objective function in accordance with their probability of occurrence. Constraints on the maximisation include a land constraint (reflecting in later seasons the assumption that crops cannot be brought into production midway through the irrigation year), a water constraint (where cumulative water use is limited to allocated entitlement at that point in time, plus (minus) purchases (sales) of water), and standard non-negativity constraints.

More formally,

$$\begin{aligned}\underset{\delta,ws}{\mathrm{Max}}\{ENPV\} = {} & twp^1 \times ws^1 - \sum_i \pi_i \times p_w \times \delta_i^1 + \sum_i \sum_m \pi_{im} \times twp_{im}^2 \times ws_{im}^2 \\ & - \sum_i \sum_j \sum_m \pi_{ijm} \times p_w \times \delta_{ijm}^2 + \sum_i \sum_j \sum_m \pi_{ijm} \times twp_{ijm}^3 \times ws_{ijm}^3 \\ & + \sum_i \sum_j \sum_k \sum_m \pi_{ijkm} \times \left(\left(\sum_{t=0}^{20} \frac{1}{(1+r)^t} \right) \frac{gm}{w_k^3} - p_w \right) \times \delta_{ijkm}^3\end{aligned}$$

subject to:
spring

$$\begin{aligned}&\frac{\delta_i^1}{w_i^1} \le a \\ &\delta_i^1 + ws^1 \le A^1 W && i = 1 \ldots 2 \\ &\delta_i^1 \ge 0\end{aligned}$$

summer

$$\begin{aligned}&\frac{\delta_{ijm}^2}{w_j^2} \le \frac{\delta_i^1}{w_i^1} && i = 1 \ldots 2 \\ &\delta_i^1 + \delta_{ijm}^2 + ws^1 + ws_{im}^2 \le A^m W && j = 1 \ldots 2 \\ &\delta_{ijm}^2 \ge 0 && m = 1 \ldots 2\end{aligned}$$

[2] This representation of horticulture's problem is an oversimplification as it implies horticulture will repeat the irrigation decision for the next 20 years. As horticulture is a high value and relatively small industry, trees are always irrigated fully, and so this assumption does not impact on the results. Taking the net present value over 20 years is an arbitrary assumption, but again, one that makes no difference in the current context.

autumn

$$\frac{\delta^3_{ijkm}}{w^3_k} \le \frac{\delta^2_{ijm}}{w^2_j} \qquad i = 1 \ldots 2$$

$$\delta^1_i + \delta^2_{ijm} + \delta^3_{ijkm} + ws^1 + ws^2_{im} + ws^2_{ijm} \le A^m W \qquad j = 1 \ldots 2,\; k = 1 \ldots 2$$

$$\delta^3_{ijkm} \ge 0 \qquad m = 1 \ldots 2$$

where a is the maximum irrigable area (ha), w is the supplementary water requirements (ML/ha), δ is the total water applied (ML), twp is the temporary water market price (\$/ML), ws is the water sales (negative for purchases) (ML), W is the water entitlement (ML), A is the allocation (%), p_w is the delivery price of water (\$/ML), gm is the gross margin (\$/ha), r is the interest rate (% p.a.), and π is the probability of subscripted state occurring. Superscripts 1, 2 and 3 refer to spring, summer and autumn, respectively; subscript i refers to state of nature for spring supplementary water requirements (wet versus dry); subscript j refers to state of nature for summer supplementary water requirements (wet versus dry); subscript k refers to state of nature for autumn supplementary water requirements (wet versus dry) and subscript m refers to state of nature for final allocations (low versus high).

3.2.3 States of nature and beliefs

Variability in supplementary crop water demands is characterised into two states per season: water required if the season is 'wet' and water required if the season is 'dry'. Values for these states are formed by first dividing the 112-year PRIDE series for each crop into wet and dry groups based on the median crop water requirement, and then taking the average of each group. While there are only two states of nature for supplementary water requirements per season, combined this gives eight (2^3) crop water demand patterns over the year.

Thus wet and dry seasons have the same *a priori* probability of occurrence for all crops (50 per cent). There is a moderate correlation between spring and summer conditions and a weaker correlation between summer and autumn conditions in the PRIDE data, and so conditional probabilities of 75 per cent for a wet summer following a wet spring and 55 per cent for a wet autumn following a wet summer were included.

To form states of nature for final allocations, the 112-year series (taken from the GSM) was first grouped by initial allocation into eight bands: initial allocations less than 60 per cent, initial allocations between 60 and 80 per cent, initial allocations between 80 and 100 per cent, etc, up to initial allocations greater than 200 per cent (see Table 1). The pattern of final allocations for each band of initial allocations was evaluated for a 'natural' grouping of high and low values, aiming for some degree of homogeneity within groups. (A more formal procedure, such as Gaussian quadrature (Miller and Rice

Table 1 Market-clearing prices across states of nature

Initial allocation	Final allocation	Crop water demand states of nature							
		WWW	WWD	WDW	WDD	DWW	DWD	DDW	DDD
< 60	Low	121.48	124.28	108.69	103.44	127.75	172.43	161.95	182.95
	High	70.06	66.58	63.48	77.19	61.41	66.42	78.05	83.21
60–80	Low	97.26	96.34	101.35	93.24	118.44	98.23	110.75	91.91
	High	70.06	66.58	63.48	77.19	61.41	66.42	78.05	83.21
80–100	Low	70.06	66.58	63.48	77.19	61.41	66.42	78.05	83.21
	High	35.11	38.78	40.92	38.82	42.75	44.71	41.11	48.61
100–120	Low	41.77	47.27	42.07	56.90	50.98	45.51	51.92	51.58
	High	35.11	34.65	34.33	38.82	42.50	43.98	38.55	48.61
120–140	Low	29.78	33.29	31.17	33.22	42.50	42.83	38.55	48.35
	High	15.05	13.68	12.70	11.64	12.61	11.56	10.80	9.96
140–160	Low	15.05	13.68	12.70	27.95	28.08	28.40	27.60	28.99
	High	15.05	13.68	12.70	11.64	12.61	11.56	10.80	9.96
160–180	Low	15.05	13.68	12.70	11.64	12.61	11.56	22.22	24.11
	High	15.05	13.68	12.70	11.64	12.61	11.56	10.80	9.96
> 180		15.05	13.68	12.70	11.64	12.61	11.56	10.80	9.96

1983), might have been followed.) Once high and low groups were formed, averages were taken to represent the values for the high and the low final allocation states of nature. If the ‘low’ state of nature value was less than the upper bound on the initial allocation band, the average was replaced with the upper bound (to ensure compliance with the rule that allocations must not decrease). The relative frequency of each group in the 112-year series was taken as the probability of occurrence.

Appels *et al*. (2004) assume a high degree of dependence between crop water demands and final allocations (as greater water use implies lower dam levels and hence increases to allocations are less likely). Somewhat surprisingly, this correlation was not evident in the PRIDE and GSM series (except for very extreme conditions), and so final allocations and crop water demands are modelled as independent variables.

Rather than be introduced as an independent source of uncertainty, expectations about water market pool prices are assumed to be linked directly to supplementary crop water demands and allocations. Although there is a growing body of market data, and Brennan (2006) estimates an econometric relationship between Watermove pool prices and allocations and rainfall, the approach here is to derive water market price expectations from a perfect information base case.

Models representing the dairy, horticulture and mixed farming industries in each region are solved analytically to provide an optimal irrigation and water market plan as a function of the temporary water market price, assuming both final allocations and seasonal supplementary crop water demands are known. Optimal plans vary with final allocations (which affect water market plans) and crop water demands (which affect irrigation plans).

The conventional approach to modelling water allocation via water markets is the spatial equilibrium approach (Samuelson 1952; Takayama and Judge 1964). To mimic Watermove and avoid linearising demand curves, an alternative Walrasian auction-type process is followed here. A hypothetical price is proposed, and using the analytical solutions discussed above, each industry's excess demand (excess supply) and associated bid (offer) price is entered into a water exchange. Trade is set as the minimum of supply and demand, and the proposed price is refined until equilibrium is reached when trade is maximised. A pool price is then calculated as the mid-point between the offer and bid prices of the marginal seller and buyer.

Pool prices for each of the 120 different hydroclimate year types (16 different states of nature for each of seven initial allocation bands and eight states for the eighth band) are shown in Table 1.

Expected prices in each of the spring, summer and autumn water markets are derived from these pool prices, by weighting the price for each possible future state by its probability of occurrence. For example, if allocations of 100 per cent and wet-wet-wet conditions were known with certainty, the market-clearing price would be \$70.06/ML (second row, first column of Table 1). If allocations were 100 per cent but conditions were wet-wet-dry, the market-clearing price would be \$66.58/ML (second row, second column). Consider an autumn water market under uncertainty, with initial allocations less than 60 per cent, high final allocations, and spring and summer both wet. Given the wet summer, there is a 55 per cent chance of a wet autumn. The expected water market price for autumn is calculated as $0.55 \times \$70.06/\text{ML} + 0.45 \times \$66.58/\text{ML} = \$68.49/\text{ML}$.

Similarly, if allocations were 100 per cent, spring wet but summer dry, expected prices in autumn would be $0.45 \times \$63.48/\text{ML} + 0.55 \times \$77.19/\text{ML} = \$71.02/\text{ML}$. Going back further in the year, expectations in the summer market following final allocations of 100 per cent and a wet spring would be weighted across the probability of summer being wet versus summer being dry, that is, $0.75 \times \$68.49/\text{ML} + 0.25 \times \$71.02/\text{ML} = \$69.13/\text{ML}$.

When this methodology is followed, farmers are indifferent about the exact timing of buying or selling water (so long as they can cover their immediate irrigation-related demands), as the expected cost of purchasing water (or expected profits from selling water) will be the same whether the purchase is conducted immediately or later in the year.

Market-clearing prices for low allocations reported in Table 1 are low relative to recent history. This can partly be explained by the out-of-date data for land use and gross margins. However, it should also be noted that for allocations only slightly less than those in the table, aggregate supply and demand curves for water become highly inelastic and equilibrium pool prices increase to around \$1000/ML, consistent with actual water market results.

3.2.4 Assumptions about information and expectations

Probabilities for states of nature are based on the historical relative frequency of occurrence, taken from the 112-year PRIDE and GSM simulations. This is generous in that it assumes irrigators have these full historic series on which to base beliefs, but is restrictive in that it assumes that this is the only source of information, in particular, it ignores Southern Oscillation Index-based forecasting techniques.

Such rationality in forming expectations may be unrealistic. Though dated now, McGuckian *et al*. (1999) found in workshops with irrigators that information about the probability of allocations increasing through the season and the relationship between allocations and the market price for water were key areas where better information was required.

4. Results

4.1 Irrigation plans under uncertainty

Behaviour under uncertainty could not be expected to replicate behaviour under certainty as (a) the structure of the problem is different, and (b) the weighted expected prices mean that irrigators face different incentives. Each industry does its best given the structure of its problem and the incentives it faces, and in that sense it is efficient. However, at an aggregate level, any discrepancy in the allocation of water from that derived in the perfect information base case is a departure from efficiency.

For horticulture across all states of nature, and dairy and mixed farming at high initial allocations, plans under uncertainty are identical to those under certainty: to irrigate all areas in each state of nature. In these situations, land rather than water is the binding constraint.

At low and medium initial allocations, binding decisions must be made on limited information, and dairy and mixed farmers may irrigate crops that they would have been better not to, or they might choose not to irrigate, when in retrospect they should have. Inefficiency is particularly evident when irrigators water areas which are subsequently abandoned. In addition, farmers tend to hold water surplus to requirements because they are not sure how much will be required at the end of the year when there are no more opportunities to trade.

To get some handle on the significance of hydroclimatic uncertainty, consider planned annual water use under uncertainty versus certainty. For dairy, with initial allocations below 80 per cent, differences in planned use under uncertainty vis-à-vis certainty approach 20 per cent in some situations (see year DWWH in Figure 4 for allocations less than 60 per cent). Differences in behaviour under uncertainty versus certainty for the dairy industry are constrained to some extent by the requirement to provide at least 50 per cent of energy requirements from irrigated pastures. Mixed farming has no such constraint, and the difference in planned water use under uncertainty is striking, with the industry often planning to use two or three times as much water, or less water, under uncertainty relative to certainty. In particular, the potential for high final allocations when initial allocations are between 100 and 140 per cent tends to induce significantly higher levels of planned water use (Figure 4).

All industries do worse on average under uncertainty, with expected costs for the dairy industry 5–7 per cent higher under uncertainty (Figure 5). The range in expected costs under uncertainty (that is, across states of nature) is smaller than under certainty, due primarily to the methodology employed to form water market price expectations. That is, in early water markets, when only limited information on the year is available, water market prices are lower, for example, than when a year is known to be water-scarce for certain, because there is still the possibility that conditions will ameliorate. The converse holds for water-plentiful years, such that the range in expected water market prices is compressed under uncertainty relative to certainty.

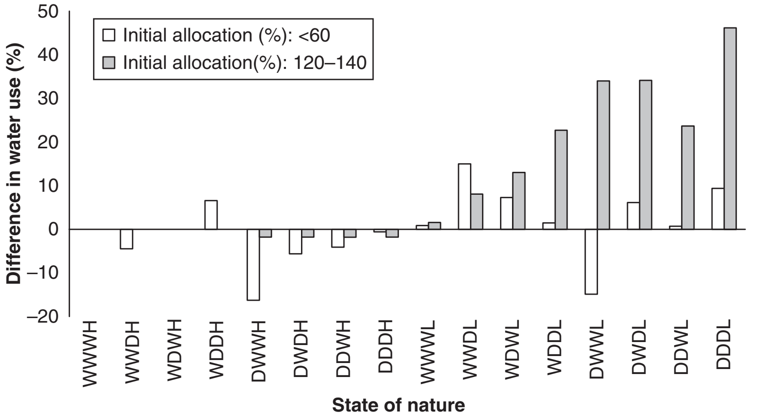

Figure 4 Difference in planned water use, expressed as a percentage of water use under certainty.

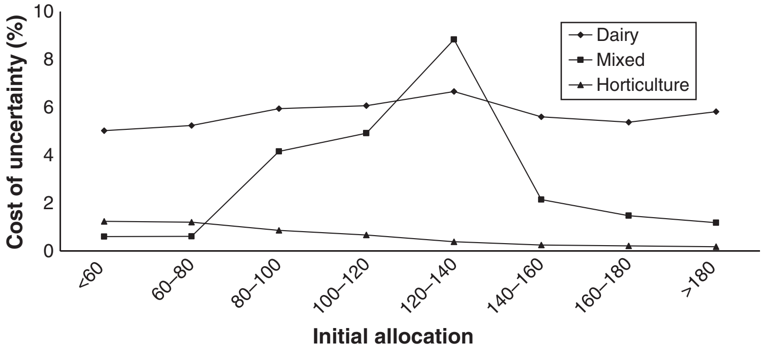

Figure 5 The cost of uncertainty, expressed as a percentage of expected values (costs for dairy) under certainty.

The cost of uncertainty is low for horticulture (Figure 5). Horticulture only has one irrigation plan, to irrigate all available areas, and thus no inefficiencies arise from pursuing the wrong irrigation plan. There are however costs associated with holding extra water to cover a dry autumn. This cost increases as the opportunity cost (the temporary water market price) increases, and so is greatest at low initial allocations. The other reason for the low cost of uncertainty is that water sales and purchases are a smaller proportion of total gross margins.

The highest expected costs of uncertainty for mixed farming occur in the 100–120 per cent and 120–140 per cent initial allocation bands, at 5 per cent and almost 9 per cent respectively (Figure 5). In the very low allocations, mixed farmers plan to irrigate very little, regardless of the state of nature that eventuates, and the costs of uncertainty are minimal. In the very high allocations, mixed farmers will always irrigate all areas, and again costs are low. But in the middle ranges, irrigation is optimal if 'high' final allocations eventuate, but it would be more profitable to sell the water instead if 'low' final allocations eventuate, and so irrigators will always have made the wrong choice *ex post* in some states of nature.

There are two notable differences in outcomes under uncertainty for mixed farming vis-à-vis dairy and horticulture:

- For dairy and horticulture, uncertainty compresses the range in costs and gross margins respectively. This is not the case for mixed farming in the middle allocations. That is, mixed farming gross margins under uncertainty are not only lower on average but also more variable than under certainty.
- For dairy and horticulture, the same basic pattern in which states are favourable (that is, lower costs for dairy and higher gross margins for horticulture) versus unfavourable prevails under uncertainty. For mixed farming however, at low allocations, the introduction of uncertainty changes the relative desirability of states, due to the different water market prices.

4.2 Water markets under uncertainty

As water market price expectations are based on weighted averages across future seasons of the irrigation year, farmers are indifferent as to the exact timing of trade. It might be reasonable to assume that farmers act to minimise trades and hence avoid any unnecessary transactions costs. In this case, if irrigators plan to purchase water in all possible future states of nature, they would buy the minimum volume they will require (as long as immediate irrigation requirements can be met). If they plan to sell water in every possible state of nature, they would sell the minimum amount they will have in surplus over all possible future states. If they plan to buy water in some situations and sell in others, we assume they make no immediate sales or purchases but rather wait for further information before entering the water market in the future.

Given this assumption, a high proportion of water (often upwards of 50 per cent of the total year trade) is traded in spring, when there is still a high degree of uncertainty (unlike in Calatrava and Garrido (2005), where trade occurs when uncertainty is resolved). However, significant volumes also trade in summer and autumn, suggesting that water markets not only serve a role in allowing water to move to highest marginal value under certainty, but are also an important means of tactical adjustment.

The highest volumes trade in spring following very low initial allocations. In these years, mixed farmers sell water and dairy farmers buy water regardless of the state of nature. The least active spring market occurs for initial allocations between 120 and 140 per cent, as both final water availability and water demands are highly uncertain in this range, so farmers wait for more information before committing to either buy or sell.

When the summer market is run, irrigators have the advantage of knowing final allocation and spring conditions, and thus the greatest volumes tend to trade in years where final allocations are low and spring is dry. A lot of water also trades when initial allocations were below 80 per cent, as excess demand is carried over from spring, particularly when spring is dry, adding to demand, and allocations are high, adding to supply. However, for initial allocations above 80 per cent, very little may trade in summer if final allocations are high and spring is wet. The exception is when initial allocations were between 120 and 140 per cent, as the high degree of uncertainty in spring inhibited trade at that time.

Generally less is traded in autumn. Volumes are not as dependent on allocation levels, as irrigators used the summer market to adjust to this information. Rather autumn markets are used to adjust to summer seasonal conditions, so that often, very little is traded in the event that summer is wet.

In summer and autumn, there is a tendency for actual prices to be somewhat lower than expected. Decisions not to irrigate are binding, and water that is no longer able to be used in production has zero value to the irrigator. We assume irrigators in this situation offer to sell water for \$0/ML and this tends to depress prices.

The biggest differences between actual and expected prices occur when demand far exceeds supply, and prices end up between \$500–\$550/ML. As noted already, these water markets are not simulated as clearing, with the largest imbalances occurring when expected prices are not sufficient to induce mixed farmers to sacrifice production and sell water to dairy farmers (because there is the chance that conditions will improve and mixed farmers would have been better to irrigate). This suggests additional costs to uncertainty than those based solely on the spring discrete stochastic program. Comparing the end-of-year (that is, post-market) actual costs (dairy) or gross margins (mixed farming/horticulture) with expected costs/gross margins at the beginning of the year shows that these market-related inefficiencies can in some situations impose even greater costs than hydroclimatic uncertainty *per se*.

Another set of expected prices might do a better job of clearing markets under uncertainty, and the problem is somewhat exaggerated here by the fact that markets are seasonal rather than weekly. On the other hand, this modelling assumes all market participants have the same set of price expectations, which tends to facilitate trade. In real life, it seems unlikely that irrigators would be able to perfectly anticipate water market prices, and thus may incur costs due to an inability to sell or secure water at the prices expected when plans are being formed.

5. Discussion

The results above were derived by (a) comparing the discrete stochastic programming output to a perfect information base case, and (b) comparing the discrete stochastic programming plans to post-market actual outcomes. Implicit in this comparison is that the discrete stochastic program is a good representation of reality. In particular, that the hydroclimate takes on one of its state of nature values.

It is difficult to assess the adequacy of the methodology for forming states of nature. However, since these methodologies involved taking averages, the extremes present in the actual hydroclimate are avoided. Including these extremes in the modelling would likely result in bigger differences in planned behaviour under uncertainty relative to certainty, and hence larger estimated costs of uncertainty.

In addition, no matter what methodology is chosen for forming states of nature, because the probability model is just a simple abstraction of the true uncertainty facing farmers, additional costs are likely to arise in adjusting to actual conditions as the season progresses.

6. Conclusions

Hydroclimatic uncertainty is a feature of the decision making environment for irrigators, and many have pointed to the modelling of tactical adjustments to seasonal hydroclimatic conditions as a desirable extension to water allocation modelling. This paper attempts to address this by explicitly considering the impacts of hydroclimatic uncertainty on irrigator decisions and water markets in the Goulburn system.

Discrete stochastic programming proved a useful means of modelling behaviour under uncertainty (see Adamson *et al*. (2007) for an alternative approach based on the state-contingent framework). It is intuitively appealing and relatively easy to implement.

In environments of abundant water, hydroclimatic uncertainty is not important: land rather than water is the binding constraint. While such plentiful supplies are frequently found in the simulated series, increasing demand for water, changes to policy (including the Victorian government's 'sales deal', which reserves 20 per cent of water for the environment), and possibly, changes to the underlying hydroclimate (towards a drier, more volatile climate) means that water made available to irrigators is not often likely to reach these levels in future. When water is scarce, hydroclimatic uncertainty does have a significant impact on plans to irrigate and the performance of water markets; this impact varies depending on actual seasonal conditions and across regions and industries.

The estimated costs of hydroclimatic uncertainty in the Goulburn system are uniformly low for horticulture, but range between 5–7 per cent for dairy, and between 1–9 per cent for mixed farming, equivalent to between \$1–4 million per annum. These figures can be used to give, for example, some indication of the potential benefits of improved hydroclimatic forecasting and adoption of this information by irrigators. As noted in the discussion, these figures may underestimate real costs as they assume that the discrete stochastic program itself is a perfect representation of reality and farmers are able to predict well water market prices under uncertainty.

Given a lack of data, there was a need to make assumptions about irrigator knowledge, beliefs and attitudes to uncertainty. The approach was to follow as basic a methodology as possible, so irrigators are modelled as risk neutral, with 'rational' expectations and beliefs. It is difficult to assess how well this methodology performed. It is interesting to note however that using equilibrium prices under certainty as the basis of expectations under uncertainty did not do an excellent job of rationing water use. This is particularly true in the middle allocation range, where the potential for high final allocations means mixed farmers plan to irrigate much more under uncertainty.

The results of the study described in this paper indicate that explicit consideration of hydroclimatic uncertainty, particularly in the context of water markets, is an important aspect of water allocation modelling. Water allocation studies with models that do not account for this uncertainty may produce significantly biased results and conclusions (for example, they may overstate the benefits of a policy change because they assume water will be allocated efficiently). As the formulation and evaluation of water policy options rely heavily on water allocation models, more attention should be paid in these models to explicitly incorporate the impacts of uncertainty on farm irrigation plans and water trade.

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