Groundwater-climate relationships, Ranger uranium mine, Australia: 1. Time series statistical analyses

Mobashwera Kabir[1], Kais Hamza[2], Gavin M. Mudd[1,*] and Anthony R. Ladson[1,3]

[1]Institute for Sustainable Water Resources, Department of Civil Engineering, Monash University, VIC 3800 Australia (* Gavin.Mudd@eng.monash.edu.au)
[2]School of Mathematics, Monash University, VIC 3800 Australia
[3]Presently SKM Consulting Pty Ltd, Melbourne, VIC Australia

Abstract. This paper presents the results of applying specific time series statistical techniques to observed historical groundwater-climate data at the Ranger uranium project. By developing and applying existing statistical techniques, rarely used in mining studies, improved confidence about the understanding of the groundwater-climate relationship at the Ranger uranium project is obtained. This forms a sound basis upon which future climate scenarios can be used to predict the response of the groundwater after rehabilitation and into the long-term, especially with respect to potential climate change impacts.

Introduction

The relationship between groundwater and climate is critical to understand in the design of uranium mine rehabilitation, especially in tropical regions with intense monsoonal rains and extended dry seasons. The Ranger uranium mine is located in the wet-dry tropics of northern Australia and is surrounded by the world heritage-listed Kakadu National Park (Fig. 1) – making it imperative to understand the groundwater-climate relationship to ensure that appropriate rehabilitation designs are implemented upon mine closure.

There are a variety of techniques which can be used to model the relationship between groundwater and climatic conditions. The complex geology, topography and climatic variability of the Ranger project area makes a deterministic process-based model a challenging task. For a simpler approach, this paper presents the application of time series statistical techniques, an approach rarely used in mining projects (companion conference papers present physical modelling approach).

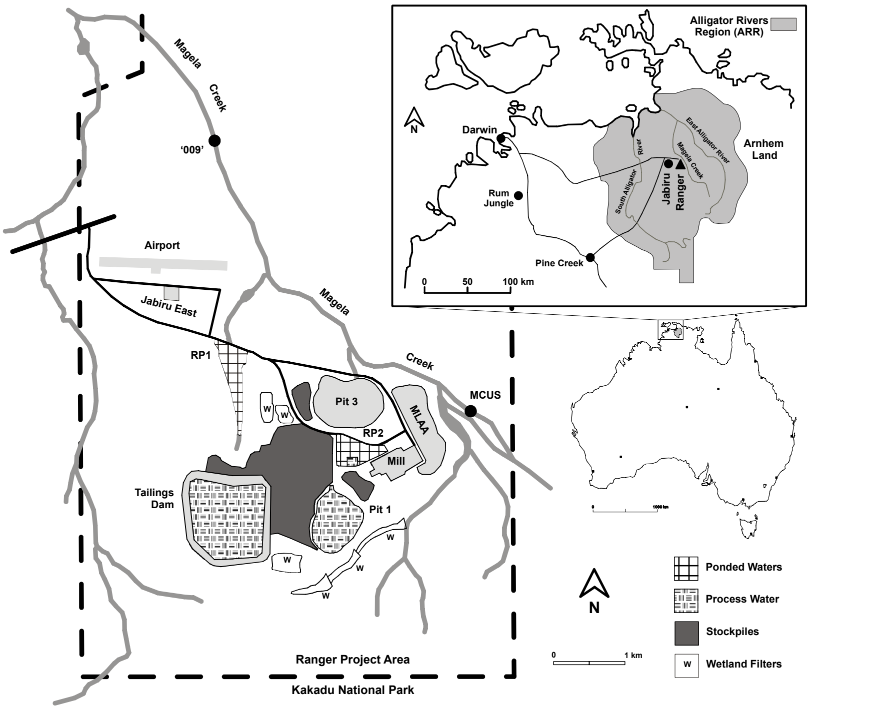


Fig.1. Location and outline of the Ranger uranium project, Northern Territory, Australia.

Ranger uranium project, Northern Territory, Australia

The Ranger uranium deposits were first discovered and 1969, and after extended controversy and debate, was approved for development in 1977. Production began in August 1981, and is currently at 5,000 t U_3O_8/year via open cut mining and a conventional mill. At present, mining is scheduled to be completed in 2012, with milling of ore stockpiles to be completed by 2020. The site is located on freehold indigenous land, controlled by the Mirarr traditional owners.

The Ranger project is located in the Alligator Rivers Region and is surrounded by the world-heritage listed Kakadu National Park (Fig. 1). The area has a wet-dry monsoonal climate, with average annual rainfall of ~1,450 mm and pan evaporation of ~2,500 mm. Virtually all rainfall occurs during the monsoonal months of December to March, leading to a strongly positive water balance over this time.

After completion of mining and milling, the Ranger site will be rehabilitated, and a key legal criterion for tailings is that they "will not result in any detrimental environmental impacts for at least 10,000 years" (Senate 2003). As groundwater is the key driver for long-term migration, it is therefore critical to understand groundwater-climate relationships (especially in light of potential climate change

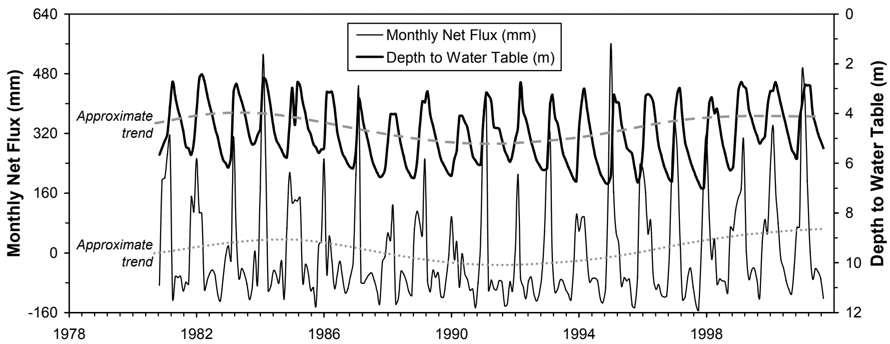


Fig.2. Monthly net flux (rainfall minus estimated evapotranspiration) versus groundwater response, Ranger site. Note both annual variation plus longer term decadal variation.

impacts). Given Ranger's location, there is a range of climate and groundwater monitoring data which can be analysed, with an example shown in Fig. 2.

Methodology and approach

Conceptual hydrologic model

The groundwater behaviour at the Ranger site is treated as a one-dimensional and effectively vertical flow system, based on the large head changes each wet season relative to minor lateral flow. In this manner, the recharge of groundwater during the wet season causes a rise in the water table, while the negative flux during the dry season (due to both soil evaporation and vegetative transpiration) leads to a subsequent decline in the water table. The monthly climatic flux is shown in Fig. 3. The extent of this annual cyclical movement of groundwater is dependent on soil types, underlying geology and relatively flat topography (see Kabir et al 2008). The groundwater bores chosen for analysis were screened based on long-term trends and no evidence of direct mining impacts on head levels (eg. seepage).

All data is obtained from monitoring of groundwater and climate (rainfall, pan evaporation) at the Ranger site, courtesy of Energy Resources of Australia Ltd (ERA, mine owner) or the Office of the Supervising Scientist (OSS, Federal agency) (further details are given in Kabir, 2008).

Time series statistical techniques – brief review

Although times series statistical techniques (TSST) methods are widely used in other disciplines (e.g. economics, hydrology), they have seen little application in groundwater studies(e.g. Fig. 2). Only a brief review is possible herein; for a more thorough treatment see Brockwell and Davis (2002).

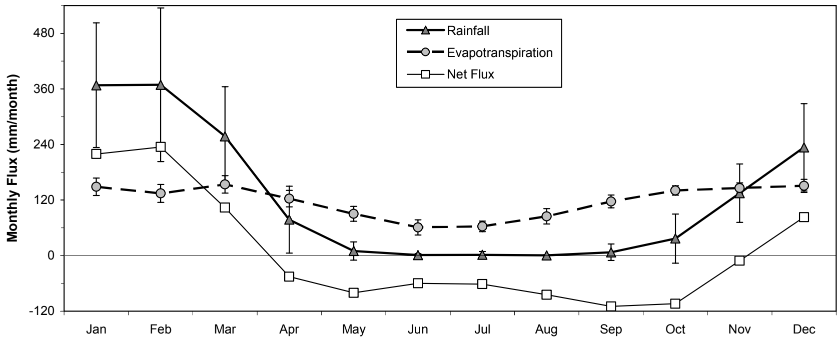


Fig.3. Monthly rainfall, estimated evapotranspiration and net flux.

At its simplest conceptual basis, time series techniques involve developing a statistical relationship between an independent variable (e.g. climate data as cause) and a dependent variable (e.g. groundwater response as effect).

In this study, exploratory data analysis was undertaken to examine seasonality, trends and random noise (e.g. Fig. 2). Classical decomposition techniques were used to address this, and represents a univariate time series model, given as (Brockwell and Davis 2002):

$$X_t = m_t + s_t + A_t \qquad \text{(Eq.1)}$$

$$\text{and} \qquad EA_t = 0,\ s_{t+d} + A_t \qquad \text{and} \sum_{j=1}^{d} s_j = 0 \qquad \text{(Eq.2)}$$

where X_t is the dependent variable at time t (ie. groundwater), m_t is the long-term trend component, s_t is the seasonal component, A_t is the random noise component (a zero-mean stationary process), EA_t is the expected value of A_t, and d is the period of seasonal components.

The seasonal component is calculated such that the period length (d) ensures the values are the same. For example, a period of 12 is used for monthly data. The algebraic sum of the 12 months seasonal components should equal zero (*Eq. 2*). The seasonal components of the net flux and groundwater level are given in Fig. 3.

A univariate autoregressive moving average (ARMA) model could explain the time series of climate and groundwater data of four selected bores, however, the causal relationship between climate and groundwater levels requires multivariate analyses. Therefore two specific TSST methods, namely the transfer function noise (TFN) model and the multivariate autoregressive (MA) model, were used for modelling the groundwater-climate data.

The first TSST model applied in this paper is the TFN model, and involves transforming data to generate zero-mean stationary data sets. The TFN model can then be represented as (Brockwell and Davis 2002):

$$Y(t) = T(B).X(t) + N(t) \qquad \text{(Eq.3)}$$

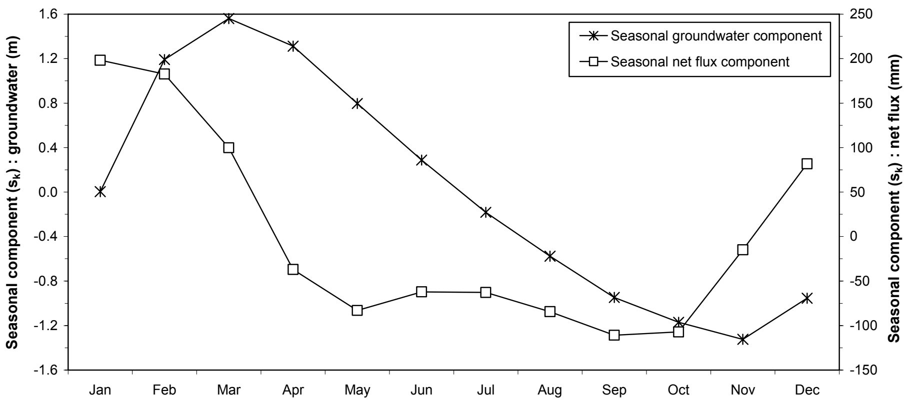


Fig.4. Seasonal components of climatic net flux and groundwater level data.

where *Y(t)* is the dependent variable (ie. groundwater), *X(t)* is the independent variable (climate), *T(B)* is a causal time-invariant linear filter, B is back shift operator and *N(t)* is a zero-mean stationary process (uncorrelated with *X(t)*).

The second TSST model developed is a Yule-Walker multivariate autoregressive (MA) model using monthly data.

Further theoretical discussion, development and references for both TSST models can be found in Brockwell and Davis (2002).

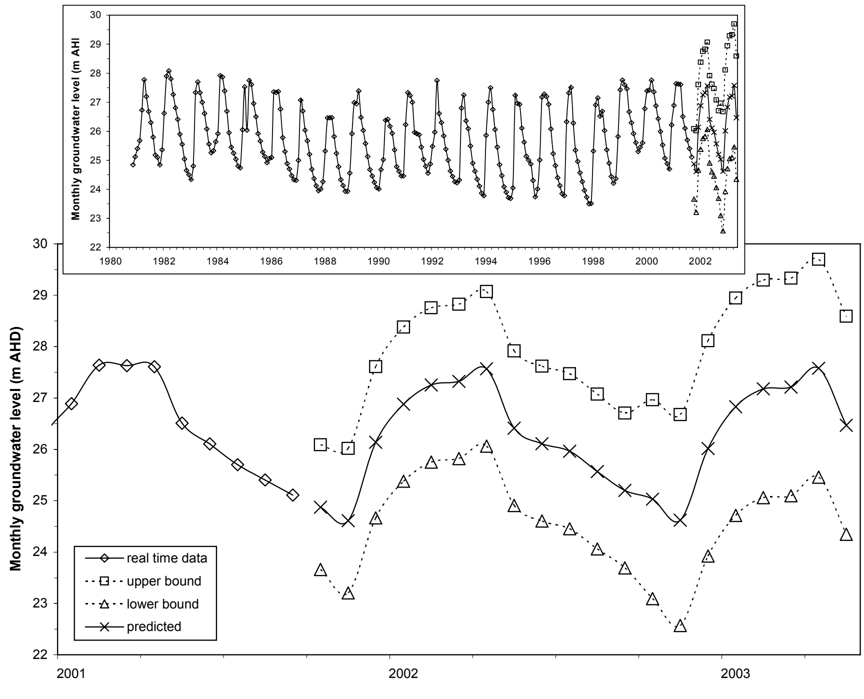


Fig.5. Predictions of groundwater level by the transfer function noise (TFN) model.

Results

Monthly groundwater levels have been predicted for twenty months by analysing twenty two years monthly data (Fig. 5) by TFN model. The monthly net flux and monthly groundwater levels have been predicted for twenty years by analysing twenty-two years monthly data, shown in (Fig. 6) by MA model.

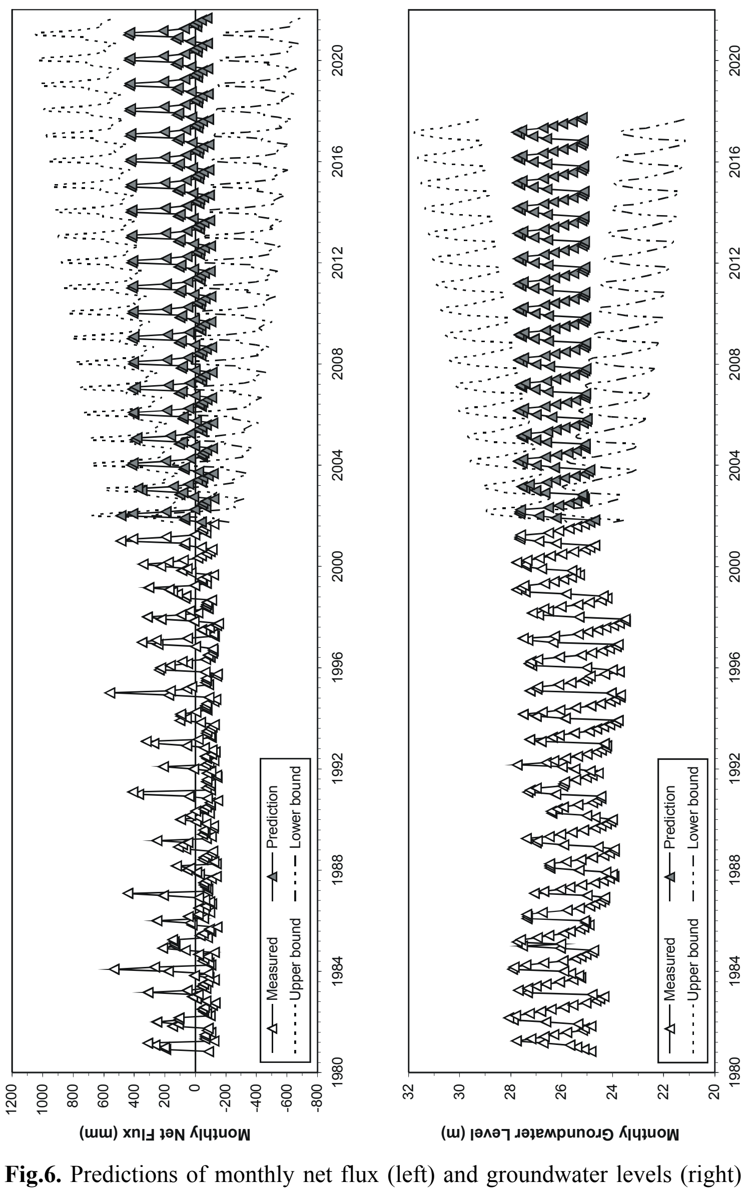


Fig.6. Predictions of monthly net flux (left) and groundwater levels (right) by multivariate autoregressive (MA) model.

The TFN model is represented by:

Input $X(t) = -0.012\ X(t-1) + 0.121\ X(t-2) + 0.266\ X(t-3) – 0.201\ X(t-4) – 0.551\ X(t-5) + Z(t) + 0.190\ Z(t-1) – 0.367\ Z(t-2) – 0.438\ Z(t-3) + 0.276\ Z(t-4) + 0.935\ Z(t-5)$ (Eq.4)

Transfer $T(B) = 1.7\ B / (1 – 0.283\ B)$ (Eq.5)

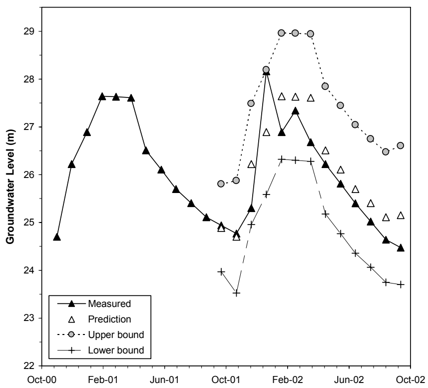
Noise $N(t) = W(t) + 0.5135W(t-1) + 0.336W(t-2) + 0.2365W(t-3)$ (Eq. 6)

Model performance was evaluated in the light of existing statistical criteria, such as model simplicity, model fitness and the Akaike Information Criterion with Correction AICC (Akaike 1969), combined with the appropriateness of the physical basis of the two methods. In Table 2, to compare the statistical performance of the monthly-based models, a number of criteria have been considered. These are the AICC statistic, root mean square error (RMSE), and square of correlation coefficient (R^2) for the models. It is found that the TFN model performs better than the AR model with respect to RMSE and R^2, while the reverse is true for the AICC statistic. The AICC statistic is a standard selection criterion when the competing models are of the same type, where a minimum value indicates the best model, but it does not make sense when comparing two different types of models. In this case, the TFN model is structurally different from the MA model. From this basis, the TFN model can be said to be better than the AR model.

The groundwater levels are predicted by the monthly TFN and MA models for the period November 2001 to October 2002 and compared to measured values (ie. a model validation test). The results are shown in Fig. 7 and confidence intervals are compared in Table 2. In the validation test the two models are similar.

Table 1. Statistical evaluation and comparison of TFN and MA models.

Model	AICC	RMSE	R^2
Transfer function noise (TFN)	6698	0.166	0.761
Multivariate autoregressive (MA)	6585	0.173	0.760



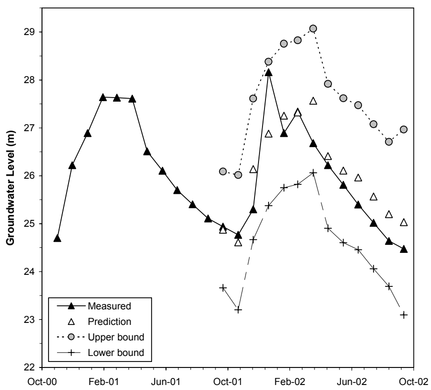


Fig.7. Validation of TFN model (left) and MA model (right) for Nov. 2001 to Oct. 2002.

Table 2. Average confidence interval range for TFN and MA models, Nov. 2001 to Oct. 2002 validation.

Model	Average range of confidence interval (m)
Transfer function noise (TFN)	2.94
Multivariate autoregressive (MA)	2.56

Technically, TFN models are superior to MA models in explaining the groundwater-climate relationship. The theory of MA model considers the mutual dependence of all the series of the process. For instance, the net flux at time t+1 is represented as function of net flux at t, t-1, t-2 … together with groundwater level at t, t-1, t-2 … as well and a noise component. However, in the TFN model, the previous values of the groundwater level series are not considered explicitly. From the scientific point of view, there does exist a strong causal relationship between net flux and groundwater level, but the relationship is not two way. That means net flux influences groundwater level but groundwater level does not influence net flux to any significant extent (ie. the influence is effectively one way). Although the evaporative flux depends on soil moisture content, which in turn is influenced by the nearness of groundwater level to the surface, the importance of this variable is much less than other factors such as intensity and duration of radiative energy, relative humidity, temperature gradient, soil thermal conductivity, vegetation type, wind speed, etc., which influence the evaporation and transpiration process. The statistical fits and confidence intervals of both models, however, are comparable. Therefore, the TFN model is more acceptable than the MA model in representing the system and predicting future groundwater levels.

Discussion

To select the appropriate method of analysis of the groundwater-climate relationship, reviews of the various classes of models were performed. The three basic features, useful for distinguishing approaches to modelling are (CRCCH 2005):

- the nature of the basic algorithms (empirical, conceptual or process-based);
- whether a statistical or deterministic approach is taken to input or parameter specification;
- whether the spatial and temporal representation is lumped or distributed.

The review of key climate feedbacks which are related to groundwater recharge and hydrologic processes suggests that to manage the complex interaction between climate and groundwater recharge, the development of a balanced modelling framework is necessary. Data-based statistical techniques are more preferable than deterministic models when the latter requires too much simplification of the complex system. Comprehensive modelling of groundwater-climate relationships could go to the ultimate extent of including a variety of processes, such as heat flow, groundwater flow and pumping, vapour fluxes, cloud cover, vegetative transpiration, soil evaporation, variable geology and soils, and so on. However, such complexity is clearly unrealistic given the large spatial and temporal uncertainties involved in all of these aspects and processes.

Climatic conditions and variability undoubtedly govern or contribute to shallow groundwater levels (e.g. Fig. 2) (see also Alley 2001; Glassley 2003; Loáiciga 2003; Michaud et al 2004), yet a complete process representation is computationally and physically unrealistic given the complex variability of processes and inter-dependence of many factors. This is not to ignore the value of sound physical or process-based models, but it highlights that different approaches such as time series statistics can be used to compliment such models and analyses, often providing efficient numerical techniques which effectively combine the complexity of natural processes into functional statistical relationships.

Conclusions

Groundwater levels will be the major driver for the potential transport of solutes from a rehabilitated Ranger uranium mine, especially levels relative to non-mine areas. To ensure that the rehabilitation achieves its legal obligations to protect the surrounding water resources and ecosystems for 10,000 years from tailings, it is vital to understand and be able to model the groundwater-climate relationship. This is a fundamental objective to ensure a sustainable post-mining land use and protection of the recognised world-heritage values of the region.

To bridge the gap between the observation scale (~monthly data) and modelling scale (long-term prediction) (Bloschl and Sivapalan 1995), we have used common time series statistical techniques. These methods identify the underlying patterns and the qualitative description of the groundwater-climate relationship, such as seasonal variability or long-term trends.

The application of a classical decomposition model to the groundwater-climate data for Ranger was used first to gain an understanding of the relationship. The timing of the peak and trough between the two seasonal data sets indicates that the lag between them is less (2 months) during high groundwater levels (wet season) and much more (4 to 5 months) during low groundwater levels (dry season). Hence the process has a variable lag throughout the year.

Thus, for improved understanding of the physics with the help of statistics, a classical decomposition model has been used with historical net flux and groundwater level data for the Ranger uranium mine site. A transfer function noise (TFN) model and multivariate autoregressive (MA) model were then developed by using the net flux and groundwater level data to predict the future groundwater level. Some of them have been found to be numerically efficient and others have the quality of best fit.

Finally the statistical performance is almost equal for both the TFN model and MA model but the physical representation is better in TFN than MA. Therefore a monthly-based TFN should be the recommended model for the prediction purpose in future research.

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Groundwater-climate relationships, Ranger uranium mine, Australia: 2. Validation of unsaturated flow modelling

Mobashwera Kabir[1], Gavin M. Mudd[1,*] and Anthony R. Ladson[1,2]

[1]Institute for Sustainable Water Resources, Department of Civil Engineering, Monash University, VIC 3800 Australia (*Gavin.Mudd@eng.monash.edu.au)
[2]Presently SKM Consulting Pty Ltd, Melbourne, VIC Australia

Abstract. This paper presents the results of applying an unsaturated flow model to observed historical groundwater-climate data at the Ranger uranium project, Northern Territory, Australia. Based on observed data, a one-dimensional model was developed to fit historical data for several bores. Statistical evaluation of varying porosity and hydraulic conductivity was undertaken, thereby giving a reasonable model configuration. The model is thus confirmed as suitable for predicting the impacts of future climate change scenarios on water table fluctuations.

Introduction

The relationship between groundwater and climate is critical in the design of uranium mine rehabilitation, especially in tropical regions with intense monsoonal rains and extended dry seasons. The Ranger uranium mine is located in the wet-dry tropics of northern Australia and is surrounded by the world heritage-listed Kakadu National Park (Fig. 1). It is imperative to understand the groundwater-climate relationship to ensure that appropriate rehabilitation designs are implemented upon mine closure (see also companion paper Kabir et al 2008).

A variety of techniques can be used to model groundwater fluctuations as a function of climatic conditions. The complex geology and climatic variability of the Ranger region makes a deterministic, detailed process-based model a difficult task. For an alternative viable approach, this paper uses the unsaturated flow model Seep/W (Krahn 2004) based on a one-dimensional conceptual model of the groundwater-climate system. Given the relatively flat topography and large annual fluctuations in the water table versus minor lateral flows, the flow system can be simplified as effectively vertical, thereby allowing direct implementation in Seep/W. The refined model can then be used for a variety of purposes.

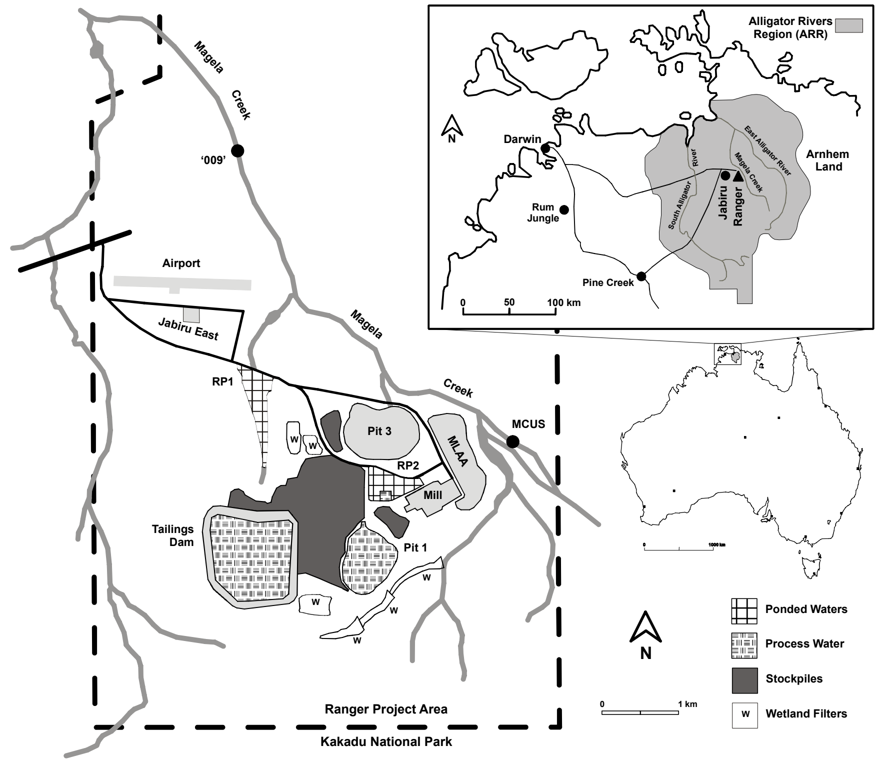

Fig.1. Location and outline of the Ranger uranium project, Northern Territory, Australia.

Hydrogeology of the Ranger site

The Ranger uranium project was briefly described in the companion paper Kabir et al (2008). Although there have been numerous studies on the hydrogeology and water balance at Ranger, only a few have directly examined the relationship between groundwater and climate, especially rainfall-evaporation and recharge (e.g. Vardavas, 1993; Woods 1994). A brief review of the hydrogeology is presented, followed by a justification of the modelling approach used for this work.

In the past, hydrogeology studies at Ranger have commonly focussed on water or tailings management issues. The hydrogeology is considered to comprise three principal aquifer types – alluvial sands and gravels (Type A), lateritic layers, clayey sands to weathered rocks (Type B), and fractured rocks (e.g. schists, dolomite) (Type C), shown in Fig. 2 (Ahmad and Green 1986; Woods 1994; Brown et al 1998). The most important shallow aquifers are found as weathered and lateritic soils (by area), with annual variations in the water table being between 1 to 5 m.

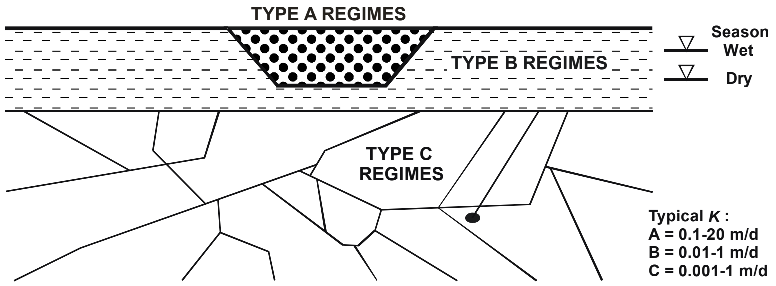

Fig.2. Conceptual hydrogeology of Ranger, including approximate wet and dry season position of the water table (adapted from Ahmad and Green 1986; Woods 1994).

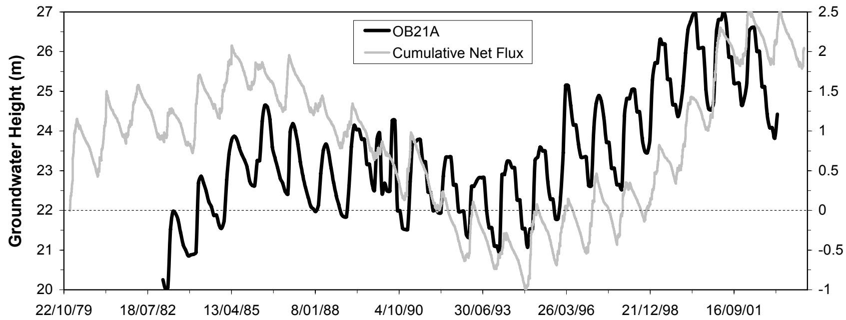

Fig.3. Variation of groundwater (bore OB21A) and cumulative climatic net flux.

One example of the seasonal groundwater movement compared to cumulative net flux (rainfall – evapotranspiration) is given in Fig. 3, showing annual variation along with long term climatic variability (ie. wetter versus dryer periods).

Seep/W model structure and development

A one-dimensional conceptual model of groundwater-climate interaction was adopted (e.g. Type B). A homogenous vertical column was defined with no-flow boundaries on all sides except the surface where net climate flux was applied (rainfall – evapotranspiration) at monthly time steps. Soil properties were based on previous work, such as porosity, saturated hydraulic conductivity and unsaturated moisture retention (characteristic) curve (e.g. Willett et al 1993; Akber 1991), while the unsaturated hydraulic conductivity function was defined from the characteristic curve (e.g. van Genuchten or Fredlund-Xing models, see Krahn 2004).

As noted above, the hydrogeology of the Ranger area is highly heterogeneous, leading to differing average responses of the water table to the annual wet season (e.g. annual fluctuation, or Δh, of 1-5 m). Obtaining reliable spatial data on all of the above properties is difficult and still includes residual uncertainty. As such a range of Seep/W models were developed with varying soil parameters to assess this uncertainty. This allowed a choice of optimum properties for each bore to be used for assessing climate change impacts (see Kabir et al 2008b). In this work, saturated hydraulic conductivity (K, 0.3 to 30 m/30 days) and effective porosity (n, 2.5% to 20%) were varied. All model results were statistically evaluated using the measures in Table 1, to ascertain the 'goodness of fit' for each model.

Table 1. Statistical objective functions[a] used to assess model fit.

Measure[b]	Expression[b]	Range	Decision Rule
E (Nash-Sutcliffe criterion)	$E = 1 - \frac{\sum_{t=1}^{T}(h_o^t - h_m^t)^2}{\sum_{t=1}^{T}(h_o^t - \overline{h_o})^2}$	-∝ to +1	+1 is desirable
r (linear correlation coefficient)	$r = \frac{\sum_{t=1}^{T}(h_m^t - \overline{h_m})(h_o^t - \overline{h_o})}{\sqrt{\sum_{t=1}^{T}(h_m^t - \overline{h_m})^2}\sqrt{\sum_{t=1}^{T}(h_o^t - \overline{h_o})^2}}$	-1 to 1	+1 is desirable, -1 is undesirable
Ratio	$Ratio = \overline{h_m} / \overline{h_o}$	0 to ∝	+1 is desirable
RMSE (root mean square error)	$RMSE = \sqrt{\sum_{t=1}^{T}(h_m^t - h_o^t)^2} \Big/ T$	0 to ∝	0 is desirable
$\overline{d}$ (mean error)	$\overline{d} = \overline{h_m} - \overline{h_o}$ where $\overline{h_m} = \sum_{t=1}^{T} h_m^t \Big/ T$	-∝ to +∝	0 is desirable
S_e (standard error)	$S_e = \sqrt{\frac{S^2}{T-1}}$ & $S^2 = \frac{\sum_{t=1}^{T}(d^t)^2}{T} - \overline{d}^2$	0 to ∝	0 is desirable
β	$\beta = \overline{\mathrm{d}} \Big/ \sqrt{\mathrm{S}^2 / (\mathrm{T} - 1)} = \overline{\mathrm{d}} \big/ S_e$	0 to ∝	0 is desirable

[a] From Zheng and Bennett (1995), Middlemis et al (2001), Nash and Sutcliffe (1970).
[b] Primary variables are *h* head; *t* time step number (T total time steps); *d* model – measured difference; Subscript 'm' / 'o' – model / observed values; ¯ (overscore) average (e.g. $\overline{h_m}$ = average modelled head).

Results

Nine model were developed with the combinations of K=0.3, 3 and 30 m/30days and n=2.5, 5 and 10%. Statistical evaluations of model runs are given in Tables 2 and 3, with an example in Fig. 4. An example of measured versus modelled groundwater heads (bore OB21A) is graphed in Fig. 5.

From Tables 2 and 3, optimum (desirable) values of criteria $\overline{h_m}$, *E*, *Ratio, RMSE,* β, $\overline{d}$, and S_e are found to in one model combination, while criterion *r* is found to be in a different model run. The difference, however, between *r* values in these models is mostly marginal. To achieve better consistency between the criteria, runs are extended to additional set of combinations for n=20%. The direction of changes of the criteria are again found to be mostly inconsistent. The best bore with consistent model parameter comes out to be OB27 with K 30 n 20.

Table 2. Statistical assessments[a] of Seep/W model runs versus soil parameters (K, n).

	$\overline{h_m}$	*E*	*r*	*Ratio*	*RMSE*	*β*	$\overline{d}$	S_e
Desired value	–	1	1	1	0	0	0	0
OB1A[b], $\overline{h_o}$ = 25.83 m, *Δh* = 3.17 m (*K* m/30 days, *n* %)								
K 0.3, n 2.5	25.43	-0.56	0.23	0.98	0.09	4.37	0.4	0.09
K 3, n 2.5	21.57	-30.2	***0.42***	0.84	0.42	12.94	4.26	0.33
K 30, n 2.5	1.83	-3781	0.3	0.07	4.62	5.47	24	4.39
K 0.3, n 5	25.69	-0.37	0.09	0.99	0.09	1.54	0.14	0.09
K 3, n 5	23.3	-11.07	0.33	0.9	0.26	11.99	2.53	0.21
K 30, n 5	22.01	-18.69	**0.35**	0.85	0.33	16.09	3.82	0.24
K 0.3, n 10	**25.82**	**-0.11**	0.16	**1**	**0.08**	**0.11**	**0.01**	**0.08**
K 3, n 10	23.94	-4.16	0.26	0.93	0.17	14.98	1.89	0.13
K 30, n 10	23.81	-0.12	0.33	0.92	0.17	16.75	2.02	0.12
K 0.3, n 20	***25.83***	***0.03***	0.21	***1***	***0.07***	***0.06***	***<0.01***	***0.07***
K 30, n 20	24.71	-0.99	0.3	0.96	0.11	13.9	1.12	0.08
OB20[b], $\overline{h_o}$ = 18.09 m, *Δh* = 1.67 m (*K* m/30 days, *n* %)								
K 0.3, n 2.5	16.82	-1.5	0.59	**0.93**	0.1	21.86	1.27	0.06
K 3, n 2.5	13.14	-42.81	***0.72***	0.73	0.41	18.18	4.94	0.27
K 30, n 2.5	9.76	-123.84	**0.63**	0.54	0.7	18.12	8.33	0.46
K 0.3, n 5	17.1	-0.67	0.59	***0.95***	0.08	19.12	0.99	***0.05***
K 3, n 5	14.39	-19.95	**0.63**	0.8	0.29	22.36	3.7	0.17
K 30, n 5	14.08	-23.53	0.61	0.78	0.31	22.49	4.01	0.18
K 0.3, n 10	***17.2***	***-0.42***	0.62	***0.95***	***0.07***	**17.79**	***0.88***	***0.05***
K 3, n 10	15.56	-7.28	0.54	0.86	0.18	30.49	2.53	0.08
K 30, n 10	15.14	-9.78	0.56	0.84	0.2	33.93	2.95	0.09
K 0.3, n 20	**17.17**	**-0.59**	0.6	***0.95***	**0.08**	***17.23***	**0.92**	0.05
K 30, n 20	16.09	-3.86	0.53	0.89	0.14	35.98	2	**0.06**
OB21A[b], $\overline{h_o}$ = 23.42 m, *Δh* = 2.14 m (*K* m/30 days, *n* %)								
K 0.3, n 2.5	24.98	-0.59	***0.75***	1.07	0.12	-22.7	-1.56	***0.07***
K 3, n 2.5	20.75	-8.13	0.66	0.89	0.29	11.34	2.67	0.24
K 30, n 2.5	17.14	-31.94	0.35	0.73	0.55	16.6	6.28	0.38
K 0.3, n 5	**24.62**	**-0.34**	0.7	**1.05**	**0.11**	**-14.97**	**-1.2**	**0.08**
K 3, n 5	20.24	-5.75	0.55	0.86	0.25	21.87	3.17	0.15
K 30, n 5	18.96	-11.53	0.34	0.81	0.34	24.09	4.45	0.18
K 0.3, n 10	***23.33***	***0.37***	**0.72**	***1***	***0.08***	***1.18***	***0.09***	**0.08**
K 3, n 10	19.86	-5.83	0.37	0.85	0.25	33.79	3.55	0.11
K 30, n 10	19.58	-7.05	0.24	0.84	0.27	32.97	3.84	0.12
K 0.3, n 20	21.77	-0.71	0.71	0.93	0.13	24.27	1.65	***0.07***
K 30, n 20	20.03	-5.05	0.34	0.86	0.24	36.91	3.39	0.09

[a] Best fits are highlighted in grey shaded bold-italic text; next closest fits are bold only.
[b] Model runs with K 3 not available.

Table 3. Statistical assessments[a] of Seep/W model runs versus soil parameters (K, n).

	$\overline{h_m}$	*E*	*r*	*Ratio*	*RMSE*	*β*	$\overline{d}$	S_e
Desired value	–	1	1	1	0	0	0	0
OB27[b], $\overline{h_o}$ = 8.87 m, Δh = 2.00 m (*K* m/30 days, *n* %)								
K 0.3, n 2.5	10.15	-1.54	0.62	1.14	0.13	-20.57	-1.28	**0.06**
K 3, n 2.5	10.92	-5.37	0.77	1.23	0.2	-21.73	-2.05	0.09
K 30, n 2.5	11.09	-6.16	0.77	1.25	0.21	-23.58	-2.21	0.09
K 0.3, n 5	10.18	-2.1	0.42	1.15	0.14	-15.78	-1.31	0.08
K 3, n 5	10.69	-3.55	0.78	1.2	0.17	-27.86	-1.81	0.07
K 30, n 5	10.46	-2.82	**0.79**	1.18	0.15	-21.31	-1.58	0.07
K 0.3, n 10	9.92	-1.84	0.42	1.12	0.13	-10.71	-1.05	0.1
K 3, n 10	9.52	-0.04	0.72	1.07	0.08	-11.2	-0.65	**0.06**
K 30, n 10	9.42	0.23	0.77	1.06	0.07	-10.54	-0.54	***0.05***
K 3, n 20	***8.61***	**0.28**	0.62	**0.97**	0.07	***4.26***	***0.27***	**0.06**
K 30, n 20	**8.56**	***0.37***	***0.81***	**0.96**	***0.06***	**5.51**	**0.31**	**0.06**
OB41[b], $\overline{h_o}$ = 14.89 m, Δh = 1.69 m (*K* m/30 days, *n* %)								
K 0.3, n 2.5	12.24	-18.29	***0.55***	0.82	0.19	25.11	2.84	0.11
K 3, n 2.5	8.77	-168.18	**0.53**	0.59	0.57	15.74	9.43	0.6
K 30, n 2.5	-20.62	-26838	0.35	-1.38	7.21	***5.22***	65.38	12.54
K 0.3, n 5	12.59	-13.31	0.36	0.85	**0.17**	23.99	**2.44**	**0.1**
K 3, n 5	10.57	-69.46	0.42	0.71	0.37	21.34	6.39	0.3
K 30, n 5	9.97	-90.09	0.38	0.67	0.42	21.26	7.15	0.34
K 0.3, n 10	**12.92**	**-9.64**	0.21	**0.87**	***0.14***	21.71	2.05	***0.09***
K 3, n 10	12.08	-26.33	0.35	0.81	0.23	23.99	3.89	0.16
K 30, n 10	12.4	-21.75	0.39	0.83	0.21	23.92	3.57	0.15
K 0.3, n 20	***12.93***	***-5.53***	-0.24	**0.89**	0.18	19.29	***1.67***	***0.09***
K 30, n 20	12	-13.5	-0.01	0.82	0.27	24.29	2.6	0.11

[a] Best fits are highlighted in grey shaded bold-italic text; next closest fits are bold only.
[b] Model runs with K 0.3-n 20 (OB27) and K 3-n 20 (OB41) not available.

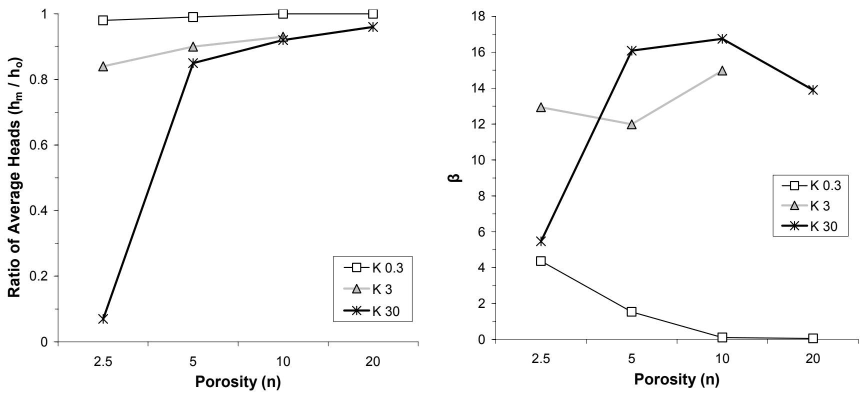

Fig.4. Example of the variation of selected statistical evaluations for bore OB1A.

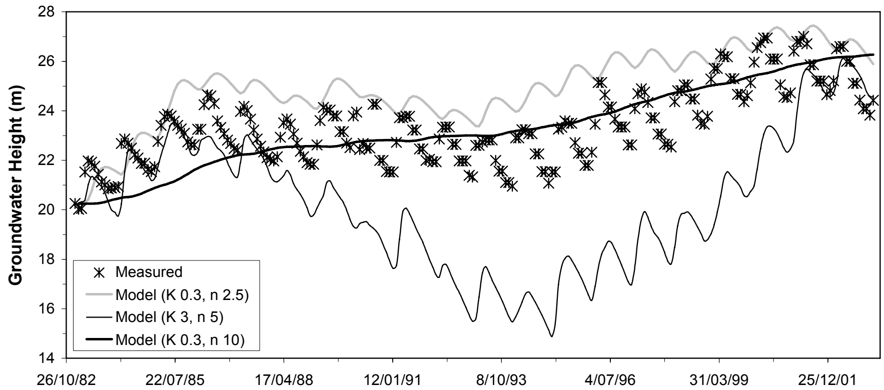

Fig.5. Observed versus modelled groundwater levels in bore OB21A.

Discussion

Based on all results above, the performance of the models for OB27 achieves the best result since this bore successfully includes the best *E* and *r* values in one combination of hydraulic conductivity and porosity. Another important aspect of the results is that the best model may not necessarily be unique, rather it corresponds to a range of parameter values for most of the bores. For example, with respect to the statistical evaluation of parameter combinations, OB41 shows a lot of scatter while OB27 shows a consistent parameter combination.

If we analyse the importance of all criteria in context to the primary objective of the modelling, the most important criterion is considered to be the *r* value as this deals with both the magnitude and direction of deviation whereas other criteria deal with magnitude only (see Middlemis et al. 2001).

The relative influence of porosity (*n*) on the annual average groundwater fluctuation (Δh) can be explored by comparing OB20 and OB21A, since they are close to each other. The model results show the importance of *n* in the amplitude of Δh. OB20 performs well with *n* of 10% to 20% and a measured average annual groundwater variation (Δh) of 1.67m, whereas OB21A performs well with *n* of 5% to 10% with Δh of 2.14m. This shows that annual fluctuations are higher for lower porosity (all other factors remaining the same).

The results also show that hydraulic conductivity is important in modelling the annual and longer term response of groundwater (as should be expected). Based on field work at Ranger (e.g. Willett et al 1993; Akber 1991), it is clear that the weathered near surface geology and aquifers at Ranger are highly variable and heterogeneous. The approach adopted in this paper is clearly a simplification which allows for efficient modelling at the expense of more thorough discretisation of model parameters (*K*, *n*, others). As such, the approach adopted herein of using a simplified one-dimensional homogenous model appears reasonable.

Conclusions

This paper presented the results of applying an unsaturated flow model (Seep/W) to observed historical groundwater-climate data at the Ranger uranium project. The approach adopted a one-dimensional groundwater-climate model to fit historical data for several bores, with varying values for hydraulic conductivity and porosity to assess uncertainty due to the heterogeneous geology of the area. All model runs were evaluated with a range of statistical measures for goodness of fit. In summary, the research approach utilised herein demonstrates that a simplified conceptual model implemented via an unsaturated flow model can achieve a robust model configuration with reasonable statistical confidence.

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Groundwater-climate relationships, Ranger uranium mine, Australia: 3. Predicting climate change impacts

Mobashwera Kabir[1], Gavin M. Mudd[1,*], Anthony R. Ladson[1,2] and Edoardo Daly[1]

[1]Institute for Sustainable Water Resources, Department of Civil Engineering, Monash University, VIC 3800 Australia (*Gavin.Mudd@eng.monash.edu.au)
[2]Presently SKM Consulting Pty Ltd, Melbourne, VIC Australia

Abstract. This paper presents the results from using a validated unsaturated flow model to predict groundwater response to climate variability and climate change at the Ranger uranium project, Northern Territory, Australia. A Monte Carlo-style approach was adopted, with 30 statistically generated replicates for each of the 5 models and 7 scenarios from the IPCC climate change projections, giving 1050 model runs in total. The results are presented in terms of predicted groundwater levels to 2100. The paper demonstrates the usefulness of this modelling approach in understanding the future impacts from climate change on groundwater levels.

Introduction

The relationship between groundwater and climate is critical in the design of uranium mine rehabilitation, especially in tropical regions with intense monsoonal rains and extended dry seasons. The Ranger uranium mine is located in the wet-dry tropics of northern Australia and is surrounded by the world heritage-listed Kakadu National Park (see companion paper, Kabir et al 2008, for location map).

Given that climate change is predicted to lead to significant hydrologic changes across northern Australia (e.g. Hennessy et al. 2007), such as changing rainfall and evapotranspiration, it is critical to use the available data to best understand what this means for groundwater recharge, levels and therefore minesite rehabilitation.

This paper develops an approach to model the potential impacts of climate change and climate variability on groundwater levels through a Monte Carlo technique. The unsaturated flow model used is taken from Kabir et al (2008), and compliments other methods to model groundwater-climate relationships such as time series statistical techniques.

Climate variability and climate change

For this research work, the processes of climate variability and climate change need to be carefully defined, followed by a brief review of northern Australia.

According to the UN Framework Convention on Climate Change (UNFCCC), climate change refers to long-term processes occurring over several decades or centuries which leads to changes in average climatic conditions, and includes both anthropogenic and natural causes (Houghton et al 2001). Climate variability is considered to range from inter-annual to inter-decadal and is related to natural phenomena. However, the Intergovernmental Panel of Climate Change (IPCC) definition of climate change means any change in climate over time, whether due to natural variability or as a result of human activity – different to the UNFCCC.

There is an abundance of literature on the processes and controls on climatic conditions across northern Australia. The most common indices used in this area include sea surface temperature (SST) differences between certain regions, such as the Southern Oscillation Index (SOI) to predict El Nino (dry, leading to 'ENSO') or La Nina (wet) climatic periods, Indian Ocean Dipole (IOD) (Ashok et al. 2003; Chang et al 2006), Pacific Decadal Oscillation (PDO) (Mantua et al 1997; Zhang et al 1997; Mantua and Hare 2002; Verdon and Frank 2006a,b) and Interdecadal Pacific Oscillation (IPO) (Power et al 1999). In general, they describe whether climatic conditions are more likely to be warm/ cool, or wet/dry, based on differential SST's between particular regions. They are commonly correlated to major continental regions, such as eastern Australia or western Americas, occur on different cycles (e.g. annual to decadal or longer) and widely used to predict likely climatic conditions. Northern Australia is influenced by the variable combination of all of these indices (with PDO perhaps being the least important).

The models used by the IPCC to predict climate change are not consistent in tropical northern Australia (Alley et al 2007), meaning for the Ranger mine site there is uncertainty regarding the nature and magnitude of change. Less than 66% of models agree on the sign of the change (increase/decrease of precipitation in Dec-Jan-Feb), and is probably related to complex interaction of multiple factors.

There is an increasing recognition that rising temperature is exacerbating the impact of any rainfall reduction (Cai 2007). As a result of reduced precipitation and increased evaporation, dryer periods are projected to intensify in southern and eastern Australia (Hennessy and Fitzharris 2007; Hennessy et al. 2007). But there has been an increasing trend in rainfall over much of north and northwest Australia over recent decades, which has contrasted with decreases over the rest of the continent. Also, Smith and Suppiah (2007) argue that the trends in rainfall totals and average intensities in northern Australia are largely unrelated to trends in ENSO and most likely reflect the influence of other factors.

The degree to which climate change will impact on the frequency or magnitude of all of the above indices and processes remains uncertain and difficult to predict. For example, ENSO events will still occur without any climate change or they may alter due to climate change, with different climate models predicting variable changes such as intensity, duration, wet/dry, warm/cool and so on (see Knutson et al 1997; Timmermann et al 1999; Collins 2000a,b; among others).

Although periods of flood and drought risk in eastern Australia have been correlated to the PDO and IPO, they appear to have minimal influence in northern tropical Australia. However, due to their importance in overall climatic conditions across Australia, they are retained in algorithms to generate net flux data sets.

A number of fundamental issues need to be considered. The non-linearity in the strength of ENSO for Australia, the occurrence of IOD in relation to ENSO for Australia, the relationship between IOD and ENSO in Australia, the uncertainty of future influence of IOD on ENSO of Australia, and the interaction of ENSO events with local climate of the Kakadu region.

There exists non-linearity in the strength of ENSO events in Australia. The differences in the strength of relationship between El Nino (La Nina) with wet (dry) condition can be described as follows.

As a typical tropical phenomenon, the evolution of the IOD is strongly linked to the annual seasonal cycle – the phenomenon develops during May/June, peaks in September/October, and diminishes in December/January (Chang et al 2006). Therefore the IOD influences the Australian winter climate (Ashok et al. 2003). The El Nino events in Australia usually emerge in the March to June period and strongest influence occurs in the six months of June to November (BoM 2007a). The cooling of La Nina is relatively strongest during October to March period (BoM 2007a). Therefore the overlapping of IOD with ENSO is more prevalent with El Nino than La Nina. However, the link between IOD and ENSO has been reported to be have been broken or weakened by climate change (Kumar et al 1999), giving rise to further uncertainty in winter climate conditions in Australia.

The increased dry conditions caused by El Nino occur during the dry season, compared to the increased wet conditions caused by La Nina which occur during the wet season. Therefore if we do not consider the influence of IOD with ENSO, the impact will be greater for both El Nino and La Nina. If we do consider the IOD influence with ENSO, the rainfall in the site being summer rainfall, it is not counteracted by IOD, thus the wet season will still be unimpacted by IOD. Similar results have been recognised by others (Bayliss, pers. comm., 2007). A tabular representation of the links between IOD and ENSO is shown in Table 1.

The predictability of interdecadal climate events remains an area of uncertainty. By reviewing the existing understanding of the ENSO, IPO, PDO, and IOD events, some conditional aspects of these natural processes have been identified. We translate this understanding, observations and possibilities into our algorithm for generating the spells of ENSO events for the Ranger site and combine this with IPCC predicted climate data to generate net flux data sets for modelling.

Table 1. Annual links between ENSO and IOD events.

J	F	M	A	M	J	J	A	S	O	N	D	J	F	M	A	M
				IOD start				IOD peak			IOD end					
		El Nino months														
								La Nina months								
Wet season				Dry season						Wet season						Dry

Modelling methodology

A Monte Carlo-style approach is adopted to generate multiple replicates of input data for numerous model runs. A multi-step algorithm is developed to generate a series of net flux data, incorporating average climate data, predicted climate change trends from IPCC global climate models (GCMs), ENSO and IOD events.

Climate change models and predicted data

The IPCC make the output data from GCMs available, and in Australia this is from the CSIRO through the OzClim software (CSIRO 2006). The OzClim data used for this report is from the Third Assessment report series, as the 2007 reports and data were not yet available.

The GCMs hydro-climate data available from OzClim were rainfall and point potential evapotranspiration (PPET). For application in flow models, however, PPET needs to be converted to areal actual evapotranspiration (AAET). All PPET data was converted to AAET based on standard methods (e.g. Morton 1983).

In 2004, Hennesy et al (2004) undertook a detailed performance evaluation of 12 GCMs for the Northern Territory, Australia, in simulating the current regional climate. Based on this study, other IPCC reports and related literature, five GCMs were selected for extracting future climate change data for the Ranger mine site, namely the CSIRO: Mk2, HadCM2, HadCM3, ECHAM4/OPY and CSIRO: DARLAM 125km GCMs. Further to the physical models, IPCC use six future emission scenarios as inputs to the various GCMs, called A1B, A1FI, A1T, A2, B1 and B2, and they have remain unchanged from the Third to Fourth Assessment reports. An additional scenario, IS92cc, was also available from OzClim, giving a total of seven scenarios for each of the five GCMs. Further details regarding all GCMs and emissions scenarios is available in the varous IPCC literature. Annual net flux data for all 7 IPCC scenarios from the HadCM3 model is shown in Fig. 1.

Climate variability algorithm

We summarise the findings of the literature review and translate these into decision rules and address ambiguity in generating the conditional random process.

<u>Decision for PDO</u>: Random selection of PDO positive (El Nino enhanced), and

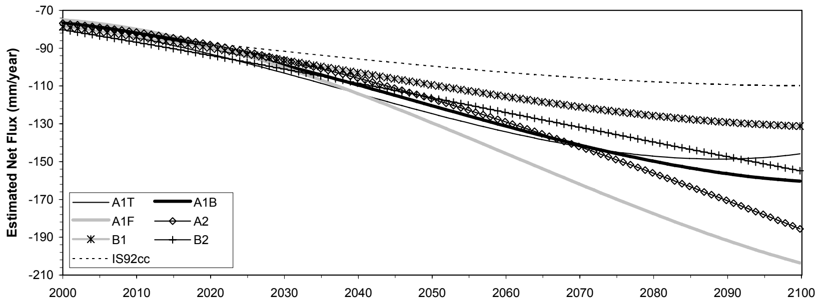

Fig.1. Estimated net flux for all scenarios (HadCM3 GCM)

PDO negative (La Nina enhanced) and PDO zero (both non enhanced)

Decision for IOD-ENSO relationship for Australia: La Nina is stronger than El Nino for Australia while IOD ENSO inverse relationship exists.

Decision for IOD-ENSO relationship for site:

- Irrespective of the existence of the link between IOD and ENSO, the site wet season is supposed to be consistently and strongly influenced by La Nina.
- With the dry season, if the link (inverse relation between ENSO and IOD) remains broken then the El Nino will be stronger for the site.
- And if the relationship is again established then the El Nino might become weakly related to dry condition for the site.

There could be concern for the IOD-El Nino relationship in future predictions but nothing for the IOD-La Nina relationship.

Ambiguity 1: PDO duration is to be randomly selected from 20 to 40 years. This broad guideline comes from the studies based on the IPO during past hundred years (e.g. Verdon and Wyatt 2004).

Ambiguity 2: The randomly selected PDO duration is covered by selecting random ENSO duration of 0 to 8 years. The guidelines for selection of frequency limit of ENSO events have been obtained by analysing the past 100 year's events in Australia (BoM 2005; BoM 2007a,b). For positive or negative PDO the cycle is selected to be 0 to 5 years and for transitional PDO the cycle is selected to be 6 to 8 years.

Ambiguity 3: The IOD-El Nino inverse relationship can exist or not.

The amplitude of ENSO events in the context of present research relate to the rainfall and AAET in ENSO months. We assume during El Nino years that when rainfall is less, AAET is also less. During La Nina years, when rainfall is more, then AAET is also more. But practically, however, this relationship is not linearly correlated, meaning rainfall is unbounded while AAET is bounded as suggested by Morton's equation (Morton 1983). We use the historical percentile records of AAET to cut off the point of wet conditions' AAET.

For the ENSO events, the ranking from ENSO1, ENSO2 … to ENSO5 goes with the 99.99, 90, 10, 5, 1 percentile values of rainfall and AAET. If PDO is for La Nina, it will be always enhanced (because it is independent of IOD), if PDO is for El Nino, it may be enhanced or not (because it depends on IOD). For enhanced La Nina we use the 99.99 percentile value, and for non-enhanced La Nina we use 90 percentile values. For El Nino we use 10, 5 and 1 percentile values. The ranges of percentile values are extracted from reviewing the indices of Expert Team on Climate Change Detection and Indices (ETCCDI) (Alexander et al. 2006, 2007).

Combining climate change and variability

We combine the net flux for ENSO and non-ENSO years and months to generate stochastically generated data. The combined data of the stochastically generated net flux is indicated by NFi,jSTO, meaning the net flux for ith month of jth year of any randomly generated century. We obtain 35 sets of net flux data from OzClim for 100 years from 2000 to 2100 and 35 sets of multiplying factors are computed as NFi,2000+jOZ(k) / NFi,2000OZ(k), where NFi,2000+jOZ(k) is used to indicate the net flux for ith month (i = 1 to 12) of jth year (j = 0 to 100) predicted by Oz-Clim for the kth set (k = 1 to 35). Therefore, the predicted data NFi,jPRED(k) is as follows:

$$NF_{i,j}^{PRED(k)} = NF_{i,j}^{STO} \text{ x } NF_{i,2000+j}^{OZ(k)} / NF_{i,2000}^{OZ(k)} \qquad \text{(Eq.1)}$$

The number of replicates is selected as 30, based on the guideline of Janssen et al (1993), where it is stated that for random sampling the number of samples to be taken should be larger than ten times the number of parameters included in the Monte Carlo analysis. We use three numbers of ambiguities, leading to 30 replicates. The overall algorithm for conditional random generation of ENSO events is shown in Fig. 2. The total number of sets of $NF_{i,j}^{PRED(k)}$ is therefore 1050 (35 GCM-scenario combinations and 30 replicates).

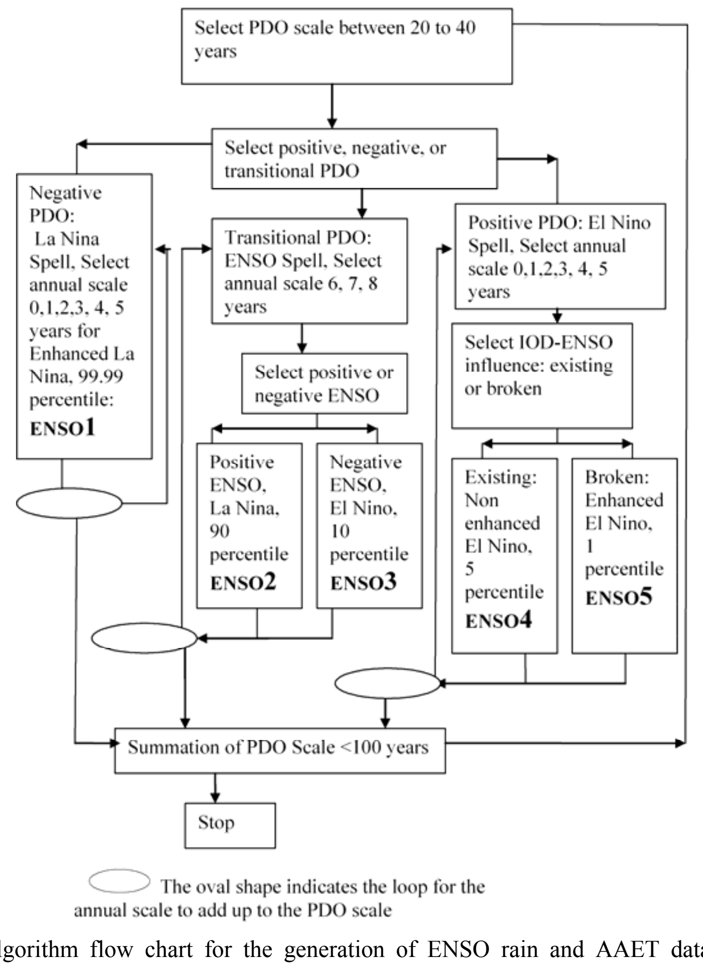

Fig.2. Algorithm flow chart for the generation of ENSO rain and AAET data (climate change and natural climatic variability) for the Ranger site

A major issue not addressed by the above approach and algorithm is extreme events such as tropical cyclones. In reality, such severe events would cause intense flooding rather than an extreme rise of the groundwater level (Kabir 2008). Therefore, in the monthly-based time series data, we neglect tropical cyclone events whose duration is normally 3 to 5 days only.

Results

One sample set of net flux data is shown in Fig. 3. The cumulative net flux was also computed to assess the influence of wet and dry periods on net flux, which can not be seen from the monthly net flux data. The SeepW model result of the computed groundwater level for that net flux is also shown in Fig. 3.

The aggregrate results from all 30 replicates and 7 scenarios of the HadCM3 GCM are shown in Fig. 4, giving mean (μ) groundwater level for each scenario and the maximum/minimum mean plus/minus standard deviation (±σ). Yohe et al (2007) used HadCM3 in IPCC's Fourth Assessment report in the assessment of global water resource availability. Complete results are given in Kabir (2008).

The results of groundwater levels in Fig's 3 and 4 establishes two key findings. Firstly, that longer term trends in climatic conditions are indeed critical in shaping overall groundwater levels (e.g. Fig. 3). Secondly, despite all 7 IPCC scenarios predicting a long-term decline in net flux and dryer overall hydrologic conditions, climate variability, giving rise to extended wetter or dryer periods, can achieve major rises or declines in groundwater levels which appear to outweigh the trends predicted under climate change scenarios.

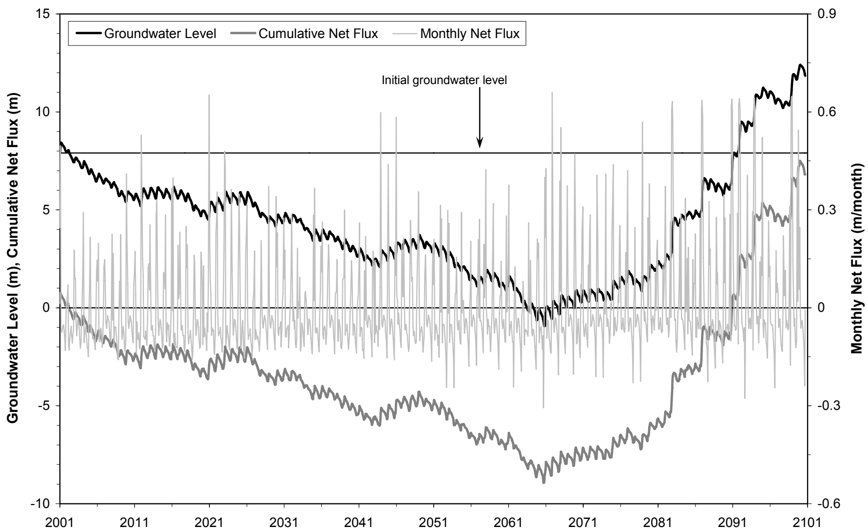

Fig.3. Generated monthly net flux, cumulative net flux and modelled level response (bore OB27, CSIRO MK2, Scenario A2).

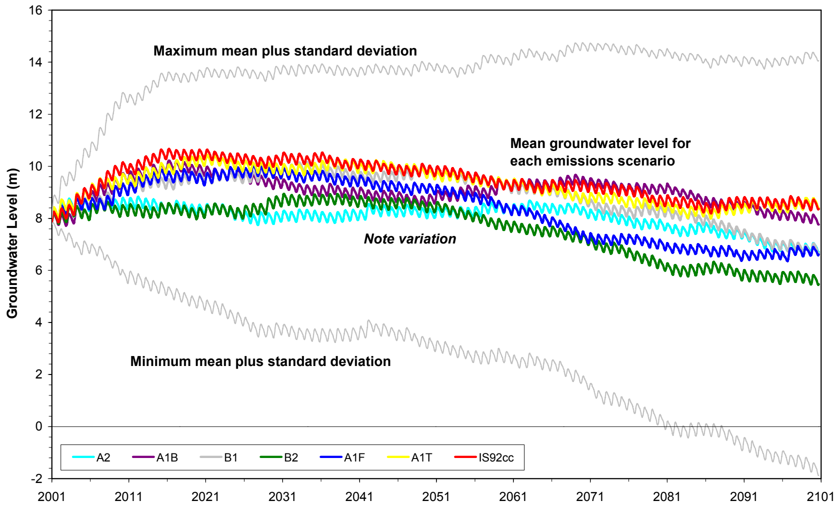

Fig.4. Modelled mean groundwater levels (bore OB27), HadCM3 GCM and A2, A1B, B1, B2, A1F, A1T and IS92cc emission scenarios; max/min mean ± standard deviation

Conclusions

This paper sought to build on previous modelling work by developing a methodology to assess the impacts on groundwater levels from potential climate change scenarios and climate variability.

Climate variability was predicted by combining the current understanding of important climate indices such as El Nino/La Nina, IPO, PDO and IOD into a stochastic algorithm for generating climate data. Data for climate change predictions were obtained from IPCC global climate models and future emissions scenarios. These two components were then combined to produce an input data set of net flux for use in the previously validated unsaturated flow model for the Ranger site. Summary results were then presented in terms of mean groundwater level over time under each scenario for the HadCM3 GCM, including maximum/minimum ± standard deviation groundwater level at each time step from all model runs. The algorithms incorporate current climate knowledge, and can be updated as new knowledge or udnerstanding comes to light.

Overall, the results show the critical importance of climate variability as well as climate change. Under extended wet periods, groundwater levels are predicted to rise significantly, while the major declines are expected under lengthy dry climatic periods. The modelling shows that although the impact of climate change could be significant, it must also be considered in the face of climate variability. The paper, combined with the two concurrent papers, therefore provides a sound basis and methodology upon which to understand the potential impacts of climate change and climate variability on groundwater levels. This, in turn, is critical with respect to different uranium mine rehabilitation approaches in a wet-dry tropical climate surrounded by a region of very high conservation and cultural values.

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