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Relating catchment attributes to parameters of a salt and water balance model

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Abstract: Salinity is recognised as a global land management issue and the use of appropriate models is vital for the management of salinity-affected areas. A major limitation associated with the modelling of salt and water transport is the heavy reliance on good quality data for model development. Measured salinity data are required for calibration of salt and water balance (SAWB) models; however these data are not available for ungauged catchments. Hence the determination of optimal salinity management strategies for these areas is difficult. A considerable amount of research has been conducted on the development of hydrological models for ungauged catchments; however a similar approach has not yet been developed for SAWB models. In this study Partial Mutual Information (PMI) is used to assess the strength of relationships between readily-obtainable catchment characteristics and the parameters of a SAWB model. This will enable the future development of SAWB modelling for ungauged catchments by eliminating the traditional calibration requirement.

In order to use the PMI to assess the strength of these relationships, a set of optimal SAWB model parameters and a set of catchment characteristics are required. The optimal set of model parameters is obtained by calibrating the model for 43 gauged catchments across Australia. CATSALT is chosen as the most appropriate SAWB model for this study due to its parsimony and reliability compared with other commonly available models. All of the inputs for CATSALT are obtained for the 43 catchments, which include values of average soil and groundwater salinity, streamflow and baseflow data. The Australian Water Balance Model (AWBM) is used to obtain the streamflow and baseflow data from measured total runoff data. Calibration of CATSALT for the 43catchments is performed using Differential Evolution, as this has been found to perform favourably compared with other calibration methods. Values for a set of 32 commonly available catchment characteristics are also obtained, including land use, vegetation and spatial attributes of the catchments.

After obtaining the set of optimal SAWB model parameters by calibration and the set of catchment characteristics, the PMI algorithm is used. PMI is a technique for input variable selection that can detect linear and non-linear relationships between variables, as well as account for redundancy between variables. It is an improvement on traditional input selection methods, such as partial correlation analysis, which can only detect linear relationships between the variables.

Using a bootstrapping procedure with 95% confidence limit as the stopping criterion for the PMI algorithm, six relevant and non-redundant catchment characteristics are found to have a significant relationship with each of the three CATSALT model parameters. This shows that there are relationships between easily obtainable catchment characteristics and the parameters of the CATSALT model. These catchment characteristics could be used in future research to develop models for the prediction of the CATSALT parameters, hence enabling CATSALT to be applied in ungauged catchments. This approach is not limited to the CATSALT model and could be applied effectively to other available SAWB models.

Keywords: *Salinity modelling, Partial Mutual Information, CATSALT, ungauged, regionalization.*

INTRODUCTION

Salinity is a globally recognised land management issue. Within Australia alone, approximately 5.7 million hectares are considered to be affected by, or at risk of, dryland salinity (DEWHA, 2001). Environmental modelling can serve as a powerful tool for developing an understanding of environmental processes, and for determining appropriate management strategies, including those for salinity management (Gibbs et al., 2008a). Environmental modelling relies on significant data inputs for model calibration and validation, but in cases of limited data this becomes difficult or even impossible. When little or no data are available for model calibration, a catchment is referred to as being ungauged.

Many rainfall-runoff (RR) models have been adapted to allow for modelling in ungauged catchments through the use of regionalisation methods (e.g. Evans and Jakeman, 1998; Boughton and Chiew, 2007). Regionalisation approaches generally take on one of the following two forms: 1) models are calibrated to spatially close and similar gauged catchment(s) (Vandewiele and Elias, 1995) or 2) relationships between model parameters and catchment characteristics are developed (Gibbs et al., 2008b). The latter method has been widely used for estimating flows and has not yet been applied to salt and water balance (SAWB) models. Consequently, such an approach has been adopted in this study.

The selection of an appropriate set of catchment characteristics is imperative in the development of such relationships. In this study the Partial Mutual Information (PMI) algorithm (Sharma, 2000) is used to assess the strength of relationships between readily obtainable catchment characteristics and the parameters of SAWB model. This will enable the future development of SAWB modelling for ungauged catchments by eliminating the traditional calibration requirement. The following sections provide relevant background and an outline of the methodology. The results are then presented, followed by a discussion and concluding remarks.

1. BACKGROUND

Several RR models, such as the Australian Water Balance Model (AWBM), have been used to model runoff in ungauged catchments. Models such as these generally have a parsimonious structure - they require fewer inputs and parameters for model calibration than models of higher complexity (Littlewood et al., 2003). Thus they are ideal for regionalisation, as the number of relationships between model parameters and catchment characteristics are kept to a minimum.

In order to develop an accurate relationship, a set of appropriate catchment characteristics must be chosen. The characteristics should form the smallest set able to adequately describe the behaviour of the system (May et al., 2008). If too many characteristics are included, the model becomes unnecessarily complicated and less accurate (Bowden et al., 2005). There are several traditional methods of input selection described by Bowden et al. (2005), including the use of *a priori* knowledge, trial and error and linear correlation techniques. However, these methods can be subjective or inaccurate, making it difficult to determine whether the optimum inputs have been chosen.

An alternative input selection method uses the concept of mutual information (MI) and overcomes the limitations of linear approaches, particularly when applied to non-linear systems, such as those found in an environmental setting. MI is a measure that makes no prior assumptions about the structure of the dependence between the variables (May et al., 2008). As such, MI can determine both linear and non-linear relationships between variables. PMI is an extension to the concept of MI, which can directly account for redundancy in the inputs. PMI measures the additional dependence that each new potential input adds to the model, which means that if two potential inputs provide the same information about the output variable, only one will be chosen for the final input set (Bowden et al., 2005). In this study, the PMI algorithm will be used to determine the strength of the relationship between easily measureable catchment characteristics and the parameters of a SAWB model.

2. METHODOLOGY

As mentioned above, the main aim of this study is to assess the strength of relationships between readily-obtainable catchment characteristics and the parameters of a SAWB model. Obtaining these relationships enables SAWB model parameters to be predicted directly from limited catchment data, eliminating the traditional data-reliant calibration requirements, hence facilitating the future development of SAWB modelling for ungauged catchments.

Figure 1 presents the generic procedure that was developed as part of this research to identify the required relationships. The most relevant catchment characteristics for each parameter of the SAWB model were identified using the PMI algorithm (Box 12). This required the development of a RR model (Box 3) and a SAWB model (Box 8). The SAWB model was required to provide a set of optimised model parameters (Box 10) so that the strength of relationships between the catchment characteristics and model parameters could be assessed (Box 12). The RR model provided the streamflow and baseflow data sets that were required as inputs to the SAWB model (Boxes 4 and 6). The strongest input variables were selected from an inventory of catchment characteristics (Box 11), which will enable the SAWB model to be applied to ungauged catchments.

The method outlined in Figure 1 was executed in three main steps:

- STEP A: Choice of an appropriate SAWB model and compilation of the input data required (Boxes 1 to 6);
- STEP B: Calibration of SAWB model parameters to obtain a set of optimal parameters (using temporal salinity records) (Boxes 7 – 9) and;
- STEP C: Identification of the catchment characteristics that displayed the strongest relationship with each of the optimised salinity model parameters using the PMI algorithm (Boxes 10 – 12).

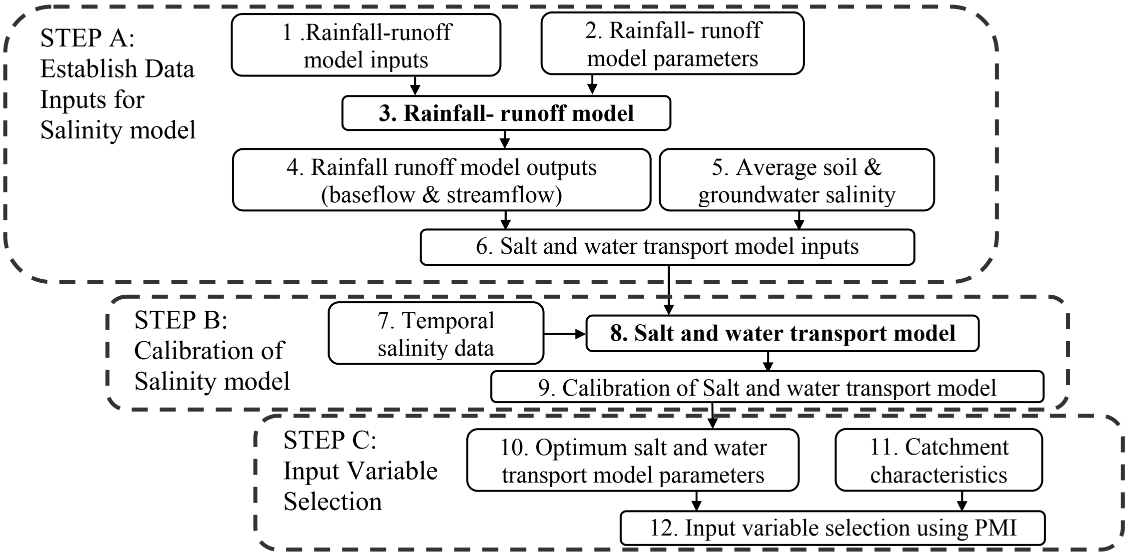

Figure 1: Methodology for identifying the strongest relationships.

2.1. STEP A: Compile data inputs for a salinity model

In order to complete Step A, two main components were required, which were the choice of an appropriate SAWB model, and the compilation of the data required as input to the chosen model.

Choice of a salt and water balance model

A number of SAWB models were compared based on predictive capability and parsimony. These included LUCICAT (Bari et al., 2003), CATSALT (Tuteja et al., 2004), 2CSalt (Weeks et al., 2005) and BC2C (Gilfedder et al., 2005). Based on model accuracy, data requirements, dynamic or steady state model capabilities, output timesteps and salt mobilisation processes included, CATSALT was found to be the most appropriate model.

The CATSALT SAWB model was originally developed to support the management of salinity-affected lands. It predicts runoff and its salinity for catchment-scale investigations of gauged catchments, and has been predominantly applied in NSW, Australia. CATSALT represents the physical processes of surface runoff, percolation and baseflow (Tuteja et al., 2004).

CATSALT includes three modules, (i) Lumped conceptual rainfall runoff model, (ii) Runoff distribution component, and (iii) Salt mobilisation and runoff. Modules (i) and (ii) form a hydrological model called SMAR, which stands alone from the salt mobilisation component. The SMAR module provides outputs of streamflow and baseflow, which are required as inputs to the salt balance part of CATSALT (Box 4, Figure 1).

The CATSALT model can be run from within a spreadsheet program to predict the salinity exports in streamflow and baseflow from a catchment. The structure and limitations of CATSALT are described in detail in Tuteja et al. (2003). In CATSALT, a catchment is typically disaggregated into sub-catchment areas, based on wetness index and landuse type. This study assumes a single wetness index and landuse type over an entire catchment due to the data limitations associated with ungauged catchments.

To apply CATSALT to an ungauged catchment, three salinity parameters needed to be estimated: α, β and K_F. This was achieved by calibration of CATSALT using data from 43 gauged catchments from across Australia. α is a dimensionless parameter that controls the non-linearity of the desorption process between the soil and water; β represents hydraulic conductivity between the exchange of the aquifer and the river; and the Freundlich constant, K_F, represents the salt exchange process between the soil and water (Tuteja et al., 2003).

3.1.2 Input data for the salt and water balance model

A total of 43 catchments were selected from all six Australian states based on data availability (Figure 2). The catchment area and stream salinities within the catchment ranged from 52 – 1735 km^2 and 0 – 45000 μs/cm, respectively. Inputs required by the CATSALT model include continuous streamflow and baseflow runoff series, as well as soil and groundwater salinity values. A continuous salt load export series was also required for calibration of the CATSALT model parameters. All of the data were obtained from state government departments.

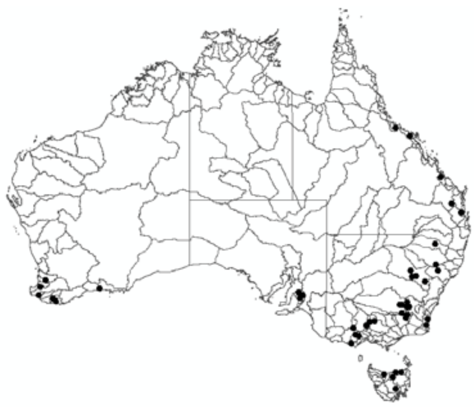

Figure 2. Location of selected catchments

To determine the streamflow and baseflow components from the total runoff data, AWBM was used. AWBM was selected over SMAR, which formed the hydrological component for the original version of CATSALT. This is because an ungauged version of AWBM (UGAWBM3) has been used previously in several studies, using inputs of rainfall and pan evaporation data (Boughton and Chiew, 2003; Boughton and Chiew, 2007). Consequently, AWBM's Base-Flow Index (BFI) parameter was used to separate the total runoff into streamflow and baseflow components, as required for input into CATSALT.

2.2. STEP B: Calibration of the salinity model

In order to determine an optimal set of SAWB model parameters, CATSALT was calibrated to continuous daily stream salt load data for the 43 selected catchments using the Differential Evolution auto-calibration method (Storn and Price, 1997). This method was found to perform best in terms of speed and accuracy when compared to three other auto-calibration techniques: Genetic Algorithm, Simulated Annealing and MS Excel Solver (a gradient method) as part of a preliminary sensitivity analysis. The Root Mean Square Error was used as the objective function during the calibration of the parameters and the Nash-Sutcliffe Coefficient of Efficiency was used as the validation assessment criterion of the optimal parameters chosen for the catchments. Therefore, for each catchment, a set of optimal CATSALT model parameter values (α, β and K_F) was obtained.

2.3. STEP C: Identification of characteristics that have strong relationships with model parameters

Two components were required in order to identify the catchment characteristics that displayed the strongest relationships with each of the optimised salinity model parameters. These were the establishment of a set of readily available catchment characteristics and the input variable selection process.

Catchment characteristics

The set of catchment characteristics used in the input selection process included a wide variety of geomorphological, climatological and biophysical characteristics (Box 11). The characteristics used in Boughton and Chiew (2003) for an ungauged hydrological approach were used, which include catchment area, annual rainfall, annual area potential evapotranspiration (APET), surface runoff, elevation, leaf area index, percentage of woody vegetation, plant-available water holding capacity (PAWHC) and soil transmissivity. A range of soil hydraulic properties and landuse data were also included, which are available for all areas in Australia from the LIZA and SHPA GIS data sets (Western and McKenzie, 2004; Western, 2005). The characteristics came from several sources and were chosen so that they would be readily available for most catchments within Australia, to ensure that the approach could be used widely throughout the country on ungauged catchments. Overall, 32 catchment characteristics were considered for use in the process of input variable selection.

Input Variable Selection

Input variable selection was undertaken with the aim of determining a set of relevant and non-redundant inputs from the set of catchment characteristics. The inputs were selected based on the strength of their relationship with each of the three CATSALT model parameters. This was done using Partial Mutual Information (PMI), which detects linear and non-linear relationships between variables, and accounts for redundancy between input variables (see May et al., 2008). PMI values range from 0 to infinity, with a high score indicating a strong dependence between the two variables (Sharma, 2000). The stopping criterion that was used for the PMI was a bootstrapping method with a 95% confidence limit. Such an approach is required, as critical values of MI cannot be obtained directly, as is the case with critical values of correlation (May et al., 2008).

3. RESULTS

Using the PMI input selection algorithm, it was found that six relevant and non-redundant catchment characteristics have a significant relationship with each of the three CATSALT model parameters. This shows that there are relationships between easily obtainable catchment characteristics and the parameters of the CATSALT model. Table 1 shows the catchment characteristics that were selected for each CATSALT model parameter. Since the PMI values have shown that they have significant relationships with the CATSALT model parameters, the characteristics from Table 1 could be used in future studies as input variables for predictive CATSALT parameters models.

Table 1: Results from the PMI Input Selection Process

α		**β**		**K_F**	
Characteristic	**PMI**	**Characteristic**	**PMI**	**Characteristic**	**PMI**
PAWHC	0.225	B_FCP	0.195	B_KSAT	0.240
Elevation 90-10%	0.178	Surface runoff Ratio	0.189	A_SAT	0.230
Pixel value	0.168	Area	0.184	B_PAWHC	0.209
Runoff Coeff	0.151	% woody	0.176	B_SAT	0.178
B_PERCNT	0.143	Pixel value	0.151	SolPAWHC	0.150
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

The most highly related characteristic for the α parameter was PAWHC, which is the plant available water holding capacity (mm), which represents the water uptake by plants. Elevation 90-10% is the 90th percentile median elevation minus the 10th percentile median elevation. Pixel value is an overall soil classification based on the total set of attributes listed in the SHPA data set (Western and McKenzie, 2004), while the runoff coefficient is the mean annual runoff divided by mean annual rainfall. B_PERCENT represents the portion of the catchment recognised to have a B soil horizon (%) and MARainfall is the mean annual rainfall in the catchment (mm).

For the β Parameter, the most relevant characteristic was B_FCP, which is the average volumetric water content of B-horizon soil at nominal field capacity (m^3/m^3). The surface runoff ratio is the ratio of the surface flow to the total runoff, and the area characteristic is the area of the catchment (km^2). The % woody characteristic is an approximation of the percentage of woody vegetation in the catchment. Similar to the α parameter, Pixel value was chosen as a highly relevant characteristic, as well as the mean annual runoff from the catchment (mm).

The most highly related characteristic for the K_F CATSALT parameter was B_KSAT, which represents the weighted average of median B horizon saturated hydraulic conductivity (m^3/m^3). A_SAT is the averaged value of saturated volumetric water content for the A-horizon (m^3/m^3), while B_PAWHC represents the PAWHC in the B soil horizon (mm). B_SAT was also selected, which are the averaged values of saturated volumetric water content for the B-horizon (m^3/m^3). The SolPAWHC is the average solum (soil that is available to be exploited by plant roots) plant-available water holding capacity (mm), and represents the free-water available in the soil profile (Western and McKenzie, 2004). Lastly, the Pixel value was also chosen as a relevant and non-redundant catchment characteristic for the K_F parameter.

Since measures of the mean annual runoff, runoff coefficient and surface runoff ratio are unlikely to be available in an ungauged catchment, these quantities would be estimated using Boughton and Chiew's (2007) procedure. According to this procedure, average annual rainfall and areal potential evapotranspiration can be used in the ungauged AWBM to estimate the average annual runoff from the catchment. It was found that two thirds of the estimates of the average annual runoff were within ±25% of the actual value, which is only slightly less accurate than estimates produced by the AWBM when it is calibrated directly against recorded runoff data.

4. DISCUSSION AND LIMITATIONS

The results of the PMI selection method were analyzed to identify whether the catchment characteristics that were selected as having significant relationships with each of the CATSALT parameters made physical sense. This was undertaken by using *a priori* knowledge to consider the relationships these CATSALT model parameters might have with catchment characteristics. Most of the chosen characteristics made physical sense, however, due to the limited prior knowledge of these relationships, the choice of some of the inputs could not be explained.

The α parameter controls the non-linearity of the desorption process between the soil and water (Tuteja et al., 2003), therefore it was expected that surface soil, rainfall or runoff characteristics would be chosen by the PMI algorithm. It is unsurprising that water uptake by plants (represented by PAWHC) was chosen as the top-ranking input for α, as it would logically influence the amount of rainfall that is converted to surface flow. The range of elevation (the second most significant input) reflects the steepness of catchment slopes, which influences infiltration and surface runoff potential (Coram and Beverly, 2003). The remaining significant inputs also relate to soil characteristics, rainfall and runoff and hence make physical sense.

The β parameter represents the hydraulic conductivity between the exchange of the aquifer and the river (Tuteja et al., 2003). Catchment characteristics expected to influence net export of salt in groundwater should relate to the volume of water leaving the catchment (and hence volume of salts contained in water), and soil properties. Hence it is unsurprising that the surface runoff ratio, %woody and the MARunoff were chosen as significant characteristics. Transmissivity is an expected choice as well, however, was not found to have a significant relationship with the β parameter using the PMI analysis on the available data.

K_F represents the salt exchange process between the soil and water (Tuteja et al., 2003), therefore it was intuitively expected that the most relevant catchment characteristics would be soil or runoff related characteristics. Therefore it made sense that all characteristics that were chosen represent specific properties of the soil within each catchment.

The major limitation of this study was the small set of data that was available for the input selection process. Greater certainty in the chosen characteristics would result from using a larger number of catchments in the study. The method is also limited to the case where soil and groundwater salinities are invariant in time, whereas they are likely to vary seasonally with variation in climatic conditions.

5. CONCLUSIONS AND RECOMMENDATIONS

Using the 95% confidence limit as the stopping criterion for the PMI algorithm, six relevant and non-redundant catchment characteristics were found to have a significant relationship with each of the three CATSALT model parameters. This shows that there are relationships between easily obtainable catchment characteristics and the parameters of the CATSALT model.

These catchment characteristics should be used in future research to develop models for the prediction of the CATSALT parameters, hence enabling CATSALT to be applied in ungauged catchments by eliminating the traditional calibration requirement. The potential applications of this study could assist in much-needed salinity prediction, prevention, management and planning in ungauged catchments across the globe. This approach is not limited to the CATSALT model and could be applied effectively to other available SAWB models.

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