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Examining differences in streamflow estimation for gauged and ungauged catchments using evolutionary data assimilation

Gift Dumedah and Paulin Coulibaly

ABSTRACT

Data assimilation has allowed hydrologists to account for imperfections in observations and uncertainties in model estimates. Typically, updated members are determined as a compromised merger between observations and model predictions. The merging procedure is conducted in decision space before model parameters are updated to reflect the assimilation. However, given the dynamics between states and model parameters, there is limited guarantee that when updated parameters are applied into measurement models, the resulting estimate will be the same as the updated estimate. To account for these challenges, this study uses evolutionary data assimilation (EDA) to estimate streamflow in gauged and ungauged watersheds. EDA assimilates daily streamflow into a Sacramento soil moisture accounting model to determine updated members for eight watersheds in southern Ontario, Canada. The updated members are combined to estimate streamflow in ungauged watersheds where the results show high estimation accuracy for gauged and ungauged watersheds. An evaluation of the commonalities in model parameter values across and between gauged and ungauged watersheds underscore the critical contributions of consistent model parameter values. The findings show a high degree of commonality in model parameter values such that members of a given gauged/ungauged watershed can be estimated using members from another watershed.

Key words | data assimilation, multi-objective evolutionary algorithms, Pareto optimality, ungauged watersheds

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INTRODUCTION

Data assimilation (DA) has been applied in several hydrological studies to improve estimation through integration of information content from imperfect observations into uncertain model outputs. DA methods merge model estimates with observation data by using the uncertainties associated with the model and the observation. DA applications are popular for estimation of soil moisture (Walker & Houser 2001; Reichle *et al.* 2008; Alavi *et al.* 2010; Dumedah *et al.* 2011), streamflow (Komma *et al.* 2008; Camporese *et al.* 2010; Xie & Zhang 2010; Leisenring & Moradkhani 2011; Dumedah & Coulibaly 2012a; Dumedah *et al.* 2012b) and land surface energy fluxes (Schuurmans *et al.* 2003; Caparrini *et al.* 2004a, b). But very few studies have actually applied DA to improve the simulation of streamflow in ungauged basins. This analysis expands the previous study in Dumedah & Coulibaly (2012b) and focuses on the potential of evolutionary data assimilation (EDA) to improve streamflow estimation in ungauged catchments in comparison to estimation in gauged ones. As a result, this paper illustrates the EDA approach to facilitate ensemble simulation of streamflow in ungauged catchments and subsequent evaluation in relation to estimation accuracy in gauged catchments. The differences in streamflow estimation for both gauged

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and ungauged catchments are examined to determine the changes in model state, parameter values and estimation accuracy.

The estimation of streamflow in ungauged catchments is common in the literature, e.g. Seibert (1999), Parajka *et al.* (2005), Laahaa & Blöschl (2006), Young (2006), Goswami *et al.* (2007), Parajka *et al.* (2007), Yadav *et al.* (2007), Oudin *et al.* (2008), Reichl *et al.* (2009), Parada & Liang (2010), Samaniego *et al.* (2010), Peel & Blöschl (2011), Samuel *et al.* (2011), Seckin (2011) and Patil & Stieglitz (2013). Other studies have employed ensemble modelling (Vineya *et al.* 2009) and averaging of ensemble estimates (McIntyre *et al.* 2005), but an explicit use of DA methods for estimating ungauged streamflow is limited in the literature. Even recent reviews of methods for estimating streamflow in ungauged catchments (He *et al.* 2011; Peel & Blöschl 2011; Razavi & Coulibaly 2013) have limited information on the application of DA methods. As a result, a demonstration of EDA to facilitate streamflow estimation in ungauged watersheds provides a unique illustration of the DA method for regionalization studies. Existing studies usually examine the estimation of streamflow in ungauged catchments, but there are limited assessments of the estimated streamflow between gauged and ungauged catchments and a detailed evaluation of their associated parameter values. As a result, this study is unique in its ensemble estimation of streamflow in ungauged catchments, assessment of streamflow estimation accuracy in both gauged and ungauged catchments, and subsequent evaluation of the degree of commonality in parameter sets between catchments.

The EDA that has been applied in Elshorbagy & El-Baroudy (2009), Dumedah *et al.* (2010), Dumedah (2012), Dumedah & Coulibaly (2012a, b) is a formulation of the multi-objective evolutionary algorithm (MOEA) into an applied DA approach. EDA combines the stochastic and adaptive capabilities of MOEAs with the cost function from the variational DA approach to evolve a population of candidate ensemble members through several cycles of evolution. As a population-based approach, EDA uses the evolutionary strategy to evaluate several candidate ensemble members before selecting a subset of the ensemble members as the updated members for each assimilation time step. The implementation procedure of EDA is detailed in the subsection on using the evolutionary strategy to assimilate observations.

This study has applied EDA to assimilate daily streamflow into the Sacramento soil moisture accounting (SAC-SMA) model for eight watersheds with natural flows in southern Ontario, Canada. The leave-one-out evaluation method was used to transfer the updated ensemble members for the remaining watersheds to the ungauged watershed at a time. Using inverse distance weighing (IDW), the updated ensemble members for the remaining watersheds are combined to determine the ensemble members for the ungauged watershed where they are used to simulate streamflow. This evaluation procedure is conducted by selecting each of the eight watersheds as an ungauged watershed at a time. It is noteworthy that the ensemble members are defined by the following components: model states and parameters and forcing data uncertainties. For each ungauged watershed, these specific model components are estimated before they are applied into SAC-SMA to simulate streamflow.

As will be shown in this study, the differences in estimation accuracy between gauged and ungauged watersheds can be examined in relation to the differences or commonalities in parameter values. The results will emphasize the critical contributions of consistent model parameter values and their impact on estimation accuracy in ungauged watersheds. The remainder of the paper is organized as follows. The next section outlines the experimental area, data sources and the EDA procedure. Illustrative outputs are presented and discussed in the Results section. The findings of this study are summarized in the Conclusions section.

DATA AND METHODS

The study area shown in Figure 1 has eight selected watersheds in southern Ontario, Canada. According to the mean annual precipitation and the average annual runoff, the area is considered moderately homogeneous. However, each watershed has unique behaviour, with each having different drainage areas, different land cover types and different dominant soil textural properties, as shown in Table 1.

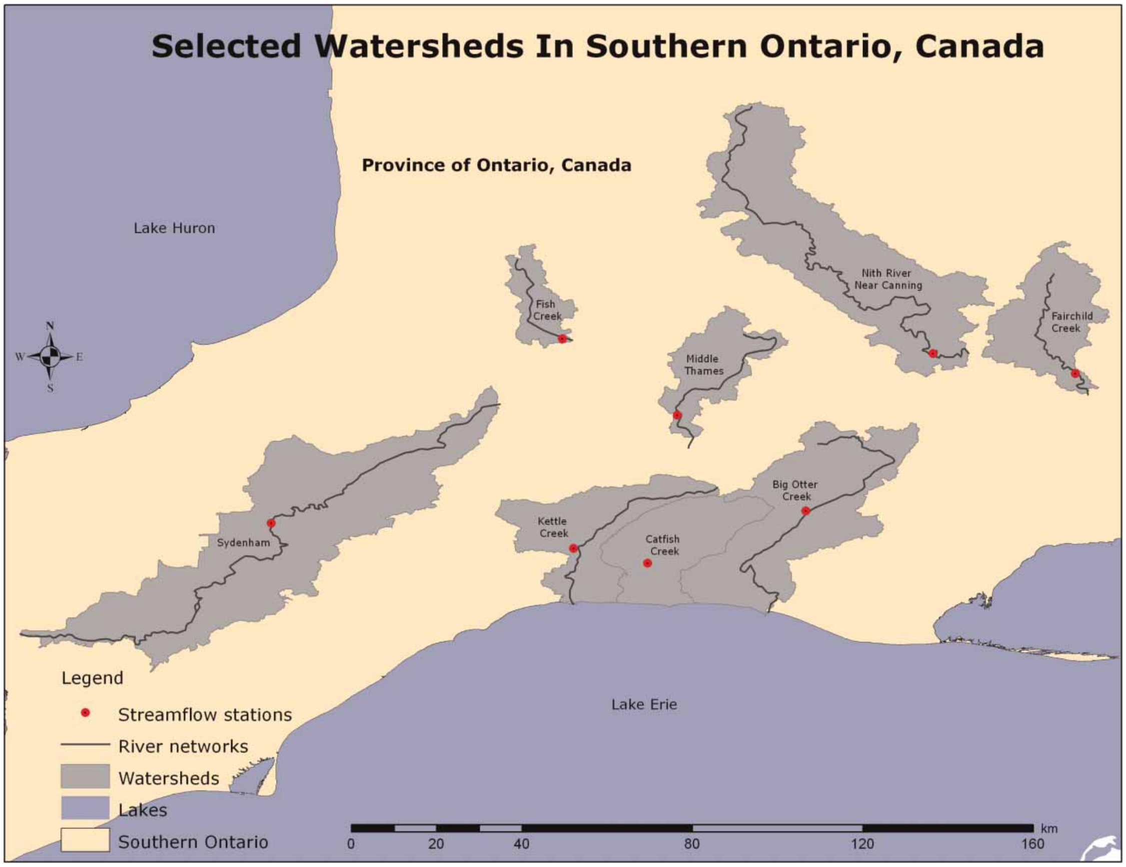

Figure 1 | Experimental area: select watersheds in southern Ontario, Canada (*Source*: Natural Resources Canada).

Table 1 | List of the selected watersheds in southern Ontario and their major physical properties

Basin name	Area (km^2)	MAD (m^3/s)	PCP (mm)	Dominant land cover	Dominant soil texture
Nith River Near Canning (02GA010)	1,030	1.037	943.11	Deciduous forest (64%)	Loam (30%)
Fairchild Creek near Branford (02GB007)	360	0.901	913.16	Deciduous forest (41%)	Silt (50%)
Kettle Creek at St. Thomas (02GC002)	329	1.009	1006.3	Deciduous forest (89%)	Loam (31%)
Big Otter Creek at Tillsonburg (02GC010)	342	1.136	1021.28	Deciduous forest (78%)	Loam (30%)
Catfish Creek near Sparta (02GC018)	287	1.092	1029.68	Deciduous forest (84%)	Loam (37%)
Middle Thames at Thamesford (02GD004)	306	1.148	986.94	Deciduous forest (83%)	Silt (51%)
Fish Creek near Prospect Hill (02GD010)	150	1.237	1013.60	Deciduous forest (84%)	Clay (53%)
Sydenham River near Alvinston (02GG002)	730	0.891	1033.69	Deciduous forest (82%)	Silt (30%)

MAD, mean annual discharge; PCP, mean annual precipitation.

The SAC-SMA model was applied to simulate the streamflow in the various watersheds. A schematic illustration of the SAC-SMA model structure is presented in Figure 2 with extended snow routine and routing components (Samuel *et al.* 2011). The SAC-SMA is a conceptual model and requires only precipitation, evaporation and temperature to account for inflows, storage and outflows in the watershed. These forcing data for the various watersheds

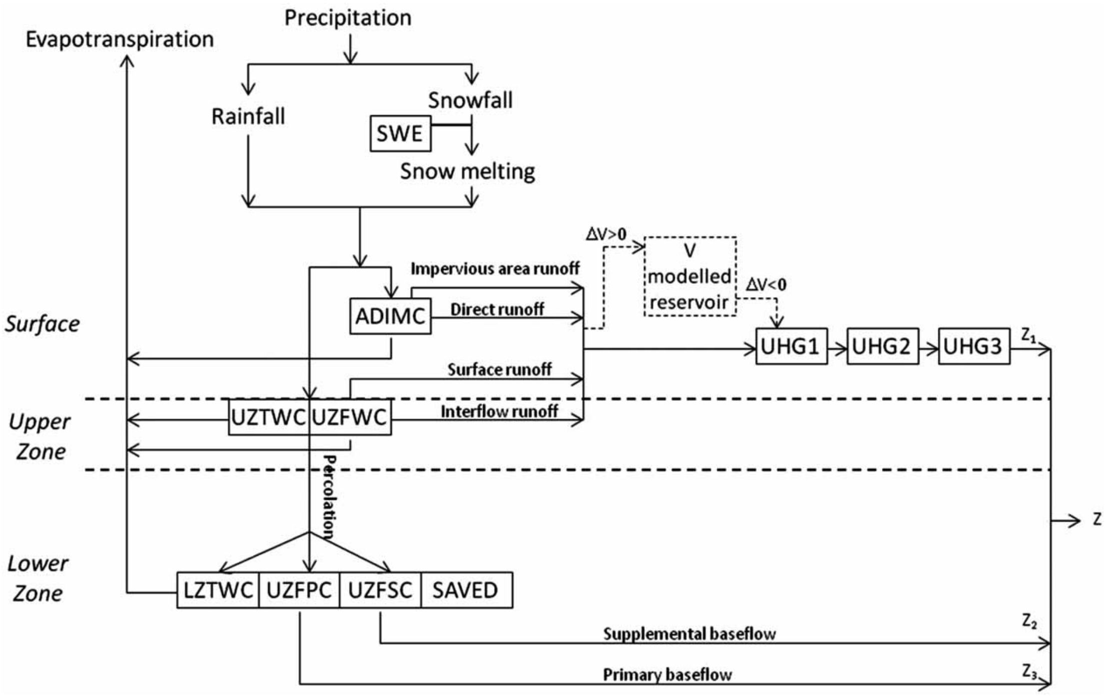

Figure 2 | Schematic illustration of the extended SAC-SMA model (including snow routine and Nash-cascade routing routine) where the rectangles refer to the various model states.

are obtained from Environment Canada weather stations in the study area.

The SAC-SMA accumulates soil water content into two layers: upper and lower soil layers, where the upper zone controls surface soil processes and interception storage. When the upper soil storage is full and precipitation exceeds the interflow and percolation capacities, then saturation of excess overland flow occurs. The lower soil storage represents deeper soil processes and groundwater storage. Nonlinear equations are used to partition precipitation into overland flow, infiltration to the upper zone, interflow, percolation to the lower zone, and fast and slow components of groundwater recession baseflow. The runoff from impervious area, direct, surface and interflow runoff are routed using the Nash cascade to produce quick response channel inflow, following Vrugt *et al.* (2006b).

The SAC-SMA has been applied in several hydrological studies, and further information can be obtained from sources including Koren *et al.* (2004), Vrugt *et al.* (2006a) and Vrugt & Robinson (2007). It is noteworthy that the selected watersheds and the SAC-SMA model are simply used to demonstrate the utility of the proposed approach and that the resulting findings of this study are applicable to other watersheds and rainfall-runoff models.

Using the evolutionary strategy to assimilate observations

The EDA procedure for sequential assimilation of streamflow is shown in Figure 3. This EDA procedure uses the Non-dominated Sorting Genetic Algorithm II (NSGA-II), which has been extensively applied in hydrology (Tang *et al.* 2006; Bekele & Nicklow 2007; Confesor & Whittaker 2007; Wohling *et al.* 2008; Dumedah *et al.* 2010, 2011, 2012a, b; Dumedah 2012; Dumedah & Coulibaly 2012a, c). EDA begins by generating a random population P_r of size $2n$ for ensemble members which comprise states, model parameters and forcing data uncertainties. The states are obtained according to Equation (1), and the forcing data are perturbed by using Equation (2). Each member of P_r is applied into the measurement model to determine the prediction in Equation (3), and the observation is perturbed using

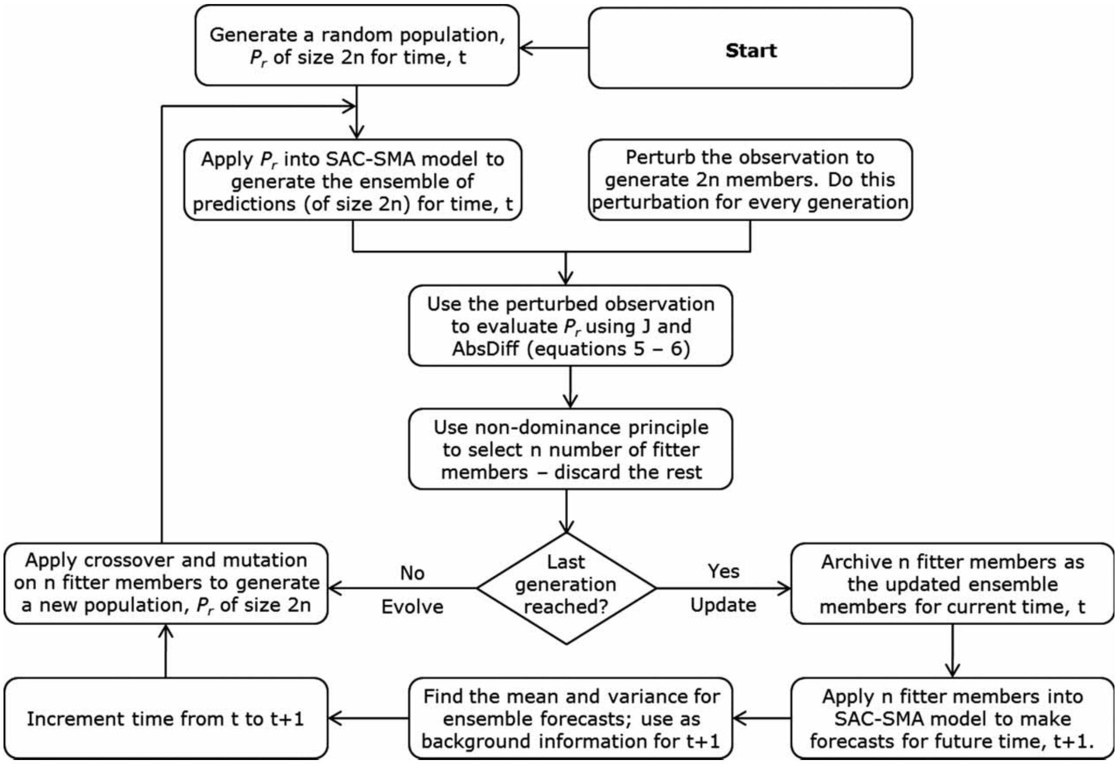

Figure 3 | An outline of the computational procedure of EDA in a sequential assimilation of streamflow (adapted from Dumedah (2012)).

Equation (4) to generate $2n$ members:

$$x_t = f[x_{t-1},\ u_{t-1},\ z_t] \tag{1}$$

$$u_t = u_t + \gamma_t,\ \gamma_t \sim N(0, \beta_t^u) \tag{2}$$

$$\hat{y}_t = f[x_t, z_t, u_t] \tag{3}$$

$$y_t = y_t + \varepsilon_t, \varepsilon_t \sim N(0, \beta_t^y) \tag{4}$$

where x_t is a vector of predicted states at time t; $f[.]$ is the measurement model; x_{t-1} is a vector of updated states for the previous time; z_t is the model parameter; u_t is the forcing data; γ_t is the forcing data error with covariance β_t^u at each time step; $\hat{y}_t$ is the ensemble prediction; y_t is the observation; and ε_t is the observation error with covariance β_t^y at each time step.

The predictions and the observations each of size $2n$ are evaluated using the cost function (denoted J) in Equation (5), and the absolute difference in Equation (6). Both objectives are minimized such that the fitter (i.e. more competitive) members have smaller values in at least one or more objectives. AbsDiff allows the determination of members with the smallest residual between the model output and the perturbed observation. The minimization of J finds members that represent the best compromise between the background value and the perturbed observation. The background value is the average estimate for forecasted ensemble members, which are determined by applying the members of the population from the previous assimilation time step into the measurement model to make a prediction for the current time step. The background value for the initial time step is determined from a randomly generated population of members:

$$J = \sum_{i=1}^{k} J(y_i) = \sum_{i=1}^{k} \left\{ \frac{(y_i - y_{b,i})^2}{{\sigma_b}^2} + \frac{(y_i - y_{o,i})^2}{{\sigma_o}^2} \right\} \tag{5}$$

$$\text{AbsDiff} = |y_i - y_{o,i}| \tag{6}$$

where $y_{b,i}$ is the background value for the ith data point; $y_{o,i}$ is the perturbed observed value for the ith data point; σ_b^2 is the variance for the background streamflow; σ_o^2 is the variance for the observed streamflow; y_i is the analysis value (i.e. prediction) for the ith data point that minimizes $J(y_i)$; and k is the number of data points.

The sorting of the members in a population is conducted using Pareto dominance (or non-dominance) to select n fitter members, where they are varied and recombined to determine new members for the population P_r of size $2n$. These procedures are repeated to evolve the population P_r through several generations where each generation attempts to increase the overall quality of members in P_r. At the referenced (i.e. the last) generation, the final n fitter members are chosen as the updated members where they are archived into the population P_e. It is noteworthy that the updated members are only a subset of all evaluated members for the current time step.

The assimilation time step is incremented from t to $t+1$ where the n members in P_e at t are used to generate n number of forecasts for future time $t+1$, and the average and its associated variance from the ensemble members are used as background information. The P_e from t is also used as a seed population for $t+1$, where it is varied and recombined to generate a new population P_r of size $2n$. This new P_r is again evolved through several generations to determine the final n updated members for $t+1$. These procedures are repeated for future assimilation time steps to evolve members through several generations, and to determine the updated members for each assimilation time step. The resulting output is an archive of n updated members for each assimilation time step.

Setup of model runs and transfer of assimilated ensembles to ungauged watersheds

EDA was run with 1000 ensemble members for a 5 year period from 2004 to 2008 for the eight gauged watersheds. A population of 40 members was chosen and was evolved through 25 generations to evaluate the 1,000 members. The number of updated members that are archived for each assimilation time step is 20, representing half the size of the evolving population. EDA generates the initial population by using the model parameter bounds and forcing data uncertainties in Table 2, where the SAC-SMA model states (also in Table 2) are updated between assimilation time steps. The streamflow observation error is estimated as the hourly variance for each day of streamflow data; as a result, this error is time variant. The model error, which is also time variant, is estimated adaptively from the ensemble members using the procedure for estimating the background error outlined in the subsection on using the evolutionary strategy to assimilate observations.

The observations are sequentially assimilated at a daily time step where individual members are evaluated using the cost function in Equation (5) together with the absolute difference in Equation (6). Given that EDA evolves ensemble members using the NSGA-II procedure (Deb *et al.* 2002), a standard crossover probability of 0.8 and a mutation probability of $1/n$ (where n is the number of variables) are used. It is noteworthy that EDA modifies the standard NSGA-II procedure to allow for archiving of members and to initiate evolution using pre-determined seed population of members.

To transfer updated members to ungauged watersheds, the 20 updated members for each assimilation time step are combined through the leave-one-out method by using IDW to estimate ensemble members for the ungauged watersheds. The IDW values, representing the inverse distance weighting between the watersheds in Table 3 are applied to weight the updated members to determine members for the ungauged watersheds. That is, each of the eight watersheds is considered as an ungauged watershed at a time where the IDW values are applied to weight updated members from the remaining seven watersheds to generate ensemble members for the ungauged basin. In this way, watersheds that are closer to the ungauged watershed are weighted more than those that are farther away. The size of the estimated ensemble members for the ungauged watershed is kept the same as the size of the updated members (i.e. 20) for the individual watersheds.

Aside from the IDW method, other transfer methods in the literature include physical similarity (Seibert 1999; Parajka *et al.* 2005; Young 2006; Oudin *et al.* 2008), regression-based methods (Parajka *et al.* 2005; Young 2006; Laahaa & Blöschl 2006; Oudin *et al.* 2008), and the kriging approach (Parajka *et al.* 2005). Among these transfer methods, the IDW has performed favourably well in several

Table 2 | Description of model parameters and state variables for SAC-SMA model

Parameter	Description	Interval
UZTWM	Upper zone tension water maximum storage (mm)	5–100
UZFWM	Upper zone free water maximum storage (mm)	5–100
LZTWM	Lower zone tension water maximum storage (mm)	100–500
LZFPM	Lower zone free water primary maximum storage (mm)	50–500
LZFSM	Lower zone free water supplemental maximum storage (mm)	250–1000
ADIMP	Additional impervious area (–)	0.01–0.4
Recession parameters		
UZK	Upper zone free water lateral depletion rate (day 1)	0.01–0.2
LZPK	Lower zone primary free water depletion rate (day 1)	0.0001–0.02
LZSK	Lower zone supplemental free water depletion rate (day 1)	0.1–0.5
Percolation and other		
ZPERC	Maximum percolation rate (–)	1–10
REXP	Exponent of the percolation equation (–)	1–10
PCTIM	Impervious fraction of the watershed area (–)	0.0–0.01
PFREE	Fraction percolating from upper to lower zone free water storage (–)	0–0.5
RIVA	Riparian vegetation area (–)	0
SIDE	Ratio of deep recharge to channel base flow (–)	0
SAVED	Fraction of lower zone free water not transferable to tension water	0
Soil moisture states		
UZTWC	Upper zone tension water storage content (mm)	
UZFWC	Upper zone free water storage content (mm)	
LZTWC	Lower zone tension water storage content (mm)	
LZFPC	Lower zone free primary water storage content (mm)	
LZFSC	Lower zone free secondary water storage content (mm)	
ADIMC	Additional impervious area content linked to stream (mm)	
Snow routine components		
DDF	Degree day factor	1–5
SCF	Snowfall correction factor	0.8–1.2
TR	Upper threshold temperature, to distinguish between rainfall, snowfall and a mix of rain and snow	0–1
ATHORN	A constant for Thornthwaite's equation	0.1–0.3
RCR	Rainfall correction factor	0.8–1.2
SWE (state)	Snow water equivalent (mm)	
Nash-cascade routing components		
RQ	Residence time parameters of quick flow	0.4–0.95
UHG1	Three linear reservoirs to route the upper zone (quick response) channel inflow (mm)	
UHG2		
UHG3		
Forcing variables		
PRECIP	Precipitation (mm)	± 5%
TEMPR	Temperature (°C)	± 5%

Table 3 | Inverse distance weights between the eight watersheds

Basin	45GA010	45GB007	45GC002	45GC010	45GC018	45GD004	45GD010	45GG002
GA010	0.000	0.487	0.051	0.164	0.062	0.141	0.074	0.021
GB007	0.631	0.000	0.043	0.122	0.053	0.082	0.050	0.019
GC002	0.021	0.014	0.000	0.074	0.700	0.096	0.051	0.045
GC010	0.136	0.079	0.149	0.000	0.280	0.253	0.074	0.029
GC018	0.024	0.016	0.665	0.132	0.000	0.096	0.039	0.027
GD004	0.096	0.043	0.159	0.207	0.167	0.000	0.291	0.037
GD010	0.081	0.042	0.135	0.097	0.109	0.462	0.000	0.075
GG002	0.055	0.040	0.293	0.095	0.187	0.146	0.184	0.000

All basin IDs are preceded with '02' so that 'GA010' becomes '02GA010'.

studies including Parajka *et al.* (2007), Goswami *et al.* (2007), Oudin *et al.* (2008) and Samuel *et al.* (2011). Given the favourable performance of the IDW method, and its straightforward approach requiring only distance between centroids of watersheds, the IDW was employed to combine the updated ensembles.

The resulting ensemble members for the ungauged watershed comprise forcing data uncertainties, and state and model parameterizations for each modelling time step where they are applied into the SAC-SMA model to estimate ensemble of streamflows (20 members) in the ungauged watershed. This procedure is repeated to estimate streamflow for all eight ungauged watersheds by selecting each watershed as ungauged at a time, where updated ensemble members from other watersheds are combined to determine ensemble members for the ungauged watershed. It is noteworthy that several transfer methods exist, such as those given by Seibert (1999), Parajka *et al.* (2005), Laahaa & Blöschl (2006), Young (2006) and Oudin *et al.* (2008), but the rationale to use the IDW to combine the updated members is its straightforward approach, requiring only distance between centroids of watersheds.

Approach to evaluate the differences/commonalities in parameter sets for gauged and ungauged watersheds

The estimated streamflows in gauged and ungauged watersheds have rarely been compared in the literature. This study is unique in its assessment of ungauged streamflow estimation, coupled with an evaluation of the distribution of parameter values that are applied into the SAC-SMA to estimate streamflow in gauged and ungauged watersheds. This section provides the approach for the assessment of the differences or commonalities in parameter values between the various watersheds. The rationale is that information on the level of variability in parameter values between the various watersheds can provide an estimate of the expected values for model states and parameters, and uncertainties for forcing data. It is noteworthy that the updated ensemble members have been independently estimated for each watershed so there are no existing relationships between the different sets of members.

The difference/commonality in parameter values is estimated using the indicator, ΔP in Equation (7), representing the overall average of the differences in parameter values between a referenced watershed and a current watershed under consideration in proportion to the parameter value from the referenced watershed. For the eight watersheds, each watershed is chosen as a referenced watershed where its parameter values are compared to corresponding parameter values from the remaining seven watersheds at a time. For each watershed, ΔP is computed for each of the 34 parameters listed in Table 2:

$$\Delta P = \frac{1}{n} \times \sum_{i=1}^{n} \left[\frac{|P_i^r - P_i^c|}{P_i^r} \right] \quad (7)$$

where P denotes a value for model state, parameter or forcing data uncertainty; n is the total number of members across the entire assimilation time period; and P_i^r and P_i^c represent the ith parameter values for referenced (r) and current (c) watersheds, respectively.

RESULTS AND DISCUSSION

Evaluation of updated streamflows

The ensemble mean of the updated members are evaluated using the Nash–Sutcliffe efficiency (NSE) in Equation (8) and the percent bias in Equation (9). The percent bias computes the proportion of the model estimation that is biased, such that a minimum value of zero indicates unbiased estimation, whereas values greater than zero indicate the level of bias in the streamflow estimation. The NSE and the percent bias evaluate different aspects of the estimated streamflow, with the NSE assessing the predictive power of the model, whereas the percent bias quantifies the overall tendency of the simulation to be larger or smaller than the observation.

The quality of the generated ensemble mean for the various watersheds is shown in the upper portion of Table 4. The watersheds have different evaluation values, but the overall performance is high across all watersheds. The temporal comparison between the observation and the estimated streamflow is shown for all watersheds in Figure 4. The temporal correlations between the observation and the ensemble mean for these sample watersheds are high, and support the computed evaluation measures.

$$\mathrm{NSE} = 1 - \left[\frac{\sum_{i=1}^{n}(Q_i^{\mathrm{obs}} - Q_i^{\mathrm{sim}})^2}{\sum_{i=1}^{n}(Q_i^{\mathrm{obs}} - \bar{Q}^{\mathrm{obs}})^2}\right] \tag{8}$$

$$\text{Percent bias} = 100 \times \left[\frac{\sum_{i=1}^{n}|Q_i^{\mathrm{obs}} - Q_i^{\mathrm{sim}}|}{\sum_{i=1}^{n} Q_i^{\mathrm{obs}}}\right] \tag{9}$$

where Q_i^{obs} is the observed streamflow at time i; Q_i^{sim} is the simulated streamflow at time i; $\bar{Q}^{\mathrm{obs}}$ is the mean of observed streamflow; and n is the number of data points.

Streamflow simulations in ungauged watersheds

The estimated ensemble of streamflows in the ungauged watersheds are compared to the observation streamflow to assess the accuracy of EDA estimation. The evaluation in Figure 5 for all watersheds compares the observation to the estimated ensemble streamflows. Due to the different orders of magnitude of streamflow for the various watersheds, the streamflow values are log-transformed so that high and low flows can be adequately visualized. These comparisons show a high temporal consistency/correlation between the observation and the estimated streamflows during both low and peak flows. The ensemble-based evaluation provides an estimate of the level of uncertainty for the ensemble mean.

The quantitative evaluations of the ensemble mean of the estimated members in the ungauged watersheds are presented in the lower portion of Table 4 using NSE and percent bias. The evaluations show that the estimated ensemble members in the ungauged watersheds performed considerably well. These results further illustrate the utility of the EDA approach to generate updated ensembles that are capable to facilitate streamflow estimation in ungauged watersheds.

The comparison in estimation accuracy between gauged and ungauged watersheds shows that the estimation accuracy declines from gauged watersheds to ungauged ones. The differences in estimation accuracy between gauged

Table 4 | Evaluation of the ensemble means for estimated streamflow in gauged and ungauged watersheds

Measure	0GA010	0GB007	0GC002	0GC010	0GC018	0GD004	0GD010	0GG002
Streamflow assimilation for gauged watersheds								
00NSE	0.647	0.937	0.806	0.914	0.766	0.784	0.826	0.898
00% Bias	0.277	0.056	0.175	0.054	0.186	0.121	0.111	0.109
Streamflow simulation for ungauged watersheds								
00NSE	0.609	0.864	0.465	0.815	0.700	0.726	0.755	0.812
00% Bias	0.381	0.200	0.482	0.230	0.318	0.258	0.258	0.262

NSE denotes Nash–Sutcliffe efficiency; % Bias is in fractions.
Evaluations are based on the ensemble mean and the observed streamflow.

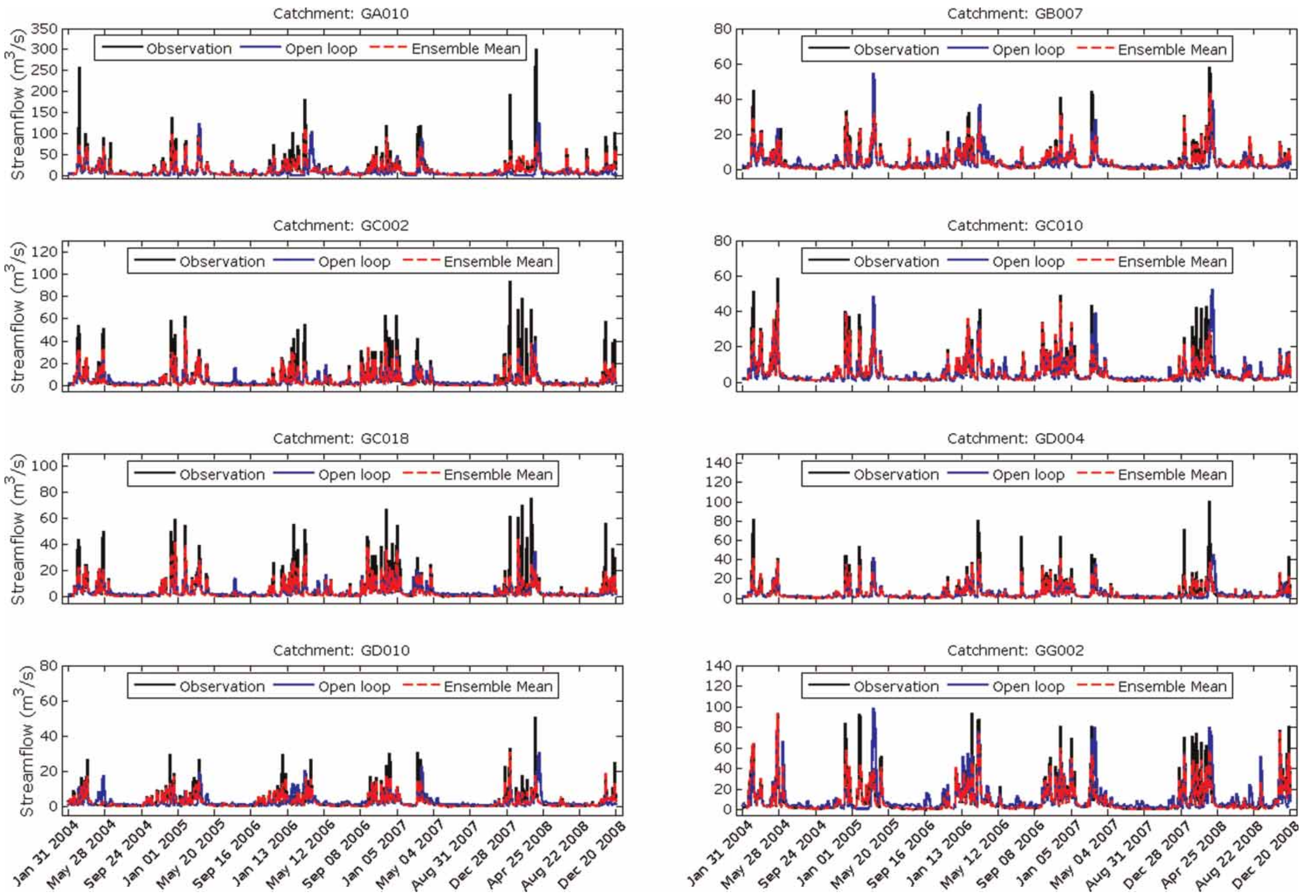

Figure 4 | Comparison between the ensemble mean and the observed streamflow for all eight watersheds. The open loop estimates are streamflow simulations with randomly generated parameter values.

and ungauged watersheds are variable across watersheds. The percentage decline in estimation accuracy across watersheds is, on average, about 12% for NSE and 120% for percent bias. The considerable difference in percentage decline for NSE and percent bias suggests that in ungauged watersheds: (a) the timing of low and peak flows are highly accurate, indicative of high temporal accuracy in NSE values and (b) the differences in volume of streamflow between observation and estimation is significant, resulting in less accurate percent bias compared to those in gauged watersheds.

Assessment of the differences/commonalities in parameter values for gauged and ungauged watersheds

The evaluation of the estimated streamflow in gauged and ungauged watersheds has shown the utility of the EDA approach, but the distribution of parameter values that are applied into the SAC-SMA to estimate streamflow are equally important. The distribution of model parameter values is presented in two cases: (i) evaluation of the model parameter differences between all eight gauged watersheds and (ii) assessment of the differences in parameter values between gauged and ungauged watersheds.

In the first case, the comparison of the differences/commonalities in parameter values for the various gauged watersheds is shown in Figure 6. The estimated differences in parameter values between watersheds is similar for most parameters, whereas about four others show a degree of variability between the watersheds. The variability shown in these four parameters (PCTIM, LZPK, UHG1 and UHG2) is mostly due to a deviation of parameter values of a single watershed from a cluster of parameter values from the majority of the watersheds. But the high

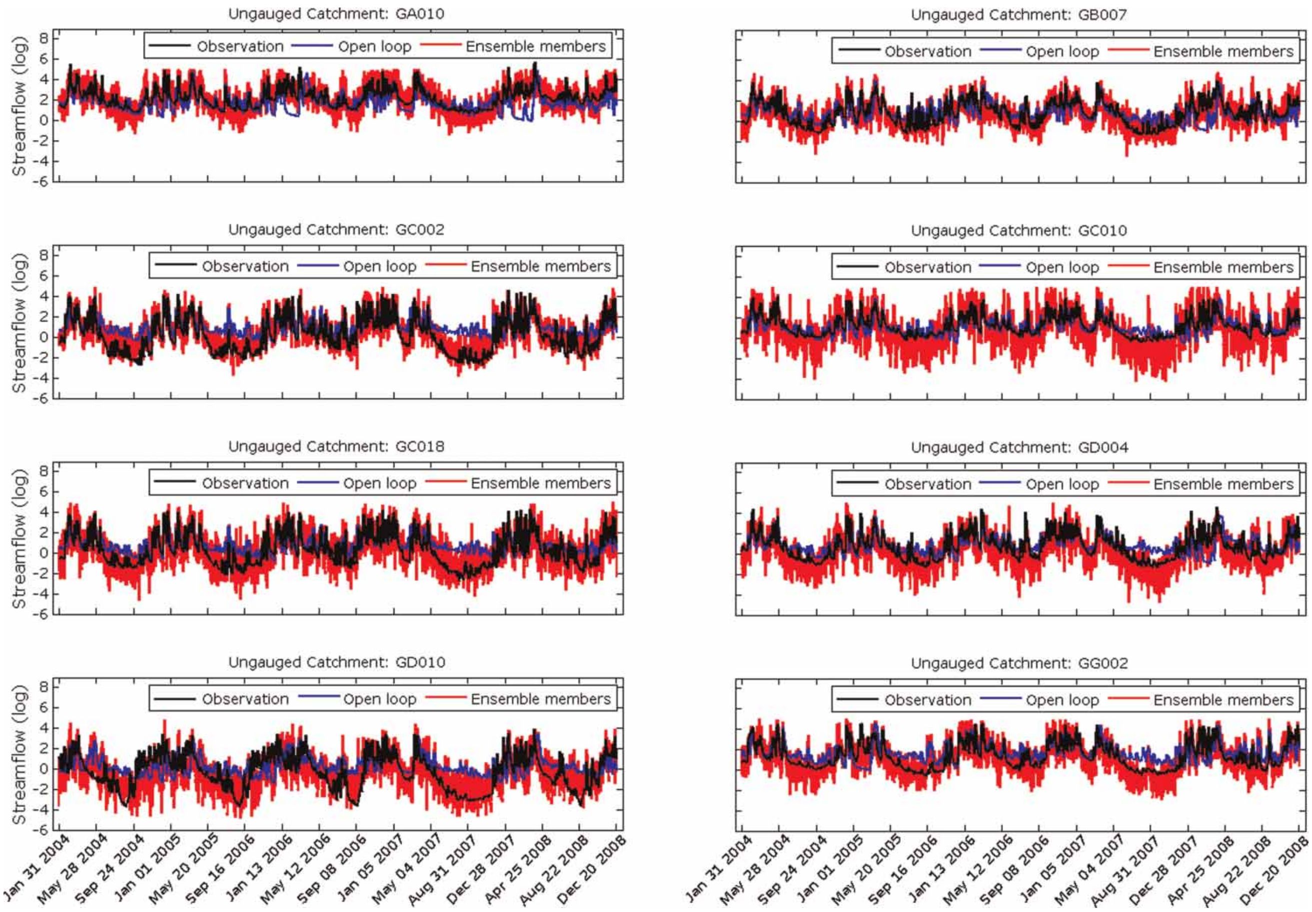

Figure 5 | Estimated ensemble streamflow (log-transform) for all eight ungauged watersheds. The open loop estimates are streamflow simulations with randomly generated parameter values.

degree of commonality for a large proportion of the parameters is notable, given the unique properties of each watershed. This is significant because, for these model parameters, the average variance of their differences is less than 1% across all eight watersheds. The significance of this commonality is that these parameters show a high degree of transferability in a way that parameter values for a given gauged/ungauged watershed can be estimated using parameter values from another watershed. It is noteworthy that the high degree of commonality is not limited to model parameters and state variables in the SAC-SMA model, but also to the uncertainties applied to the forcing data variables: precipitation and temperature.

In the second case, comparisons are undertaken to evaluate the differences in parameter values between gauged and ungauged watersheds. In accordance with Equation (7), the gauged watershed is considered the referenced watershed, whereas the ungauged watershed is considered the current watershed. In this case, the evaluation of the differences in parameter values identifies model parameters that are significantly different in a way to estimate the expected level of change in parameter values between gauged and ungauged watersheds. The estimated differences/commonalities in parameter values between gauged and ungauged watersheds is shown in Figure 7. It is important to emphasize that these differences/commonalities represent the overall difference in parameter values between the gauged watershed (when updated members were estimated for the watershed), and the ungauged watershed (where ensemble members are estimated for the same watershed using updated members from other watersheds).

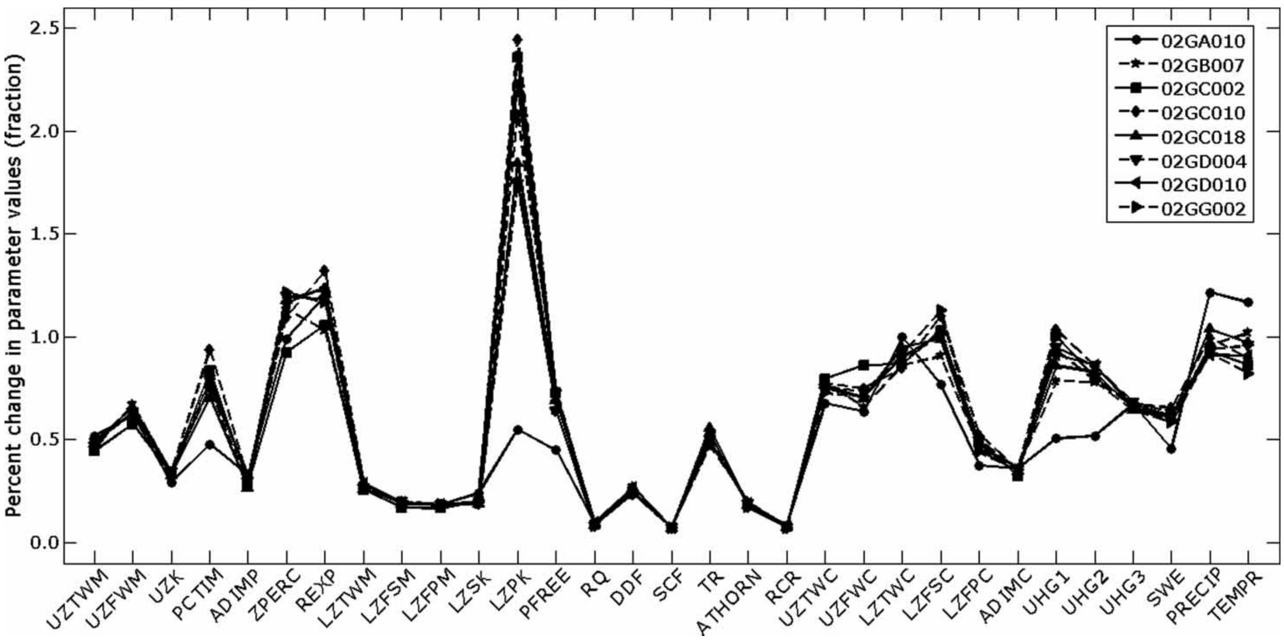

Figure 6 | Percentage change in parameter values between updated ensemble members of various watersheds across assimilation time steps.

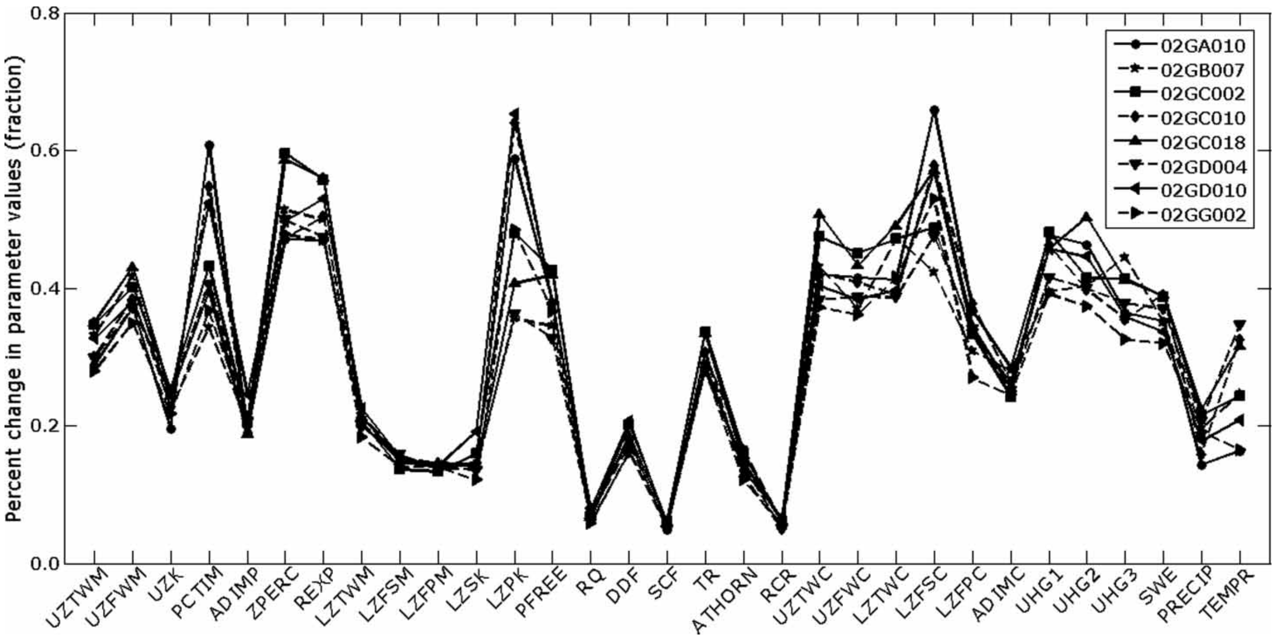

Figure 7 | Percentage change in parameter values between gauged and ungauged watersheds across assimilation time steps.

The comparisons show that the differences in parameter values are low, to about 0.5%, for SCP and high, to about 65%, for LZPK. However, across watersheds, the differences in parameter values show a clustering pattern, with most model parameters converging to a single cluster. It is noteworthy that the pattern of clustering observed for each model parameter is similar in both Figure 6 and Figure 7. On a parameter by parameter basis, this clustering pattern illustrates a high degree of commonality between watersheds. The differences in parameter values are variable from watershed to watershed, but the overall difference is about 5% across watersheds. That is, the estimated difference in model parameter values between the gauged and ungauged watersheds is variable to about 5% from another gauged/ungauged watershed.

Furthermore, it is important to emphasize the illustration of the sensitivity of model parameters for the differences between the watersheds in Figure 6, and also between gauged and ungauged ensemble members in Figure 7. In both cases, the highly sensitive model parameters are the ones that converged to a single cluster, whereas the less sensitive model parameters show a degree of variability across watersheds. The convergence of the differences in model parameter values to a single cluster across several watersheds is significant because it illustrates consistency between updated members for extended assimilation time steps, hence the high degree of commonality. These results illustrate the capability of the proposed method to examine the different aspects of model parameters and their critical contributions for a better estimation in gauged and ungauged watersheds.

CONCLUSIONS

This study has illustrated the EDA approach to facilitate estimation of streamflow in gauged and ungauged watersheds. EDA has been shown to generate updated ensemble members for several watersheds, where the archived members for selected watersheds are combined using IDW to estimate ensemble members for ungauged watersheds. The estimated ensemble members comprise model states and parameters, and uncertainties for forcing data, which are applied into the SAC-SMA model to generate several scenarios of streamflow in the ungauged watersheds.

The updated members for the individual gauged watersheds show a high temporal correlation between the estimated streamflows and the observed streamflows. The transfer of these updated members to ungauged watersheds shows an accurate estimation of streamflow based on NSE and percentage bias. Additionally, the estimated ensemble members provide information on the uncertainty of the simulated streamflows in the ungauged watersheds. A key illustration is the estimation of a small number of updated members and their subsequent evaluation for ungauged watersheds. The performance of this small number of updated members for the evaluated ungauged watersheds shows that they can facilitate operational real-time estimation of streamflow in ungauged catchments.

Further evaluation of the updated members in parameter space was undertaken to explore the differences and commonalities both between the various watersheds, and between gauged and ungauged watersheds. The evaluation has shown a high degree of commonality in model parameter values between watersheds, and has provided estimates of the expected differences for each parameter between a reference watershed and another watershed. Additionally, the deterioration of streamflow estimation accuracy from gauged watershed to ungauged ones has been illustrated by the differences in parameter values between gauged and ungauged watersheds. The high degree of commonality in model parameter values between the watersheds illustrates the versatility of EDA to provide a consistent trend of parameter values for watersheds with unique behaviours. EDA has been shown to provide information on the sensitivity of model parameters that is consistent across several watersheds.

These findings are important to further improve estimation in both gauged and ungauged watersheds, but they also raise new questions for future investigation. The estimated differences in parameter values should be examined as a new method of transferring ensemble members from gauged watersheds to ungauged ones and compared to existing methods. The method should be evaluated in real time through the estimation of updated members for one watershed and a continuous evaluation for these members in several neighbouring watersheds.

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