INCORPORATING BEHAVIOURAL AND BIOPHYSICAL FACTORS IN IRRIGATION DEMAND MODELLING

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ABSTRACT

It is clear that irrigators around Australia are facing an increasingly complex and uncertain farming atmosphere. The operation of water markets, the potential for reduction in entitlements and seasonal allocations, climate change, water policy changes, ongoing drought conditions, and other challenges, have meant that decision-making on the farm has arguably never been harder. As a result, water ordering by irrigators has become a more complex procedure compared to 10 or 15 years ago. Traditionally, irrigation demand models have focused on the biophysical factors that affect water orders. This has become increasingly untenable as human behavioural factors clearly play an important role.

In this paper we present the results of an innovative approach to modelling irrigation water demand by integrating key behavioural and biophysical factors. We have modelled human behaviour by incorporating two conflicting farming objectives: maximize gross margins and minimize risk of suffering a water shortage. A compromise set of crop mixes are calculated based on varying degrees of risk-averseness and profit focus amongst irrigators. The expected crop water requirements for these crop mixes are then calculated based on biophysical factors. The advance water orders are estimated based on these crop water requirements and a range of rainfall outlooks, which are also related to risk preferences. The model also incorporates variability in crop sowing dates and uncertainty in soil, crop, on-farm irrigation properties. As a result, the model produces a probability distribution of water orders for each day of the irrigation season. This information can then be used by irrigation system operators, planners and modellers to make informed and transparent decisions.

The model has been successfully applied to the Shepparton Irrigation District and initial results of the model's application to the Finley Irrigation District (NSW) are presented in this paper.

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INTRODUCTION

The term "irrigation demand" can refer to the volume of water ordered by irrigators from the water supply authority, the irrigation application volume, or the crop water requirement. The Next Generation Irrigation (NGenIrr) demand model estimates these three demand volumes at a daily time-step for an irrigation farm/region. The model is intended to be used to help with irrigation systems operations, planning and management. Thus the model may be useful for rural water supply and irrigation companies, regulatory agencies dealing with water resources allocation, and other stakeholders interested in water policy/reform related to the irrigation sector.

Some of the common irrigation demand modelling approaches include:

- Mathematical programming models (e.g. Jayadi *et al.* 2000; Hall 2001; Haouari and Azaiez 2001; Jairaj and Vedula 2003)

- Biophysical (process) models (e.g. Hook 1994; Dereffye and Houllier 1997; Ozier-Lafontaine *et al.* 1998; SKM 1998; Perez *et al.* 2002; DNR 2003; Hornbuckle *et al.* 2005)
- Empirical time-series models (multi-variate regression, artificial neural networks, etc.) (e.g. Abu Rizaiza and Al-Osaimy 1996; Smajstrla and Zazueta 2002; Pulido-Calvo *et al.* 2003; Pulido-Calvo *et al.* 2007)

Programming models aim to represent the farming decision making process by optimizing one or more objectives, e.g. maximize farm gross margins, minimize labour hours, etc. The decision variables tend to be crop areas and the model uses constraints to represent technical, biophysical, and financial considerations in the decision making process. The irrigation demand is calculated by multiplying the crop areas by appropriate estimates of crop water requirements or usage (in ML/ha). Biophysical models concentrate more on the crop growth stages, soil water movements, climatic variables and irrigation processes. Normally the crop areas are model inputs. These models are useful to estimate the impacts of different management practices on irrigation demand. Time-series models rely on historic (observed) data to derive cause-affect relationships between different variables. These models are useful for short-term forecasting but are not very useful for policy and management analyses.

The NGenIrr demand model integrates mathematical programming and biophysical modeling approaches to estimate irrigation demand. The model can be used for forecasting purposes and analyzing “what if” type of scenarios at the farm or district (region) level. The model relies on techniques used in multi-criteria decision analyses (Romero and Rehman 2003) and an existing biophysical crop-water model (Hornbuckle *et al.* 2005). Some background details about NGenIrr are provided in Zaman *et al.* (2008). In this paper, we discuss in more detail how the model integrates behavioral and biophysical factors affecting irrigation demand.

In the next section a description of how NGenIrr models irrigators’ behavior is provided. Then the key biophysical factors used in the model are described. The integration between these two types of factors is then discussed before the results of the model’s application to the Finley Irrigation District are presented. Then some general conclusions are provided at the end of the paper.

BEHAVIORAL FACTORS

In our modelling approach, we have selected two conflicting objectives to describe irrigators’ farming strategy: profit maximization and risk minimization. In particular we are focusing on the risk of suffering a water shortage during the season. As shown in Figure 1, these objectives tend to be in conflict and a compromise strategy needs to be taken. In the example farm, with an initial allocation of 50%, the irrigator can adopt a no risk strategy by sowing 50ha, so that the expected water usage is equal to the allocated volume (200ML). This option will yield an expected profit of $20,000. Alternatively, the irrigator may decide to accept more risk of water shortage to increase the expected profit and plant a larger area (e.g. 100ha) requiring 400ML of water over the season. In this option the expected profit is $40,000 but there is a high risk (80%) of suffering a water shortage as the water supply authority has announced that there is only a 20% chance of reaching the required allocation of 100% (400ML allocated volume). Of course there is a range of options between the two given in the example, depending on the relative weighting a irrigator gives to each of the conflicting objectives (maximising profit and minimising risk). Also the example can be extended to include different crops, with various expected water usages and profits (gross margins).

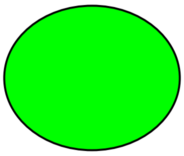
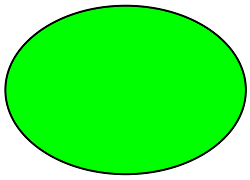
Example Farm: Irrigable area = 200ha Water Entitlement volume = 400 ML Expected profit = $400/ha Normal water usage = 4 ML/ha	***Example Allocation Scenario:*** Initial allocation = 50% (200 ML allocated volume) Final allocation probabilities: >=50% allocation = 100 % chance >=80% allocation = 80% chance >=100% allocation = 20% chance
Option 1: No Risk and Low Profit  Irrigation area = 50ha Expected profit = $20,000 Expected water use = 200ML Risk of water shortage = Chance of not getting 50% allocation = 100% – 100% = 0%	Option 2: High Risk and High Profit  Irrigation area = 100ha Expected profit = $40,000 Expected water use = 400ML Risk of water shortage = Chance of not getting 100% allocation = 100 %– 20% = 80%

Figure 1: Example Farm and Allocation Scenario

The NGenIrr model employs compromise programming optimization to capture this kind of trade-off behaviour. The basic assumption underlying this approach is that the optimal values of the two conflicting objectives can not be obtained (it is infeasible) and thus a compromise solution is identified based on the relative weightings between the two objectives.

The modelling framework requires the two objectives to be conflicting, without specifying what the objectives are. In addition, the coefficients of the objective functions have to be in terms of unit area, e.g. $/ha, % probability/ha, or hours/ha, etc. In our study we have adopted gross margin maximization ($/ha) and water usage minimization (ML/ha). These objectives were chosen as a practical representation of irrigators' behaviour given the available data. The latter objective has been used as a proxy for minimizing the risk of suffering a water shortage. It can be shown mathematically that the risk of suffering a water shortage during the season is directly proportional to the expected crop water requirement or usage (CWR) (see Figure 2). In the example provided, the irrigator starts to incur the risk of water shortage when the crop area exceeds 50ha. This is because the expected crop water requirement is 5 ML/ha and the current allocation volume is 250ML. As the irrigator plants a larger area, the chance of suffering a water shortage increases, as the allocation may not rise during the season. The degree of chance is related to the volume required for the crop and the rate of change in chance with respect to allocated volume. This rate is determined by allocation probabilities, which are normally published by the water supply authority. In the example provided in Figure 2, the rate is 0.13% chance/ML for allocations between 50-80% and 0.80 % chance/ML for allocations between 80-100%. Thus a risk averse irrigator my plant 60 ha, requiring 300ML of water, with a 7% chance of suffering a water shortage during the season. A less risk averse irrigator (and more profit orientated) may chose to plant 90 ha and be happy with a 60% chance of water shortage.

In future NGenIrr versions, it is intended to include another behavioural factor, which can be called "Activeness". This factor will measure to what extent an irrigator gathers information related to water orders. For example, some irrigators use soil probes and on-farm weather stations to track soil moisture conditions and evapotranspiration rates during the season. Others may base their water ordering decisions more on experience and "gut feel". Including such a factor will give more realism to our model and lead to further integration between behavioural and biophysical factors. At the moment this type of behaviour is captured simplistically in the model by specifying different scheduling methods (cumulative ETc or soil moisture deficit) and various over/under irrigation application rates.

Given that: chance of water shortage is proportional to volume of water required

Let: chance of shortage = k x volume required

Where: k = rate of change in chance with respect to allocated volume, this is determined by allocation probabilities.

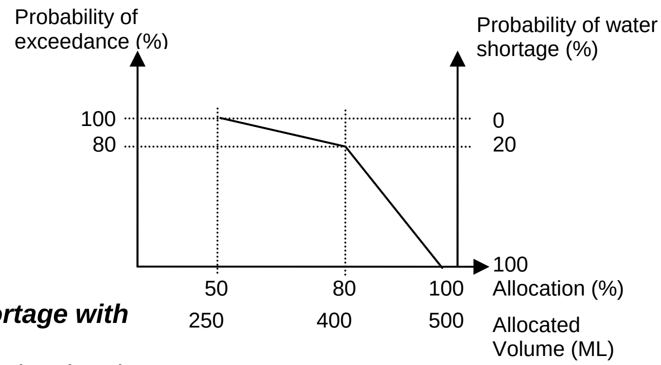
Then for a unit area of a crop: (chance of shortage / area) = k x (volume required / area)

Thus: chance of water shortage is proportional to crop water requirement (CWR)

Therefore: minimising CWR is equivalent to minimising chance of suffering a water shortage

Example Farm:
Irrigable area = 100ha
Water Entitlement volume = 500 ML
Expected crop water required = CWR = 5 ML/ha

Example Allocation Scenario:
Initial allocation = 50%
(allocations can not decrease)
Final allocation probabilities:
>=50% allocation = 100 % chance
>=80% allocation = 80% chance
>=100% allocation = 0% chance



Rate of Change in Chance of Water Shortage with respect to Allocated Volume (k):
This is the gradient of the line in the graph showing the allocation probabilities.
From 250-400ML: k = 20/150 = 0.13 % chance / ML
From 400-500ML: k = 80/100 = 0.80 % chance / ML

Risks with Different Crop Areas:

Crop Area (ha)	Water Required (ML)	Calculation	Probability of shortage (%)
40	200	Less than current allocated volume	0
50	250	Equal to current allocated volume	0
60	300	(300-250)*0.13	7
70	350	(350-250)*0.13	13
80	400	(400-250)*0.13	20
90	450	20 + (450-400)*0.8	60
100	500	20 + (500-400)*0.8	100

Figure 2: Relationship between crop water requirement and risk of suffering a water shortage

BIOPHYSICAL FACTORS

The main biophysical factors associated with irrigation demand include: crop factors, soil properties, climate variables, and irrigation system characteristics. These factors are combined in the NGenIrr model to form unique cropping units (see Figure 3). These cropping units can be considered similar to paddocks, whereby you can have two cropping units with the same crop and irrigation system but different soil types.

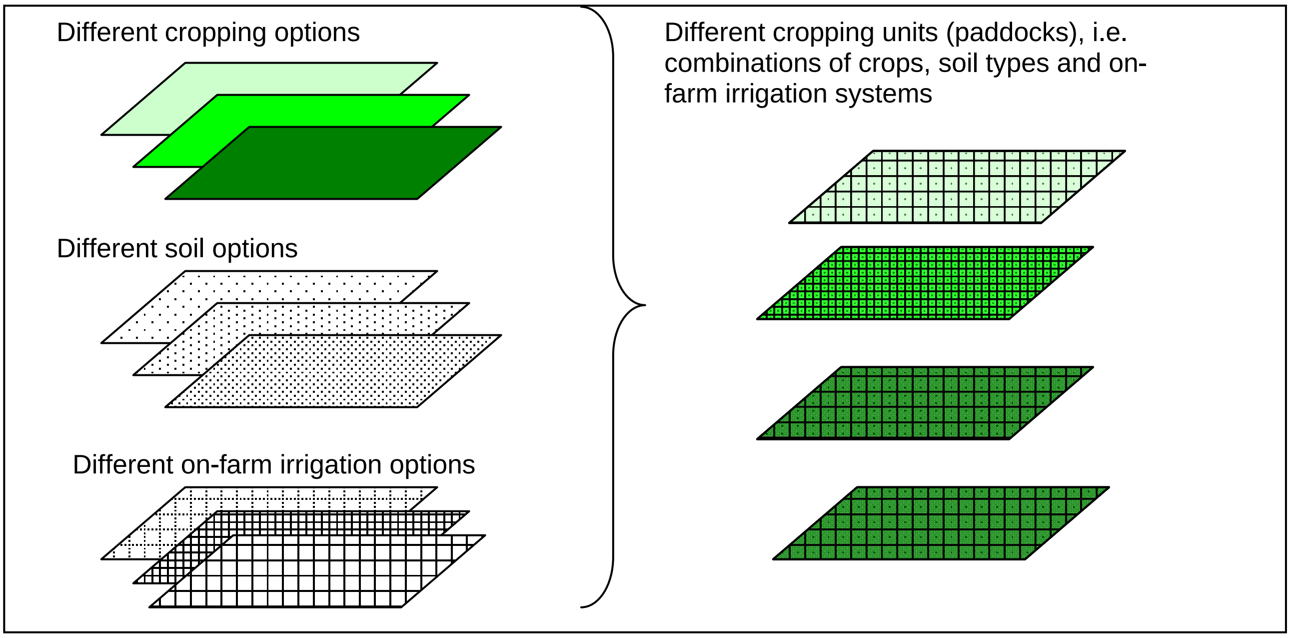


Figure 3: Formation of Cropping Units from Different Crops, Soils and On-farm irrigation Systems

In the current version of the model, the cropping units are not spatially connected, i.e. runoff from one cropping unit does not run onto another unit. In the model, a proportion of any runoff from the cropping units is collected in the on-farm storage/recycling system and the remainder is collected in the drainage system.

INTEGRATION

The behavioural factors are integrated with the biophysical factors through two modelling processes. The first one integrates the factors by setting cropping unit areas through multiobjective optimization. This process represents the tradeoffs made at key points in the irrigation season, for example during sowing of crops. The second integration method is related to how irrigation water orders are rejected. Both of these methods are described in this section.

The optimization routine employs a compromise programming technique to find the trade-offs between different levels of risk-averseness and profit motivations. These different levels are entered into the model as relative weightings between the two conflicting objectives. The different weightings result in different compromise solutions (crop mixes) representing different trade-offs made by irrigators. Also constraints in the optimization routine take into account of other factors that influence cropping areas, e.g. expected water availability, financial capital, available land area, crop rotations, etc.

The second integration between behavioural and biophysical factors is involved in modelling the rejection of irrigation orders due to intense storms. As with irrigation scheduling, different irrigators will have different rainfall thresholds before rejecting an advance water order. This is incorporated by associating different rain-rejection events with different crops.

Another way behavioural and biophysical factors can be integrated is in the manner different expectations of rainfall are modelled. Before an advance water order is placed, the model takes into account differing expectations of daily rainfall, and therefore crop evapotranspiration (ETc) and soil moisture deficit. A very risk-averse irrigator may place an order with the expectation that there will be no rain over the coming days – despite the weather forecasts. Whereas other irrigators may take a bit more risk and place an order assuming there will be some rainfall in the days before the ordered water arrives to the farm. These attitudes will be reflected in the water order volume, which takes into account the expected crop water demand, irrigation requirement and delivery time from supply storage. Currently, in the model a conservative assumption of no rainfall during delivery time is used. It is intended that later versions of the model will implement this integration feature fully.

INCORPORATING UNCERTAINTY

The NGenIrr model also incorporates uncertainty in the behavioural and biophysical parameters. The model requires as inputs a probability distribution of objective weights and a measure of the uncertainty associated with the probabilities of each weight (the coefficient of variation). The model uses this information to assign probabilities to the compromise solution crop areas produced by the optimisation routine. The optimal value of the coefficient of variation is obtained during model calibration. The larger the value, the more uncertainty there is in the behavioural parameters of the model.

The uncertainty in the biophysical parameters is lumped together by using another coefficient of variation. This error term is multiplied to the crop water requirements from each compromise crop mix. The optimal value of the coefficient is obtained during model calibration.

As a result of incorporating these two sources of uncertainty, the model produces a distribution of water demand in each time step. This distribution captures the modelling uncertainty and therefore a wider distribution in the estimated water demand represents more uncertainty in the model output and vice versa. Irrigation system operators and planners can use such model outputs to make more informed water resources decisions.

MODEL TESTING

The model has been tested at the regional level by modelling an irrigation district as mixed farming enterprise. An application of the NGenIrr model to the Shepparton Irrigation District can be found in Zaman et al. (2008). The initial results of the application of this model to the Finley Irrigation District for the 2001/2 season are presented in this section. Observed water orders are from advances irrigation orders for the Mulwala Canal. From 1st Aug '01 to 21 Jul '02, the total rainfall and ETo was 322mm and 1703mm respectively (from SILO data drill at lat/long 35 39'S 145 36'E). In this season, the allocation increased from 14% in August '01 to 86% in February '02. Usually, the starting allocation is higher. It was assumed that with a starting allocation less than 50%, there is a 10% chance of the allocation increasing above 50%, 80% chance of reaching 100% and 10% chance of reaching 150%. Thus the expected final allocation at the start of the season was 100%. On this basis and other land availability and technical constraint, several feasible crop mixes were estimated by the model (see Table 1).

Crop Mix	Expected Gross Margin $m	Expected Water Use ML	Annual Pasture ha	Rice ha	Winter Cereals ha	Perennial Pasture ha	Horticulture ha
1	106	1,143,000	61,000	33,000	33,000	24,000	4,000
2	105	1,035,000	61,000	33,000	33,000	12,000	4,000
3	103	980,000	50,000	33,000	33,000	12,000	4,000
4	24	400,000	50,000	1,000	0	12,000	4,000
5	21	393,000	50,000	1,000	0	12,000	3,000

Table 1: Feasible Crop Mixes

The first crop mix would provide an expected gross margin of $106m with an expected water usage of 1.14GL for the District. The crop mix with the least water usage (0.39 GL), would provide $21m in gross margin. Based on the assumed distribution of irrigators' objectives (shown in Figure 4), which is slightly profit-orientated, two compromise crop mixes were obtained. The assumed distribution can be interpreted in two ways. Firstly, it can be used to describe the expected distribution of irrigators' objectives in the district, i.e. 9% of irrigators are very risk averse, 60% risk neutral, 27% moderately profit focused, 4% very profit focused. Alternatively, the distribution can used to describe the likely objectives of a hypothetical irrigator managing the mixed-farming enterprise representing the irrigation district, i.e. there is a 60% chance that the hypothetical irrigator is risk neutral. The compromise optimisation routine in the model estimated a 91% chance of Crop Mix 3 and 9% chance of Crop Mix 5 being present in the District.

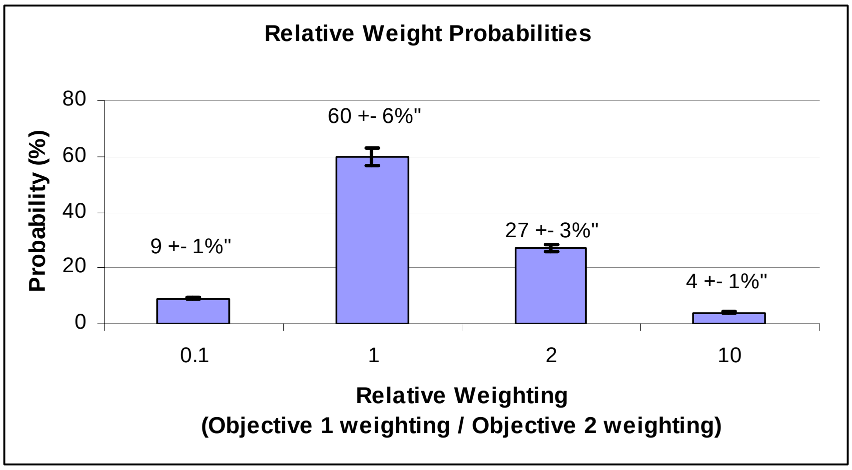


Figure 4: Distribution of Weightings of Irrigators' Objectives

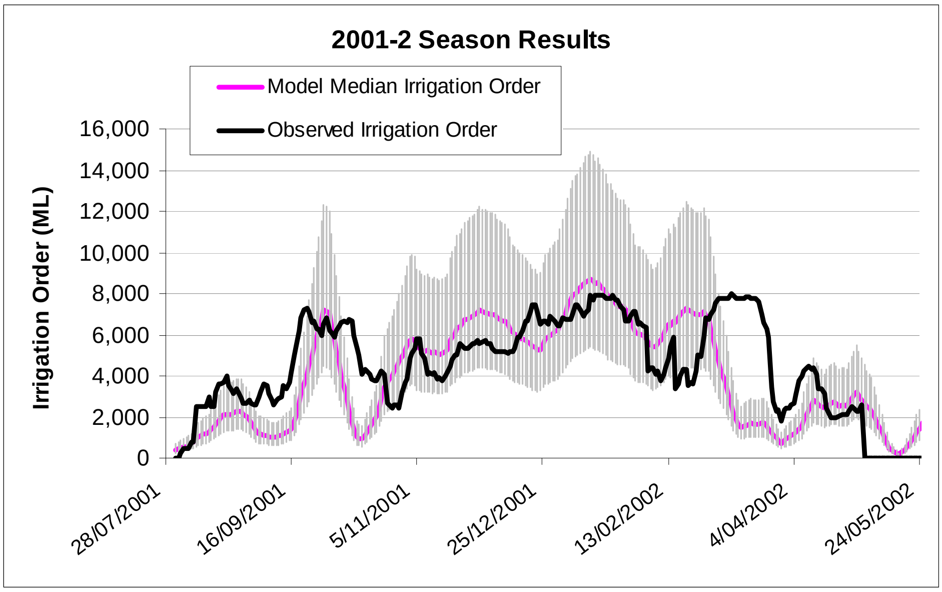


Figure 5: NGenIrr Model Results for Finley 2001-2 Season (with 90% confidence intervals)

As shown in Figure 5, the NGenIrr model is able to reflect the general trends in daily water orders. The correlation (r^2) between the observed water orders and the median of the modelled water order distribution was 0.50. There are several periods where the model over-predicts the water order, e.g. December and February. Also, the model underestimates the water orders in August, October and March. The initial underestimation is likely due to incorrect initial conditions of soil moisture conditions in the model. The over and underestimation in other parts of the season are likely due to crop growth stages not matching those on the ground. Another reason is that the observed data includes volumes of water passed through Mulwala Canal as a bypass around the Barma Choke and other small irrigation areas. The sharp drop in observed water orders needs to be checked further to ensure there are no errors in the original data.

The large modelling uncertainties can be seen in the 90% confidence interval errors bars shown in Figure 5. Further calibration is required to identify a better model parameter set that can reduce the modelling uncertainty. Investigations into identifying the relative proportions that behavioural and biophysical uncertainties contribute to the overall modelling uncertainty. This will give an idea of where to make further investments to reduce modelling uncertainty, e.g. survey irrigators' cropping and water ordering decisions, collect more soil data, improve estimations of crop factors, etc.

CONCLUSIONS

The Next Generation Irrigation (NGenIrr) demand model can be used by irrigation system operators and planners and water resources managers for forecasting and policy/management analyses. The model integrates behavioural and biophysical factors associated with irrigation demand. The model has been successfully tested on two irrigation districts.

The initial results for the Finley Irrigation District have been presented in this paper. The model captures the general trend in water orders, which is encouraging. The model needs further testing in other irrigation seasons and also the modelling uncertainty needs to be classified in terms of contributions from behavioural and biophysical uncertainties. When this is done, the NGenIrr model has the potential to be a useful tool to assist irrigation systems operations and planning especially in the context of water resources reforms.

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