ORIGINAL ARTICLE

Streamflow modeling in a fluctuant climate using SWAT: Yass River catchment in south eastern Australia

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Abstract Hydrological models play vital roles in understanding and management of surface water resources. The physically based distributed model Soil and Water Assessment Tool (SWAT) was applied to a small catchment in south eastern Australia to determine its ability to mimic low and high streamflows. The model was successfully calibrated using 1993–2002 streamflow data and validated using 2003–2011 data with a combination of manual and auto-calibration techniques for both monthly and daily time steps. Sensitivity analysis indicated that curve number for moisture condition II (CN2) is the most sensitive parameter for both time steps. In general, the model performance statistics indicated "very good" agreement between measured and simulated discharges for both calibration and validation periods. The model was able to satisfactorily simulate both low and high flows of the Yass River. Analysis of water balance components indicated that more than 90 % of the rainfall is lost as evapotranspiration and about 45 % of the streamflow is base flow. The calibrated and validated SWAT model can be used to analyze the effect of climate and land use changes on catchment wide hydrologic process.

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Introduction

Hydrological modeling is an effective tool in understanding, planning, and management of surface water resources. As a result, simulation of streamflow through hydrological models is always a key interest for the hydrologists and water resources planners. Distributed hydrological modeling platform with embedded Geographical Information System (GIS) is becoming a popular tool among the hydrologists as it allows the users to perform modeling with a combination of climate and GIS data in a simpler way (Zhang et al. 2012). For a long-term scenario analysis, it is important that a model be able to predict both low and high flows with sufficient accuracy. However, simulation of catchment yield under seasonal and annual climate variability which results in low and high streamflow is often a challenge. This is especially so in arid and semiarid regions (Wheater 2007) such as Australia, where climate is highly variable and water availability is limited (Greg 2006).

Australia is the driest inhabited continent where some parts of south eastern Australia fall in the high to very high water stress regions (DFAT 2008; World Water Council 2010). More than 80 % of the country has average annual rainfall below 600 mm and 90 % of this rainfall evaporates directly back to atmosphere (National Water Commission

2012; Bureau of Meteorology 2011). South eastern Australia recently (1997–2009) experienced the worst instrumental recorded drought followed by wettest 2-year (2010–2011) period (CSIRO 2012) which indicates the extreme variability in Australian weather. The Murray–Darling Basin (MDB) is the largest and most important catchment for agricultural production in Australia. It covers 1.06 million km^2 or about 14 % of the total area of Australia. It accounts for approximately 40 % of the gross value of Australian agricultural production (ABS 2008). For example, in 2005–2006, irrigated agriculture in the MDB utilized about 66 % of all irrigated water used for agriculture in Australia, but produced 44 % of the gross value of irrigated agriculture (ABS 2008). The major irrigation areas within the basin include Goulburn-Murray, Murray, Murrumbidgee and Coleambally. The Murrumbidgee and Coleambally irrigation areas are located in the Murrumbidgee catchment, which utilizes bulk water for food production, industry and urban water supplies. The Murrumbidgee River is one of the most important rivers in the MDB and it covers an area of approximately 84,000 square kilometres, is home to approximately 545,000 people and incorporates Australia's capital city, Canberra. It is located in central New South Wales (NSW) and covers a range of soil and vegetation types typical of much of Australia.

Recently, several hydrological modeling studies have been conducted to understand the hydrology of the Murrumbidgee River which have highlighted that major water savings could be realized through reducing non-beneficial water usage in the catchment (Khan et al. 2005). However, no hydrological modeling studies were reported considering the processes in the sub-catchments such as the Yass. The first river model for the upper Murrumbidgee was developed in the Integrated Quantity and Quality Model (IQQM) under the Murray–Darling Sustainable Yield Project (Gilmore 2008). This model used the Sacramento rainfall-runoff model for IQQM implementation. Schreider et al. (2002) studied the impact of farm dams construction on Potential Streamflow Response (PSR) for 12 catchments of MDB using Identification of unit Hydrographs and Component flows from Rainfall, Evaporation and Streamflow (IHACRES) model and found a decreasing trend in PSR of the Yass River. A daily rainfall-runoff model was used in the Integrated Catchment Management System (ICMS) software platform to study the Yass River water allocation problems, but no hydrological study details were reported (Gilmour and Watson 2001). Considering the importance of the Yass River catchment in the Murrumbidgee River system, it was realized that a comprehensive physically based modeling study of this river system is essential to understand different anthropogenic and natural effects on the flow.

Soil and Water Assessment Tool (SWAT) is a public domain physically based distributed model which is suitable for long-term scenario analysis at a watershed scale (Neitsch et al. 2011). It has been successfully applied in different regions for solving a wide range of hydrological problems (Gassman et al. 2007). However, its application for Australian condition is very limited (Labadz et al. 2010; Sun and Cornish 2006). In this study, a SWAT model was developed for the Yass River sub-catchment in the Murrumbidgee River catchment. Two automatic calibration algorithms, Sequential Uncertainty Fitting (SUFI-2) and Parameter Solution (ParaSol), were used for this study. The suitability of the model to predict flow for both low and high flow periods was tested by simulating the flow in a drought and a flood period separately and compared with the measured data.

Study area

The Yass River is a tributary of the Murrumbidgee River in the MDB of Australia. About two-thirds of the annual flow of the Murrumbidgee River system comes from the Burrinjuck and Blowering dams of the upper Murrumbidgee catchment (CSIRO 2011). The Yass River is a major tributary of this area which drains directly into the Burrinjuck dam (Green et al. 2011). The Yass River originates near the south Bungendore and flows 120 km in the north and northwest direction and ends in the Burrinjuck dam (Geographical Names Board of NSW 1969). Being in the higher elevation part of the Murrumbidgee catchment with relatively high amount of rainfall, the Yass River contributes significant amount of flow to the Burrinjuck dam (NSW Office of Water 2013a). The Yass catchment covers an area of 1,597 km^2 upstream of Burrinjuck dam. It is located between 34.70° and 35.29°S latitudes and 148.73° and 149.40°E longitudes (Fig. 1). The elevation of the catchment varies from 373 to 934 m. The average annual rainfall of the catchment is 675 mm. The dominant land use of the catchment is grassland/pasture. The Yass River catchment is often affected by drought and flood conditions (Gilmour and Watson 2001). Soil erosion, turbidity, salinity and phosphorus discharged from effluent treatment plants also reduced the quality of water (Yass Valley Council 2008; DECC 2008).

Methodology and data

SWAT model

Soil and Water Assessment Tool is a watershed scale semi-distributed, physically based hydrological model developed
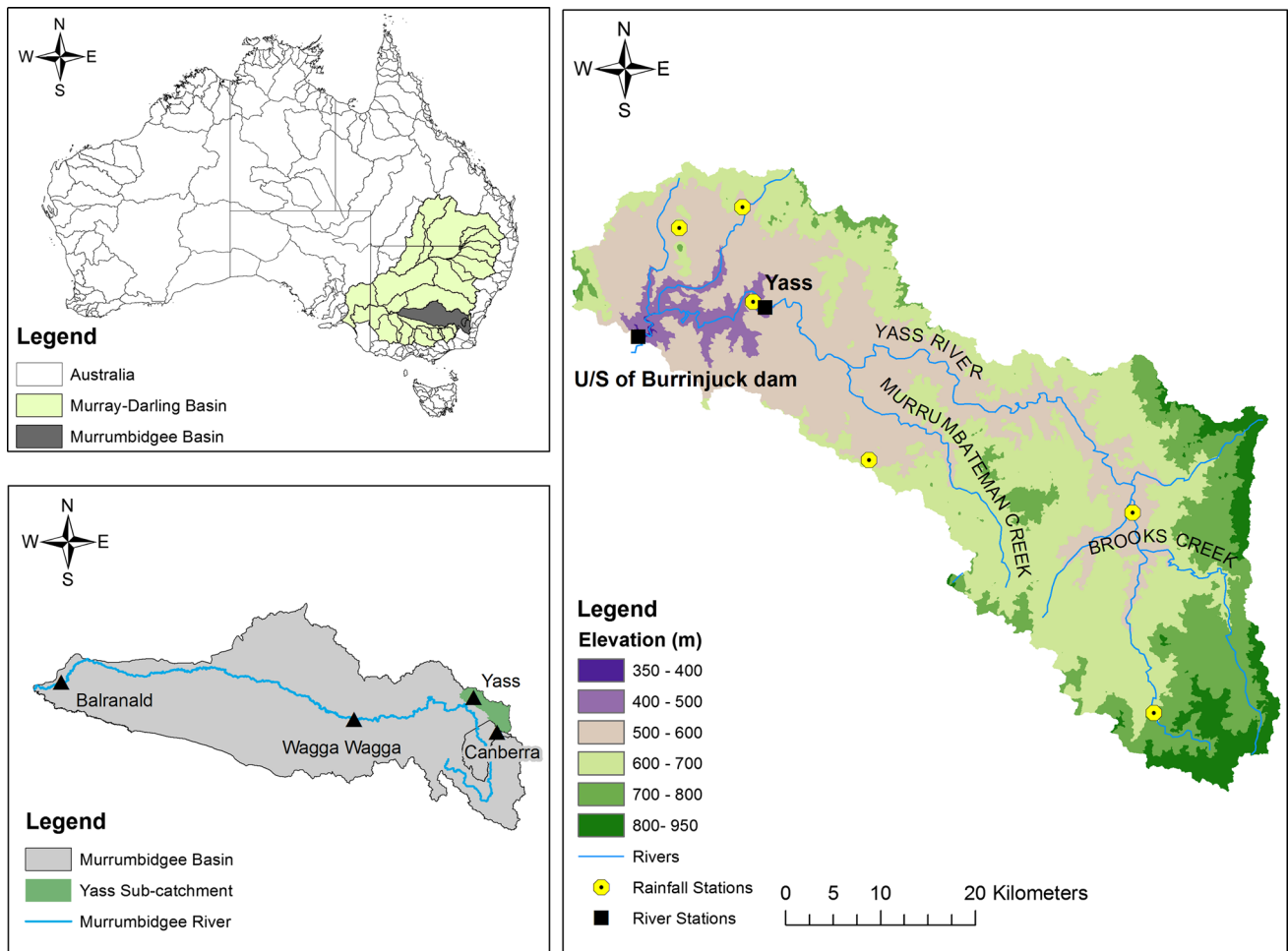
Fig. 1 Location of the Yass River catchment in south eastern Australia

at the USDA-ARS (Arnold et al. 1998). It runs on daily time step and is capable of continuous simulation over a long duration (Gassman et al. 2007). It is suitable to assess the long-term impact of land management practices on water, sediment and agricultural chemical yields in large, complex watersheds with varying soils, land use and management conditions (Arnold et al. 1998; Neitsch et al. 2011). In order to characterize spatial heterogeneity, the watershed is divided into multiple sub-basins. Depending on the homogeneity of land use, soils and slope characteristics, these sub-basins are further subdivided into hydrologically homogenous units called hydrological response units (HRUs) (Gassman et al. 2007). HRUs are the basic units for which soil water content, surface runoff, nutrient cycles, sediment yield, crop growth and management practices are simulated. The outputs from the HRUs are aggregated to get the outputs at sub-basin scale. SWAT simulates the hydrological cycle based on the following daily water balance equation:

$$SW_t = SW_0 + \sum_{i=1}^{t}(R_{day} - Q_{surf} - E_a - w_{seep} - Q_{gw})_i.$$

(1)

where SW_t is the soil water content on day t (mm), SW_0 is the initial soil water content on day i (mm), t is the time (days), R_{day} is precipitation on day i (mm), Q_{surf} is surface runoff on day i (mm), E_a is evapotranspiration on day i (mm), W_{seep} is water entering the vadose zone from the soil profile on day i (mm) and Q_{gw} is return flow (sub-surface flow) on day i (mm).

Surface runoff can be calculated using either Soil Conservation Service (SCS) curve number (Soil Conservation Service 1972) or Green and Ampt infiltration method (Green and Ampt 1911). SCS curve number method was used in this study. Penman–Monteith method was adopted to determine potential evapotranspiration whereas variable storage method was used to route flow in channels.

Table 1 Data used for SWAT model development in this study and the data sources

| Variable	Data source
Digital elevation model	Geoscience Australia
Land use/land cover map	NSW office of environment and heritage
Soil map	Bureau of rural sciences, Australia
Observed discharge	NSW office of water, Australia
Observed climate data	Bureau of meteorology, Australia
River network map	Hydroshed, USGS

Data preparation

SWAT needs several data sets as input to develop a model using the ArcSWAT interface. Some data are compulsory to develop a SWAT model, while the others are optional as per required output. Digital Elevation Model (DEM), soil, land use and weather data are mandatory whereas river discharge, reservoir information, sediment, pesticide, fertilizer, chemical and water quality data are optional as per the purpose of the model development. List of data used in this study and their sources is presented in Table 1. The processing of the respective data is described in this section.

Digital elevation model (DEM)

SWAT uses DEM and stream network map to delineate a watershed and its sub-basins. The sub-basin parameters such as slope gradient, slope length of the terrain, and the stream network characteristics (channel slope, length and width) are derived from the DEM. For this study, a 30 m resolution hydrological DEM derived from Shuttle Rader Topography Mission (SRTM) DEM was used (Geoscience Australia 2011). DEM for the Yass study area was masked for the SWAT model development (Fig. 1). Stream network data for Yass River along with associated tributary and distributaries were downloaded from the HydroSHEDS (Lehner et al. 2006).

Land use/land cover data

The NSW land use data developed by NSW Office of Environment and Heritage were used for HRU delineation in ArcSWAT. This data were derived from satellite imagery and aerial photographs in the period 1999–2006 with confirmation of field verification of specific land use types. The data were reclassified to match the SWAT land use classes (Fig. 2a).
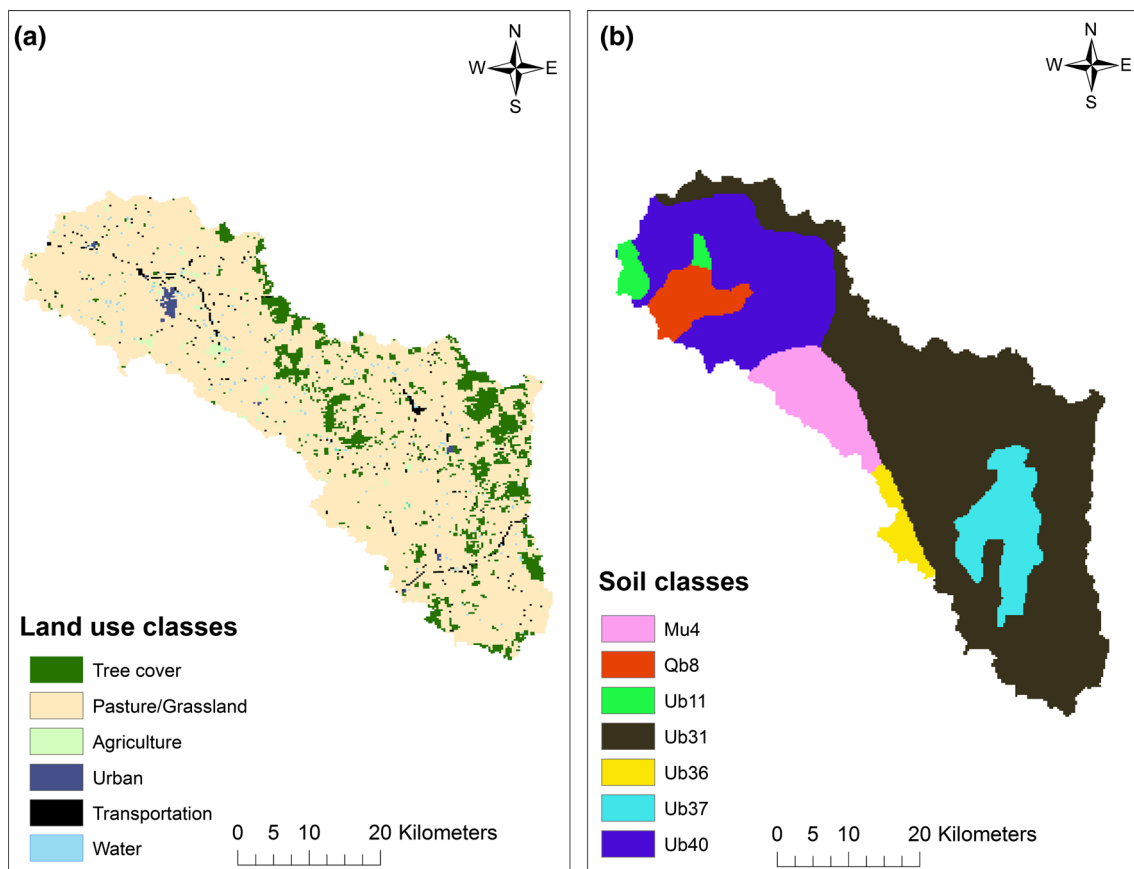
Fig. 2 Land use map (**a**) and soil map (**b**) of the Yass River catchment

Soil data

The SWAT model requires soil map and a database table of soil texture, available water content, hydraulic conductivity, bulk density and organic carbon content for different layers of each soil type (Setegn et al. 2010). The soil map of the study catchment was clipped from Digital Atlas of Australian Soil (BRS 2000) (Fig. 2b). A "usersoil" database table was created for the study catchment from the available interpretations and lookup tables (McKenzie et al. 2000; Western and McKenzie 2004).

Climate data

The SWAT model requires daily or sub-daily observed meteorological data of rainfall, temperature (maximum and minimum), relative humidity, solar radiation and wind speed. Maximum half hourly rainfall data are also required to create the weather generator database table in SWAT. The weather data were obtained from the Australian Bureau of Meteorology (BOM). Daily data of six BOM stations were used. In addition, weather generator database was created for one station (Canberra airport comparison, BOM station number 072008) due to the availability of all data for this station. Homogeneity of the all meteorological data series used in this study was tested using the RAIN-BOW software (Raes et al. 2006) which uses Buishand test (Buishand 1982), one of the most commonly used absolute tests, to check homogeneity of a data series. All the data were found to be homogeneous as homogeneity could not be rejected with 99 % probability level for any of the data series.

River discharge

Measured river discharge data at two stations, upstream of Burrinjuck dam (station number 410176) and at Yass (station number 410026), were used for model calibration and validation (NSW Office of Water 2013b).

Model development and evaluation

The SWAT model development involves model set-up and model evaluation. The model set-up comprises data preprocessing, watershed delineation, HRU definition and importing weather data. The evaluation process comprises sensitivity analysis, calibration and validation.

Model set-up

The watershed was delineated through automatic watershed delineation. Stream network of the study area was superimposed on the DEM to delineate the streams accurately. A threshold for minimum sub-basin area was selected for the stream network and outlet calculation. The Yass River gauging station at upstream of Burrinjuck dam was selected as a watershed outlet which delineated a watershed of 1,597 km^2 with 20 sub-basins. The land use and soil maps were imported and linked with the respective database table creating appropriate lookup tables. Multiple HRU option resulted in 482 HRUs for the watershed.

Model evaluation

Evaluation of a model's ability to simulate watershed response accurately is vital before further application of the model. Model evaluation comprises three sequential steps: sensitivity analysis, calibration and validation. A period of 10 years (1993–2002) was selected for calibration and 9 years (2003–2011) for validation. In addition, 3 years was kept as warm-up period for both simulations. Warm-up period allows the model to get a fully operational hydrological cycle and thus helps to stabilize the model (Setegn et al. 2010).

Sensitivity analysis Sensitivity analysis is the process to determine the rate of change of model outputs in response to changes in different input parameters (Moriasi et al. 2007). This step identifies sensitive parameters for calibration process. A combination of Latin Hypercube (LH) and One-factor-At-a-Time (OAT) sampling procedure embedded into the ArcSWAT extension was followed in this study. In a LH loop, a unique set of parameters was selected to run a baseline simulation and then, using OAT, a parameter was chosen randomly and its value was changed in the next run. This procedure was repeated until all the parameter values were varied. After finishing a LH loop, another set of parameters was selected for the next LH loop (Veith and Ghebremichael 2009). The sensitivity analysis was performed for all the 26 flow parameters listed in the ArcSWAT sensitivity analysis tool.

Calibration Model calibration requires establishing statistical relationships between model parameters and the characteristics of the catchment. In the model calibration process, model parameters are adjusted either manually or automatically until the measured system outputs and model simulations show an acceptable level of agreement (Gorgan et al. 2012). In this study, the model calibration was done for both monthly and daily time steps. The model was first calibrated for monthly time step and then daily calibration was performed on the monthly calibrated model. Model calibration was done with a combination of manual and auto-calibration techniques. The manual calibration was performed by changing the parameter values in Arc-SWAT interface and then run the model in the statistical

package R (R Core Team 2012). Running SWAT in R environment gives the advantage of calculating evaluation statistics and generating the plot of observed and simulated values simultaneously with the model simulation which was not possible in default ArcSWAT interface.

Auto-calibration of this study was performed using a public domain software Soil and Water Assessment Tool Calibration and Uncertainty Procedure (SWAT-CUP) (Abbaspour 2011). Two methods, ParaSol and SUFI 2 algorithms, were used in this study. ParaSol is a method to assess model parameter uncertainty using optimization and statistical techniques (van Griensven and Meixner 2004). Aggregating objective functions (OF's) into a Global optimization criterion (GOC), ParaSol uses Shuffle complex Evolution (SCE-UA) algorithm to minimize these OF's or a GOC and performs uncertainty analysis using either χ^2 or Bayesian statistics (Abbaspour 2011). ParaSol uses Sum of the Squares of the Residuals (SSQ) as OF

$$\text{SSQ} = \sum_{i=1}^{n} \left[\left(\text{TF}(X_i^{\text{obs}}) - \text{TF}(X_i^{\text{sim}}) \right) \right]^2. \tag{2}$$

where X_i^{obs} and X_i^{sim} sim are the observed and simulated values for ith time step and TF is a user-defined transformation function (van Griensven and Meixner 2004). For several OFs or multi objective calibration, GOC can be used as

$$\text{GOC} = \sum_{i=1}^{m} \frac{\text{SSQ}_m \times N_m}{\text{SSQ}_{m,\text{min}}}. \tag{3}$$

where $\text{SSQ}_{m,\text{min}}$ is equal to the minimum of all SSQs and N_m is the number of observations (van Griensven and Meixner 2004; van Griensven and Meixner 2006).

SUFI-2 is a model calibration and uncertainty estimation algorithm which combines optimization with uncertainty analysis and can handle large number of parameters (Abbaspour et al. 2007; Abbaspour et al. 2004). The step-by-step procedure of SUFI-2 was described by Yang et al. (2008). The goodness of calibration and prediction uncertainty is assessed based on the values of p-factor and r-factor which theoretically range from 0 to 100 % and 0 to infinity, respectively. P-factor values close to 100 % and r-factor values close to 1 are considered as good simulations (Yang et al. 2008). SUFI2 is suitable for quick calibration results, but ParaSol can produce more accurate results (Gorgan et al. 2012).

Model performance indices Four quantitative statistics, Nash–Sutcliffe efficiency (NSE), ratio of the root mean square error to the standard deviation of measured data (RSR), coefficient of determination (R^2) and correlation coefficient (r) are commonly used to evaluate the performance of a watershed model (Moriasi et al. 2007; Krause

et al. 2005; Eckhardt and Arnold 2001; Zhang et al. 2009; Mango et al. 2011; Setegn et al. 2010).

Nash–Sutcliffe efficiency (NSE) NSE is the most widely used statistical parameter to evaluate the predictive power of a hydrological model. It is a dimensionless statistics to determine the relative magnitude of the residual variance compared to observed data variance. It indicates the accuracy of simulated versus observed data against the 1:1 line (Nash and Sutcliffe 1970). NSE is defined as:

$$\text{NSE} = 1 - \frac{\sum_{i=1}^{n} \left(Q_i^{\text{obs}} - Q_i^{\text{sim}} \right)^2}{\sum_{i=1}^{n} \left(Q_i^{\text{obs}} - \bar{Q}^{\text{obs}} \right)^2}. \tag{4}$$

where Q_i^{Obs} and Q_i^{sim} are representing the measured and simulated data for ith observation and $\bar{Q}^{\text{Obs}}$ and $\bar{Q}^{\text{sim}}$ are the mean of measured and simulated data, respectively.

NSE values range between $-\infty$ and 1 where 1 is the optimal value with perfect match between observed and simulated data. NSE = 0 indicates that the model simulations are as accurate as the mean of the measured data, NSE <0 indicates that the mean of the observed data is better than the prediction from model simulation (Moriasi et al. 2007).

Although NSE is the most widely used performance indicator for hydrological model's flow simulation, it is not suitable for low flow condition (Krause et al. 2005). NSE overestimates larger values and neglects lower values due to the use of square of difference between observed and simulated discharge (Legates and McCabe 1999). To overcome this, modified NSE versions were used by several researchers to evaluate low and high flow conditions (Poretta-Brandyk et al. 2010; Krause et al. 2005; Oudin et al. 2006). Logarithm NSE was introduced for evaluation of low flow as

$$\text{NSE}_{\ln Q} = 1 - \frac{\sum_{i=1}^{n} \left(\text{Ln}(Q_i^{\text{obs}} + \varepsilon) - \text{Ln}(Q_i^{\text{sim}} + \varepsilon) \right)^2}{\sum_{i=1}^{n} \left(\text{Ln}(Q_i^{\text{obs}} + \varepsilon) - \text{Ln}(Q^{\text{obs}} + \varepsilon) \right)^2}. \tag{5}$$

where, ε is an arbitrary chosen small value to avoid problems with nil observed or simulated discharges.

Another modified NSE version was used by Oudin et al. (2006) using square root of observed and simulated values which gives an indication of overall hydrograph fit as

$$\text{NSE}_{\text{sqrt}Q} = 1 - \frac{\sum_{i=1}^{n} \left(\sqrt{Q_i^{\text{obs}}} - \sqrt{Q_i^{\text{sim}}} \right)^2}{\sum_{i=1}^{n} \left(\sqrt{Q_i^{\text{obs}}} - \sqrt{\bar{Q}^{\text{obs}}} \right)^2}. \tag{6}$$

Although the classical version of NSE is good enough to evaluate the high flow, another modified version was adopted for high flow evaluation (Poretta-Brandyk et al. 2010).

$$NSE_h = 1 - \frac{\sum_{i=1}^{n}(Q_i^{obs} + \bar{Q}^{obs})(Q_i^{obs} - Q_i^{sim})^2}{\sum_{i=1}^{n}(Q_i^{obs} + \bar{Q}^{obs})(Q_i^{obs} - \bar{Q}^{obs})^2}. \qquad (7)$$

RMSE-observations standard deviation ratio (RSR)
Although Root mean squared error (RMSE) is the most
commonly used error index in statistics, there is no
accepted reference values of RMSE (Moriasi et al. 2007).
Based on the standard deviations of observations, Singh
et al. (2004) recommended a guideline of RMSE. Fol-
lowing that guideline, Moriasi et al. (2007) developed a
model evaluation statistics, RMSE-observations standard
deviation ratio (RSR) (Eq. 8). RSR incorporates a nor-
malization factor with the error index, so that the resulting
RSR values can apply to various constituents.

$$RSR = \frac{RMSE}{STDEV_{obs}} = \frac{\sqrt{\sum_{i=1}^{n}(Q_i^{obs} - Q_i^{sim})^2}}{\sqrt{\sum_{i=1}^{n}(Q_i^{obs} - \bar{Q})^2}}. \qquad (8)$$

The optimal value of RSR is 0 which indicates perfect
model simulation and higher values indicate poorer
performance of the model.

Coefficient of determination (R^2) The R^2 value is an
indicator of the strength of the linear relationship between
the observed and simulated values (Santhi et al. 2001). The
R^2 values range from 0 to 1 where 0 indicates no linear
relation of model output and the observed values and 1
indicates perfect linear relation. A score of R^2 above 0.5 is
considered acceptable (Green et al. 2006). R^2 is defined as

$$R^2 = \frac{(\sum_{i=1}^{n}(Q_i^{Obs} - Q^{sim})(Q^{sim} - \bar{Q}^{sim}))^2}{\sum_{i=1}^{n}(Q_i^{Obs} - \bar{Q}^{obs})^2 \sum_{i=1}^{n}(Q^{obs} - \bar{Q}^{obs})^2}. \qquad (9)$$

Correlation coefficient (r) The Pearson correlation coef-
ficient, r measures the linear association of two variables
(Hirsch et al. 1993). The value of r ranges from -1 to $+1$.
For two sets of variables x and y, the Pearson correlation
coefficient r is defined as

$$r = \frac{S_{xy}}{\sqrt{S_{xx}S_{yy}}} \qquad (10)$$

Where $S_{xx} = \sum_{i=1}^{n}(x_i - \bar{X})^2$, $S_{yy} = \sum_{i=1}^{n}(y_i - \bar{Y})^2$,
$S_{xy} = \sum_{i=1}^{n}(x_i - \bar{X})(y_i - Y)$.

Model validation Model validation (also known as test-
ing) is an attempt to check the performance of the model by
running the model for a different period than the calibration
using optimal parameter values obtained during the cali-
bration process (Moriasi et al. 2007). Optimized SWAT
parameter values obtained during calibration were used to
simulate the model for the validation period. Calibration

and validation was performed for the Yass station at Yass.
The calibrated model outputs were compared with the Yass
River station upstream of Burrinjuck dam for additional
verification.

Results and discussion

Sensitivity analysis

The sensitivity analysis was performed for both monthly
and daily time steps. Ranking of the sensitivity of the
model parameters was found to be different for different
time steps. The list of nine most sensitive parameters
(ranked 1–9 for both the time step) is summarized in
Table 2. Among the 26 flow parameters for which sen-
sitivity analysis was done, initial curve number for
moisture condition II (CN2) was found to be the most
sensitive parameter for the Yass River watershed at both
monthly and daily time steps. The soil evaporation com-
pensation factor (ESCO) was ranked 2nd for monthly
time step, but lowered to 4th for daily flow. On the
contrary, the baseflow alpha factor (ALPHA_BF) was
found to be more sensitive for daily flow (2nd) than for
monthly flow (5th). The available water content
(SOL_AWC), threshold depth of water in the shallow
aquifer for revap or percolation to occur (REVAPMN)
and maximum canopy storage (CANMX) were found to
be relatively highly sensitive at both time steps. Routing
parameter Manning's roughness coefficient (CH_N2) and
effective hydraulic conductivity of main channel
(CH_K2) were found to be highly sensitive for daily flow
but less sensitive for monthly flow. The threshold depth
of water in the shallow aquifer for return flow to occur
(GWQMN) was found highly sensitive for monthly flow
but less sensitive for daily flow. Optimized values of the
most sensitive parameters are shown in Table 2. The
relatively high value of CN2 indicates that there is high
runoff potential in the catchment. The water holding
capacity of the lower soil layer is higher than that of the
top layer. This might have a restricting effect on perco-
lating water and aquifer return flow.

Calibration and validation

The model performance statistics for the calibration pro-
cess are summarized in Table 3. From Table 3, it can be
observed that manual calibration resulted in better results
than the auto-calibration for monthly time step. However,
the performance of auto-calibration improved when simu-
lation is done using manual calibration parameters. All the
manual calibration performance parameters can be rated as
"very good" for the model developed in this study

Table 2 Sensitivity ranking of SWAT parameters and their optimized values for Yass River catchment

Ranking (monthly)	Ranking (daily)	Parameter name	Unit	Change option	Range	Optimized value
1	1	CN2	–	r	−25 to 25 %	57 to 87
2	4	ESCO	–	v	0 to 1	0.52
3	16	GWQMN	mm of H_2O	v	0 to 5,000	1.06
4	7	SOL_AWC(1)[a]	mm of H_2O/mm of soil	r	−50 to 50 %	0.15
		SOL_AWC(2)[a]	mm of H_2O/mm of soil	r	−50 to 50 %	0.15 to 0.23
5	2	ALPHA_BF	Days	v	0 to 1	1
6	10	SOL_Z(1)[a]	mm of H_2O/mm of soil	r	−50 to 50 %	225 to 507
		SOL_Z(2)[a]	mm of H_2O/mm of soil	r	−50 to 50 %	758 to 843
7	9	CANMX	mm of H_2O	v	0 to 100	12.498
8	5	REVAPMN	mm of H_2O	v	0 to 500	0.9
9	15	GW_REVAP	mm of H_2O	v	0.02 to 0.2	0.186
16	3	CH_N2	–	v	−0.01 to 0.3	0.08
11	6	CH_K2	mm/h	v	−0.01 to 500	70
13	8	SURLAG	–	v	0 to 24	10

v change in absolute value and, *r* change in relative value of parameter

[a] Values inside the parenthesis denote the soil layer number

(Moriasi et al. 2007).This indicates that the input data and model assumptions are adequate enough to simulate the streamflow of the Yass River with acceptable accuracy. The model was able to capture about 81 % of the variance on monthly observed streamflow data.

Auto-calibration using ParaSol resulted in "very good" NSE values, whereas SUFI-2 output was "good" according to the guideline recommended by Moriasi et al. (2007). Auto-calibration of the model with the manually calibrated parameters was found to be the best way to optimize the model parameters for this study. NSE increased from 0.707 to 0.859 for SUFI-2 and 0.799 to 0.864 for ParaSol when manually calibrated parameters were used for auto-calibration. The reasons why auto-calibration was not able to find out the best parameter values might be wide range of some parameters and discrepancy in values where auto-calibration changes the relative values of the parameters.

Table 3 SWAT model evaluation statistics at different stages of calibration

Stages	NSE	RSR	R^2	r
Default simulation	−1.835	1.684	0.633	0.796
Manual calibration	0.81	0.436	0.811	0.9
Auto-calibration (SUFI-2)	0.707	0.541	0.722	0.85
Auto-calibration (ParaSol)	0.799	0.448	0.814	0.902
SUFI-2 after manual calibration	0.859	0.375	0.859	0.927
ParaSol after manual calibration	0.864	0.369	0.872	0.934
Daily simulation	0.124	0.936	0.372	0.61
Daily auto-calibration (ParaSol)	0.55	0.671	0.559	0.748
Monthly after daily	0.786	0.462	0.837	0.915

For this study, GWQMN and REVAPMN ranges were reduced by manual calibration to 0–2 and 0–1, respectively. It was observed that auto-calibration does not give good results for parameters whose values change in a relative sense. For example, soil available water capacity (SWOL_AWC) for layer 1 and layer 2 for some soil classes had inaccurate values. So, when relative values of all parameters were changed during auto-calibration, the soil classes which already have good value were changed to incorrect values and subsequently reduced the model performance. Despite very good model evaluations statistics for monthly calibration, the indicators were very low for daily simulation. Monthly calibrated model resulted in an NSE value of 0.12 for daily time step which is unsatisfactory. The model was over predicting some of the high flow events. However, overall predictions were not accurate for daily time step. So, calibration was performed for daily time step for the nine most sensitive parameters using ParaSol as it produced best output in previous iterations. NSE reached up to 0.55 following some manual adjustments after auto-calibration for daily time step but it reduced the monthly NSE from 0.864 to 0.786. Although the NSE value decreased for monthly time step, still it was above the "very good" range and overall model was more accurate to predict flow even at daily time step.

The model was validated using river flow data at two stations: the Yass station at Yass and the Burrinjuck dam station just upstream of Burrinjuck dam. The latter is the outlet of the watershed. The parameter values obtained from the daily flow calibration were used for model verification and further application. Visual observation of the time series of observed and simulated monthly discharges

(Fig. 3) shows that the shape and timing of the observed and simulated hydrographs agree for most part of the calibration and validation periods. Exceptions are slight under estimation of the peak discharges during the calibration and validation periods. Table 4 shows the model performance parameters during the validation period for the two gauging stations. The performance of the model can be evaluated as "very good" with NSE >0.75 and RSR <0.50 for both the calibration and validation periods (Moriasi et al. 2007). The other two performance statistics are also "good" for both the periods.

Figure 4 shows the correlation plots for calibration and validation periods with corresponding coefficient of determination. In general, there is a very good agreement between measured and simulated discharges. However, the model underestimated (8 %) the discharge for the whole catchment during the validation period (the validation period was relatively dry period in the region with annual average rainfall of 564 mm for the first 7 years of the validation compared to 659 mm for the calibration period).

Drought period and high-rainfall period streamflow simulation

The MDB was receiving below average rainfall since 1997 (Potter et al. 2008) and the basin was declared as drought in
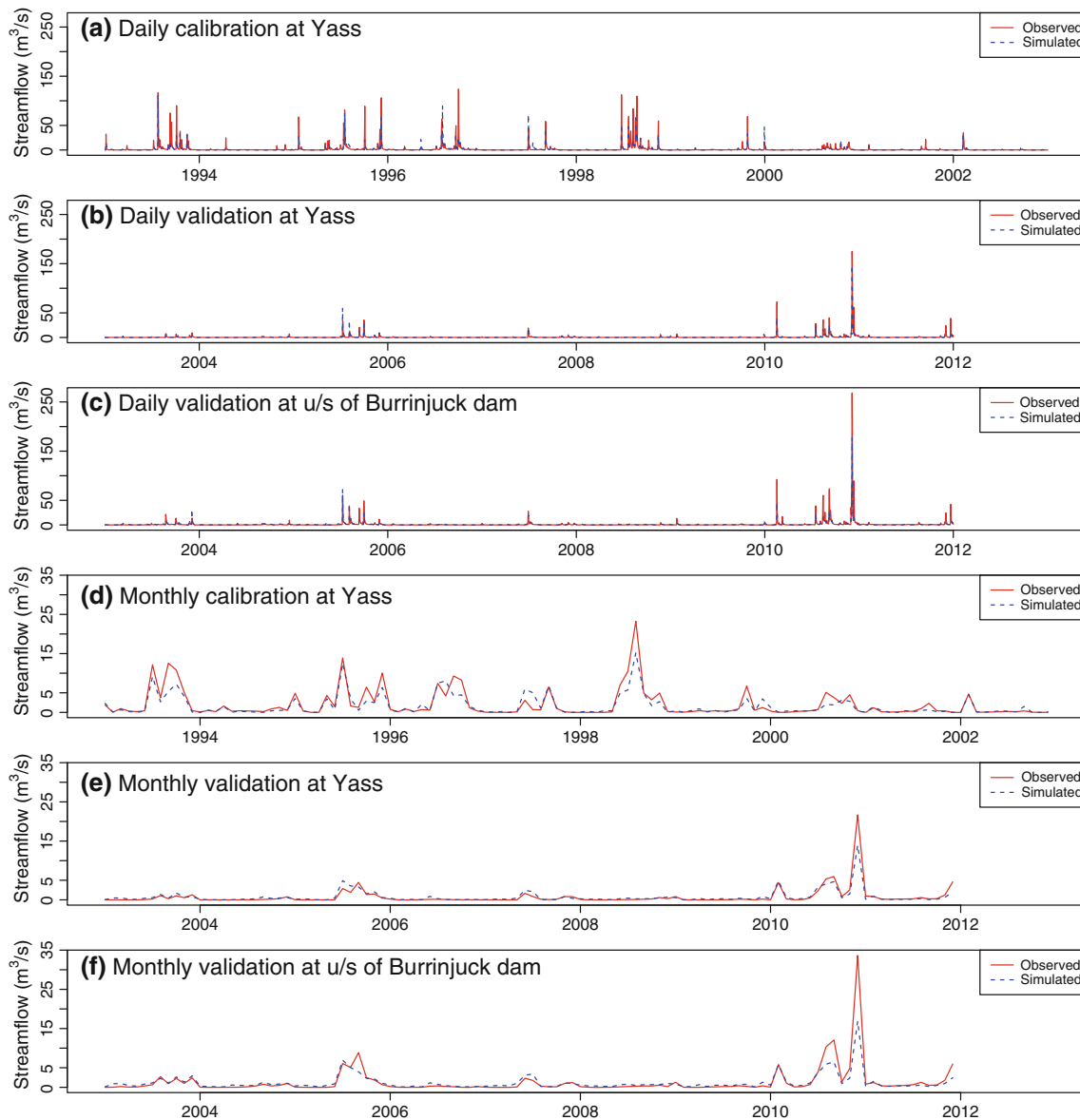

Fig. 3 Observed and simulated streamflows during the calibration (1993–2002) and validation (2003–2011) periods: **a** daily calibration at Yass, **b** daily validation at Yass, **c** daily validation at upstream of Burrinjuck dam, **d** monthly calibration at Yass, **e** monthly validation at Yass and **f** monthly validation at upstream of Burrinjuck dam

Table 4 Model evaluation statistics for validation period at two gauging stations in the Yass River catchment

Stages	Model performance parameters			
	NSE	RSR	R^2	r
Yass station-daily	0.807	0.439	0.818	0.904
Upstream of Burrinjuck dam-daily	0.711	0.537	0.809	0.899
Yass station-monthly	0.846	0.392	0.905	0.951
Upstream of Burrinjuck dam-monthly	0.74	0.51	0.906	0.952

2004 (NSW Office of Water 2013a). After the above-average-rainfall during the summer of 2009–2010, the whole NSW was declared to be out of drought at the end of 2010 (Department of Primary Industries 2010) with south eastern NSW experiencing a flood at the end of 2010 (Ministry of Police and Emergency Services 2013). Considering these conditions, the validation period (2003–2011) of this study was divided into two periods with 2003–2009 considered as low flow period and the remaining 2 years (2010–2011) as high flow period. Figure 5 shows the observed and simulated flows for the drought period (2003–2009) and the high-rainfall/high streamflow period (2010–2011). The model performance parameters presented in Table 5 indicates that SWAT was able to simulate the two flow regimes with sufficient accuracy. Additional criteria NSE_{lnQ}, NSE_{sqrtQ} for drought period and NSE_h for the high-rainfall/high streamflow periods were used. All the criteria can be stated as "very good" to "excellent" except NSE_{lnQ} for the drought period. This value falls in the category of "satisfactory" according to Poretta-Brandyk et al. (2010). The only exceptions are during peak flow periods: the model over-estimates few peaks during the drought period and under-estimated it during the high-rainfall/high streamflow periods. Considering the fact that the model was not

calibrated for single-event high flow condition, this is an acceptable result.

Catchment soil water balance

The Yass River baseflow was separated using a base flow filter program based on the methodology described by Arnold and Allen (1999). Measured and simulated base-flow during the calibration and validation periods is shown in Fig. 6. It was estimated that 42 % of the annual streamflow during the calibration period is baseflow. SWAT simulated 48 % of the streamflow during the same period as baseflow which indicates that the calibrated model was able to generate baseflow with acceptable accuracy. During the validation period, baseflow was found to be 40 % of the observed streamflow compared to 43 % for SWAT simulated flow.

The water balance in Eq. (1) (methodology section) indicates that change in the soil water storage is estimated as a residual of the input and outputs of the water balance components. The main input component is rainfall (PREC), while the output components are ET, surface water and ground water. Surface water flow includes surface flow (SURQ) and lateral flow (LATQ). LATQ or sub-surface flow is the amount of water that flows laterally through the soil profile and enters the main channel. PERC is the amount of water percolation from the soil profile and GWQ is the part of PERC which returns to the streamflow through shallow aquifer. The water balance equation can be represented as:

$$\text{Change in soil water} = \text{PREC} - \text{ET} - \text{SURQ} - \text{LATQ} - \text{PERC}. \quad (11)$$

Table 6 summarizes average values of the different components of the water balance for the Yass River catchment during calibration and validation periods.

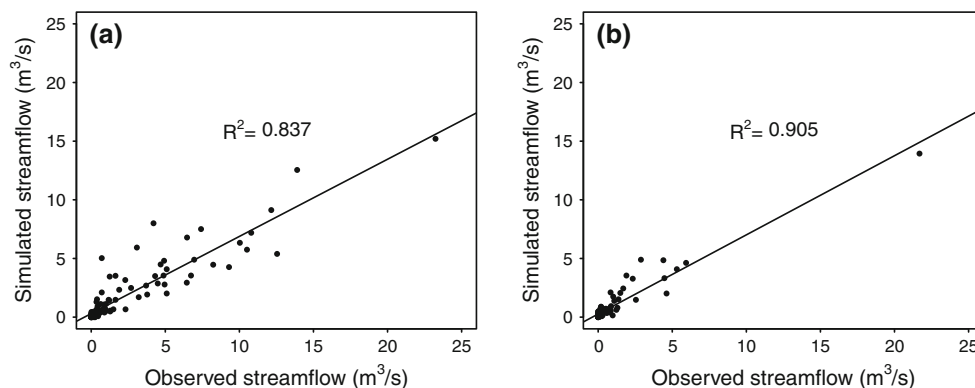Evapotranspiration (ET) was found to be the major component of the water balance through which water is

Fig. 4 Scatter plot of monthly measured and simulated streamflows during (**a**) calibration (1993–2002) and (**b**) validation (2003–2011) periods

Fig. 5 **a** Drought/low
streamflow (2003–2009) and
b high-rainfall/high streamflow
period (2010–2011) flow
simulation plots for the Yass
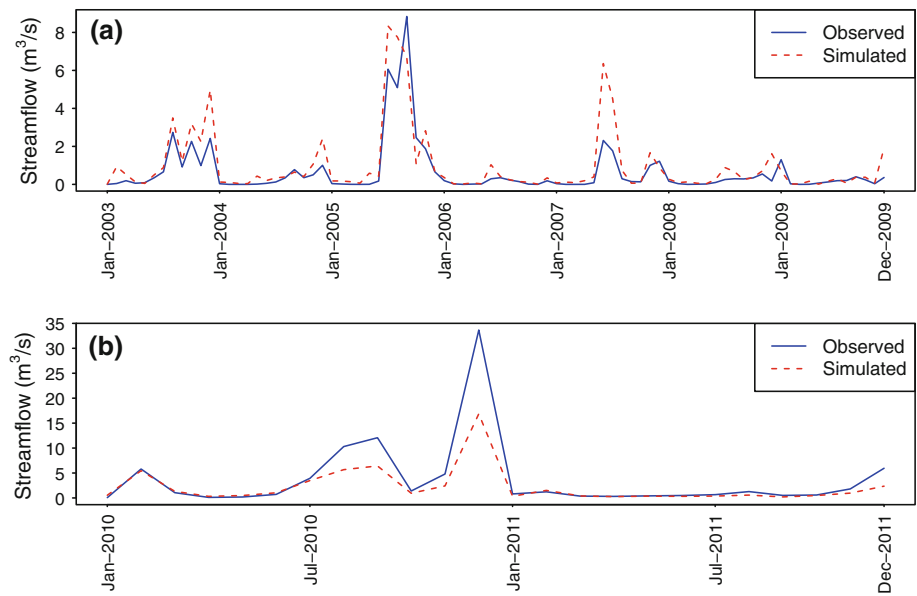River at upstream of Burrinjuck
dam

Table 5 SWAT model performance statistics during drought/low
streamflow and high-rainfall/high streamflow periods for Yass River
catchment

Criteria	Drought period (2003–2009)	High-rainfall period (2010–2011)
NSE	0.739	0.697
RSR	0.511	0.550
R^2	0.779	0.970
r	0.883	0.985
NSE_{lnQ}	0.210	
NSE_{sqrtQ}	0.572	
NSE_h		0.680

lost from the watershed. It accounted for 89 and 94 % of
the total precipitation falling on the watershed during the
calibration and validation periods, respectively. This is
similar to 90 % of ET lost from rainfall at Australia
scale. As a result, the water yield of the catchment is
very low compared to the rainfall amount. ET depends
on available water. During some dry years, ET exceeds
the rainfall amount implying loss of soil water which
leaves very low amount for other components of the
water balance.

Although SWAT offers several advantages as a physi-
cally based distributed model for watershed scale model-
ing, it has some limitations as well. SWAT is more suitable
for long-term scenario analysis than a detail single-event
flood simulation (Neitsch et al. 2011). This study also
found that, overall, the model performance was better for
monthly simulation than the daily simulation. SWAT
generates missing data from weather generator station. The

possibility of ambiguous outputs from the model increases
when number of weather generator stations is limited and
several stations of a study area have missing data with
variable rainfall distribution inside the catchment. SWAT
simulations are highly affected by the variability of input
parameters such as inherent heterogeneity in soil or land
use (Shirmohammadi et al. 2008). Although extensive
effort and care was made to optimize the parameters values
to represent the catchment, further improvement in the
model performance can be achieved through more accurate
soil and plant information.

Conclusion

This study applied the distributed hydrological model
SWAT to a south eastern Australian Yass River catch-
ment. The model was successfully calibrated and vali-
dated with "very good" values for several of the model
performance indicators. SUFI-2 and ParaSol algorithms
were used for auto-calibration and it was found that the
performance was improved when auto calibration was
done after manual calibration. Adjustment of parameter
ranges also increased the performance of the auto-cali-
bration. The water balance analysis revealed that about
90 % of the rainfall is lost by evapotranspiration
resulting in low stream and ground water flows. The
calibrated model was able to simulate both low and high
flows with adequate accuracy: satisfactory results for low
flow period and excellent results for high flow period.
The calibrated model can be used for further analysis
including climate and land use changes and their impact
on hydrological process of the watershed. Further

Fig. 6 Observed and simulated time series plot of baseflow for the Yass River at Yass station: **a** calibration (1993–2002) and **b** validation (2003–2011) periods
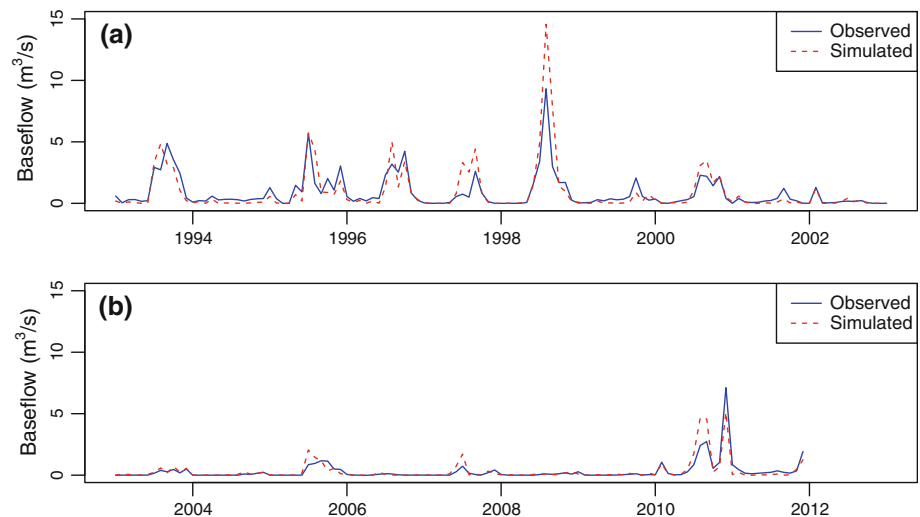

Table 6 Annual average water balance components of Yass River catchment during the calibration (1993–2002) and validation (2003–2011) periods

Period	Unit	PREC	SURQ	LATQ	GWQ	PERC	ET	SW
Calibration	(mm)	659.7	26.3	11.8	10.7	43.0	587.1	29.1
	(%)	100.0	4.0	1.8	1.6	6.5	89.0	4.4
Validation	(mm)	612.5	14.3	9.5	1.6	12.8	576.7	18.3
	(%)	100.0	2.3	1.6	0.3	2.1	94.2	3.0

calibration for sediment and different nutrient parameters will allow this model to be applied in sediment yield and water quality evaluation.

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