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Impact of Uncertainty in Behavioural Factors on Irrigation Demands

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Abstract: In this paper, analyses of uncertainty in the results of modelling irrigation demands in two irrigation areas are presented. The Next GENeration IRRigation (NGenIrr) demand model has been used for the analyses. This model incorporates behavioural and biophysical irrigation demand factors and associated uncertainties. On-farm decision making is represented using compromise programming, where tradeoffs between conflicting objectives are modelled, e.g. when deciding on crop areas at the start of an irrigation season, the model chooses crop mixes that achieve a compromise between maximising gross margins and minimizing risk of suffering a water shortage during the season. In the NGenIrr model, behavioural factors affect crop areas and irrigation scheduling. Biophysical factors affect crop water usage, soil water balances and on-farm storage volumes.

Several irrigation seasons with varying climatic and water availability conditions were simulated for Shepparton and Coleambally Irrigation Districts. After establishing satisfactory performance of the model for the two districts, the uncertainties in behavioural and biophysical parameters were each varied systematically. The measure used to determine the effects of these changes was the number of observed data points remaining outside the 90% confidence interval of the model outputs.

The modelling results show that the contribution of uncertainty in demand estimates from uncertainty in behavioural and biophysical parameters are likely to vary from region to region. In annual cropping regions, uncertainty in human behavioural factors can play a more important role than uncertainty in biophysical factors. Thus for the Coleambally Irrigation District, where annual cropping dominates, the uncertainty in behavioural factors contributed more to the uncertainty in demand estimates. However, in the Shepparton Irrigation District, which is dominated by perennial and horticultural crops, uncertainty in biophysical factors can account for most of the uncertainty in irrigation demand estimates.

The results for both districts showed that with minimal modelling uncertainty the number of points outside the 90% confidence interval was quite high: 43 and 47 for Shepparton and Coleambally respectively (out of 60 points). For Shepparton, the number of outlying points decreases asymptotically to 19 as more and more uncertainty is added to the model. For Coleambally, the number of outlying points decreases to 5.

Keywords: *Irrigation demand modelling, modelling uncertainty, Shepparton, Coleambally, compromise programming*

1. INTRODUCTION

The impact of uncertainty in behavioural factors on irrigation demand is an important water industry issue. The industry would benefit from better characterization and estimation of uncertainty in irrigation demands. The term "irrigation demand" can vary in meaning depending on the context. For example, it can mean the "economic" demand for irrigation water, or the biophysical crop water requirement. In this paper, the term has been used in the context of water allocations and delivery at the irrigation system and catchment scales. In this context, we use the term irrigation demand to mean water orders by irrigators to the water supply authority. Irrigation demand can be modelled in several ways, which include empirical or time series approaches (Abu Rizaiza and Al-Osaimy, 1996), quasi-economic approaches, models based on individual behaviour, models based on crop water requirements under particular climatic conditions (which tend to ignore water trading) and a blend of the above (Leenhardt et al. 2004, Dinar and Letey 1996, Erlanger et al. 1992). Traditionally irrigation demand has been estimated using biophysical factors, such as climatic conditions, crop types and crop growth stages. However, with the introduction of water markets, on-farm storage regulation and drought conditions, behavioural factors play an increasing role in determining irrigation demand (Zaman et al. 2006). These factors include farming objectives (e.g. maximize profits, minimize risks, etc.) and activeness (the willingness to collect and act on water-related information). Some models do incorporate economic drivers such as maximizing social benefit and agricultural gross margins, utilising water trade opportunities, and increasing water productivity. However, these models tend to simplify the biophysical processes.

Another limitation of many irrigation demand models is the inability to incorporate uncertainties in model parameters. Often to assess modelling uncertainty, the user needs to conduct a Monte Carlo type of exercise where many (thousands of) model simulations are required. This can be a potentially costly exercise, especially if the models are complex and have relatively long runtimes or cover large areas, e.g. the Murray Darling Basin.

We have developed a process based simulation model that incorporates behavioural factors and biophysical factors related to irrigation water demands. This Next GENeration IRRigation (NGenIrr) demand model also incorporates uncertainties in these factors to give stochastic model outputs. The model has been tested in several irrigation districts, including Shepparton (Zaman et al. 2008a) and Finley (Zaman et al. 2008b).

In the next section a brief description of the NGenIrr model is provided. In the third section the case study irrigation sites are described. The simulation results are provided in the fourth section, followed by discussion and conclusion sections.

2. THE NGENIRR MODEL

Behavioural factors, such as the decisions of farmers regarding the use of irrigation water are key considerations in NGenIrr. Due to the unpredictable nature of seasonal rainfall and changes in water allocations from water authorities, the behaviour of farmers can greatly affect their irrigation use. The amount of land farmers choose to irrigate depends on their propensity to take the risk that it will be a good year and they will receive sufficient rainfall and water allocations. Also the variable nature of soils, crop types, irrigation systems and on-farm storages adds to the complexity. The NGenIrr model tries to model this complexity through three modules:

- Module A – crop mix module: calculates feasible crop areas based on farmer objectives and constraints using multi-objective linear optimization (using SIMPLEX method).
- Module B – trade-off module: works out most likely crop areas from the feasible set based on weightings of farming objectives using compromise programming. This module also takes into account of uncertainty in the farm objective weightings.
- Module C – crop water module: estimates the likely water order volumes, based on crop water requirements and soil water balances. This module takes into account of uncertainty in biophysical parameters.

Behavioural factors are modelled by finding the compromise between two conflicting objectives (maximize gross margins and minimize risk of crop water-stress). The weightings on farmer's objectives are input as a discrete distribution to represent varying degrees of irrigators' risk-averseness. The relative weightings of the two conflicting objectives are a key component of compromise programming. Relative weightings represents how risk averse or profit oriented the water user might be. In NGenIrr, relative weightings are included as model parameters. If given a relative weighting of 0.1, the model indicates that the farmer is risk averse and prefers to minimize chance of suffering a water shortage 10 times more than gross margins. If given a relative weighting of 10, this indicates that the farmer gives 10 times more importance to maximizing gross margins than to minimizing chance of water shortage.

The model parameters, set in an MS Access database, include crop, soil, irrigation and optimization parameters. Crop parameters involve the sow dates, root depths, length of crop growth stages, and crop coefficients. For each soil layer, several properties need to be specified: the depth of the soil layer, wilting point, field capacity, initial and saturated water content, and hydraulic conductivity. Irrigation parameters include scheduling method, trigger level, and application efficiencies. Drainage parameters include tile drain depth and spacing, start and end dates of tile drainage operation and hydraulic conductivities of soils in tile drain. Other model parameters include water entitlement volume, allocation probabilities, on-farm storage properties, on-farm delivery efficiency, time lag (in days) for water order to arrive at farm gate and delivery (or pumping) capacity. Further details about the model structure and procedures can be found in Zaman et al (2007, 2008a and 2008b).

Optimization parameters are defined for several different allocation categories; normal, high, low. For example if it is a "low" allocation year, as defined by the model user, then the model will adopt the parameters given for the "low" allocation year (in Module A). This function allows for the fact that in low allocation years, different crop areas are irrigated, compared to normal allocation years.

2.1. Uncertainties in Behavioural Parameters

The NGenIrr model incorporates uncertainty in the behavioural parameters. The model requires as inputs a probability distribution of relative weights:

$$\mathrm{Re}\,lative\,Weight = \frac{Objective\,1\,weight}{Objective\,2\,weight} \tag{1}$$

The relative weighting term is used as a measure of irrigator's preference between the two objectives. The user needs to input a frequency distribution of relative weights (in tabular form) in the Access database. As shown in Figure 1 the distribution of frequencies for each relative weighting is defined by an expected frequency and a coefficient of variation value (CV_{HB}) representing the uncertainty in the expected frequency (EF). The model assumes that the uncertainty in the relative frequencies follows a log-normal (LN) distribution with mean EF and a coefficient of variation (CV_{HB}). CV_{HB} represents human behavioural uncertainty in the NGenIrr model. The model uses this information to assign probabilities to the compromise solution crop areas. The appropriate 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.

In order to represent uncertainty in the frequency of relative weightings, a stochastic value is used. The value is sampled a user-specified number of times (default = 100) from the log-normal distribution represented by the two parameters provided by the user (expected frequency and CV_{HB}). Therefore, if 100 samples are taken, then there are 100 probability estimates for each of the relative weight frequencies. The model ensures that for each sample (replicate) set the sum of the probabilities add up to 1, (i.e. 100%):

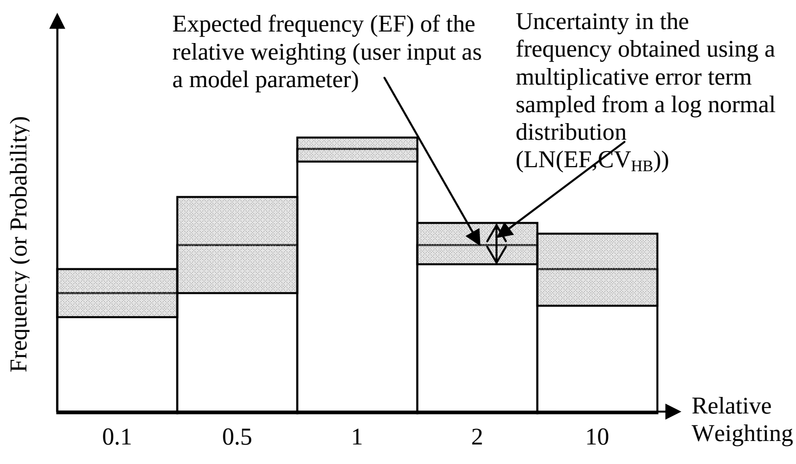


Figure 1. Method of Capturing Uncertainty in Relative Weightings Frequencies in Trade-off Module (Module B)

$$\sum_{i}^{N} RWfreq_{i,r} = 1 \tag{2}$$

$$RWfreq_i = stochastic\_value \tag{3}$$

$$stochastic\_value = \exp(z\_value) \tag{4}$$

$$z\_value = EV\_z\_value + SD\_z\_value * prob \tag{5}$$

$$EV\_z\_value = \log(mu_i) + 0.5 * SD\_z\_value \tag{6}$$

$$SD\_z\_value = (VAR\_z\_value)^{0.5} \tag{7}$$

$$VAR\_z\_value = \log(1 + CV_i * CV_i) \tag{8}$$

Where: N = total number of relative weights;

$RWfreq_{i,r}$ = r^{th} replicate of the frequency (or probability) for relative weight *i*.

prob = random number from standard normal distribution;

mu = expected frequency (EF) of relative weight *i*; and

CV_i = CV_{BH} of relative weight *i*.

2.2. Uncertainties in Biophysical Parameters

The uncertainty in the biophysical parameters is lumped together by using another coefficient of variation. This stochastic (multiplicative error) value is sampled from a log-normal probability distribution: LN (1,CV_{BP}). CV_{BP} is the coefficient of variation of the distribution and is a user input. The stochastic value is multiplied to the estimated water order volume in each timestep:

$$WO_{C,t,r} = WO_{C,t} * ME_r \tag{9}$$

$$ME_r = \exp(z\_value) \tag{10}$$

Where: $WO_{C,t,r}$ = r^{th} sample (replicate) of water order at timestep t for compromise point C;

$WO_{C,t}$ = best estimate of water order at timestep t for compromise point C estimated by the water order routines (in Module C);

ME_r = r^{th} sample of the multiplicative error term, randomly sampled from LN(1, CV_{BP}); and

z_value = calculated as in equations (5) to (8) and in this case mu=1 and CV_i is CV_{BP}.

The optimal value of CV_{BP} is obtained during model calibration. For this biophysical multiplicative error term a user-specified number of samples (default sample size is 100) is taken from the log-normal distribution. In the default case of 100 samples, the 100 error values are multiplied to the best estimate of water order to give 100 water order estimates for each compromise crop mix in each timestep.

As a result of incorporating these two sources of uncertainty, the model produces a distribution of water demand in each time step. This set of expected water orders ($EWO_{t,r}$) is obtained in each timestep by combining the water order replicates for each compromise point ($WO_{C,t,r}$) with the sample frequencies of each compromise point ($CPfreq_{C,r}$):

$$EWO_{t,r} = \sum_{1}^{C} WO_{C,t,r} . CPfreq_{C,r} \tag{11}$$

$$CPfreq_{C,r} = \sum_{i}^{I} RWfreq_{i,r} . \tag{12}$$

Where: $EWO_{t,r}$ = r^{th} sample (replicate) of expected water order at timestep t;

$WO_{C,t,r}$ = r^{th} sample of water order for compromise point C at timestep t; and

$CPfreq_{C,r}$ = r^{th} sample of frequency (probability) for compromise point C, which is obtained by summing the relative weight frequencies associated with that compromise point. This can be one or more (up to I) relative weights (I<= number of relative weights defined by the user).

In the default case of 100 samples, for each compromise point the 100 water order estimates are multiplied to the 100 frequency values. The resulting set represents a distribution of expected water orders for the timestep. This distribution of water orders takes into account uncertainty in crop areas (arising from behavioural uncertainty) and uncertainty in biophysical parameters. This distribution is the main output from the NGenIrr model.

In order to proceed to the next timestep, the user needs to specify a percentile water order that the model should select from the distribution of expected water orders. The default setting is the median (50th percentile) value.

3. CASE STUDY SITES

3.1. Shepparton Irrigation District

Shepparton Irrigation District SID is located in the Goulburn-Broken Catchment in north Victoria. Irrigation water is supplied by Goulburn-Murray Water, primarily from Eildon Reservoir. The travel time for the water from the main storage to the district is about four days. The historical average delivery volume is around 174,000 ML/yr and average irrigated area is about 51,000 ha. Dairying is the dominant agricultural activity in the district. Other activities include horticultural cropping and mixed (livestock and grains) farming. The area has experienced drought conditions since 1997. Irrigation water order and allocation data were obtained from Goulburn-Murray Water. Climate data (daily rainfall and reference crop evapotranspiration (ETo)) has been obtained from SILO Data Drill for Lat, Long: -36.30, 145.30”.

Table **1**. Case Study Site Details

Feature	Colembally	Shepparton
Area Normally Irrigated (ha)	79,000	51,000
Total Cropping Area (ha)	297,000	81,750
Entitlement Volume (ML)	610,000	181,500
Approximate water usage (ML/yr)	400,000	200,000
Main Agricultural Activities	Rice, cereal crops, pastures	Dairying, stone and pome fruit, mixed cropping and grazing

As shown in Figure 2, in the 5 irrigation seasons studied the seasonal allocation has not exceeded 100%. As shown in Table 1, during the 5 seasons analysed (2001 to 2006), the mean monthly irrigation demand (12,692 ML/month) varied considerably (Coefficient of variation = 0.85).

3.2. Coleambally Irrigation District (CID)

CID is part of the Murrumbidgee Valley in NSW and receives water from the Murrumbidgee River. The district covers some 79,000 ha of intensive irrigation, 42,000 ha of irrigation/dry farms and 297,000 ha of outfall district stations delivering water supply to 473 farms owned by 364 business units.

Rice is the prevalent crop grown in the region. Wheat and other crops are often planted in the rice off-season. The district produces a range of other crops, including; soybeans, maize, sorghum, sunflower, and faba beans, canola, barley, oats, lucerne, grapes, prunes and pastures (perennial and annual) for sheep and cattle.

This area has also been suffering from extended drought conditions. Water order and allocation data was obtained from the CID website. Climate data was obtained from SILO Data Drill for Lat, Long: -34.80, 145.89".

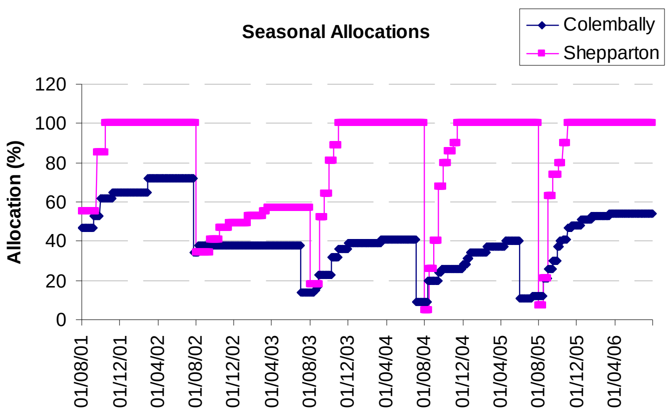


Figure 2. Seasonal Allocations for Case Study Sites

The seasonal allocations in Coleambally were considerably lower than those in Shepparton. This is mainly due to the different ways water resources are managed in Victoria and NSW. In general, water rights are more secure in Victoria, because the authorities try to ensure that 100% allocation is provided over two seasons. Thus in Victoria, allocations do not easily exceed 100%. From 2001 to 2006, the mean monthly irrigation demand in CID (24,667 ML/month) varied considerably (Coefficient of variation = 0.88).

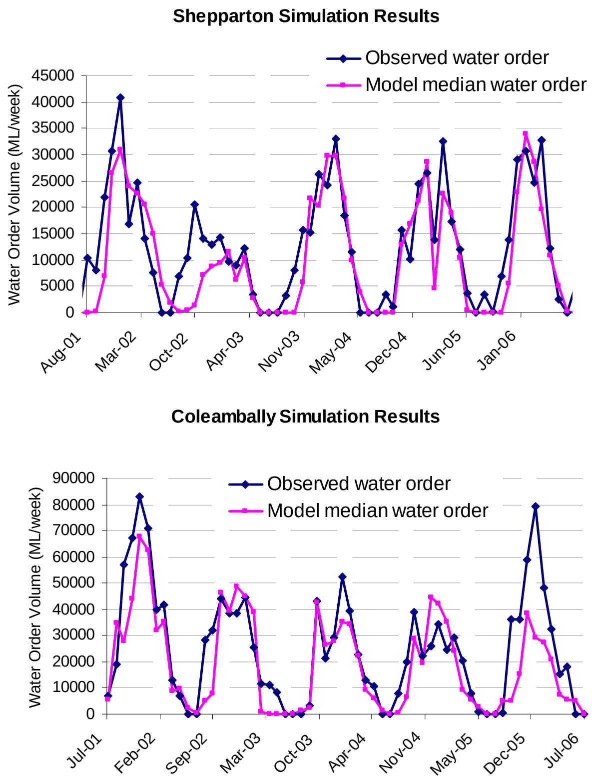


Figure 3. Simulation results for 5 irrigation season

4. SIMULATION EXPERIMENTS

Both districts have been modelled as single mixed-farming enterprises for five irrigation seasons (2001 to 2006). The models were run at a daily timestep and results have been analysed on a monthly basis. Detailed information about the parameter values used in the simulations are provided at www.ngenirr.pbwiki.com. Both models were calibrated manually.

4.1. Shepparton

Figure 3 shows that reasonable simulation results were obtained for SID, except for the 2002/3 season. The r^2 value for the 60 data points is 0.73. There are 9 zero values in the observed data (mainly in June and July months) and 10 zero values in the model outputs (5 matching with observed values). The importance of these zero values is discussed in the next section.

4.2. Coleambally

Figure 3 also shows that reasonable simulation results were obtained for CID, except for the 2005/6 season. The r^2 value for the 60 data points is 0.70. There are 11 zero values in the observed data (mainly in June and July months) and 7 zero values in the model outputs (5 matching with observed values).

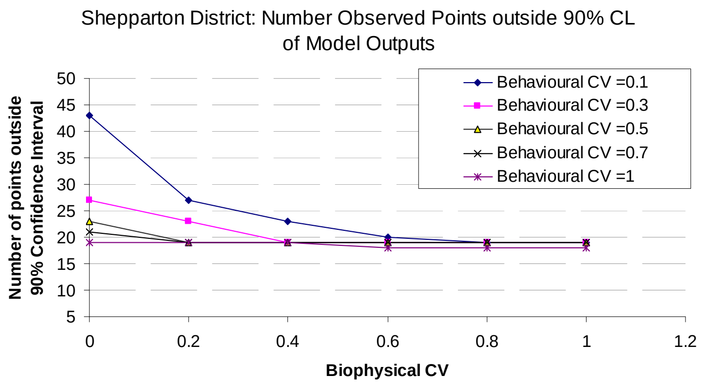
After establishing satisfactory performance of the model for the two districts, the two CV values were varied systematically. This was done to add uncertainty (or noise) to the model outputs from the two main parameter sets: biophysical (CV_{BP}) and behavioural (CV_{HB}). The measure used to determine the effects of these changes was the number of observed data points remaining outside the 90% confidence interval of the model outputs. As the uncertainty range of the model outputs increase, more and more of the observed data should fall within the specified confidence interval and thus the number of points remaining outside the interval should decrease. In this way, the importance of uncertainty in behavioural factors was determined.

5. DISCUSSION

The Shepparton allocations in the 2002/3 season (Figure 3) were considerably lower than the other seasons. As observed crop areas were not available it was not possible to determine the accuracy of the estimated model areas. Similarly the Coleambally allocations for the 2005/6 season were also unique compared to the other four irrigation seasons. Thus the model struggled to match the water orders for this season. However, due to r^2 values equal to and greater than 0.70 and good approximation of irrigation demand trends, these results were considered adequate for the purposes of this paper.

As shown in Figure 4, the results of the simulation experiments confirm that as modelling uncertainty increases, the number of observed data points remaining outside the 90% confidence interval decreases. The figure clearly shows that the response of the Shepparton model is quite different to that of the Coleambally model. First of all, it was observed that with minimal modelling uncertainty (CV_{HB}=0.1 and CV_{BP}=0) the number of points outside the 90% confidence interval was quite high: 43 and 47 for Shepparton and Coleambally respectively. For Shepparton, the number of outlying points decreases asymptotically to 19 as more and more uncertainty is added to the model. Due to the multiplicative error structure, the zero values estimated by the model do not have any error bars (confidence interval) and therefore increases in modelling uncertainty will not have an effect in these timesteps. Thus, for Shepparton the potential minimum number of outlaying points is 5 (10 zero model estimates minus 5 matching observed zero values). The potential minimum for Coleambally is also 5. Figure 4 clearly shows that the greater influence of behavioural uncertainty (changes in CV_{HB}) allow the model to get closer to the potential minimum for Coleambally compared to Shepparton. Unlike the results for Shepparton, the profile of the curves for Coleambally continues sloping downwards as CV_{HB} is increases.

If the upper and lower curves (CV_{HB} = 0.1 and 1) are considered as edges of a windsock, then the influence of the two sources of uncertainty can be described qualitatively as follows. The greater the influence of uncertainty in biophysical parameters, the more the windsock will show “high winds”. Conversely, if the windsock indicates little to no wind, then uncertainty of behavioural factors contributes more to the uncertainty in demand estimates.



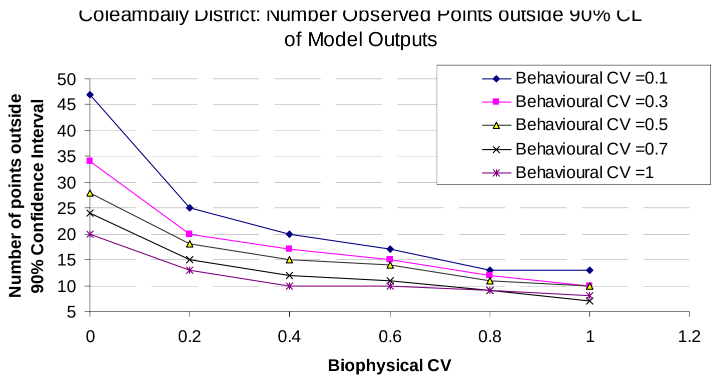


Figure 4. Effects of Changing CV_{HB} and CV_{BP} on the number of observed points falling outside of 90% confidence intervals of model outputs

6. CONCLUSIONS

Two key sources of uncertainty for estimating irrigation demands are incorporated in the NGenIrr model: uncertainty in biophysical parameters and in behavioural factors. In this study, simulation experiments were conducted to determine which uncertainty plays a more important role in different irrigation systems. The results suggest that behavioural uncertainty is more important for annual cropping systems (like Coleambally) and uncertainty in biophysical parameters is more important in more permanent cropping systems (like Shepparton).

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