Abstract: In western Victoria, southeast Australia, the watertable has been declining for the last 10-15 years, and this is attributed to either the low rainfall over this time and/or a substantial change in land use, with grazing land replaced by cropping and tree plantations. To determine the relative impact of climate and land use on the watertable, groundwater level fluctuations were modelled using two different approaches: Predefined Impulse Response Function In Continuous Time (PIRFICT) model (a transfer function-noise model), and an auto-regressive model, Hydrograph Analysis: Rainfall and Time Trends (HARTT). HARTT does not take evapotranspiration into account, and this is a serious drawback in areas with shallow groundwaters, because PIRFICT modelling showed that these areas have significant seasonal evaporation. However, the average trends calculated using both models differ only slightly. Most of the groundwater level fluctuations are explained by climatic variables (90%). The average non-climate trend is statistically insignificant, indicating that groundwater levels are not rising/falling due to changes in landuse, at least not during the observation period. However, bores screened in one aquifer, the Port Campbell Limestone, show a substantial negative trend (-0.3 m/yr) due to groundwater pumping from irrigation bores. The HARTT analysis showed that the impact of recharge on groundwater level occurred with less than a month’s lag time, and the PIRFICT modeling calculated that the impact stays in the system 5.7 years on average. This is an indication of the time needed for the groundwater storage to move to a new state of hydrologic (physical, pressure-related) equilibrium. The short groundwater response times mean that the effect of massive clearing more than 50 years ago on the water table could not be detected. These response times are much more rapid than those derived from groundwater flow system concepts. Overall, the results of the modelling allow the impacts of land management change on groundwater resources and dry land salinity to be more reliably predicted and therefore better managed.

Key Words: system response, time-series modeling, groundwater dynamics, spatio-temporal modeling, hydrology, climate variable.

1 Introduction

There has been land clearing of native vegetation across much of the western Victoria, Australia, since European settlement since 160 years ago, resulting in increased recharge. Consequently the groundwater level has risen. However, the water table have been declining for at least the last 10-15 years, and this is attributed to the consistently low rainfall for these years, although over the same period of time there has been substantial change in land use, with grazing land replaced by cropping and tree plantations appearing in some areas. Hence, it is important to determine the relative effect of the climate and land use factors on the water table changes.

Information about hydrogeological systems and water table fluctuations is important for water management and is needed to assess choices for long-term water management policy. Knowledge about the spatio-temporal dynamics of the water table is important to optimize and balance economical and ecological land uses (Von Asmuth and Knotters, 2004).

Water table dynamics can be modelled in several ways. Transfer function-noise (TFN) models describe the dynamic relationship between precipitation and the water table (Box and Jenkins, 1976; Hipel and McLeod, 1994; Tankersley and Graham, 1994; Van Geer and Zuur, 1997). Basically, these models can be seen as multiple regression methods, where the system is a black box that transforms a series of input observations (the explanatory variables) into a series of outputs (the response variables). Time series parameters address the temporal variation of the water table, while the spatial component can be accessed by regionalizing the outputs (Knotters and Bierkens, 2000). To link the response characteristics of the water table to the dynamic behaviour of the input, Von Asmuth et al. (2002) presented a method based on the use of a transfer function-noise model in continuous time, the Predefined Impulse Response Function in Continuous Time (PIRFICT) model.
Impulse Response Function In Continuous Time (PIRFICT) model. An important advantage of the PIRFICT model as compared to discrete-time TFN-models is that it can deal with input and output series which have different observation frequencies and irregular time intervals.

The dynamics of the groundwater system in western Victoria have been previously modelled to determine the climatic influence in water table fluctuations, using linear regression analysis (Pillai, 2003; Leblanc, 2007). These studies estimated trends in individual bores and thereby predicted areas most at risk from shallow or rapidly rising groundwater.

The aim of the present study is to refine the previous studies by quantifying the relative influence of landuse and climate on groundwater levels in western Victoria, particularly in the Glenelg-Hopkins Catchment Management Area (GHCMA). We applied two different types of model, with different theoretical starting-points.

First, the continuous time transfer function noise model PIRFICT was applied. In this study, a standardized PIRFICT computer package Menyanthes (Von Asmuth et al., 2002) was used to statistically estimate trends in groundwater levels and identify the properties that determine the dynamics of groundwater system. This model is optimized for use on hydrogeological problems and estimates the impulse response function of the system from the temporal correlation between time series of groundwater level and precipitation surplus.

Secondly, we applied an auto-regression model, HARTT.

We calibrated both models using 82 time series of hydrographs from boreholes. The results were validated and cross checked using estimated parameters from a physical knowledge of the area.

2 Materials and methods

Data

Climatic data

Daily and monthly rainfall data is available from the Bureau of Meteorology for rainfall gauges throughout western Victoria. Rainfall records were chosen on the length of the record (continuous data for most sites from 1960 to date) and their location in relation to the monitoring bores. Recorded and estimated (patched) evaporation data were obtained from the SILO website (www.nrm.qld.gov.au/silo/).

Groundwater data

The groundwater data are from the Victorian Water Resources Data Warehouse. A set of 82 bores were selected based on monitoring period (6 to 33 years), aquifer, spatial distribution, lack of influence of abstraction and data reliability (Fig.1). The surface elevation of the bore ranges from 36 to 437 m.a.s.l while the depth to water table ranges from near surface to 56 m below surface. Most of the groundwater bores were installed after 1994; unfortunately this means that the data includes an extended period of below average rainfall since 1997.

2.1 Study area

The study area lies predominantly within the Glenelg-Hopkins catchment, which is located in the sub-humid region of south-eastern Australia (Fig.1). The region experiences a Mediterranean climate, with hot, dry summers and cool, wet winters. Average annual rainfall ranges from 500 - 910 mm, with higher rainfall typically occurring in coastal regions.

Most of the study region is dedicated to agriculture, and regionally there has been a significant shift from grazing to cropping in recent years. These agricultural practices have replaced native grasslands since the 1930s, and as a result less than 20% of the original vegetation remains in the region (Ierodiaconou et al., 2005). The grazing land in the Glenelg–Hopkins region has changed substantially over the last two decades, 4.84% from 1980 to 1995, and 13.85% from 1995 to 2002 (Ierodiaconou et al., 2005). Groundwater flow patterns have altered following clearing of deep-rooted native vegetation and groundwater extraction. The region is considered to be one of the areas most at risk from rising water tables and dryland salinity.

The study area lies largely within the volcanic plains of western Victoria. These are topographically subdued with an average elevation of ~200 mAHD, gently increasing to the northeast (Fig.1). Drainage is typically poor with many ephemeral swamps/lakes. Several volcanoes rise above the plain.

![Fig.1 Study area watershed and location of the observation wells (•).](image-url)
aquifer, the Miocene Port Campbell Limestone, which is mostly confined beneath the Pliocene-Quaternary Newer Volcanics Basalt aquifer. In the centre of the catchment Miocene and Pliocene ligneous clays, sands and gravels, called deep leads, infill the pre-existing stream system incised deeply into the highly weathered early Cainozoic palaeo-surface. These sediments are also overlain by Newer Volcanic Basalts.

2.2 The PIRFICT-model (TFN modeling)

The behaviour of linear input-output systems can be completely characterized by their impulse response (IR) function (Ziemer et al., 1998; Von Asmuth et al., 2002). The response of water table depth to impulses of precipitation can be modelled by a transfer function-noise (TFN) model (Box and Jenkins, 1976; Hipel and McLeod, 1994; Von Asmuth and Knotters, 2004). For water table depths, the dynamic relationship between precipitation and water table depth can also be described using physical mechanistic groundwater flow models. However, by using much less complex TFN models, predictions of the water table depth can be obtained which are often as accurate as those obtained by physical mechanistic modelling (Von Asmuth and Knotters, 2004).

The noise component of TFN models is often applied to distinguish between natural and man-induced components of groundwater series (Van Geer and Zuur, 1997). The PIRFICT model, introduced by Von Asmuth et al., (2002), is a specific type of TFN model and an alternative to discrete-time TFN models. For the simple case of a linear, undisturbed phreatic system that is influenced by precipitation surplus/deficit only (Von Asmuth et al., 2002):

\[ h(t) = h^*(t) + d + r(t) \]  

(1)

where:

- \( h(t) \) is observed water table depth at time \( t \);
- \( h^*(t) \) is predicted water table depth at time \( t \) attributed to the precipitation surplus/deficit, relative to \( d \); \( d \) = level of \( h^*(t) \) without precipitation, or in other words the local drainage level, relative to ground surface;
- \( r(t) \) = residuals series;
- \( p(t) \) = precipitation surplus/deficit intensity at time \( t \);
- \( \theta(t) \) = transfer Impulse Response (IR) function;
- \( W(t) \) = continuous Wiener white noise process.

TFN models are identified by choosing mathematical functions which describe the Impulse Response (IR) and the autoregressive structure of the noise. \( \theta(t) \) is a Pearson type III distribution function (PIII df, Abramowitz and Stegun, 1964). Because of its flexible nature, this function adequately models the response of a broad range of groundwater systems.

The PIRFICT model was applied in this study because the model can describe a wide range of response times with differences in sampling frequency between input series and output series. For the western Victoria situation, it is particularly useful, because different water table behaviour can be found even in small catchments due to geological complexity.

2.3 The HARTT model (Auto-regressive modeling)

Ferdowsian et al. (2001) presented a statistical approach for analysing hydrographs, called HARTT (Hydrograph Analysis: Rainfall and Time Trends). The method is able to distinguish between the effect of rainfall fluctuations and the underlying trend of groundwater levels over time. Rainfall is represented as an accumulation of deviations from average rainfall, and the lag between rainfall and its impact on groundwater is explicitly represented.

Two forms of accumulative residual rainfall were used and compared. The first was accumulative monthly residual rainfall (AMRR):

\[ AMRR_i = \sum_{i=1}^{t} (M_{i,j} - \overline{M}_j) \]  

(4)

where \( M_{i,j} \) is rainfall (in mm) in month \( i \) (a sequential index of time since the start of the data set) which corresponds to the \( j \)th month of the year, \( \overline{M}_j \) is mean monthly rainfall (in mm) for the \( j \)th month of the year, and \( i \) = months since the start of the data set.

The second was accumulative annual residual rainfall (AARR):

\[ AARR_i = \sum_{i=1}^{t} (M_i - \overline{A}/12) \]  

(5)

where \( \overline{A} \) is mean annual rainfall (in mm). Because \( \overline{A} \) is a constant, the fluctuations in \( M_i \) are not moderated as they are for AMRR, so AARR has higher within-year fluctuations. For both AMRR and AARR, construction of the variables was based on data sets pre-dating the earliest recording of depth to groundwater. This allowed for long term lag effects of rainfall on groundwater to be detected, if they occurred. Lags of up to a few years were investigated.

In order to draw conclusions about the relationship between groundwater trends and rainfall records, the HARTT method (equation 6) was used.

\[ \text{depth}_t = k_0 + k_1 \cdot \text{AMRR}_{t-\Delta} + k_2 \cdot t \]  

(6)

where depth is the depth of groundwater below the
ground surface, \( t \) is the months since observations commenced, \( L \) is the length of time lag (in months) between rainfall and its impact on groundwater, \( k_0, k_1 \) and \( k_2 \) are parameters to be estimated, and AMRR is the accumulative monthly residual rainfall.

Parameter \( k_0 \) is approximately equal to the initial depth to groundwater, \( k_1 \) represents the impact of above/below average rainfall on the groundwater level, and \( k_2 \) is the trend rate of groundwater rise/fall over time.

### 3 Results

**PIRFICT modeling using Menyanthes**

Results of the 82 time series models are summarized in Table 1, where the minimum, median, and maximum values of the parameters are given, along with their 95% confidence interval. The median value of \( r^2 \) shows that the fit of most models is good, although there are clearly outliers in the results, as the extremes of most parameter estimates are not within a range that is physically plausible. Most of the groundwater level fluctuations are explained by climatic variables and non-climatic trend (90%).

Table 1 Range of model results and parameter estimates for all 82 ground water head series (PIRFICT modelling)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Minimum (±2σ)</th>
<th>Median</th>
<th>Maximum (±2σ)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( R^2 ) adj (%)/m (mm)</td>
<td>23/0.02 (±0.12)</td>
<td>90/0.5</td>
<td>99/1 (±0.2)</td>
</tr>
<tr>
<td>RMSE (m)</td>
<td>0.04/0.02 (±0.32)</td>
<td>0.184/0.5</td>
<td>5/1 (±0.2)</td>
</tr>
<tr>
<td>RMSI (m)</td>
<td>0.04/0.02/0.150</td>
<td>0.150/0.5</td>
<td>3/1 (±0.2)</td>
</tr>
<tr>
<td>( M_0, f ) (m/mm)</td>
<td>0.25/0.02 (±0.12)</td>
<td>1.5/0.5</td>
<td>32/1 (±0.2)</td>
</tr>
<tr>
<td>( D ) (m)</td>
<td>63/0.02 (±0.32)</td>
<td>179/0.5</td>
<td>411/1 (±0.2)</td>
</tr>
<tr>
<td>Response time (yr) =3*( M_1/M_0 )</td>
<td>0.6/0.02 (±0.12)</td>
<td>8.42/0.5</td>
<td>5059/1 (±0.2)</td>
</tr>
<tr>
<td>Non-climatic trend (m/yr)</td>
<td>-0.58/0.02 (±0.002)</td>
<td>-0.04/0.03</td>
<td>0.14/0.03</td>
</tr>
</tbody>
</table>

\( R^2 \) adj = Percentage of explained variance; RMSE = Root Mean Squared Error (meters); RMSI = Root Mean Squared Innovation (meters); \( σ \) = standard deviation; \( D \) = Drainage Base (meters); \( f \) = evaporation factor.

The plausibility checks to guide in assessing whether the results of the transfer model are physically realistic include the model residuals, the evaporation factor \( f \), the local drainage base \( d \), and the moments of the impulse response functions and their standard deviations. Non-random patterns of the residuals in space or time reveal the fact that there are still stresses missing in the model. In addition, the moments of the impulse response functions of the different stresses provide relevant information. Moments can be used to characterize the functioning of the ground water system and can be related to its geo-hydrologic properties (Von Asmuth and Maas 2001; Von Asmuth and Knotters 2004). The zero-order moment \( M_0 \) of a distribution function is its area, and \( M_1 \) is related to the mean of the impulse response function. The relation \( M_1/M_0 \) is a measure of the system’s memory. It takes approximately 3 times the mean time \((M_1/M_0)\) for the effect of a recharge event to disappear completely from the system.

Only 52 time series modelling out of 82 were considered as a reliable trend estimate using the diagnostic criteria mentioned above to cross check the plausibility of the result.

**HARTT**

Using HARTT, the effects of unusual/atypical climatic conditions were identified from the observed hydrograph; the resulting residual time series thus represents the combined effects of both changes in recharge processes and non-average climatic conditions.

Overall, the model fitted the data well, explaining 79% (median value of \( r^2 \)) of the variation in groundwater level using the climatic variable (rainfall only), with a small, probably statistically insignificant trend (-0.066 m/yr, on average; Table 2).

Table 2 Range of model results and parameter estimates for all 82 ground water head series (HARTT)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Minimum</th>
<th>Median</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r^2 )</td>
<td>0.1</td>
<td>0.79</td>
<td>0.97</td>
</tr>
<tr>
<td>( k_0 ) (m)</td>
<td>0</td>
<td>11</td>
<td>56</td>
</tr>
<tr>
<td>( k_1 ) (m/mm)</td>
<td>0</td>
<td>0.80</td>
<td>5.8</td>
</tr>
<tr>
<td>Lag time (month)</td>
<td>0</td>
<td>0</td>
<td>11</td>
</tr>
<tr>
<td>( k_2 ) (m/yr)</td>
<td>-0.335</td>
<td>-0.066</td>
<td>0.216</td>
</tr>
</tbody>
</table>

However, some limitations were identified with the HARTT method. In shallow bores, the water depth of less than 5 m requires the addition of further variables to the model, because the close vicinity of the discharge zone means that evaporation rate and hydraulic gradient affect the groundwater level fluctuations. The HARTT model may therefore be compromised by factors such as geological and geographical characteristics of the monitored sites.

To analyse the results, the significance of each variable was checked using the level of significance (p-value), to see if the means and measure of dispersion of two variables are statistically different from each other. If the
p-value is less than 0.05 then the variable is significant. If the trend \( k_2 \) is not significant, then the rate of rise/fall is uncertain. Also, if the rainfall variable \( k_1 \) is not significant, then there is lack of certainty regarding the effect and delay period. Parameters with values which were not significantly different from zero were omitted to avoid model redundancy.

From the HARTT analyses and the cross-check procedures, only 44 out of 82 bores modelled were considered to give reliable trend estimates.

### 3.1 Trends

The auto-regressive model (HARTT) showed that the groundwater level variation can be explained largely by climate variation (79%), supporting the relative insignificance of the non-climatic trend identified by PIRFICT model. The downward trend could be due to the recent affects of tree plantations on groundwater discharge; the modeling separates this effect from the impact of the ongoing drought.

The overall average trends estimated from PIRFICT and HARTT modeling are comparable. However, the correlation between these trend estimates is not strong. The difference is most significant for bores with shallow groundwater levels, because HARTT does not incorporate the effect of significant seasonal evaporation. Moreover, the non-climatic trend identified by PIRFICT modeling excludes both rainfall and evaporation, and should better reflect land use changes than the non-climatic trend from HARTT, which excludes only rainfall. Therefore, in this study the trends estimated by PIRFICT modeling were chosen for further analysis.

#### Table 3 PIRFICT parameter estimates (median values)

<table>
<thead>
<tr>
<th>Aquifer</th>
<th>Non-climate trend (m/yr)</th>
<th>Response (yrs)</th>
<th>R² (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NVB</td>
<td>-0.027</td>
<td>5.6</td>
<td>89</td>
</tr>
<tr>
<td>Deep lead</td>
<td>-0.029</td>
<td>12.3</td>
<td>94</td>
</tr>
<tr>
<td>PCL</td>
<td>-0.30</td>
<td>3.4</td>
<td>90</td>
</tr>
<tr>
<td>All</td>
<td>-0.039</td>
<td>5.7</td>
<td>91</td>
</tr>
</tbody>
</table>

Bores screened in the Newer Volcanic basalt (NVB) show insignificant trends and relatively fast responses (Table 3); bores screened in the deep lead aquifer also have insignificant trends but slow responses. The slow response of the deep lead is in agreement with the conceptualization of this aquifer as a regional groundwater flow system, where flow paths can be up to 60 km before the groundwater is forced to move upward by geological constrictions (Raiber et al., 2009).

There was a significant negative trend in bores screened in the Port Campbell Limestone (PCL; Table 3). These bores might have been affected by nearby groundwater pumping, resulting in a reduction in groundwater level in the last decade. The bores in the Port Campbell Limestone (PCL) aquifer show fast responses (Table 3). This could be due to karstic features which allow fast water movement.

The average non-climatic trend in the groundwater levels was -0.04 m/yr (Table 3). This is indicative of equilibrium over the observation period. The fast response time of the system (Table 1) supports this. There is no evidence of the rise in groundwater level due to change in land use since 1860, caused by increased groundwater recharge resulting from replacement of deep-rooted native vegetation by shallow-rooted pasture grass and crops (Allison et al., 1990). This is probably because most groundwater level series in this study started only after 1991.

#### 3.2 Interpretation of the lag time

Rancic et al. (2009) postulated that the estimated lag between standing water level and rainfall consists of up to three components: \( Tr \), the time needed for recharge to infiltrate and reach groundwater. \( Te \), the time needed for the portion of the storage that recharges mainly via vertical flux to reach equilibrium. \( Tl \), the time needed for the pressure impulse to laterally propagate down the system, from the highest recharge point to the lowest discharge point.

Shorter lags characterise the study area, suggesting that the recharge response is relatively fast (\( Tr \) small). The size of the system affects the \( Te \) component, as small systems move to a new equilibrium faster than large systems. The longer lag times in a few bores might be, therefore, a consequence of the larger groundwater systems found in these areas, where the flux propagates laterally through a sequence of unconfined and confined units.

The response time identified by PIRFICT modeling gives new information on the dynamical memory of the system, which is a continuity of the lag time identified by HARTT.

#### 4 Conclusion

Two programs for modelling of bore hydrographs (PIRFICT and HARTT) were employed to analyse data from western Victoria, to estimate the relative influence on groundwater levels of climate variables and human intervention. PIRFICT modelling takes into account both rainfall and evaporation, whereas HARTT uses only rainfall. Moreover the input variables in PIRFICT modeling were at daily time scales, which allowed the seasonal groundwater variation and response time of the
system to be better modeled than in HARTT, which allows only monthly time steps.

The conclusion from the PIRFICT modeling is that most of the groundwater level fluctuations can be explained ($R^2=90\%$) by meteorological variables. The average nonclimate trend is insignificant (-0.027 m/yr) for the Newer Volcanic Basalt and deep lead aquifers, but is substantial (-0.30 m/yr) for the Port Campbell Limestone. The latter trend is largely related to groundwater pumping from nearby irrigation bores.

From the HARTT analysis, there is less than a month lag time between recharge and its impact on groundwater level. PIRFICT modeling further identified that an impact stays in the system for 5.7 years on average.

Therefore, the effect of massive clearing in the study area on the water table could not be detected, because most vegetation change took place more than 50 years ago and groundwater response times occur over much shorter time frames than this.

The lag times and processes identified in this study indicate the time needed for the groundwater storage to move to a new state of hydrologic (physical, pressure-related) equilibrium. This will allow the impacts of land management change on groundwater resources and salinity to be more reliably predicted and therefore better managed.

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References:


