Towards the Next Generation of Rural Water Demand Modelling

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EXTENDED ABSTRACT

In this paper a review of the existing rural water demand modelling approaches employed by various agencies across Australia is provided. From our review we conclude that existing models do not reflect the behavioural complexities and uncertainties associated with current irrigated farming practices. Thus, a better modelling approach is needed to improve the demand components of broader water allocation and catchment models. To address this need, a next generation rural demand model has been developed based on the conceptual approach shown in Figure 1. This modelling approach integrates hydrologic, biophysical and behavioural factors associated with irrigation water demand. This modelling approach also caters for data input and modelling errors explicitly, generating a probability distribution of water demand to support more informed decision making. The outputs from the proposed rural water demand model can be used as stochastic demand inputs to a broader catchment models. However, at present this model can not be fully realised due to data limitations. Therefore, a modified (interim) approach is outlined in this paper to take into account of data availability realities. This approach is based on stochastic multi-objective optimisation and crop-water simulations. It is contended that this modelling approach is a considerable step towards the next generation of rural water demand modelling. This research work is part of larger eWater CRC projects investigating uncertainty analysis in models and improving water management decisions.

The key benefits of the proposed model include: integration of economic, hydrologic, climatic and biological factors related to irrigation water demand and stochastic model output.

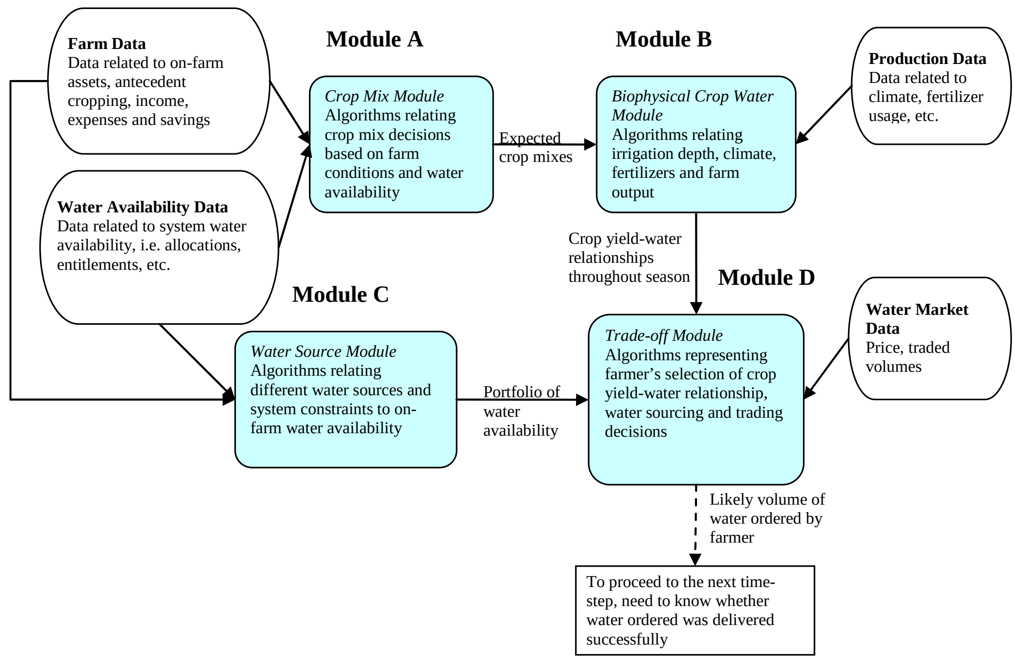

Figure 1. Conceptual Rural Demand Model. This is how the next generation of rural demand models should look.

1. INTRODUCTION

Reliable demand models are critical tools for effective water resources and catchment management. Effective demand modelling can allow policy-makers and managers to gain insight into the potential consequences of system changes, be they regulatory changes, infrastructure changes, climatic or other physical changes. In the rural context, demand modelling is made especially important due to the complexity and variability of potential demands between users and through time.

Historically, existing water demand models have been applied with success in the context of policy formulation. However, the current generation of models is not well positioned to deal with future needs. This is primarily since they have been built on relatively inflexible assumptions and processes reflecting historical system and user behaviour. New options open to irrigators and the changing nature of irrigation technology means that a more flexible modelling environment has become necessary, especially in terms of modelling user behaviour. Furthermore, these models have traditionally produced deterministic outputs without explicit recognition of the uncertainty of the model structure, parameters, processes or inputs. Whilst the application of deterministic outputs may be appropriate for some analyses, consideration of uncertainty is important to improve the robustness of decision-making.

This paper outlines a next generation approach to demand modelling reflecting the need to better model user behaviour and explicitly reflect uncertainty. This research builds on the substantial current knowledge base embodied in a wide range of existing demand models. This paper begins with a summary of existing demand modelling approaches in Section 2, and then an ideal modelling approach, which is a long-term goal, is proposed in Section 3. Finally, a modified (interim) modelling approach, which takes into account current data availabilities, is described in Section 4. The process of how this approach is currently being applied to two irrigation districts, in the form of prototype models, is presented in Section 5. Finally, the conclusions of our review and proposed modelling approaches are provided in the last section.

2. EXISTING DEMAND MODELS

A number of definitions are provided here to ensure readers understand the meaning of terms used when discussing existing demand modelling approaches.

Predicting user demands in a rural context is extremely complex. Demands vary significantly according to the type of use, climatic considerations, individual user characteristics such as their risk propensity, the potential water sources available and water trading considerations. Water trade modelling is perhaps the most uncertain component of water allocation modelling since little data exists to calibrate and validate trading processes. Water trading itself involves a number of parameter and forcing variables such as commodity prices, the comparative price of water, the risk profile of users, the flexibility of trading policies and of course, the water allocation itself. In fact, the interdependency of the volume of water trade (particularly temporary trade) and water allocation is a significant complicating factor in a demand modelling structure. This usually means a sub-optimisation module is required to model water trading within the overall allocation model (unless a time series or empirical approach is taken which is difficult given the sparse data sets often available in practice).

In response to these issues a number of approaches have been applied to modelling demand. Some of these include empirical or time series approaches, quasi-economic approaches, models based on individual behaviour, models based on crop water requirements under particular climatic conditions (which ignore water trading) and a blend of the above. However, the lack of baseline data presents significant challenges in calibrating any of the above demand approaches.

To illustrate this, several irrigation demand models that have been reviewed and compared are listed in Table 1 (adapted from Zaman et al., 2006a). The review focused on how existing models included key factors that affect irrigation water demand:

- Biophysical factors – crop-soil-climate interactions;
- Behavioural factors – farming objectives that are driving/influencing management decisions; and
- Supply factors – water availability.

The review included seven biophysical water demand models and three models that primarily are based on the economic drivers of irrigation water demand (TERM-Water, WRAM and SALSA). Economic drivers include maximizing social benefit and agricultural gross margins, utilising water trade opportunities, increasing water productivity, etc. This review focuses on models (and methods) that are mainly used as water management tools at the catchment scale (rather than on farms).

Table 1. Summary of existing demand model characteristics (adapted from Zaman et al. (2006))

Model	Biophysical Factors	Behavioural Factors	Supply Factors	Time-step	Spatial scale
PRIDE	Crop factors, soil characteristics	Autumn irrigation, reduction factors	Main channels	Daily to monthly	Farm to district
IQQM Crop Model 2	Crop factors, soil characteristics	Risk-taking behaviour for initial planting area	On farm losses	Daily to Monthly	Farm to district
CLASS CGM	Detailed crop and soil characteristics	Stubble management options	Climate conditions	Sub-Daily to monthly	Farm to district
Tiddalik	Detailed crop and soil characteristics	Over and under irrigation options	On-farm storage	Daily to monthly	Paddock to district
SWAGMAN Farm	Detailed crop and soil characteristics	Net profit maximization	Allocations	Daily to Monthly	Paddock to Farm
MSM	Rainfall and temperature	None	Allocations, water availability	Monthly	District
PERFECT	Detailed crop and soil characteristics	Crop planting and tillage options	None	Daily	Farm to district
TERM-Water	Simple production functions	Substitution options	Allocations	Annual	ABS Statistical division
WRAM	As in PRIDE or IQQM Crop Model 2	Maximise net return (regional)	Water availability constraints	Annual	District to catchment
SALSA	Simple production functions	Maximise net return (regional)	Key hydrologic processes	Annual	Catchment

In this review of existing water demand models, several major limitations have been identified. First, these models do not explicitly incorporate the key behavioural factors underlying irrigation water demand, and in particular, variable risk preferences. Although IQQM Crop Model 2 has risk functions these are aggregated at an irrigation district level, i.e. the spatial scale is not sufficiently disaggregated. This limitation becomes clear if policymakers want to capture the different responses of two neighbouring farms, with similar crop mixes, which have different water usage. The level of aggregation and the lack of sufficient variables for behavioural factors mean that existing models can not be used to address such questions. Another major limitation of the existing models is that the factors related to irrigators' water demand are handled in a deterministic manner. Not only does this limit the robustness of these models, but also introduces errors during model inputs / processes. The next generation of irrigation demands should model key variables and parameters in a stochastic manner. For example, rather than have a single (average) crop factor for a plant (as in PRIDE and IQQM Crop Model 2), it would be better to have a distribution of crop factors. This approach would be more likely to represent reality at the farm level where the crop yield varies from field to field. The stochastic approach would also make it easier to incorporate uncertainty in model inputs and processes, which is discussed below. This would be particularly useful in ungauged catchments where there tends to be increased uncertainty due to sparse data availability.

A further limitation of existing models is that the variety of water source options available to irrigators is not adequately modelled. For example, in PRIDE, Crop Growth Model 2 and the economic models, there are no options to include on-farm storage as a potential source of water. Only IQQM Crop Model 2 and Tiddalik provide some alternative water sourcing options at irrigation centres.

3. CONCEPTUAL RURAL DEMAND MODEL

A conceptual rural demand model, shown in Figure 1, was developed after reviewing existing models, irrigation demand literature and consultation with farmers and water supply authorities. This conceptual model captures the key processes related to intra-seasonal and inter-seasonal irrigation water demand. Although the components are discussed below at the farm-scale level, the model can easily be applied at a regional level. The difference would be in the distributions of the input data and model parameters.

3.1. Module A – Crop Mix Module

At the start of each season, a farmer makes critical decisions with regards to the areas planted. These complex decisions are primarily based on the farm's financial situation, geographical location, permanent water entitlement and expectations about how the season will unfold (adapted from Zaman et al., 2006b). In particular, the farmer forms some expectations about climatic conditions, irrigation water availability, water market activity and farm input and output prices. The farmer's risk-profile also plays an important part in these decisions, e.g. a farmer willing to take greater risk that wet climatic conditions will prevail would plant a larger area of annual crops than another farmer who takes less risk. The output from this module will give a range of expected crop mixes. This module should consist of algorithms representing physical and behavioural processes. By using statistical distributions of farmers' risk profiles (or functions), this module should allow flexibility in how irrigators' behaviour is incorporated in the model.

3.2. Module B – Biophysical Crop Water Module

This module is required to incorporate the tradeoffs involved in irrigation depth and crop yields, subject to climatic and other factors (such as fertilizer usage). This module, operating at a weekly/monthly time-step, would take in as input the crop mixes and water usage from previous time steps. This module could be similar to the CLASS CGM model. However, the module will output a set of crop water requirement profiles for the remainder of the season, which will be used as inputs to the Water Trade-off Module (Module D). There should be no behavioural relationships / parameters in this module, i.e. it is a module of biophysical processes only.

3.3. Module C –Water Source Module

This module would play an important role in setting constraints to farmers' decisions related to water availability (supply). It would operate at a weekly/monthly time step and incorporate information about water allocations, supply (irrigation delivery), on-farm storage and groundwater resources. The module would provide a set of water usage possibilities from multiple sources. The output from this module will be required as input to the Water Trade-off Module (Module D), as the volume of water available to the farmer is an important factor in the farmer's water trading and ordering decisions. There will be no behavioural relationships/parameters in this module, i.e. it is a module of physical processes. This module could be populated by output from water allocation models such as REALM and IQQM.

3.4. Module D – Trade-Off Module

This is a key element of the preferred rural water demand model structure. This module would take in water availability factors and water-crop yield relationships from the other modules. Then, combined with risk-return profiles and propensity to act parameters, the module will output the expected volume of water ordered at given probabilities, as shown in Figure 2. This can be on a monthly basis with probabilities of non-exceedance, e.g. we could say in August there is a 90% chance that the volume of water ordered will not exceed 40ML (see top chart in Figure 2). The monthly outputs can then be combined to make estimates for the annual volume of water ordered at different exceedance probabilities, e.g. we would be able to say there is a 10% chance that the total volume ordered by March would exceed 300ML in the season being modelled (see lower chart in Figure 2). Module D would consist of algorithms representing behavioural processes. The Water Trade-off Module is envisaged to operate at various time-steps. In the short-run (weekly/monthly time-step) decisions to order, buy or sell would be made based on expectations of water market movements, changes to allocations, on-farm rainfall, etc. At longer-time steps (annual/inter-annual) decisions related to trading permanent water entitlements would be modelled.

The outputs from the preferred rural water demand model would be used as stochastic demand inputs to a broader water resources planning model, such as REALM and IQQM. The latter would also incorporate urban demands, physical distribution features, and other key water system processes.

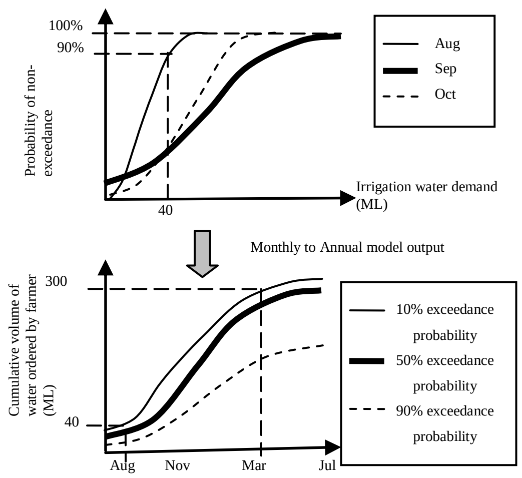

Figure 2. Expected output from Module D

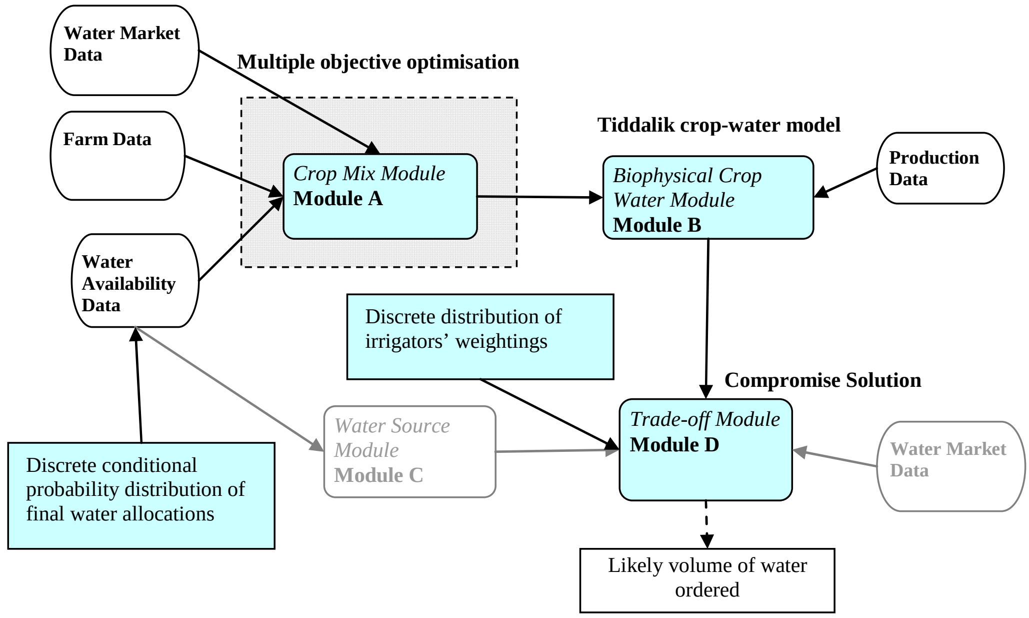

Figure 3. Proposed Model Structure, taking into account current data availability.

4. PROPOSED MODELLING APPROACH

The conceptual model is being delivered in two stages: proof of concept using available data, followed by full implementation using data collected specifically to support demonstration of this model. This section describes the initial stage with the modified modelling approach.

The proposed model structure, shown in Figure 3, can be described as a lumped, stochastic, multiple objective optimisation model. The model will be lumped because it will treat the biophysical variables associated with an irrigation area as one mixed-farming entity. The model will be stochastic since key parameters are represented by distributions rather than single values. The model also optimizes the farmers' profit and risk averseness objectives (through linear programming); hence it will be a multiple objective optimisation model. The trade-off between the two conflicting objectives will be found using a compromise programming (CP) approach (Romero and Rehman 2003).

The key model parameters are the distribution of relative weightings between the two objectives and the probability distribution of final allocations in the irrigation system. The distribution of weightings should capture the range of profit maximizing and risk averseness underlying irrigators' behaviour in the modelled area. The probability distribution of final allocations will provide a measure of the likely water availability at different allocation levels during the season. For example, given an allocation of 60% in September, there may be a 10% chance of a final allocation of 70% in March, a 30% chance of a final allocation of 80%, etc.

The proposed model can also be used in a distributed fashion by setting up several realisations of this demand model as nodes to represent different subareas in an irrigation district. Thus, the key model parameters can be varied depending on the location of the farm, the farm type and the farmers' behaviours.

In relation to the Conceptual Rural Demand Model (Figure 1), the multiple objective optimisation procedure corresponds to Module A (see Figure 3). In other words, the irrigators' behavioural factors are incorporated as two objectives:

- maximise wealth (measured as gross margin ($/ha)) – subject to expected final water allocation, irrigable areas, expected water market activity, biophysical crop water demand; and
- minimise risk of suffering a water shortage (% probability/ha) - subject to the same constraints as above.

The optimisation procedure produces the feasible set of crop mixes, which are then fed into Module B. This module is a modified version of Tiddalik, which is a crop-water simulation model (Hornbuckle et al., 2005). This module provides an estimate of the volume of water required for each of the feasible cop mixes produced in Module A.

In the modified prototype mode, all water source information would be included as constraints in Module A. This removes the need for a separate Module C.

Module D contains the compromise programming procedure where the trade-offs between the two competing objectives are modelled. The compromise between these two conflicting objectives is analogous to risk-return tradeoffs in investments. Ideally, one would like a high return (large gross margins) with no risk. In most cases this is not feasible and a compromise solution that is closest to this ideal point is sought. The distribution of weightings between the two objectives would be used in this Module and the best compromise solution for each weighting will be chosen from the feasible set produced in Module A. The associated water demand with the best compromise solutions will be obtained from the information passed on from Module B.

After the initial, feasible crop areas are determined by Module A (multi-objective optimisation procedure) at the start of the season, the module only runs again when certain conditions occur. At this stage of the model development, the decision to run the optimisation component will depend on two criteria:

- crop growth stage; and
- significant changes to on farm water availability, i.e. a few days of heavy rainfall, or a sharp rise in the allocation, marked changes in market water price, etc.

These trigger conditions reflect situations when further trade-offs (compromises) made by irrigators need to be modelled. These criteria are set exogenously as trigger points for running the optimisation component during the season.

5. PROTOYPE MODELS

Currently prototype models based on the above proposed modelling approach are being developed for the Finley and Shepparton Irrigation Districts (ID).

The basic features of the case study areas are provided in Table 2. The Finley ID is quite extensive, with rice, cereal crops and pastures as the main agricultural activities. Shepparton ID is a concentrated irrigation area with an overall application rate of about 40 ML/ha/yr on average for dairying, horticultural and mixed farming activities.

Table 2. Basic Features of Shepparton Irrigation District

Feature	Finley	Shepparton
Area Normally Irrigated (ha)	150,000	51,000
Total Area (ha)	403,700	81,750
Entitlement Volume (ML)	900,000	181,500
Approximate water usage (ML/yr)	500,000	200,000
Main Agricultural Activities	Rice, cereal crops, pastures	Dairying, stone and pome fruit, mixed cropping and grazing
Water Order Data	Daily from 1998-2004	Weekly from 1994-2004
Climate Data	Daily data up to 2004	Daily data up to 2004
Cropping Data	Areas annual from 1998	Areas and yield for few years

The models have been developed in The Invisible Modelling Environment (TIME), which is based on the .Net framework.

5.1. Data

The model requires daily rainfall, reference crop evapotranspiration and seasonal allocation data as time-series input. Other key parameter information required are soil properties, crop factors, sowing dates, irrigation system details and on-farm storage/recycling information. In the context of ungauged catchments, some of these parameter values may not be known accurately. The level of uncertainty can be represented in the output of the model, which is generated stochastically.

Other data requirements for the optimisation component include: gross margins of crops ($/ha) and their variations; crop rotation constraints. These data are readily available from ABARE, relevant water supply authorities and agronomic technical reports.

For the prototype models, daily water order and climate data are available for the Finley area from Murray Irrigation. However, water order data for the Shepparton Irrigation Area is available at weekly time-step only from Goulburn-Murray Water.

The distribution of likely water allocations will be based on water allocation simulation models used by the relevant water authorities. For example, the Goulburn Simulation Model (GSM) can estimate the monthly allocations for Shepparton ID for a 100-year period (DSE 2003). The uncertainties introduced by relying on separate model output are one of the limitations accepted in the initial

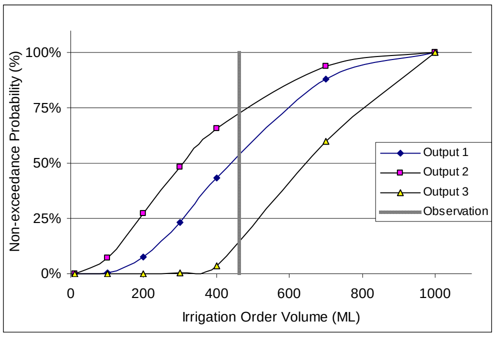

Figure 4. Calibration of Stochastic Output to a Single Time Series Observation

modelling stage which will be improved with full implementation of the conceptual model.

5.2. Proposed Model Calibration and Validation Procedure

The prototype models are calibrated (and currently being validated) with observed water order data and crop areas. As the models output a distribution of water orders for each time-step, robust model calibration/validation depends on setting appropriate criteria. For example, the calibration can be based on the observed data series being consistently near the median of the output distribution. The method of maximum-likelihood estimation has been used to calibrate the prototype models. An example of how the models are calibrated is shown in Figure 4. If matching the median was the only criterion, this would mean that the parameter set producing Output 2 would be chosen. A more relaxed calibration criterion can be the selection of the parameter set that ensures the observed water orders lie in the 90% probability range of the distributions in each time step.

Several parameters have been adjusted to calibrate the models. These include the distribution of weightings of the irrigators' objectives, final allocation probability distributions, crop gross margins, crop factors and the criteria for running the optimization component (OC).

A survey of irrigators will be conducted later this year as part of the model validation process. The survey will attempt to obtain irrigators' risk preferences, farming objectives, water ordering logic, etc. It is hoped that data collection constraints due to lack of available water in case study regions, will be eased.

6. CONCLUSIONS

There is a clear need for better integration of the biophysical and behavioural factors related to irrigation water demand. This integrated approach has been proposed in the preferred model structure, which incorporates several modules that would estimate: crop mixes, crop-water relationships, water sourcing options and irrigators' trade-off decisions. The proposed model would also be stochastic so that uncertainties in model inputs and processes could be incorporated explicitly. This approach overcomes major limitation of existing demand models.

The key benefits of the proposed model include:

- integration of economic, hydrologic, climatic and biological factors related to irrigation water demand;
- incorporation of irrigator's behaviour (profit maximising and risk minimising objectives); and
- stochastic model output.

We are on track to have calibrated and validated prototype models by the end of 2007.

7. REFERENCES

DSE (2003). Goulburn Simulation Model Users' Manual. Department of Sustainability and Environment, Melbourne.

Hornbuckle, J. W., E. W. Christen, G. Podger, R. White, S. Seaton, J.-M. Perraud and J. Rahman (2005). Tiddalik: An Irrigation Area Model for Predicting and Managing Drainage Return Flows. ANNUAL ANCID CONFERENCE, Mildura, Australian National Committee on Irrigation and Drainage.

Romero, C. and T. Rehman (2003). Multiple criteria analysis for agricultural decisions. Boston, Elsevier.

Zaman, A. M., T. Etchells, H. Malano and B. Davidson (2006). Review of existing irrigation demand modelling methods. Internal Milestone Report, eWater CRC, Melbourne.

Zaman, A. M., K. M. Jones, T. Etchells, H. Malano and B. Davidson (2006). Factors Affecting Irrigation Water Demand in Water Allocation Models. In: Proceedings of the 30th Hydrology & Water Resources Symposium [CD ROM], 4 – 7 December 2006. Launceston, Tasmania.