



Research papers

Regionalising rainfall-runoff modelling for predicting daily runoff: Comparing gridded spatial proximity and gridded integrated similarity approaches against their lumped counterparts

Hongxia Li^a, Yongqiang Zhang^{b,*}^a State Key Laboratory of Hydraulics and Mountain River Engineering, Sichuan University, Chengdu 610065, China^b CSIRO Land and Water, PO BOX 1700, Canberra ACT 2601, Australia

ARTICLE INFO

Article history:

Received 10 December 2016

Received in revised form 8 May 2017

Accepted 9 May 2017

Available online 11 May 2017

This manuscript was handled by Tim R. McVicar, Editor-in-Chief, with the assistance of Shengping Wang, Associate Editor

Keywords:

Rainfall-runoff modelling

Regionalisation

Runoff prediction

Spatial proximity

Integrated similarity

Data-sparse region

ABSTRACT

Rainfall-runoff models are widely used for regionalisation studies to predict daily runoff time series in ungauged catchments. Most studies focus mainly on a particular region or a small scale, and are applied in a lumped way. It is not clear how grid-based regionalisation methods perform at continental or global scale, particularly for data-sparse region. This study uses 605 unregulated catchments widely distributed across Australia to evaluate two grid-based regionalisation approaches—gridded spatial proximity (SP_g) and gridded integrated similarity (IS_g)—and their lumped counterparts (SP_l and IS_l). To test robustness of the regionalisation methods, each was tested using two rainfall-runoff models: SIMHYD and Xinanjiang. We found that overall the gridded and lumped regionalisation approaches are marginally different and the two models show consistent regionalisation results. However, the IS_g approach outperforms the others in the dry and sparsely located catchments, and it overcomes the unnatural tessellated effect obtained from the SP_g approach. It is promising to use the IS_g approach for runoff estimates and water accounts in the Australian continent and possibly in other parts of world.

© 2017 Elsevier B.V. All rights reserved.

1. Introduction

Large-scale runoff predictions from a continental to global scale are often conducted using global hydrological models and global land surface models (Beck et al., 2016a; Zhou et al., 2012). A major challenge for these models is that they have very complex model structure with numerous model parameters. Therefore, it is very difficult to calibrate land surface models/global hydrological models across large regions. Additionally, global hydrological or land surface modellers seek to maintain model parameters with physical meaning and are reluctant to calibrate their global models (Beck et al., 2016a). Using the default parameter sets, these global models perform considerably poorer than traditional smaller scale rainfall-runoff models (Zhang et al., 2016; Gudmundsson et al., 2012).

Compared to most global models, rainfall-runoff models have simple model structure and can be easily calibrated for predictions in ungauged catchments (Blöschl and Sivapalan, 1995). The

rainfall-runoff models mainly use regionalisation approaches to transfer calibrated parameters from gauged (donor) to ungauged (target) catchments (Blöschl and Sivapalan, 1995). The most popular regionalisation approaches include (1) a spatial proximity approach (SP) (Parajka et al., 2005; Reager and Famiglietti, 2009), in which the entire set of parameter values are transferred from the geographically closest catchment to the target ungauged catchment; (2) a physical similarity approach (PS) (Reichl et al., 2009; Samuel et al., 2011), in which the entire set of parameter values are transferred from a physically similar catchment whose attributes (climatic and physical) are similar to those of the target ungauged one; (3) a regression method (Reg) (Young, 2006), in which a relationship between the parameters calibrated on gauged catchments and catchment attributes is established and then the parameter values for the ungauged catchments are estimated from its attributes and the established relationship; (4) a regional calibration approach (RC), in which the models are calibrated simultaneously against observations in multiple catchments across a wide region to obtain a more generalisable parameter set for all catchments (Parajka et al., 2007; Zhang et al., 2011a); (5) the hydrological signature similarity approach (HSS), in which the parameters are transferred from a catchment with similar hydrological indices,

* Corresponding author at: CSIRO Land and Water, Clunies Ross Street, Canberra 2601, Australia.

E-mail address: yongqiang.zhang@csiro.au (Y. Zhang).

such as the runoff coefficient and baseflow index (Masih et al., 2010; Wagener et al., 2007; Yadav et al., 2007); and (6) the integrated similarity (IS) methods, such as the integration of spatial proximity and physical similarity (Zhang and Chiew, 2009a), in which several regionalisation approaches are combined based on the effectiveness of the different methods.

Most of the regionalisation methods have been applied for a particular region or a small country, such as 308 catchments in Austria (Merz and Blöschl, 2004), 260 catchments in the UK (Young, 2006), 913 catchments in France (Oudin et al., 2008), and 227 catchments in southeastern Australia (Li et al., 2010). Table 1 summarises the recent regionalisation studies carried out in Europe, Australia, USA and globe. In Australia, most of these studies focus on southeastern Australia, where dense streamflow gauges are available. It is not clear how the various regionalisation approaches perform in other parts of Australia, particularly for the data-sparse inland Australia.

Furthermore, most of the studies listed in Table 1 were carried out in a lumped way. This means that each regionalisation approach transfers the calibrated parameters to entire ungauged catchments, rather than to each computational grid cells. Take the SP approach for instance, the calibrated parameter sets is transferred to a target ungauged catchment from its closest donor catchment selected using the geographic distance between the centroids of the ungauged and donor catchments. It is not clear how the lumped regionalisation approaches will perform when they are modified to transfer the parameters to each grid cell. This is particularly important for continental to global water accounts that need runoff time series estimated from each grid cell. To achieve this, it requires the development of gridded regionalisation approaches to transfer calibration parameter sets to each grid cell.

Only in the last couple of years has the hydrological community started continental to global regionalisation studies. Bock et al. (2016) developed a parameter regionalisation scheme for a monthly water balance model by grouping the conterminous United States into 110 calibration regions based on similar parameter sensitivities and produced parameter sets for each calibration region. Beck et al. (2016b) conducted the regionalisation of the Hydrologiska Byråns Vattenbalansavdelning (HBV) model parameters at the global scale in 1787 catchments using a hydrological signature similarity approach and found that the spatial patterns in regionalised parameter values corresponded well with spatial patterns in the climate. Zhang et al. (2016) evaluated two rainfall-runoff models (GR4J and SIMHYD) using a spatial proximity

approach against a global dataset of streamflow from 644 catchments and evapotranspiration from 98 flux towers. Although these studies were conducted on a large scale using large number of catchments, most of them carried out in a lumped way by using one regionalisation method, which may not fully demonstrate the strength of regionalisation. Therefore, more efforts should be devoted to the gridded regionalisation methods in continental or global studies.

In this study, we used two rainfall-runoff models (SIMHYD and Xinanjiang) for predicting the daily runoff time series for the continental Australia. For each model, gridded SP (SP_g) and gridded IS (IS_g) regionalisation methods were used for the continental regionalisation study, and compared to their traditional modes (i.e. lumped counterparts: SP_l and IS_l). The specific aims of this study include:

- to develop a gridded IS approach for runoff prediction in each grid of continental Australia;
- to compare the relative merits among the four regionalisation approaches (two lumped and two gridded);
- to investigate if the relative merits are consistent between the two rainfall-runoff models; and
- to stratify the regionalisation results using precipitation and regionalisation distance.

2. Data

Both models were driven by daily meteorological time series of maximum temperature, minimum temperature, incoming solar radiation, actual vapour pressure and precipitation from 1975 to 2012 at $0.05^\circ \times 0.05^\circ$ ($\sim 5 \text{ km} \times 5 \text{ km}$) grid cells from the SILO Data Drill of the Queensland Department of Natural Resources and Water (www.nrw.gov.au/silo). The SILO data were interpolated from approximately 4600 point observations across Australia using the geostatistical methods described in Jeffrey et al. (2001). The ordinary kriging method was used to interpolate daily and monthly precipitation, whereas the thin plate smoothing spline was used to interpolate other daily climate variables. Cross validation shows that the mean absolute error for maximum daily air temperature, minimum daily air temperature, vapour pressure, and precipitation at 1.0°C , 1.4°C , 0.15 kPa and 12.2 mm/month indicated reasonably good data quality (Jeffrey et al., 2001).

Except for the climate forcing data, the two models require remote sensing leaf area index, land cover and albedo data that

Table 1
A summary of the regionalisation approaches conducted using large datasets. SP: spatial proximity approach; PS: physical similarity approach; Reg: regression method; RC: regional calibration approach; HSS: hydrological signature similarity approach; and IS: integrated similarity.

| Studies | Region | Catchment number | Model | Regionalisation method |
|----------------------------------|---|------------------|-------------------------|------------------------------------|
| Merz and Blöschl (2004) | Austria | 308 | HBV | Reg |
| McIntyre et al. (2005) | UK | 127 | PDM | PS and Reg |
| Parajka et al. (2005) | Austria | 320 | HBV | SP, PS, and Reg |
| Kay et al. (2006) | UK | 119 | PDM and TATE | PS and Reg |
| Young (2006) | UK | 260 | PDM | Reg and PS |
| Oudin et al. (2008) | French | 913 | GR4J and TOPMO | SP, PS, and Reg |
| Reager and Famiglietti (2009) | Southeast Australia | 210 | Xinanjiang | SP and PS |
| Reichl et al. (2009) | Southeast Australia | 184 | SIMHYD | SP, PS, and Reg |
| Zhang and Chiew (2009a) | Southeast Australia | 210 | Xinanjiang and SIMHYD | SP, PS, and IS |
| Li et al. (2010) | Southeast Australia | 227 | Three-parameter FDC | SP, PS, Reg, and HSS |
| Masih et al. (2010) | Karkheh river basin, Western part of Iran | 11 | HBV | HSS |
| Zhang et al. (2014) | Southeast Australia | 228 | An index model and GR4J | SP, Reg |
| Bock et al. (2016) | USA | 1575 | MWBM | RC |
| Viviroli and Seibert (2015) | Switzerland | 49 | PREVAH | HSS |
| Steinschneider et al. (2015) | USA | 73 | abcd | Combining Reg and SP |
| Patil and Stieglitz (2015) | USA | 756 | EXP-HYDRO | SP |
| Beck et al. (Beck et al., 2016b) | Global | 1787 | HBV | HSS |
| Zhang et al. (2016) | Global | 664 | GR4J and SIMHYD | SP |
| This study | Australian continent | 605 | SIMHYD, Xinanjiang | SP, IS, gridded SP, and gridded IS |

Download English Version:

<https://daneshyari.com/en/article/5770756>

Download Persian Version:

<https://daneshyari.com/article/5770756>

[Daneshyari.com](https://daneshyari.com)