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The efficacy of calibrating hydrologic model using remotely sensed evapotranspiration and soil moisture for streamflow prediction

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SUMMARY

Calibration of spatially distributed hydrologic models is frequently limited by the availability of ground observations. Remotely sensed (RS) hydrologic information provides an alternative source of observations to inform models and extend modelling capability beyond the limits of ground observations. This study examines the capability of RS evapotranspiration (ET) and soil moisture (SM) in calibrating a hydrologic model and its efficacy to improve streamflow predictions. SM retrievals from the Advanced Microwave Scanning Radiometer-EOS (AMSR-E) and daily ET estimates from the CSIRO MODIS ReScaled potential ET (CMRSET) are used to calibrate a simplified Australian Water Resource Assessment – Landscape model (AWRA-L) for a selection of parameters. The Shuffled Complex Evolution Uncertainty Algorithm (SCE-UA) is employed for parameter estimation at eleven catchments in eastern Australia. A subset of parameters for calibration is selected based on the variance-based Sobol' sensitivity analysis. The efficacy of 15 objective functions for calibration is assessed based on streamflow predictions relative to control cases, and relative merits of each are discussed. Synthetic experiments were conducted to examine the effect of bias in RS ET observations on calibration. The objective function containing the root mean square deviation (*RMSD*) of ET result in best streamflow predictions and the efficacy is superior for catchments with medium to high average runoff. Synthetic experiments revealed that accurate ET product can improve the streamflow predictions in catchments with low average runoff.

1. Introduction

Significant research has been done in the past to develop efficient calibration algorithms to attain reliable streamflow predictions at gauged catchments. Calibration of hydrologic/land surface models is carried out usually using streamflow since it gives time-integrated information about water output from the catchment. However, lack of streamflow observations and other ground data in the vast majority of areas makes hydrological model calibration a difficult task. Particularly, accurate estimation of runoff at ungauged catchments is a growing concern for the hydrologic community (Sivapalan, 2003; Wagener and Montanari, 2011).

Alternative approaches to the conventional streamflow-based calibration for ungauged locations include estimation of parameters from prior information on catchment physical characteristics (e.g., soil hydraulic properties and vegetation properties) (Atkinson et al., 2003; Koren et al., 2003) and regionalization. For example, in parameter regionalization, a model is calibrated for a number of gauged watersheds and the model parameters are derived from a regression relationship between the watershed characteristics and parameters (Abdulla and Lettenmaier, 1997; Jakeman et al., 1992; Parajka et al., 2007; Post et al., 1998; Sefton and Howarth, 1998; Viney et al., 2009; Wagener and Wheater, 2006; Wagener et al., 2004; Zhang et al., 2011). Yadav et al. (2007) modified the approach by regionalizing flow characteristics and by incorporating uncertainty in the regressed estimates. However, the drawbacks of these approaches have been reviewed previously (Beven, 2000; Wagener and Montanari, 2011; Wagener and Wheater, 2006): uniqueness in topography, geology, vegetation features and anthropogenic modification for the watersheds within similar climatic region can make individual watersheds respond to input in widely different manners (Beven, 2000). Wagener and Wheater (2006) stated that through regionalization, model structural uncertainty is transferred to the optimized parameters, which can result in biased calibration. To explore methods that can

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overcome these issues associated with the regionalization, we investigate the efficacy of RS data in calibration and its utility as an alternative source of observational data to constrain our model parameter estimates for ungauged locations.

Typically, RS data provides spatially distributed land surface parameters with a regular temporal repeat across much of the globe, and the volume and quality of data have greatly increased over the past decades providing extensive datasets for hydrologic modelling. The RS data has been widely used in land use and land cover classification (e.g., soil and land use pattern) and the estimation of vegetation indices, surface SM and evapotranspiration (ET) (Asner et al., 2003; Chen and Cihlar, 1996; Congalton, 1991; Gupta et al., 2008; Kustas et al., 1994; Ottlé et al., 1989; Owe et al., 2008; Sucksdorff and Ottle, 1990). Resulting land surface products have enhanced overall capability of hydrologic modelling from local to global scales. For example, several studies demonstrated that annexation of RS land surface temperature, SM, leaf area index (LAI) and fraction vegetation cover data improves hydrologic modelling (Andersen et al., 2002; Corbari and Mancini, 2013; Crow and Ryu, 2009; Garcia-Quijano and Barros, 2005; Parajka et al., 2006; Renzullo et al., 2008; Silvestro et al., 2015; Sutanudjaja et al., 2014; Zhang and Wegehenkel, 2006). LAI estimated by the MODerate resolution Imaging Spectrometer (MODIS) onboard Terra and Aqua satellites can be used with the Penman–Monteith equation to produce 8-day composite ET (Cleugh et al., 2007; Leuning et al., 2008; Zhang et al., 2008). Satellite-derived products, such as ET, SM and vegetation biomass, have become important parts of hydrological modelling.

ET retrieved from AVHRR (Advanced Very High Resolution Radiometers) (Nemani and Running, 1989; Taconet et al., 1986) and MODIS (Cleugh et al., 2007; Guerschman et al., 2009; Leuning et al., 2008; Zhang et al., 2008) satellites and microwave SM retrievals from the Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E) (Njoku et al., 2003; Owe et al., 2008), Soil Moisture and Ocean Salinity (SMOS) (Kerr et al., 2001) of European Space Agency (ESA), and Advanced Scatterometer (ASCAT) (Bartalis et al., 2007) have widely been used in hydrology. Immerzeel and Droogers (2008) calibrated the Soil Water Assessment Tool (SWAT) model with MODIS ET using Gauss–Marquardt–Levenberg (GML) algorithm which increased correlation between simulated and observed ET resulting in improved streamflow predictions. Using a two-parameter surface conductance (G_s) model, optimized by catchment water balance estimates of ET (precipitation minus runoff), Zhang et al. (2008) generated 8-day composite ET (E_{RS}) from MODIS LAI. The E_{RS} was useful in estimating long-term runoff using the concept of water balance. But the study did not address the capability of E_{RS} in calibrating rainfall–runoff models. Zhang et al. (2009) concluded that multi-objective calibration of SimHyd model with streamflow and E_{RS} produced better daily and monthly runoff compared to calibration with streamflow alone. Droogers et al. (2010) showed that optimization of the Soil-Water-Atmosphere-Plant (SWAP) model using satellite-derived actual ET can predict irrigation demand with acceptable accuracy.

Hydrological application of RS SM has been primarily on its assimilation into land surface models to improve profile SM and other outputs linked to the soil (Crow and Van den Berg, 2010; Han et al., 2012; Pauwels et al., 2001; Reichle and Koster, 2005; Renzullo et al., 2014). Recent studies have shown that assimilation of satellite SM can improve streamflow predictions of rainfall–runoff models (Alvarez-Garreton et al., 2014, 2015; Crow and Ryu, 2009; Parajka et al., 2006; Pauwels et al., 2001). Similarly, the assimilation of a Soil Wetness Index (SWI) derived from ASCAT into a continuous distributed hydrologic model resulted in improved discharge predictions (Brocca et al., 2010, 2012).

Very few studies have incorporated satellite SM in model calibration. Campo et al. (2006) used SM retrievals from European Remote Sensing (ERS) scatterometer signals to optimize the parameters of soil dynamics in distributed hydrologic model. Parajka et al. (2009) used ERS scatterometer signals to calibrate semi-distributed hydrologic model along with runoff. Although both studies demonstrated improved streamflow predictions, Campo et al. (2006) study was limited to the areas with no or sparse vegetation while the study by Parajka et al. (2009) showed deterioration in SM predictions. Zhang et al. (2011) calibrated the Australian Water Resource Assessment landscape model (AWRA-L) with streamflow, NOAA-AVHRR LAI and TRMM-MI (Tropical Rainfall Measuring Mission – Microwave Imager) SM using multi-objective criteria. Even though the study resulted in marked improvement of LAI and SM, the improvement of streamflow was marginal. Sutanudjaja et al. (2014) calibrated a physically based large-scale coupled groundwater-land surface model, called PCR-GLOBWB-MOD, using SWI derived from ERS scatterometer and discharge data. The resulting optimum parameter set predicted discharge, SM and groundwater dynamics with acceptable accuracy.

Challenges in using remote sensing data for model calibration and data assimilation are discussed comprehensively in Van Dijk and Renzullo (2011). One of the major challenges is that the information content of RS observations varies based on transient vegetation (Barrett and Renzullo, 2009; Campo et al., 2006) and topography (Parajka et al., 2009). Appropriate specification of errors, as part of the retrieval process, is critical for effective calibration and data assimilation (Alvarez-Garreton et al., 2014). Suitability of coarse-resolution remote sensing data for small-scale studies is also a concern.

Previous studies show that RS data can be used to optimize the model parameters under certain conditions (Kunnath Poovakka et al., 2013; Mohanty, 2013; Zhou et al., 2013). Zhang et al. (2008) suggest that RS ET and SM can be used in the calibration of rainfall–runoff models to improve runoff estimations in ungauged catchments. A calibration scheme which relies soley on remote sensing data will be greatly beneficial in modelling at ungauged catchments, especially if it can be demonstrated to result in improved estimation compared with uncalibrated model. In this study, Microwave SM retrievals from the AMSR-E and daily estimates of ET from CSIRO MODIS ReScaled potential ET (CMRSET) model are used to calibrate a hydrologic model using 15 different objective functions considering various combinations of *RMSD* and correlation of ET and SM. The Shuffled Complex Evolution (SCE) calibration algorithm is used to calibrate a grid-based hydrologic model modified from the Australian Water Resource Assessment – Landscape (AWRA-L) model. Main research objectives of this study are to investigate (1) how effective RS ET and SM are in calibrating the model and (2) how biases in RS ET affects prediction of calibrated models.

2. Materials and methods

2.1. Study catchments

The efficacy of calibrating AWRA-L with RS ET and SM is assessed for 11 catchments in eastern Australia. First, the calibration method is developed and tested in the Loddon River catchment at Newstead, Victoria, Australia and then the method is evaluated in 10 catchments along eastern Australia (Fig. 1). The Loddon River catchment contains the Wombat flux tower station upstream and is one of the hydrologic reference stations maintained by the Australian Bureau of Meteorology (BoM). The observed ET and SM data from the Wombat station are used to evaluate the satellite data.