Research papers

Using an improved SWAT model to simulate hydrological responses to land use change: A case study of a catchment in tropical Australia

Hong Zhang, Bin Wang, De Li Liu, Mingxi Zhang, Lance M. Leslie, Qiang Yu

ABSTRACT

Land use change is one of the dominant driving factors of watershed hydrological change. Thus, hydrological responses to land use changes require detailed assessments to ensure sustainable management of both water resources and natural ecosystems. The Soil and Water Assessment Tool (SWAT) model has been widely used to simulate the impacts of land use change on water balance. However, the original SWAT model has poor performance in estimating the leaf area index (LAI) of different vegetation types for tropical areas. The objective of this study was to simulate the impact of different land use change scenarios (deforestation, afforestation and urbanization) on the water balance, using an improved SWAT model with vegetation growth calibrated from MODIS LAI data. The North Johnstone River catchment in wet tropical eastern Australia was selected as the case study area. Results showed that the modified SWAT model was able to reproduce smoothed MODIS LAI with |PBIAS| ≤ 5% (|PBIAS| ≥ 42% for default SWAT), R2 ≥ 0.94 (R2 ≥ 0.90 for default SWAT). It is noted that SWAT-T had |PBIAS| ≤ 10% while |PBIAS| > 20% for default SWAT. Land use change impacted all hydrological variables, with the impact on surface runoff being the most notable at yearly scale (8.9%, 5.7%, −9.5% and 15.9% for scenario 1, 2, 3 and 4, respectively). Absolute changes of surface runoff under land use change scenarios differed across months, with the most notable absolute change occurring during the wet season (December to May) (1.2 ~ 6.6 mm, 1.0 ~ 3.5 mm, −7.3 ~ −1.1 mm and 3.0 ~ 9.0 mm for scenario 1, 2, 3 and 4, respectively). Urbanization increased surface runoff (5.7% and 15.9% for scenario 2 and 4, respectively) and decreased lateral runoff (−0.7% and −1.3%) and ground water (−0.9% and −3.5%), but produced no clear change in total runoff (0.2% and 0.2%), actual evapotranspiration (−0.3% and −0.3%), and soil water (0.5% and 0.7%) at the annual time scale. Furthermore, afforestation could decrease surface runoff (−9.5% for scenario 3) and soil water (−2.0%), increase evapotranspiration (1.7%), and lead to slight changes (absolute values ≤0.8%) in other hydrological variables at the annual time scale. A strong positive correlation (r ≥ 0.94) was observed between annual rainfall and total runoff for forest-evergreen, range-grasses, and urban land use. Forest-evergreen generally produced less total runoff than range-grasses and urban land use under conditions of the same rainfall, terrain slope, and soil texture. In addition, urban land use generally produced more surface runoff and less lateral runoff and groundwater than forest-evergreen and range-grasses under the same conditions. These results contribute important information for development of effective adaptation strategies and future policy plans for sustainable water management in tropical eastern Australia.

Abbreviations: LUCC, land use/cover change; SWAT, Soil and Water Assessment Tool; SWAT-CUP, SWAT Calibration and Uncertainty Programs; SWAT-T model, modified SWAT model for tropical areas; LAI, leaf area index; HRU, hydrologic response unit; FRSE, forest-evergreen; FRST, forest-mixed; FRSD, forest-deciduous; RNGB, range-brush; RNGE, range-grasses; WETL, wetlands; AGRL, agricultural land-generic; URBN, urban; SURQ, surface runoff; LATQ, lateral runoff; GWQ, groundwater; ET, evapotranspiration; SW, soil water

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1. Introduction

Urbanization, agricultural development, deforestation, and other human activities lead to spatial and temporal changes in land use/land cover, that can affect water flow pathways and the water balance (Welde and Gebremariam, 2017). Land use/cover change (LUCC) plays an important role in earth-atmosphere interactions and biodiversity loss and is a major factor influencing sustainable development (Turner et al., 1995). LUCC can directly affect global carbon budgets, biodiversity, and ecosystem function (Aide et al., 2013). Many regions worldwide have experienced massive LUCC over recent decades (Schirpke et al., 2012). Although the net decrease of natural forest area was slowing down globally in the period from 2000 to 2010 (Meyfroidt and Lambin, 2011), deforestation remains one of the major processes of LUCC, with multiple implications for global environmental change (Lambin and Geist, 2008). For example, a large amount of natural land in China, including wetlands and forests, has been developed into arable land and human settlements due to rapid urbanization over the past two decades (Song and Ding, 2009; Yu et al., 2011). Extensive deforestation occurred in Latin America and the Caribbean during the first decade of the 21st century, but extensive areas also recovered land use change in watersheds with different land use, soils, and management conditions (Arnold and Fohrer, 2005). In general, managing vegetation growth is necessary in distributed hydrological models because evapotranspiration is an important component of the water cycle (Abbaspour et al., 2015). A simple plant growth model is used in SWAT to simulate growth and yield of all kinds of vegetation (Abbaspour et al., 2015). The plant growth model in SWAT was developed for temperate areas and is not suitable for monsoon-driven or tropical regions (Wagner et al., 2011). For instance, the day length-driven dormancy used in temperate areas to separate annual plant cycles is not consistent with plant growth in the tropics. Therefore, the model’s suitability to simulate plant growth has not been reflected critically in most SWAT research for tropical areas, possibly because model calibration and validation are normally based on streamflow and/or water quality outputs (Strauch and Volk, 2013). However, successfully reproducing these outputs does not imply a correct simulation of the internal hydrological processes in a catchment (Strauch and Volk, 2013). Therefore, a few studies have been conducted to improve the plant growth model in SWAT globally including tropical areas (Strauch and Volk, 2013; Alemayehu et al., 2017; Guo et al., 2019; Ma et al., 2019). For instance, Strauch and Volk (2013) presented an alternative approach to automatically trigger new growing seasons during the transition from dry to wet season based on changes in soil moisture for tropical areas. Meanwhile, a general improvement (independent of whether or not the area is in tropics) has been implemented with the LAI decline rate modified to a logistic function which provides a sigmoidal decrease toward the minimum LAI. Their results showed that the modified plant growth model could reasonably represent seasonal dynamics of the LAI, and the modified model should be useful for large parts of the model community. Alemayehu et al. (2017) modified the SWAT model for the tropics using a straightforward but robust soil moisture index (a quotient of rainfall and reference evapotranspiration) to trigger a new growth cycle within a predefined period, and results indicated that this index was reliable for triggering a new annual growth cycle. In addition, Ma et al. (2019) integrated downscaled high quality MODIS LAI into modified SWAT plant growth model and reported a high accuracy in the validation of streamflow in the sub-tropics. However, to the best of our knowledge, the SWAT model with an improved plant growth model has never before been applied to tropical regions of Australia. Consequently, we selected a catchment representative of the tropics in Australia to explore and assess the performance of the modified SWAT (SWAT-T) model, as improved by Strauch and Volk (2013).

The aim is to evaluate the performance of SWAT-T and to assess hydrological responses to land use/cover change in wet tropical Australia. We selected the North Johnstone River catchment as a case study. The specific objectives of this study were to: (1) evaluate the performance of the SWAT-T and default SWAT model for simulating climate change on the water cycle cannot be determined. Since the 1970s, with the development of computer science, geographic information systems and remote sensing technologies, hydrological models have been more widely used to determine LUCC impacts in water cycle studies. Hydrological models provide a framework for conceptualizing and studying the relationships among climate change, land use change, and the water cycle. Among these models, distributed hydrological models have significant applications because they directly relate model parameters to characteristics of the earth’s surface (Legesse et al., 2003). Therefore, determining how to construct a distributed hydrological model to study the hydrological response to LUCC is a question that must be researched in depth.
leaf area index (LAI) and streamflow of the North Johnstone River catchment; (2) using both models (SWAT-T and default SWAT) to forecast changes in simulated surface runoff, lateral runoff, groundwater, total runoff, actual evapotranspiration, and soil water under different land use change scenarios; and (3) identify rainfall-runoff relationships of different land covers to explain water availability changes caused by land use/cover change.

2. Materials and methods

2.1. Study area

The North Johnstone River catchment (Fig. 1) is situated in the wet tropics of North Queensland. The catchment area is about 924 km² with elevation ranging from 18 m to 1370 m. In this catchment, the mean annual temperature is about 21.4 °C, mean annual rainfall is approximately 2740 mm and mean annual runoff is about 1995 mm (averaged from 1967 to 2017). Rainfall is affected by monsoons and tropical cyclones/lows/depressions and is strongly seasonal with 78% of the total annual rainfall occurring during the wet season from December to May (Fig. 2). The catchment also receives regular rainfall throughout the year in contrast to dry tropical areas. The Johnstone River catchment is divided into three distinct regions: the upper (tablelands or hinterland), the central (the Range or World Heritage), and the lower (coastal or floodplain) regions. The two key tributaries that discharge into the Great Barrier Reef lagoon are the North Johnstone and South Johnstone Rivers. The other major streams are the Moresby River, Liverpool Creek, and Maria Creek. These three streams are lowland waterways, whereas the North and South Johnstone Rivers begin in the upland “mixed land use” tablelands. Agriculture, residential, and industrial developments (including roads) can have important impacts on the way water flows through the landscape (https://wetlandinfo.des.qld.gov.au/wetlands/facts-maps/sub-basin-north-johnstone-river/). Thus, understanding how land use/cover changes influence regional streamflow regimes is essential for deciding how best to manage the catchment and to protect its resources.

2.2. The SWAT model

The SWAT hydrological model (SWAT2012) is used to represent the main hydrological processes within the catchment. SWAT is a process-based and semi-distributed hydrological model that simulates the major water balance components continuously at a daily time step (Arnold et al., 1998). SWAT can simulate watershed hydrological characteristics under different land use and climate conditions, making it a widely used hydrology-related tool for land use and climate change research (Li et al., 2011; Reshmidevi et al., 2017; Shrestha et al., 2017). However, examples from tropical Australia are limited with most studies concentrated in the eastern and southeastern part of the country (Saha and Zeleke, 2015). The model was selected based on considerations such as its ability to represent the physical processes related to water movement, support documentation, and additional software (SWAT-CUP, SWAT Calibration and Uncertainty Programs) for model calibration and validation. The Hargreaves method available in the SWAT interface was used to calculate potential evapotranspiration (Reshmidevi et al., 2017) using air temperature as input data (Brown et al., 2015). In this study, surface runoff and infiltration is computed with daily rainfall using the Soil Conservation Service (SCS) Curve Number (CN) method (USDA, 1972). Further model details can be found in Neitsch et al. (2011).

However, the original SWAT model performs poorly in estimating LAI of different vegetation types for tropical areas, thus, an improved SWAT model (SWAT-T) (Strauch and Volk, 2013) was used in this study. This approach used simulated plant available water in the upper soil layers as a trigger for a new growing cycle. In the SWAT-T model, two new parameters TRAMO₁ and TRAMO₂ were implemented to define the first and the last month of a region-specific ‘transition period’ from dry to wet season. In this study, based on the MODIS LAI, the default values of TRAMO₁ and TRAMO₂ were set to 7 (July) and 8 (August) in the sub-basin input files, respectively. In addition, for this
SWAT-T model, a logistic function that provides a sigmoidal decrease towards the minimum LAI was used to modify the LAI decline rate. Further model details can be found in Strauch and Volk (2013). According to the user’s manual from Strauch and Volk (2013), no management settings in the operations schedule were defined for the SWAT-T model in this study. Furthermore, the SWAT-T model was calibrated and validated only against streamflow. The model simulations were not calibrated and validated with actual evapotranspiration and soil water content due to a lack of field data for these variables. The absolute values of actual evapotranspiration and soil water content should therefore not be used directly. However, comparing the relative changes in the simulations is still reasonable and valuable because the hydrological model mimics the actual water cycle.

2.3. Data preparation

Multiple data sets are required in SWAT as input to develop a semi-distributed model using the ArcSWAT interface. This section describes the processing of the respective data. The data for SWAT model development, data sources, and relevant characteristics are listed in Table 1.

2.3.1. Digital elevation model (DEM), land use, and soil data

SWAT primarily relies upon defined hydrologic response units (HRUs) that are based on land use maps, soil maps, and slope characteristics (Pignotti et al., 2017). In this study, five slope classes (i.e., 0–10%, 10–20%, 20–30%, 30–50%, and > 50%) were defined for slope discretization and 778 HRUs were produced using a multiple HRU generation method with land use, soil, and slope input (thresholds of 2%-2%-2%) using the SWAT interface. The details of DEM, land use, and soil data used in this study are given below.

DEM data are required in SWAT for watershed and river network delineation, and sub-basin generation. In this study, 33 sub-basins were generated (Fig. 1). From DEM, sub-basin parameters (e.g., slope gradient and slope length of the terrain) and river network characteristics (e.g., channel length, width, and slope) were obtained. A 1-second resolution Shuttle Rader Topography Mission (SRTM) derived DEM from Geoscience Australia (https://elevation.fsdf.org.au/) was used in this study. DEM was masked for SWAT model development in the North Johnstone River catchment (Fig. 1).

The land use data developed by NASA LP DAAC at the USGS EROS Center with 500 m spatial resolution (https://lpdaac.usgs.gov/products/mcd12q1v006/) was used and reclassified to match the SWAT land use classes for HRU delineation in the SWAT model (Fig. 3a). There were eight land use classes in this catchment (Fig. 3a): forest-evergreen (FRSE), forest-mixed (FRST), forest-deciduous (FRSD), forest-savanna (FRSA), forest-grassland (FRGA), forest-shrubland (FRSH), forest-wetland (FRWT), and urban (URBN).

A soil map and a database table of soil characteristics (e.g., soil hydrologic group, maximum rooting depth of the soil profile, moist bulk density, etc.) for different soil layers are required by the SWAT model (Saha et al., 2014). We created a “usersoil” database table to delineate HRU in SWAT for the North Johnstone River catchment.

2.3.2. Climate data and river discharge

Daily maximum temperature, minimum temperature, and rainfall from 1967 to 2017 at 10 climate stations (Fig. 1) within or near the catchment were collected from the Australian Government Bureau of Meteorology (BOM) website (http://www.bom.gov.au/climate/data/). These climate data were used for driving SWAT model simulations. According to the default setting in SWAT, one climate station was assigned to each sub-basin which was closest to sub-basin’s centroid (Sirisena et al., 2018). For streamflow calibration and validation, daily observed discharge at the Tung Oil gauge (Fig. 1) also were collected from the Australian Government BOM website (http://www.bom.gov.au/waterdata/). For streamflow calibration, a calibration period that includes wet, normal and dry years was selected so that the model parameters were set for a wide range of climate conditions and also for the validation period. Accordingly, daily observed streamflow data for the periods of 2008–2017 (2005–2007 as warm-up) and 2003–2007 (2000–2002 as warm-up) were used for streamflow calibration and validation, respectively, whereas daily observed climatic and hydrological data for the 1967–2017 period were used to assess land use change impacts on water availability with the calibrated SWAT-T model. To be consistent with the calibration and validation periods for streamflow, the same periods were used for LAI calibration and validation.

2.3.3. Leaf area index

It was found that the default SWAT model could not well reflect the dynamics of LAI. Therefore, SWAT-simulated LAI was calibrated to MODIS-derived, four-day LAI composites using the SWAT-T model (Strauch and Volk, 2013) for tropical plant growth. This SWAT-T model has been shown to improve the representation of shifts between plant dormancy and growth in tropics by using soil moisture, rather than day-length, to represent crucial phenological thresholds (Strauch and Volk, 2013). A 4-day composite MCD15A3H V6 LAI dataset with 500 m pixel size was used in this study. For each of the land cover classes, 4-day median LAI time series were extracted from 2003 to 2017 using methods according to previous studies (Strauch and Volk, 2013; Alemayehu et al., 2017). Additionally, the BFAST method (Verbesselt et al., 2010) was used to smooth the 4-day raw-median LAI time series for different land use covers (see Supplementary Materials S1) (Hoyos et al., 2019). Since LAI was HRU-related outputs, we derived the area-weighted HRU mean for comparison with the smoothed median MODIS LAI (Strauch and Volk, 2013) and calibrated the LAI parameters manually. Additionally, we aggregated daily simulated LAI to 4-day scale to calibrate LAI parameters using a trial-and-error process such that the SWAT-T simulated 4-day LAI mimicked the MODIS 4-day LAI. According to the smoothed LAI data (Supplementary Materials S1), AGRL and WETL had maximum LAI values (~2.4) in March, and minimum values (1.8 and 1.9) in July and August, respectively. FRSE and FRSD peaked in October (6.0 and 5.3) and February (5.3 and 5.1) and reached minimum values (3.7 and 4.0) in June. RNGB and RNGE had maximum LAI values (3.5 and 2.4) in February and reached minimum values (2.9 and 2.0) in July. The high values of smoothed LAI

Table 1

<table>
<thead>
<tr>
<th>Data</th>
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<tr>
<td>Digital elevation model (DEM)</td>
<td>Geoscience Australia</td>
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<tr>
<td>Land use/land cover map</td>
<td>NASA LP DAAC at the USGS EROS Center</td>
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<tr>
<td>Soil map</td>
<td>Bureau of rural sciences, Australia</td>
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<tr>
<td>Observed streamflow</td>
<td>Australian Government Bureau of Meteorology</td>
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<tr>
<td>Observed meteorological data</td>
<td>MODIS LAI products MCD15A3H V6</td>
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<th>Relevant Characteristics</th>
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<tr>
<td>1 s SRTM Derived DEM</td>
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<td>500 m spatial resolution</td>
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<td>The maps were published at a scale of 1:2,000,000</td>
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<tr>
<td>Average daily discharge (1967–2017)</td>
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<td>Maximum and minimum daily temperature and rainfall (1967–2017)</td>
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<td>500 m spatial resolution, 4-day composites (2003–2017)</td>
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were generally observed during the wet season (December to May) (Supplementary Materials S1), which indicated consistency in the smoothed LAI time series. Thus, the plant growth module in the SWAT-T model was calibrated and validated using the smoothed LAI time series (Alemayehu et al., 2017).

2.4. Model calibration and evaluation approach

SWAT Calibration and Uncertainty Programs (SWAT-CUP), a standalone computer program developed for calibration, validation, and uncertainty analysis of SWAT, was used to optimize SWAT model parameters (Abbaspour, 2013). SWAT-CUP links five different calibration procedures, which are Sequential Uncertainty Fitting Ver. 2 (SUFI-2) (Abbaspour et al., 2007), Generalized Likelihood Uncertainty Estimation (GLUE) (Beven and Binley, 1992), Particle Swarm Optimization (PSO) (Zhang et al., 2015), Parameter Solution (ParaSol) (Van Griensven and Bauwens, 2003), and Markov Chain Monte Carlo (MCMC) (Marshall et al., 2004). The program SUFI-2 was selected in this study for SWAT-T calibration, validation, and uncertainty analysis because it was found to be quite efficient for time-consuming large-scale models (Yang et al., 2008). Two types of sensitivity analysis methods are allowed in the SUFI-2 program: global sensitivity method and one-at-a-time sensitivity analysis method (Abbaspour, 2013). The global sensitivity analysis method was used to rank the sensitivity of 22 parameters in SWAT-T. In this sensitivity analysis method, the smaller the p-value and the larger the absolute value of t-stat, the more sensitive the parameter is (Abbaspour, 2013).

Uncertainty in SUFI-2 parameters, conveyed as ranges (uniform distributions), accounts for total sources of uncertainties like uncertainty in driving variables (e.g. rainfall), observed data, conceptual models, and parameters (Abbaspour, 2013). Propagation of the parameter uncertainties results in uncertainties in the SWAT model output variables, which are manifested as the 95% probability distributions (Abbaspour, 2013). These are computed at 2.5% and 97.5% levels of the cumulative distribution of model output variables produced by the propagation of the uncertainties in parameters using Latin hypercube sampling (Abbaspour, 2013). This is called the 95% prediction uncertainty (i.e., 95PPU). Two statistics “P-factor” and “R-factor” were created to quantify the fit between simulation results (95PPU) and observation data with its error (Abbaspour et al., 2015). The P-factor is the proportion of observed data enveloped by the simulation results, the 95PPU, while the R-factor is the breadth of the 95PPU envelope.

Monthly observed and simulated discharge for the period of 2008–2017 and 2003–2007 were used for SWAT-T calibration and validation, respectively. The results for water balance components all were presented at a monthly or annual time step. Therefore, calibrating discharge at a monthly time step rather than daily time step makes the calculation process faster and more efficient. Monthly streamflow was calibrated with SUFI-2 using 500 simulations per iteration (4 iterations) by maximizing the value of Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliffe, 1970). In this study, we followed Shi et al. (2011) by using NSE, percent bias (PBIAS), and coefficient of determination (R2) as statistical evaluation criteria. NSE is one of the most commonly used standards for comparing simulations of hydrological models with observed data (Le and Pricope, 2017). NSE values vary from -∞ to 1 with a value of 1 indicates that the model-simulated results and observed data are perfectly matched, hence, the closer the NSE is to 1, the better performance the SWAT model will have. PBIAS evaluates the average trend of the model simulations to be greater or less than their observed counterparts. A positive value of PBIAS demonstrates an overestimation bias while a negative value indicates an underestimation (Shi et al., 2011). Therefore, the smaller the absolute value of PBIAS, the better. NSE, PBIAS, and R2 were calculated as follows:

\[ \text{PBIAS} = 100 \left( \frac{\sum_{i=1}^{N} (Q_{\text{obs},i} - Q_{\text{sim},i})}{\sum_{i=1}^{N} (Q_{\text{obs},i})} \right) \]  \hspace{1cm} (1)

\[ \text{NSE} = 1 - \frac{\sum_{i=1}^{N} (Q_{\text{obs},i} - Q_{\text{sim},i})^2}{\sum_{i=1}^{N} (Q_{\text{obs},i} - \bar{Q}_{\text{obs}})^2} \]  \hspace{1cm} (2)

\[ R^2 = \frac{\left( \sum_{i=1}^{N} (Q_{\text{obs},i} - Q_{\text{obs}})(Q_{\text{sim},i} - \bar{Q}_{\text{sim}}) \right)^2}{\sum_{i=1}^{N} (Q_{\text{obs},i} - Q_{\text{obs}})^2 \sum_{i=1}^{N} (Q_{\text{sim},i} - Q_{\text{sim}})^2} \]  \hspace{1cm} (3)

where \( Q_{\text{obs}} \) and \( Q_{\text{sim}} \) are the observed and SWAT-T model-simulated monthly streamflow (m^3/s), respectively; \( \bar{Q}_{\text{obs}} \) and \( \bar{Q}_{\text{sim}} \) are the mean observed and SWAT-T model-simulated monthly streamflow (m^3/s), respectively; \( N \) is the number of samples, and \( i \) is the \( i \)th sample.

2.5. Different land use scenarios

The most common land cover classes of the North Johnstone River catchment were FRSE (forest-evergreen) and RNGE (range-grasses), which accounted for around 63.7% of the total region. To evaluate the hydrological response to land use changes in the catchment, four scenarios (Table 2) were considered. These changes were achieved by using the Land Use Update tool in the ArcSWAT interface at the sub-basin scale (Marhaeno et al., 2017). For instance, FRSE can be considered to be replaced by RNGE only if both land use types exist in the

![SWAT land use class and Soil class](image-url)
same sub-basin (Shrestha et al., 2017). Therefore, these partial conversion scenarios mainly occurred in the northwestern part of the catchment where there is less rainfall distribution compared to the downstream part (the forest part) of the catchment (Fig. 3). Scenario 1 supposes that all current FRSE will be changed to RNGE while the rest of the land covers will remain unchanged. This means an 11.5% increase in RNGE area over the entire catchment. Scenario 2 supposes that all current FRSE will be converted to URBN, representing a 2.3% increase in URBN area over the entire catchment. Scenario 3 supposes that all current RNGE will be changed to FRSE, representing a 14.1% increase in FRSE area over the entire catchment. Scenario 4 supposes that all current RNGE will be converted to URBN, representing an 8.4% increase in URBN area over the entire catchment. These four land use change scenarios (i.e. deforestation, deforestation/urbanization, afforestation, and urbanization) were on the basis of present land use conditions and potential future land use plans (residential development) in the North Johnstone River catchment (Wang et al., 2008). The land use change scenarios are shown in Table 2 and the percentage areas of the four scenarios are shown in Fig. 4. FRST was classified as FRSD in Fig. 4 because of its small area proportion shown in Fig. 3.

3. Results

3.1. SWAT-T LAI calibration

Table 3 presents the calibrated values for LAI which were adjusted using a manual calibration method. The minimum LAI (ALAI_MIN) for each land use was defined according to long-term MODIS LAI. As suggested by Strauch and Volk (2013), the total number of heat units needed to bring plants to maturity (PHU_PLT) was calculated using the long-term daily mean temperature. The shape coefficients (FRGW1, FRGW2, LAIMX1, LAIMX2, and DLAI) for the LAI curve and the remaining parameters were calibrated by a trial-and-error process to ensure that the LAI simulated by SWAT-T mimicked the smoothed MODIS LAI. The calibrated values and calibration methods for each LAI parameter and each land use are shown in Table 3. The LAI parameters of FRST were not calibrated because of the small area proportion in the catchment. Thus, the LAI parameters of FRSD was used for FRST.

Fig. 5 shows the comparison between 4-day smoothed MODIS LAI with the SWAT-T-simulated LAI using calibrated parameters for the different vegetation types in both the calibration and validation periods. The degree of agreement for MODIS and simulated LAI were assessed both qualitatively (visual comparisons) and quantitatively (statistical evaluations). From a visual comparison, it is clear that the plant growth cycles of the different vegetation types simulated by the SWAT-T model corresponded much better with the MODIS LAI data than the default SWAT results. For instance, the minimum LAI values simulated by the SWAT-T model (1.8, 4.0, 3.7, 2.9, 2.0, and 1.9) were similar to the MODIS LAI (1.8, 4.0, 3.7, 2.9, 2.0, and 1.9) for AGR, FRSD, FRSE, RNGB, RNGE, and WETL, respectively, while the minimum LAI simulated by the default SWAT was zero for all types of vegetation covers. Fig. 5 also provides the values of the statistical evaluation indices used to assess the performance of SWAT-T-simulated LAI. For FRSE, which was the dominant land cover in the catchment, the SWAT-T model performed quite well for LAI, with the values of NSE > 0.79 during the calibration and validation periods. In contrast, calibration and validation performance for WETL and RNGE was low when the NSE values were > 0.59. However, R2 values were higher than NSE values for all plants types during calibration and validation, ranging from 0.70 to 0.91, and PBIAS values were always within a reasonably small range (± 2.5%), indicating overall good model performance.

3.2. Discharge calibration and validation

The 22 parameters were calibrated and ranked for the discharge calibration in the SWAT-T model in the North Johnstone River catchment (Table 4). These parameters were ranked according to their sensitivities using the global sensitivity analysis method. The sensitivity analysis in SWAT-CUP suggested that 10 parameters (ranked 1–10, Table 4) had significant influence on calibration (P ≤ 0.05). Ground-water delay (GW_DELAY) was found to be the most sensitive calibration parameter in the North Johnstone River catchment. Fig. 6 shows the monthly SWAT-T-simulated streamflow compared with the observed streamflow during calibration and validation periods. Visual comparison showed the simulated hydrograph reproduced the observations reasonably well and closely replicated the temporal variation. Fig. 7 shows that monthly observed runoff and the SWAT-T-simulated runoff were highly correlated (R2 ≥ 0.94, NSE ≥ 0.92, and |PBIAS| ≤ 10%) with slopes within 15% of the 1:1 regression during the calibration and validation periods in the North Johnstone River catchment. Furthermore, a comparison of SWAT-T and the default SWAT model was shown in Supplementary Materials S2 and results showed that SWAT-T simulated streamflow process better than default SWAT with larger R2 (0.94 > 0.92 and 0.94 > 0.90) and NSE (0.93 > 0.91 and 0.92 > 0.90) in calibration and validation period, respectively. However, compared to SWAT-T, the default SWAT model produced smaller absolute percent bias (0.9% < 7.3% and 4.9% < 10.0%) in calibration and validation period, respectively.

3.3. Hydrological responses to land use change scenarios

The calibrated SWAT-T model was applied to simulate the monthly surface runoff (SURQ), lateral runoff (LATQ), groundwater (GWQ), total runoff, actual evapotranspiration (ET), and soil water (SW) under the four land use change scenarios in 1967–2017 in the North Johnstone River catchment. Fig. 8 shows monthly SURQ, LATQ, GWQ, total runoff, ET, and SW and their changes under different land-use scenarios, and Table 5 summarizes changes in average annual SURQ, LATQ, GWQ, total runoff, ET, and SW under different land-use scenarios. It can be seen from Fig. 8 that SURQ, LATQ, GWQ, total runoff, ET, and SW had obvious monthly variations, with values generally greater in December–May (summer-autumn) and less in June–November (winter-spring). In addition, Fig. 8 shows that monthly changes among different land use scenarios of SURQ were more notable than changes of other outputs from SWAT-T. Meanwhile, absolute changes of SURQ under different land-use scenarios differed across months, with the most remarkable changes occurring during the wet season from December to May. Furthermore, Fig. 8 indicates that monthly SURQ increased under Scenarios 1, 2, 4 (deforestation or urbanization), and decreased under Scenario 3 (afforestation), and similar results can be found for default SWAT (Supplementary Materials S3).

This result was the same for SURQ at the annual time scale.

Table 2

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Land use change</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario 1</td>
<td>Deforestation</td>
<td>Supposes that all present FRSE will be converted to RNGE, and the rest of land uses remain unchanged, i.e. 11.5% increase in RNGE area</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>Urbanization</td>
<td>Supposes that all present FRSE will be converted to URBN, and the rest of land uses remain unchanged, i.e. 2.3% increase in URBN area</td>
</tr>
<tr>
<td>Scenario 3</td>
<td>Afforestation</td>
<td>Supposes that all present RNGE will be converted to FRSE, and the rest of land uses remain unchanged, i.e. 14.1% increase in FRSE area</td>
</tr>
<tr>
<td>Scenario 4</td>
<td>Urbanization</td>
<td>Supposes that all present RNGE will be converted to URBN, and the rest of land uses remain unchanged, i.e. 8.4% increase in URBN area</td>
</tr>
</tbody>
</table>
Table 5 indicates that the mean annual surface runoff increased under deforestation (Scenarios 1 and 2) and urbanization (Scenarios 2 and 4). For example, surface runoff increased 25 mm (8.9%) under Scenario 1 (11.5% decrease in FRSE area), 16 mm (5.7%) under Scenario 2 (2.3% increase in URBN area), and 44 mm (15.9%) under scenario 4 (8.4% increase in URBN area) using SWAT-T. In contrast, the 14.1% increase in FRSE area (Scenario 3) led to a 26 mm (9.5%) decrease in surface runoff. The annual total runoff also increased under deforestation and urbanization, and decreased under afforestation, but the extent of increase and decrease was much smaller than observed for surface runoff. For instance, Table 5 indicates that total runoff increased by just 11 mm (0.6%) under Scenario 1 (11.5% decrease in FRSE area) and decreased 14 mm (0.7%) under Scenario 3 (14.1% increase in FRSE area) using SWAT-T. However, annual changes of LATQ and GWQ to urbanization (Scenarios 2 and 4) were opposite to those of SURQ and total runoff. As shown in Table 5, LATQ and GWQ decreased under urbanization. For example, a 2.3% increase in URBN area (Scenario 2) led to 0.7% and 0.9% decreases in LATQ and GWQ, respectively, while an 8.4% increase in URBN area (Scenario 4) contributed to 1.3% and 3.5% decreases in LATQ and GWQ, respectively.

In addition to runoff, Table 5 also shows the SWAT-T-simulated changes in average annual actual evapotranspiration and soil water under the four scenarios. Results show that mean annual ET decreased by 11 mm (1.3%) with an 11.5% reduction in forest area (Scenario 1) and increased by 14 mm (1.7%) with a 14.1% increase in FRSE area (Scenario 3) using SWAT-T. That is, under the deforestation scenario (Scenario 1), the mean annual ET declined with decreased forest area, and under the afforestation scenario (Scenario 3), the mean annual ET increased with increased forest area. In addition, Table 5 suggests that the change of soil water in different land use scenarios was opposite to ET, with a 1.5% increase under deforestation (Scenario 1) and a 2.0% decrease under afforestation (Scenario 3).

According to Table 5, changes in average annual total runoff under Scenarios 1 and 3 were more remarkable than under Scenarios 2 and 4. The spatial distributions of average annual total runoff under land use Scenario 0 and average annual total runoff change under Scenarios 1 and 3 compared with Scenario 0 using SWAT-T and default SWAT in different sub-basins in the North Johnstone River catchment are shown in Fig. 9. These spatial distributions show that average annual runoff in the eastern sub-basins of the catchment were generally greater than the western sub-basins (Fig. 4).

### Table 3

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Calibrated value $^1$</th>
<th>AGRL</th>
<th>FRSD</th>
<th>FRSE</th>
<th>RNGB</th>
<th>RNGE</th>
<th>WETL</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALAI_MIN</td>
<td>Minimum leaf area index (m²/m²)</td>
<td>1.82*</td>
<td>4.01*</td>
<td>3.68*</td>
<td>2.85*</td>
<td>2.00*</td>
<td>1.87*</td>
<td></td>
</tr>
<tr>
<td>BLAI</td>
<td>Maximum potential leaf area index (m²/m²)</td>
<td>2.85**</td>
<td>5.30**</td>
<td>6.00**</td>
<td>3.50**</td>
<td>2.45**</td>
<td>2.55**</td>
<td></td>
</tr>
<tr>
<td>DLAI</td>
<td>Fraction of PHU when LAI begins to decline</td>
<td>0.72**</td>
<td>0.53**</td>
<td>0.57*</td>
<td>0.75**</td>
<td>0.70**</td>
<td>0.80**</td>
<td></td>
</tr>
<tr>
<td>FGRWR1</td>
<td>Fraction of PHU corresponding to the 1st point on the optimal leaf area development curve</td>
<td>0.30**</td>
<td>0.07**</td>
<td>0.00**</td>
<td>0.00**</td>
<td>0.12*</td>
<td>0.21*</td>
<td></td>
</tr>
<tr>
<td>FGRWR2</td>
<td>Fraction of PHU corresponding to the 2nd point on the optimal leaf area development curve</td>
<td>0.67**</td>
<td>0.22**</td>
<td>0.29*</td>
<td>0.50**</td>
<td>0.58**</td>
<td>0.70**</td>
<td></td>
</tr>
<tr>
<td>LAIMX1</td>
<td>Fraction of BLAI corresponding to the 1st point on the optimal leaf area development curve</td>
<td>0.13*</td>
<td>0.15*</td>
<td>0.14*</td>
<td>0.16*</td>
<td>0.17*</td>
<td>0.20*</td>
<td></td>
</tr>
<tr>
<td>LAIMX2</td>
<td>Fraction of BLAI corresponding to the 2nd point on the optimal leaf area development curve</td>
<td>0.88*</td>
<td>0.93*</td>
<td>0.92*</td>
<td>0.94*</td>
<td>0.90*</td>
<td>0.95*</td>
<td></td>
</tr>
<tr>
<td>PHU_PLT2</td>
<td>Total number of heat units or growing degree days needed to bring plants to maturity</td>
<td>2780</td>
<td>4145</td>
<td>7797</td>
<td>3415</td>
<td>3415</td>
<td>3415</td>
<td></td>
</tr>
<tr>
<td>LAI_INIT</td>
<td>Initial leaf area index (m²/m²)</td>
<td>1.94</td>
<td>4.90</td>
<td>5.32</td>
<td>3.33</td>
<td>2.30</td>
<td>2.12</td>
<td></td>
</tr>
</tbody>
</table>

$^1$ MODIS, $^*$manual adjustment during calibration. $^2$ Values estimated from local temperature records and default SWAT values for T_BASE (minimum temperature for vegetation growth (°C)).
those in the western sub-basins. This was primarily due to the uneven spatial distribution of rainfall, with higher rainfall occurring in the eastern area and lower rainfall in the western area. Compared with Scenario 0, average annual runoff increased in Scenario 1 (under an 11.5% reduction in FRSE area) in some sub-basins (#4-#7, #9, #10, #14, #15, #19, #20, #24-#28 and #30), while it decreased in Scenario 3 (under a 14.1% increase in FRSE area) in the same sub-basins. The reason why changes of average annual runoff occur only in these sub-basins is that the replacement of one land use by another land use can be considered only if both land uses are present in the same sub-basin, as we described in the Materials and Methods section. Furthermore, Fig. 9 showed that absolute total runoff changes simulated by default SWAT were much smaller than the SWAT-T model. The vertical dashed lines indicate the termination of the calibration period and the start of the validation period.

4. Discussion

4.1. Model comparison and evaluation

It was found that in the default plant growth model of SWAT simulated LAI was zero for all plants at the beginning of each simulation year, which is not true for plants in tropical areas. Previous studies (Mwangi et al., 2016; Alemayehu et al., 2017; Hoyos et al., 2019) reported similar simulations, revealing that the default SWAT has some shortcomings in modelling vegetation growth in tropical regions. While the calibrated SWAT-T model was generally able to replicate BFAST-
filtered MODIS LAI values for each land cover type (Fig. 5), it failed to represent the bimodal seasonality of LAI because the model is capable of simulating only one wet/dry transition within a year (Hoyos et al., 2019). However, the default SWAT LAI mean values failed to correctly represent both LAI seasonality and range for all plants (Fig. 5). Moreover, the precision of MODIS LAI is also very important because it is directly used to calibrate the parameters of hydrological models. The average LAI of 4.85 (average of maximum LAI 6.0 and minimum LAI 3.7) for FRSE (the dominant land cover in the study area) was approximately equal to values previously reported (4.71 ± 0.37) in the literature (Hill et al., 2006) for tropical rainforests across Australia. Overall, the LAI results simulated by the SWAT-T model were acceptable.

Groundwater delay (GW_DELAY) was found to be the most sensitive calibration parameter in the North Johnstone River catchment (Table 4). In addition, half of the parameters identified as sensitive (P ≤ 0.05) had an impact on either soil moisture or groundwater flow. This may be due to the abundance of groundwater in this area (Fig. 8 and Table 5), so the flow in this catchment was dominated by baseflow. The baseflow ratio was about 0.44 calculated by “GWQ/total runoff”.

Table 4
The 22 calibrated parameters for the SWAT-T model in the North Johnstone River catchment, Queensland, Australia. The parameters are ranked according to their sensitivities based on global sensitivity analysis.

<table>
<thead>
<tr>
<th>Ranking</th>
<th>Adjustment and parameter name</th>
<th>Definition</th>
<th>Adjustment range</th>
<th>Calibrated range</th>
<th>Fitted value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>V_GW_DELAY.gw</td>
<td>Groundwater delay (days)</td>
<td>0 to 300</td>
<td>0 to 100</td>
<td>28.1</td>
</tr>
<tr>
<td>2</td>
<td>V_ALPHA_BNK.rte</td>
<td>Baseflow alpha factor for bank storage</td>
<td>0 to 1</td>
<td>0.09 to 0.64</td>
<td>0.28</td>
</tr>
<tr>
<td>3</td>
<td>R_HRU_SLP.hru</td>
<td>Average slope steepness</td>
<td>-0.7 to 0.25</td>
<td>-0.61 to -0.19</td>
<td>-0.33</td>
</tr>
<tr>
<td>4</td>
<td>R_SOL_AWC(2).sol</td>
<td>Available water capacity of the soil layer</td>
<td>-0.9 to 0.5</td>
<td>-0.8 to -0.4</td>
<td>-0.68</td>
</tr>
<tr>
<td>5</td>
<td>R_CN2.mgt</td>
<td>SCS runoff curve number for moisture condition II</td>
<td>-0.25 to 0.25</td>
<td>-0.25 to 0.1</td>
<td>0.05</td>
</tr>
<tr>
<td>6</td>
<td>V_RCHRG_DP.gw</td>
<td>Deep aquifer percolation fraction</td>
<td>0 to 0.5</td>
<td>0.01 to 0.06</td>
<td>0.05</td>
</tr>
<tr>
<td>7</td>
<td>V_CH_N2.rte</td>
<td>Manning’s n value for the main channel</td>
<td>0.014 to 0.15</td>
<td>0.05 to 0.12</td>
<td>0.07</td>
</tr>
<tr>
<td>8</td>
<td>V_CH_K2.rte</td>
<td>Effective hydraulic conductivity of main channel</td>
<td>0 to 250</td>
<td>39 to 104</td>
<td>53.9</td>
</tr>
<tr>
<td>9</td>
<td>R_LSUSUBBSN.hru</td>
<td>Average slope length</td>
<td>-0.5 to 0.25</td>
<td>-0.46 to -0.12</td>
<td>-0.37</td>
</tr>
<tr>
<td>10</td>
<td>R_SOL_Z(2).sol</td>
<td>Depth from soil surface to bottom of second soil layer</td>
<td>-0.7 to 0.25</td>
<td>-0.59 to -0.18</td>
<td>-0.33</td>
</tr>
<tr>
<td>11</td>
<td>V_GW_REVAP.gw</td>
<td>Groundwater revap coefficient</td>
<td>0.02 to 0.2</td>
<td>0.023 to 0.03</td>
<td>0.023</td>
</tr>
<tr>
<td>12</td>
<td>R_CANMX.hru</td>
<td>Maximum canopy storage</td>
<td>-1 to 0.5</td>
<td>-1 to -0.85</td>
<td>-0.93</td>
</tr>
<tr>
<td>13</td>
<td>V_GWQMN.gw</td>
<td>Threshold water level in shallow aquifer for base flow (mm)</td>
<td>0 to 2500</td>
<td>61 to 217</td>
<td>206</td>
</tr>
<tr>
<td>14</td>
<td>V_RSCD.hru</td>
<td>Soil evaporation compensation factor</td>
<td>0 to 1</td>
<td>0.22 to 0.65</td>
<td>0.48</td>
</tr>
<tr>
<td>15</td>
<td>V_CH_N1.sub</td>
<td>Manning’s n value for the tributary channels</td>
<td>0.014 to 0.15</td>
<td>0.04 to 0.09</td>
<td>0.05</td>
</tr>
<tr>
<td>16</td>
<td>R_SOL_AWC(1).sol</td>
<td>Available water capacity of the soil layer</td>
<td>-0.9 to 0.5</td>
<td>-0.8 to -0.4</td>
<td>-0.77</td>
</tr>
<tr>
<td>17</td>
<td>V_EPCO.hru</td>
<td>Plant uptake compensation factor</td>
<td>0 to 1</td>
<td>0.4 to 0.95</td>
<td>0.48</td>
</tr>
<tr>
<td>18</td>
<td>V_REVAPMN.gw</td>
<td>Threshold depth of water in the shallow aquifer for revap to occur (mm)</td>
<td>0 to 750</td>
<td>450 to 630</td>
<td>626</td>
</tr>
<tr>
<td>19</td>
<td>V_ALPHA_BF.gw</td>
<td>Baseflow alpha factor (days)</td>
<td>0 to 1</td>
<td>0.23 to 0.7</td>
<td>0.54</td>
</tr>
<tr>
<td>20</td>
<td>V_SURLAG.hrn</td>
<td>Surface runoff lag time</td>
<td>0.05 to 6</td>
<td>1.5 to 4.5</td>
<td>3.06</td>
</tr>
<tr>
<td>21</td>
<td>R_SOL_Z(1).sol</td>
<td>Depth from soil surface to bottom of first soil layer</td>
<td>-0.7 to 0.25</td>
<td>-0.61 to -0.19</td>
<td>-0.22</td>
</tr>
<tr>
<td>22</td>
<td>V_OV_N.hru</td>
<td>Manning’s n value for overland flow</td>
<td>-0.25 to 0.25</td>
<td>-0.24 to -0.02</td>
<td>-0.23</td>
</tr>
</tbody>
</table>

Fig. 6. The observed and SWAT-T-simulated monthly streamflow for the calibration period (January 2008–December 2017) and for the validation period (January 2003–December 2007) in the North Johnstone River catchment, Queensland, Australia.
was 31.579 m³/s (i.e. baseflow ratio was 0.47) from 1 July 2005 to 1 July 2013. Previous studies (McMahon and Finlayson, 2003; Brown et al., 2015) also reported that Australia’s perennial rivers were dominated by baseflow. SWAT parameters associated with baseflow and soil moisture were consistently identified as being highly sensitive to calibration by a review of SWAT applications (Gassman et al., 2007), supporting the results and suggesting that model operators should focus on these parameters during calibration, to guarantee that the SWAT model is conceptually consistent with regional hydrological conditions.

According to the general performance ratings suggested by previous studies (Moriasi et al., 2007; Shi et al., 2011; Wallace et al., 2018), streamflow modelling is deemed reasonable if NSE > 0.50, $R^2 > 0.50$, and PBIAS within ±25%. Therefore, it was shown that the SWAT-T model simulated monthly streamflow well in the North Johnstone River catchment, with |PBIAS| ≤ 10%, NSE ≥ 0.92, and $R^2 ≥ 0.94$ during both calibration and validation periods. Furthermore, the uncertainty analysis resulted in a P-factor of 0.92 and an R-factor of 0.50 for SWAT-T calibration after four iterations, while the P-factor was 0.85 and the R-factor was 0.50 for the validation period. Values for P-factor of >0.7 and for R-factor of about 1 (the smaller the better) are suggested for streamflow simulations (Abbaspour, 2013). Therefore, SWAT-T was judged to reasonably simulate streamflow and can be used for further analysis in the North Johnstone River catchment.

Furthermore, results (Supplementary Materials S2) showed that SWAT-T simulated streamflow process better than default SWAT with larger $R^2 (0.94 > 0.92$ and $0.94 > 0.90$) and NSE (0.93 > 0.91 and 0.92 > 0.90) in the calibration and validation periods, respectively. Using $R^2$ and NSE as statistical evaluation criteria to compare SWAT-T and the original SWAT model is consistent with previous studies. For instance, Ma et al. (2019) integrated downscaled high quality MODIS LAI into modified SWAT plant growth model and found that predicted flows with MODIS LAI basically matched the observed flows better than original SWAT supported by an improvement of $R^2$ and NSE values. However, compared to SWAT-T, the default SWAT model produced smaller absolute percent bias (0.9% < 7.3% and 4.9% < 10.0%) in the calibration and validation periods, respectively. This is most probably because both the default SWAT and the SWAT-T model underestimated streamflow in the North Johnstone River catchment. According to Fig. 5, LAI values simulated by SWAT-T were much better and larger than the default SWAT, this would lead to greater actual evapotranspiration simulated by SWAT-T than the default SWAT (Table 5), leading to lower streamflow simulated by SWAT-T (Table 5). Therefore, a larger absolute percent bias was produced by the SWAT-T model. However, achieving good agreement between model simulation and observed streamflow through model calibration does not imply correct description of the underlying processes and parameterizations (Wagner et al., 2011), because good streamflow simulations might be achieved by parameters calibration even with unrealistic underlying premises or without any improvement of the vegetation growth module (Strauch and Volk, 2013). Therefore, it is more reasonable to use the SWAT-T model for land use impacts study as it successfully accounted for seasonal vegetation dynamics (Fig. 5) which is an important part of the water cycle.

4.2. Modelled hydrological responses to different land use change scenarios

The obvious monthly variations in SURQ, LATQ, GWQ, total runoff, ET, and SW, with values generally greater in December-May (summer-autumn) and less in June-November (winter-spring) (Fig. 8), were consistent with the inter-annual distribution of rainfall (Fig. 2). This is because rainfall is the main factor affecting runoff, ET, and soil water content (Fekete et al., 2004), and the catchment that was selected is a summer rainfall dominant region. Meanwhile, changes of SURQ under different land-use scenarios differed across months, with the most remarkable changes occurring during the wet season from December to May. The impacts of vegetation changes on seasonal water yield with the largest volume changes occurred during the wet season and small volume changes during the dry season are consistent with previous studies (Brown et al., 2005). Total runoff is composed of surface runoff (SURQ), lateral runoff (LATQ), and groundwater (GWQ). Surface flow into rivers is mainly controlled by dominant climate conditions and is usually greatest during and shortly after storm or rain events. Groundwater, i.e. baseflow, is the major source of flow during the dry period (Brown et al., 2015). LUCC has been shown to be capable of altering baseflows and river discharges (Costa et al., 2003). Fig. 8 and Table 5 indicated that surface runoff increased under deforestation (Scenarios 1 and 2) and decreased under afforestation (Scenario 3) at monthly and annual time scales, and is similar to previous studies (Foley et al., 2005). This is because forest vegetation increases ET rates, dissipates raindrop energy, slows surface flow velocity, and increases soil organic matter, all of which result in larger infiltration and smaller surface runoff (Alibuyog et al., 2009). Results presented in Table 5 also showed that total runoff increased slightly under deforestation (Scenarios 1 and 2) and decreased slightly under afforestation (Scenario 3) at the annual time scale. Similar results for runoff response to LUCC also occurred in other hydrological simulation studies. For example, Weber
et al. (2001) found that streamflow simulated by hydrological models increased when forest area decreased and grassland area increased. This is because trees commonly consume more water (extracting water from shallow aquifer storage due to deep root systems and transpiring more due to larger aerodynamic conductance), and, therefore, forest catchments will produce less runoff (Wang et al., 2008; Mwangi et al., 2016). In contrast, data shown in Fig. 8 and Table 5 indicated that LATQ and GWQ decreased while SURQ increased under urbanization (Scenarios 2 and 4) at monthly and annual time scales. This decrease in LATQ and GWQ under urbanization may be attributed to increased surface runoff and decreased infiltration as a result of conversion of vegetation land use to urban land use (Alibuyo et al., 2009). Additionally, the rainfall-runoff relationships in Fig. 10c-h explain why runoff changes under urbanization generally produced more SURQ and less LATQ and GWQ than FRSE and RNGE with the same rainfall amounts.

In addition to runoff, Fig. 8 and Table 5 indicated that ET decreased under deforestation (Scenarios 1 and 2) and increased under afforestation (Scenario 3) at monthly and annual time scales. This is because forests generally produced more evapotranspiration than other land use types due to higher leaf area and deeper rooting depth (Costa et al., 2003; Li et al., 2009). Furthermore, it can be seen from Table 5 that soil water slightly increased (1.5%) under deforestation (Scenario 1, 11.5% increase in RNGE area), and slightly decreased (2.0%) under afforestation (Scenario 3, 14.1% increase in FRSE area) at the annual time scale using SWAT-T. The greater infiltration for forest may lead to an increase in soil water compared with other vegetation, but the larger evapotranspiration and water use may cause a decrease in soil water, so that the overall change in soil water may be insignificant due to the counterbalancing effects of these two processes under deforestation and afforestation. Chen et al. (2009) also reported that the effect of greater vegetation cover on soil moisture content was still debatable as it increased transpiration loss and rainfall interception whereas it decreased evaporation loss through shading. Hence, dense vegetation cover reduces soil moisture because of larger transpiration and less rainfall falling on the ground due to greater interception by leaves. In contrast, the soil is shaded more by the greater canopy vegetation, thereby reducing direct radiation absorption, and leading to lower soil temperature and soil evaporation rates, and higher soil moisture (Chen et al., 2009). Therefore, the relationship between soil water and vegetation is complex, and the positive or negative impacts of vegetation cover on...
soil moisture likely depend on climate and the length of dry or wet periods (Chen et al., 2009). Typically, when forest canopy cover exceeds a certain threshold level, the forest would produce less runoff and soil water but more ET than other land cover types (Li et al., 2009). Hydrological responses to land use change scenarios using a default (original) SWAT model were shown in Table 5, Figs. 9–10 and Supplementary Materials S3 using calibrated parameters from SWAT-T model. SWAT-T showed greater simulated actual evapotranspiration (ET) and lower streamflow (SURQ, LATQ, GWQ and total runoff) than the default SWAT (Table 5) at annual timescale. At monthly timescale, seasonal dynamics of ET and SW simulated by default SWAT (Supplementary Materials S3) were slightly different from those simulated by SWAT-T (Fig. 8) while seasonal variability of other hydrological factors were similar. In addition, monthly changes of hydrological factors under different land use change scenarios simulated by default SWAT (Supplementary Materials S3) were similar to that simulated by SWAT-T (Fig. 8), except for ET and SW. Furthermore, Fig. 9 showed that absolute total runoff changes simulated by default SWAT were much smaller than those from SWAT-T in 33 different sub-basins and may be explained by the smaller difference between annual rainfall and total runoff relationship for default SWAT model (Fig. 10 b) compared to SWAT-T (Fig. 10 a). In general, these differences were probably caused by the difference of seasonal LAI simulated by SWAT-T and default SWAT (Fig. 5). 4.3. Limitations and uncertainties

Even though it met the criteria for satisfactory model performance,
similar to other SWAT model applications, calibration and validation hydrograph (Fig. 6) showed that most of the peak flows (Shrestha et al., 2016) and low flows (Wu and Johnston, 2008) were underestimated. In addition, the model overestimated a few peaks during the dry period and underestimated it during the high flow period, which also was the case for other Australian catchments studied by Saha et al. (2014). This was an acceptable result considering the fact that the SWAT model was not calibrated for single-event high streamflow condition (Saha et al., 2014). Furthermore, low capacity to simulate both low flows and peak flows also occur in other hydrological models (Eum et al., 2017). Thus, the default SWAT in the North Johnstone River catchment, Queensland, Australia. The reason why sub-basin #4 was selected to analyze the rainfall-runoff relationship for FRSE, RNGE, and URBN was that sub-basin #4 ranked third among the 33 sub-basins in area, and the area proportions for FRSE, HRU 41 for RNGE, and HRU 52 for URBN in sub-basin #4) with the other two larger sub-basins (#5 and #10).

5. Summary and conclusions

The default (original) SWAT model has poor performance in estimating the LAI of different vegetation types for tropical areas. For the first time, the SWAT-T model (Strauch and Volk, 2013) with an improved vegetation growth module was used to analyze the hydrological sensitivity of a tropical catchment in Australia under different land use change scenarios. Prior to the simulation of land use change scenarios, the SWAT-T model was parameterized, calibrated, and validated with NSE ≥ 0.59 (NSE < 0 for default SWAT), R² ≥ 0.94 (R² ≥ 0.90 for default SWAT), and |PBIAS| ≤ 10% (|PBIAS| ≥ 2% for default SWAT) for LAI and NSE ≥ 0.92 (NSE ≥ 0.90 for default SWAT), and |PBIAS| ≤ 2.5% (|PBIAS| ≥ 42% for default SWAT) for LAI and NSE ≥ 0.92 (NSE ≥ 0.90 for default SWAT), R² ≥ 0.94 (R² ≥ 0.90 for default SWAT), and |PBIAS| ≤ 10% (|PBIAS| ≤ 5% for default SWAT) for streamflow. Therefore, the SWAT-T model was judged to perform satisfactorily in this catchment according to surface runoff (Tessoma et al., 2014). If we quantify the impacts of different LUCC scenarios on surface runoff with this kind of hydrological model, it may underestimate or overestimate the magnitude of LUCC effect. However, investigating the implications of peak flows and low flows underestimation or overestimation on the LUCC effect analysis on the surface runoff are beyond the scope of our present study and needs to be explored in future studies.

The study also found that land use change had only a small effect on water balance components except surface runoff. This is in line with findings reported in other studies (Shrestha et al., 2017). For instance, Brown et al. (2015) assessed the impact of forestry on streamflow in southeastern Australia using SWAT and found that the modelled impact of plantation forestry did not significantly change streamflow. Karlsson et al. (2016) also pointed out that land use changes only affected the mean flow by a few percentage points. This result may also be caused by our hypothetical land use scenarios where land use change area in each scenario accounted for <15% of the total catchment area. In fact, previous studies (Bosch and Hewlett, 1982; Svednick, 1996) stated that forest land changes of <15–20% do not influence the annual water yield. Besides, the small effect found in this study may also be due to the partial conversion scenarios occurring mainly in the northwestern part of the catchment where there is less rainfall distribution compared to the downstream part (the forest part of the catchment), hence the implemented scenarios might not cause remarkable changes in the hydrological processes, particularly at the annual scale. In addition to land use scenarios, a large number of uncertainty sources (hydrological models, calibration periods, objective function, etc.) may influence the impact analysis. Sources of uncertainty for the hydrological model can be present because of the model structure (e.g. model assumptions and functions) as well as input data (e.g. lack of relevant temporal and spatial variability of data on rainfall, land uses, soils and topography) (Marhaeno et al., 2018). Another important issue is the calibration practices, including calibration period and calibration approach (van der Spek and Bakker, 2017; Wallach et al., 2019). Soroshian et al. (1983) claimed that it is not the length of data used but the information contained in it, and the efficiency with which that information is extracted (i.e. the choice of a stochastically appropriate objective function), that are important. Parameterization of hydrological models is also a well-known source of uncertainty and have been discussed previously a few times as related to impact studies (Karlsson et al., 2016). However, studying these additional sources of uncertainty is beyond the scope of this study, and will be addressed in future research. Furthermore, the current study was focused only on the North Johnstone River catchment. Moreover, even though this catchment was deemed to be representative of all such tropical catchments, this study lacked replication at the catchment scale. Accordingly, additional catchments will need to be chosen in future studies to stand for the large range of climate, physical conditions, and runoff characteristics throughout tropical Australia, and to afford insights for future water management.
general performance indices. Overall, the SWAT-T model performed better in predicting monthly streamflow than the default SWAT model, based on our major statistical indicators, in an Australian tropical catchment.

For the first time, we used both models (SWAT-T and default SWAT) to quantify hydrological responses to land use change scenarios in the selected tropical catchment. Results showed that LUC affected all hydrological variables, of which the impact on surface runoff was the most remarkable at both monthly and annual time scales. Moreover, changes of SURQ under different land-use scenarios differed across months using SWAT-T, with the most obvious changes occurring during the wet season from December to May, and similar results can be found for default SWAT. The simulations also indicated that urbanization (converting FRSE or RNGE to URBN) resulted in increased surface flow and decreased lateral flow and groundwater, with no notable change in total runoff, ET, and SW using SWAT-T. For instance, surface runoff increased 16 mm (5.7%) with a 2.3% increase in URBN area, and 44 mm (15.9%) with an 8.4% increase in URBN area. The decreases of LATQ and GWQ under urbanization were < 3.5%, while the impact of urbanization on total runoff, ET, and SW were < 0.7%. Additionally, afforestation (Scenario 3, 14.1% increase in FRSE area) decreased SURQ by 26 mm (9.5%) and led to slight changes in other hydrological variables (within ± 2.0%). Annual rainfall and total runoff were strongly positively correlated (r ≥ 0.94) for FRSE, RNGE, and URBN, and FRSE generally produced less total runoff than RNGE and URBN for the same rainfall amounts. Furthermore, URBN generally produced more SURQ and less LATQ and GWQ than FRSE and RNGE for the same rainfall amounts, as shown in the scatter diagrams of rainfall-runoff relationships (Fig. 10). Furthermore, we found that SWAT-T showed greater simulated actual evapotranspiration (ET) and lower streamflow (SURQ, LATQ, GWQ and total runoff) than the default SWAT at annual time scale. In contrast, at a monthly scale, seasonal dynamics of ET and SW simulated by default SWAT were slightly different from those simulated by SWAT-T while seasonal variability of other hydrological factors were similar. These differences can be attributed to the diversity of seasonal LAI simulated by SWAT-T and default SWAT. Therefore, we conclude that using SWAT-T is more reasonable in tropical catchments as it captures seasonal vegetation dynamics.

The remarkable increase in surface runoff from deforestation and urbanization can threaten the health of both people and the biosphere. For instance, urbanization has enlarged impermeable surface area, increased runoff coefficient, reduced concentration time, and increased peak flow and frequency of floods in city rivers (Yaa et al., 2012). In addition, increased surface runoff will carry a large amount of sediment and pollutants, degrading river ecosystems and, for this particular catchment, thereby threatening the health of the Great Barrier Reef as the North Johnstone River is a key tributary that discharges into the Great Barrier Reef lagoon. Strategies to ameliorate the effects of land use change include increasing green space in urban areas to reduce runoff (Foley et al., 2005), reducing nutrient and sediment inputs, improving the management of drainage systems, and others. The results of studies such as reported here will provide important information for developing sustainable management of water resources in tropical eastern Australia. The research methods described in this study can be further extended to other tropical catchments for LUC impact assessments.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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