Use of Remotely Sensed Actual Evapotranspiration to Improve Rainfall–Runoff Modeling in Southeast Australia

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ABSTRACT

This paper explores the use of the Moderate Resolution Imaging Spectroradiometer (MODIS), mounted on the polar-orbiting Terra satellite, to determine leaf area index (LAI), and use actual evapotranspiration estimated using MODIS LAI data combined with the Penman–Monteith equation [remote sensing evapotranspiration (E\_RS)] in a lumped conceptual daily rainfall–runoff model. The model is a simplified version of the HYDROLOG (SIMHYD) model, which is used to estimate runoff in ungauged catchments. Two applications were explored: (i) the calibration of SIMHYD against both the observed streamflow and \( E_{\text{RS}} \), and (ii) the modification of SIMHYD to use MODIS LAI data directly. Data from 2001 to 2005 from 120 catchments in southeast Australia were used for the study. To assess the modeling results for ungauged catchments, optimized parameter values from the geographically nearest gauged catchment were used to model runoff in the ungauged catchment. The results indicate that the SIMHYD calibration against both the observed streamflow and \( E_{\text{RS}} \) produced better simulations of daily and monthly runoff in ungauged catchments compared to the SIMHYD calibration against only the observed streamflow data, despite the modeling results being assessed solely against the observed streamflow data. The runoff simulations were even better for the modified SIMHYD model that used the MODIS LAI directly. It is likely that the use of other remotely sensed data (such as soil moisture) and smarter modification of rainfall–runoff models to use remotely sensed data directly can further improve the prediction of runoff in ungauged catchments.

1. Introduction

Improving the accuracy of runoff predictions in ungauged catchments is one of most challenging tasks in hydrology (Franks et al. 2005; Goswami et al. 2007; Sivapalan et al. 2003). Parameter regionalization in lumped rainfall–runoff models is a commonly used method to transfer optimized parameter values to target ungauged catchments. Various regionalization methods have been developed, such as nearest neighbor, kriging, site similarity, and regression methods (Kay et al. 2006; Merz and Bloschl 2004; Parajka et al. 2005; Young 2006). In all these methods, lumped rainfall–runoff model inputs are precipitation and potential evapotranspiration (or air temperature), and rainfall–runoff model parameters are generally optimized only against observed streamflow. Rainfall–runoff models seldom consider vegetation processes, which can play an important role in midlatitude catchments (Huang and Zhang 2004; Tuteja et al. 2007; Yildiz and Barros 2007). Because of the lack of surface vegetation information in rainfall–runoff modeling inputs, calibrated lumped rainfall–runoff models may not estimate water balance components, evapotranspiration, and water storage change accurately, which possibly limits their ability to estimate runoff in ungauged catchments.

Remotely sensed data provide temporally dynamic and spatially explicit information on land surface

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characteristics—such as fractional vegetation cover and leaf area index (LAI), which is defined as the ratio of total upper-leaf surface of vegetation divided by the surface area of land on which the vegetation grows. Remote sensing fractional vegetation cover and LAI data have been widely used in distributed hydrological models. Andersen et al. (2002) used LAI time series data derived from Advanced Very High Resolution Radiometer (AVHRR) in a distributed hydrological model and found remote sensed LAI can better represent the spatial heterogeneity in model simulations and improve simulated hydrographs in the Senegal River basin. Garcia-Quijano and Barros (2005) and Gebremichael and Barros (2006) combined satellite-based estimates of LAI and fractional vegetation cover into a distributed photosynthesis-hydrological model and showed that daily variation of evaporation and photosynthesis can be captured by the interaction of biophysical and hydrological processes. Zhang and Wegehenkel (2006) added remote sensed LAI time series data to a spatially explicit water balance model and found a strong LAI seasonal control on evapotranspiration and runoff in a German catchment. McMichael et al. (2006) showed that the use of remote sensed LAI in distributed hydrological modeling can reduce uncertainty of streamflow predictions in a semiarid catchment in central California. Yildiz and Barros (2007) used remotely sensed LAI and fractional vegetation cover in the distributed 3D land hydrology model (LHM-3D) and found that vegetation processes have a key role in controlling hydrological processes in a midlatitude catchment, which is especially critical during the spring-summer transition. As the studies mentioned earlier have shown, the use of remote sensing vegetation data can improve distributed hydrological modeling. This paper explores whether the use of remote sensing data in a lumped conceptual rainfall–runoff model can improve daily and monthly runoff prediction in ungauged catchments.

Zhang et al. (2008) used the Moderate Resolution Imaging Spectroradiometer (MODIS) mounted on the polar-orbiting Terra satellite to determine LAI, which together with the Penman–Monteith equation is used to estimate remote sensing evapotranspiration ($E_{RS}$). This is then used to estimate steady-state catchment runoff ($Q$) as long-term precipitation ($P$) minus $E_{RS}$ in 120 catchments in southeast Australia. Their results show that the mean annual runoff estimated using $E_{RS}$ is relatively good and is comparable with that estimated using daily lumped rainfall–runoff models. This application raises another possibility that the use of $E_{RS}$ together with rainfall–runoff models may lead to improved daily or monthly runoff estimates in ungauged catchments.

This paper also investigates whether the inclusion of MODIS LAI and $E_{RS}$ in a daily lumped rainfall–runoff model, a simplified version of the HYDROLOG (SIMHYD) model, can improve daily and monthly runoff estimates. Specifically, we investigate whether daily or monthly runoff estimation for ungauged catchments can be improved by comparing three modeling experiments: (i) calibrating the SIMHYD model only against observed streamflow data; (ii) calibrating the SIMHYD model against both observed streamflow and $E_{RS}$; and (iii) modifying the SIMHYD model structure to directly use MODIS LAI data. Data from the same 120 relatively unimpaired catchments in southeast Australia used by Zhang et al. (2008) were used for this study.

### 2. Rainfall–runoff and evapotranspiration models
#### a. SIMHYD rainfall–runoff model

SIMHYD is a seven-parameter lumped conceptual daily rainfall–runoff model that simulates daily runoff using daily precipitation and Priestley–Taylor potential evapotranspiration as input data (Chiew et al. 2002). The structure of SIMHYD and the algorithms that describe water movement into and out of the storages are shown in Fig. 1 and Table 1. SIMHYD has been extensively used for various applications across Australia (Chiew and Siriwardena 2005; Chiew et al. 2002; Siriwardena et al. 2006; Viney et al. 2008; Zhang et al. 2008).

In SIMHYD, daily rainfall is first intercepted by the plant canopy. The maximum daily interception is the lesser of the interception storage capacity and potential evaporation. Rainfall incident on the soil surface occurs only when daily rainfall exceeds the maximum daily interception capacity.

Rainfall at the soil surface that exceeds the infiltration capacity becomes infiltration excess runoff. The remaining moisture is subject to a soil moisture function that diverts water to the stream (as saturation excess runoff and interflow), the soil moisture store (SMS), and to the groundwater store (recharge). Saturation excess runoff/interflow is first estimated as a linear function of soil wetness [soil moisture level divided by the soil moisture store capacity (SMSC)]. SIMHYD simulates both the interflow and saturation excess runoff processes, with the soil wetness being used to reflect parts of the catchment that are saturated from which saturation excess runoff can occur. Groundwater recharge is then estimated, also as a linear function of the soil wetness. The remaining moisture flows into the soil moisture store.

Total evapotranspiration in SIMHYD includes the evaporation of water from the interception store and plant/soil evapotranspiration from the soil moisture.
store. The plant/soil evapotranspiration is modeled as a linear function of the soil wetness. Baseflow is simulated as a linear function of the groundwater storage.

b. The Penman–Monteith evapotranspiration model

The Penman–Monteith equation can be written as

\[ E = \frac{1}{\lambda} \left( \Delta (R_n - G) + \rho_a C_p D G_a \right), \]

where \( E \) is evapotranspiration, \( \lambda \) is the latent heat of vaporization, \( \Delta = d e^a dT_a \) is the slope of the curve relating saturation water vapor pressure to temperature, \( D = e^a (T_a) - e_a \) is the vapor pressure deficit of the air, \( e^a (T_a) \) is the saturation vapor pressure at a given air temperature, \( e_a \) is the actual vapor pressure, \( \gamma = \frac{1}{1 + G_a/G_a} \) is the psychrometric constant, \( \rho_a \) is the air density, \( C_p \) is the specific heat capacity of air, \( R_n \) is the net radiation, \( G \) is the soil heat flux (assumed to be zero here), \( G_a \) is the aerodynamic conductance, and \( G_s \) is the surface conductance.

Leuning et al. (2008) developed an algebraic, biophysical six-parameter surface conductance model:

\[ G_s = G_c \left\{ \frac{1 + \frac{\tau G_a}{(1 + \varepsilon)G_c} \left[ f - (\varepsilon + 1)(1 - f)G_c \right] + G_a}{e G_c} \right\} \]

\[ 1 - \tau \left[ \frac{f - (\varepsilon + 1)(1 - f)G_c}{G_a} \right] + \frac{G_a}{e G_c} \]

and

\[ G_c = g_{ssx} k_Q \left[ \frac{Q_h + Q_{50}}{Q_h \exp(-k_Q LAI) + Q_{50}} \right] \left( 1 + D/D_{50} \right), \]

where \( \varepsilon = \Delta/\gamma \), \( G_i = \gamma (R_n - G)/(\rho_a C_p D) \) is the isothermal conductance (Monteith and Unsworth 1990), \( G_c \) is canopy conductance, \( \tau = \exp(-k_A LAI) \) is the fraction of available energy transmitted downward at LAI, \( g_{ssx} \) is the maximum stomatal conductance, \( k_Q \) is the extinction coefficient for photosynthetically active radiation, \( k_A \) is the attenuation of net all-wave irradiance, \( Q_h \) is the photosynthetically active radiation at the top of canopy, \( Q_{50} \) is the value of absorbed photosynthetic active radiation when stomatal conductance \( g_s = g_{ssx}/2 \), and \( g_{ssx} \) is the maximum value of \( g_s \), \( D_{50} \) is the value of \( D \) when the stomatal conductance is reduced (\( g_{ssx}/2 \)), and \( f \) is the fraction of equilibrium evaporation at soil surface (varying between 0 and 1).

The terms \( R_n, \Delta, \gamma, \rho_a \), and \( D \) in Eq. (1) are calculated from the daily meteorological time series. Albedo data are also required to calculate \( R_n \). The term \( G_s \) in Eq. (1) is assigned constant values of 0.033, 0.0125, and 0.010 m s\(^{-1}\) for forests, shrubs, grassland and crops, respectively, because of lack of routinely available high-quality wind speed data (Zhang et al. 2008). The term \( G_s \) in Eqs. (2) and (3) is calculated from the daily time series of LAI.
The daily meteorological and LAI time series are described in sections 3b and 3c, respectively. Albedo and land cover data are described in section 3d.

This surface conductance model was combined into the Penman–Monteith equation to estimate \(E_{RS}\) by Leuning et al. (2008). Their results showed good agreement between the estimated \(E_{RS}\) and flux-measured values from 15 global flux-measured ecosystems, which is indicated by an average systematic root-mean-square error (RMSE) in daily mean \(E_{RS}\) 0.27 mm day\(^{-1}\), accounting for 16.9% of the daily mean \(E_{RS}\).

The six-parameter surface conductance \(G_s\) model is sensitive to parameters \(g_{xs}\) and \(f\). These parameters can be calibrated against water balance evapotranspiration estimates, whereas the other four parameters—\(k_Q, k_A, Q_{50}, \) and \(D_{50}\)—are relatively insensitive and can be fixed to values of 0.6, 0.6, 2.6 MJ m\(^{-2}\) day\(^{-1}\), and 0.8 kPa, respectively (Zhang et al. 2008). Evapotranspiration estimated with the Penman–Monteith equation is taken as \(E_{RS}\). Zhang et al. (2008) applied the Leuning surface conductance model with the Penman–Monteith approach to estimate catchment \(E_{RS}\) in 120 gauged catchments in the Murray–Darling basin in southeast Australia for the period 2001–05. The mean annual catchment \(E_{RS}\) compared well with water balance estimates (precipitation minus runoff), indicated by a RMSE of less than 80 mm yr\(^{-1}\). The mean annual runoff estimates (precipitation minus \(E_{RS}\)) are also relatively good and are comparable with those estimated by SIMHYD for ungauged catchments.

3. Data

a. Streamflow time series data

Daily streamflow data from 120 relatively unimpaired catchments in southeast Australia (Fig. 2), from the Australian Land and Water Resource Audit Project (Peel et al. 2000), were used. The catchment areas range from 50 to 2000 km\(^2\). Data from 2001 to 2005 were used, which coincide with the Terra MODIS LAI data.

b. Meteorological time series data

The daily gridded 0.05° × 0.05° (~5 km × 5 km) time series of maximum temperature, minimum temperature, incoming solar radiation, actual vapor pressure, and precipitation data from 2001 to 2005 were obtained from the SILO Data Drill of the Queensland Department of Natural Resources and Water (available online at http://www.longpaddock.qld.gov.au/silo/; Jeffrey et al. 2001). The SILO gridded data were interpolated from point measurements made by the Australian Bureau of Meteorology.

c. MODIS LAI time series data

To construct the daily MODIS LAI series, the 8-day composite LAI products (MOD15A2, collection 4) were obtained from the Land Processes Distributed Active Archive Centre (LP DAAC, available online at http://lpdaac.usgs.gov) for the period 2001–05. The MODIS LAI provides reasonable estimates for most Australian vegetation types (Hill et al. 2006). To enable an easy access to the MODIS data, we developed a method to change, clip, save, access, transform, control, and interpolate these data (Zhang and Wegehenkel 2006). The quality control and the interpolation were the two most important steps to produce long-term and high-quality MODIS data. The quality assessment (QA) flags in the database were used to check the quality of the MODIS LAI data. The LAI QA data with cloud cover were excluded from further processing. The 8-day LAI data were interpolated into the daily LAI data using a piecewise cubic hermite interpolating polynomial. All the interpolated daily LAI data were then smoothed by the Savitzky–Golay filtering method,
a widely used method for filtering remotely sensed vegetation data (Fang et al. 2008; Ruffin et al. 2008).

d. Other data

Land cover data required to estimate $G_a$ in Eq. (1) were obtained from the yearly MODIS Land Cover classification product (MOD12Q1, available online at https://lpdaac.usgs.gov/lpdaac/products/modis_overview). Four land cover types are included in the MOD12Q1. We used the type 1 dataset, which includes 17 vegetation classes defined according to the International Geosphere–Biosphere Programme (IGBP).

The albedo data required to calculate $R_n$ in Eq. (1) were obtained from an annual average albedo product at the 5-km resolution for Australia (Dilley et al. 2000, 14–24). All the remote sensing and meteorological data were reprojected, clipped to the Murray–Darling basin boundary and resampled to obtain 1-km gridded data for the Murray–Darling basin. The gridded data in each catchment were then averaged to obtain aggregate daily data series for model inputs.

4. Modeling experiments

Three modeling experiments (Exp1, Exp2, and Exp3) were carried out to evaluate the benefits of using remotely sensed data in rainfall–runoff modeling (Table 2). SIMHYD in Exp1 was calibrated against the observed streamflow data. SIMHYD in Exp2 was calibrated against both the observed streamflow data and $E_{RS}$. SIMHYD in Exp3 was modified to use the MODIS data directly and calibrated against the observed streamflow data. The three experiments were carried out separately for the model calibrations against daily and monthly runoff in each of the 120 catchments. Then, for each experiment, optimized parameter values were used for parameter regionalization (see section 6) to predict daily and monthly runoff for all of these 120 gauged catchments, each of which was artificially regarded as an “ungauged” catchment.

a. Exp1—Benchmark calibration with runoff

The SIMHYD model was calibrated to maximize the Nash–Sutcliffe efficiency (NSE; Nash and Sutcliffe 1970) of runoff, which is defined as

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

(4)

where $Q_{\text{sim}}$ and $Q_{\text{obs}}$ are the simulated runoff and observed streamflow, respectively, $\bar{Q}_{\text{obs}}$ is the arithmetic mean of the observed runoff, and $N$ is the number of samples.

b. Exp2—Calibration with runoff and $E_{RS}$

The SIMHYD model was calibrated against both observed streamflow and $E_{RS}$. The $E_{RS}$ data used in Exp2 were the same as the evaportranspiration outputs of the Penman–Monteith evapotranspiration model in Zhang et al. (2008), in which two parameters, $g_{sx}$ and $f$, were optimized by using long-term catchment water balance evapotranspiration estimates (rainfall minus runoff).

The SIMHYD model was calibrated to maximize the sum of the NSE of runoff defined earlier, and the coefficient of determination in the simulated evapotranspiration and $E_{RS}$ was defined as

$$R^2 = \left[\frac{\sum_{i=1}^{N}(E_{\text{sim},i} - \bar{E}_{\text{sim}})(E_{\text{RS},i} - \bar{E}_{\text{RS}})}{\sqrt{\sum_{i=1}^{N}(E_{\text{sim},i} - \bar{E}_{\text{sim}})^2 \sum_{i=1}^{N}(E_{\text{RS},i} - \bar{E}_{\text{RS}})^2}}\right]^2,$$

(5)
where $E_{\text{sim}}$ is the simulated evapotranspiration, $\bar{E}_{\text{sim}}$ and $\bar{E}_{\text{RS}}$ are the arithmetic means of the simulated evapotranspiration and $E_{\text{RS}}$, respectively. Equal weights are given to NSE and $R^2$. Thus, the objective function for this experiment is $\text{NSE} + R^2$ (Table 2).

The coefficient of determination between the simulated evapotranspiration and observed $E_{\text{RS}}$ was used instead of the NSE because although the simulated evapotranspiration and observed $E_{\text{RS}}$ may not have the exact same definition and hence the same values, they should be strongly correlated.

For the calibration of daily runoff, the correlations of evapotranspiration terms at a daily and a monthly time step were considered (Table 2). This is because the simulated and observed evapotranspiration may show better agreement at the monthly time step than at a daily time step.

c. Exp3—Calibration of the modified SIMHYD with runoff

The following modifications were made to the original SIMHYD to use the MODIS LAI data directly:

1) The plant/soil evapotranspiration in SIMHYD ($E$ in Fig. 1) is replaced by $E_{\text{RS}}$ calculated using the Penman–Monteith evapotranspiration model [Eqs. (1)–(3)].

2) The soil wetness in SIMHYD (SMS/SMSC, see Fig. 1) is used as an estimate for the parameter $f$ in Eq. (2). The soil evaporation factor $f$ has been considered a parameter in previous studies (Leuning et al. 2008; Zhang et al. 2008), whereas in reality it is a variable that is directly dependent on the moisture status of surface soil. Here, SMS/SMSC dynamically estimates soil moisture status in the whole catchment, and is used as the estimate for the parameter $f$.

3) The maximum stomatal conductance $g_{s\alpha}$ in Eq. (2) is treated as a parameter to be optimized together with the seven SIMHYD parameters.

The original and modified SIMHYD models will be referred to as “modified SIMHYD” and “original SIMHYD,” respectively. The inputs for the original model include precipitation and potential evapotranspiration (Fig. 1) calculated by the Priestley–Taylor method (Priestley and Taylor 1972) using the meteorological variables maximum temperature, minimum temperature, incoming solar radiation, and actual vapor pressure. The inputs for the modified SIMHYD include the variables for estimating potential evapotranspiration, precipitation, and the additional variable LAI.

As in Exp1, the modified SIMHYD was calibrated against the observed streamflow (Table 2).

5. Model calibration

The particle swarm optimization (PSO) toolbox in MATLAB was used to optimize the parameters of the SIMHYD models. The PSO method was first presented by Eberhart and Kennedy, inspired from the behavior of schools of fish or flocks of birds (Eberhart and Kennedy 1995). It originates from the swarm paradigm, called particle swarm, and is expected to provide the so-called global or near-global optimum. The PSO method has been successfully applied in rainfall–runoff model parameter optimization (Chau 2006; Gill et al. 2006). The SIMHYD modeling was carried out from 2001 to 2005, with 2001 used to warm up the model and simulations from 2002 to 2005 used to calibrate the model.

6. Parameter regionalization

To assess the model predictions of daily and monthly runoff in ungauged catchments, each of the 120 catchments was removed in turn and considered as an ungauged catchment, and the entire set of parameter values from the geographically nearest gauged catchment (donor catchment) was used to model runoff in this ungauged catchment. It is likely that nearby catchments have similar behaviors (Oudin et al. 2008), and the use of parameter values from the nearest gauged catchment to model runoff in an ungauged catchment generally gives results that are almost as good as or better than the more complex regionalization methods based on the similarities of catchment attributes (Merz and Bloschl 2004; Oudin et al. 2008; Young 2006).

7. Model assessment

The observed streamflow data were used to assess simulated runoff results from the three modeling experiments for both model calibration and model regionalization. Two criteria were used for the model assessment: the NSE described by Eq. (4) and water balance error (WBE) percentage, which is defined as

$$\text{WBE} = 100 \left( \frac{\sum_{i=1}^{N} Q_{\text{sim},i} - \sum_{i=1}^{N} Q_{\text{obs},i}}{\sum_{i=1}^{N} Q_{\text{obs},i}} \right).$$

8. Results

a. Modeling monthly runoff

The monthly modeling results (where the daily SIMHYD model is calibrated against monthly runoff and
ERS) are summarized in Fig. 3 and Table 2. As expected, the calibration NSE results for Exp1 were better than those for Exp2 because in Exp1, SIMHYD was calibrated directly against the NSE of monthly runoff. The modified SIMHYD model in Exp3 was also calibrated against NSE of monthly runoff, and the results for Exp3 were similar to the results for Exp1 (Fig. 3a). However, the regionalization results (model application to ungauged catchment) for Exp2 and Exp3 were similar, and their results were significantly better than the results for Exp1 (Fig. 3c). This is reflected in the higher NSE values in Fig. 3, and the higher median values and smaller 25th–75th percentile NSE ranges for Exp2 and Exp3 compared to Exp1 (Table 2). The better result in Exp2 compared to Exp1 is interesting because the model in Exp2 is calibrated against both runoff and ERS, but the results are assessed only against the modeled runoff. The results thus indicate that the use of ERS to help calibrate SIMHYD (Exp2) and the modification of SIMHYD to use MODIS LAI data directly (Exp3) can improve the estimation of monthly runoff in ungauged catchments.

The water balance results in the model regionalization (runoff estimation in ungauged catchments) also showed slightly better agreement between the modeled mean annual runoff and observed mean annual runoff in Exp3 and Exp2 compared to Exp1 (Fig. 4).

b. Modeling daily runoff

The daily modeling results are summarized in Fig. 5 and Table 2. As with the monthly simulations, the calibration NSE results for daily runoff for Exp1 were better than those for Exp2a and Exp2b because SIMHYD was calibrated against runoff in Exp1 but against both runoff and ERS in Exp2a and Exp2b. The modified SIMHYD model in Exp3 was also calibrated against NSE of daily runoff, and the results for Exp3 are similar to the results for Exp1 (Fig. 5a).

In the regionalization results (model application to ungauged catchment), the modified SIMHYD model in Exp3 showed by far the best simulation of daily runoff (Fig. 5c and Table 2). The results for Exp2a (calibration against daily runoff and daily ERS) and Exp2b (calibration against daily runoff and monthly ERS) were similar and also better than the results for Exp1. Therefore, the results here also indicate that the use of ERS to help calibrate SIMHYD (Exp2a and Exp2b) and the modification of SIMHYD to use MODIS LAI data directly (Exp3) can improve the estimation of daily runoff in ungauged catchments. For water balance error results, unlike the model calibration against monthly data in section 8a, the daily calibration against daily runoff directly with the original SIMHYD model (Exp1) resulted in the best...
FIG. 4. Simulated mean annual runoff from the monthly modeling experiments vs observed mean annual runoff.

FIG. 5. Same as Fig. 3 but from the daily modeling experiments.
estimation of mean annual runoff in ungauged catchments (see Fig. 6). So, it is useful to use MODIS LAI and $E_{RS}$ for modeling daily runoff but not in mean annual runoff.

c. Nash–Sutcliffe efficiency in different runoff conditions

To further explore the regionalization results from the three experiments under different runoff conditions, Fig. 7 shows the improvement in NSE values in Exp2 and Exp3 relative to Exp1 plotted against the observed mean annual runoff. The plots again show that Exp2 and Exp3 modeled the monthly and daily runoff better than Exp1, particularly in the catchments with lower runoff.

9. Discussion and conclusions

The results indicate that the use of remotely sensed evapotranspiration data for model calibration and the use of MODIS LAI data as inputs to a modified SIMHYD model can improve the modeling of daily and monthly runoff series in ungauged catchments. In the ungauged catchment prediction results, in which optimized parameter values from the closest calibration catchment were used to estimate runoff for the ungauged catchment, the SIMHYD calibration against both the observed streamflow and remotely sensed evapotranspiration estimates produced better simulations of daily and monthly runoff than the SIMHYD calibration against only the observed streamflow data, despite the modeling results being assessed solely against the observed streamflow. This demonstrates that calibration against appropriate multiple objective criteria, such as observed streamflow and remotely sensed evapotranspiration, used here can improve modeling results. The runoff simulations were even better for the modified SIMHYD model where the SIMHYD model was modified to use MODIS LAI data directly.

Vegetation plays an important role in controlling hydrological processes by affecting interception, evapotranspiration, and soil moisture dynamics (Andersen et al. 2002; McMichael et al. 2006). The use of MODIS LAI data directly is interesting because it accounts for the time-varying changes in vegetation properties. The role of LAI time series data in rainfall–runoff modeling is further investigated here by comparing the modeling results of Exp3 where a daily LAI time series was used (as reported above) with the results where only a constant mean LAI value was used as input for the entire simulation. The results are summarized in Fig. 8, where the regionalization results indicate that the modeled
runoff with daily LAI series are better (higher NSE values) than the modeled runoff with a constant LAI value. The improvement for monthly runoff is more evident than that for daily runoff. This is likely because the runoff response to vegetation process is much slower than that to precipitation, and a daily scale, precipitation is the main driver controlling runoff. At monthly-to-seasonal scales, LAI changes influence vegetation evapotranspiration and soil moisture, and then control runoff processes. This control becomes critical during the spring–summer transition in the midlatitude catchments (Wilcox 2002; Yildiz and Barros 2007).

Dynamic remote sensing vegetation data can be used to calculate not only actual evapotranspiration but also...
other water balance and energy balance components. The current study included only MODIS LAI time series data in the modified SIMHYD for estimating actual evapotranspiration. Another potential application is to incorporate LAI observations to estimate canopy interception, which depends strongly on LAI (Zhang and Wegehenkel 2006). This study used only the annual mean albedo to estimate download solar radiation and net radiation. It is possible to use dynamic albedo data in rainfall–runoff modeling. For example, the 16-day MODIS albedo products are available globally with resolutions of 500 m and 1 km (available online at https://lpdaac.usgs.gov/lpdaac/products/modis_product_table). Aerodynamic conductance in Eq. (1) was estimated for each of the vegetation types by assuming a constant wind speed in this study, and this approximation may have limited effect on the modeling results (Zhang et al. 2008).

It is likely that a more detailed integration of remotely sensed vegetation and actual evapotranspiration data can further improve runoff modeling in ungauged catchments, particularly when used with rainfall–runoff models with multiple layers that can better assimilate the remotely sensed data. The use of other remotely sensed data, such as microwave soil moisture together with actual evapotranspiration, to help calibrate the rainfall–runoff models and to constrain the model parameterization is also likely to further improve the runoff modeling in ungauged catchments.

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