

# REGIONALISATION OF POSTERIOR PROBABILITY DISTRIBUTION OF MODEL PARAMETERS: PREDECTION ON UNGAGUED BASIN

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In the case study presented here, the calibrated parameters of a Conceptual Rainfall-Runoff (CRR) model could not be uniquely identified. Moreover, the Posterior Probability distribution (PPD) of Model Parameters varied among basin depending upon the basin attributes and data aspects. So the assessment of parameter uncertainty of CRR models should become the integral part of regionalisation. For that reason, we proposed a regionalisation scheme which instead of regionalizing the single best value of model parameters, regionalizes the PPD of model parameters. Subsequently the number of model parameters are sampled from the estimated distribution and fed into the model. Regionalisation of PPD addresses the effect of model parameter uncertainty in the result of regionalisation. The uncertainties in model prediction quantified from proposed methods closely followed the prediction uncertainties quantified from PPD of model parameters conditioned on observation in the presented case study.

**Key Words:** Posterior probability distribution, Rainfall-runoff models, Regionalisation, Uncertainty

## 1. INTRODUCTION

Conceptual Rainfall Runoff models (CRR) are popular tools for modeling flow at gauged site. Though some parameters of CRR model have a physical basis, they are effective values at the catchments scale and are hardly measurable in the field. Therefore, they are obtained by calibrating the model against observed data. This need to calibrate the parameters has led to linking of model parameters of CRR models with catchment attributes in order to model flow at ungauged site. Number of methods for transferring or regionalizing the parameters have been explored in the past<sup>1), 2)</sup>. Among various method, the use of multiple regressions to relate Model Parameters (MPs) to measurable Catchments Attributes (CAs) is widely used in modeling ungauged basin<sup>2), 3)</sup>. This typically results in set of multiple regression equation which estimates one model parameter at a time rather than equations that jointly estimate model parameters. Thus any information about covariances and variances of model parameter is usually lost.

Regionalizations using multiple regressions are straight forward, but are illusive due to the existence of multiple optima and high interaction between

subsets of fitted MPs. The need to address various sources of uncertainty that arises during the process of regionalisation of the parameters has drawn much attention in recent years. Merz and Blöschl<sup>1)</sup> addressed the issue of the uncertainties in MPs through a comparison of MPs for two sub periods. Sequential regression (SR) addresses this issue by combining model calibration with regionalization. Moreover, Regional calibration<sup>4), 5)</sup> also referred to as indirect calibration method addressed this issues by skipping the direct calibration of models. This approach calibrates the MPs at all site simultaneously in an attempt to achieve the best regional relationship. Similarly, Wagener et al.<sup>2)</sup> used weighted regression in higher weighted is provide to the parameters having higher identifiability and vice versa to reduce the influence of gauged catchment parameters that were poorly identified during calibration.

However, none of these approaches explicitly used posterior distribution of model parameters while doing regionalization. Though SR relaxes the assumption that the model parameters are independent and helps in improving the identifiability of MPs, it is difficult to apply without introducing bias into the regionalized parameters<sup>2)</sup>.

Similarly, regional calibration method failed to identify the unique regional relationship thereby inducing considerable uncertainties in model prediction<sup>4)</sup>. Weighted regression also does not introduce weights to allow for the model's local performance and neglects the interdependency among model parameters. Furthermore, the determination of identifiability is dependent on the sample size. In this context, this paper aimed at developing an approach for the regionalisation of parameters of CRR models considering the uncertainty in the calibrated model parameters. The methodology is demonstrated through a case study that includes number of small to medium size basin located in different geographic and climatic regions.

## 2. METHODOLOGY

In most CRR models, the model parameters are typically strongly correlated leading to the existence of multiple optima. Thus such information should be included in deriving a regionalisation procedure. To accomplish this, it is assumed that the Posterior Probability Distribution (PPD) of MPs of parsimonious models can be approximated by multivariate normal distribution (i.e. the posterior mean and entries of variance covariance matrix) and they vary among basin depending on basin attributes and data aspects. Consequently, the determination of functional relationship between the characteristic parameters of PPD of MPs and basin attributes is plausible.

The outline of the regionalisation schemes proposed in this study is as follows:

1. Select a number of gauged basin and estimate vectors of relevant catchment attribute.
2. Calibrate the MPs of the selected hydrological model for all basins using Markov Chain Monte Carlo method. Subsequently estimate the Multivariate Posterior joint Probability Distribution function  $p(\theta|D)$  (PPD) of hydrologic model parameters for all basins assuming that it can be sufficiently approximated by multivariate normal distribution (Eq.1).

$$p(\theta|D) \propto \exp\left(-\frac{1}{2\sigma^2}(\theta - \mu)^T \Sigma^{-1}(\theta - \mu)\right) \quad (1)$$

where  $\Sigma$  is a variance covariance matrix,  $\mu$  (posterior mean),  $\theta$  is the model parameter.

3. Identify the posterior mean vector  $\mu$ , and the set of pair wise covariances  $\text{Cov}(X_i, X_j)$ , including the variance  $\text{Var}(X_i)$  from the estimated PPD of model parameters.
4. Identify the functional relationship between the characteristic parameters of PPD of model parameters and catchment attributes.
5. Reconstruct the PPD of model parameters at

ungauged basin from the functional relationship derived in step 4. Subsequently sample model parameters ( $\theta$ ) falling in a pre-specified confidence region i.e. the parameters set that satisfies Eq.2.

$$(\theta - \mu)^T \Sigma^{-1}(\theta - \mu) < \chi^2_{\alpha-1,p} \quad (2)$$

where  $\alpha$  is the significance level.

6. Estimate the ensemble of simulated flow from number the parameters sampled in step 5

This approach relaxes the assumption that parameter is independent and thereby preserves the information on the correlation between MPs.

## 3. CASE STUDIES

### (1) Study area and data aspects

The 26 small to medium size basins situated in different geographic and climate zones (Table 1) were selected. The 21 catchments were considered for calibration of regional model and 5 catchments each located in 5 different countries (e.g., 330, Ukaibashi, H744010, 27035 and 215004) were presumed ungauged for the appraisal of the performance of regionalisation schemes.

To link the calibrated values of model parameters with easily measurable basin attributes, number of landscape attributes were selected in this study, which are as follow: (1) area (km<sup>2</sup>), (2) average topographic index (Ave. Topographic index), (3) shape factor (km/km<sup>2</sup>), (4) Basin average saturated transmissivity (Ave. Transmissivity) (cm/h), (5) basin average maximum root zone depth (Ave. SRMAX) (m), (6) mean Elevation (m), (7) average basin slope (%), (8) drainage density (km/km<sup>2</sup>).

**Table 1** Description of selected basins

ID	Catchment	AreaKm <sup>2</sup>	ID	Catchment	AreaKm <sup>2</sup>
1	330 <sup>a</sup>	1980	14	J3024010 <sup>e</sup>	43
2	795 <sup>a</sup>	1148	15	J4124420 <sup>e</sup>	32
3	390 <sup>a</sup>	554	16	J4712010 <sup>e</sup>	142
4	Torinkyo <sup>b</sup>	1095	17	H2001020 <sup>e</sup>	98
5	Arakawa <sup>b</sup>	927	18	Y5615030 <sup>e</sup>	297
6	66011 <sup>c</sup>	344	19	K0753210 <sup>e</sup>	371
7	62011 <sup>c</sup>	893	20	K0813020 <sup>e</sup>	193
8	23006 <sup>c</sup>	331	21	V3517010 <sup>e</sup>	25
9	27034 <sup>c</sup>	510	22	395.5 <sup>a</sup>	683
10	204017 <sup>d</sup>	82	23	Ukaibashi <sup>b</sup>	487
11	302200 <sup>d</sup>	448	24	K0744010 <sup>e</sup>	181
12	218001 <sup>d</sup>	93	25	27035 <sup>c</sup>	282
13	145018 <sup>d</sup>	81	26	204016 <sup>d</sup>	104

a) catchments located in Middle mountain physiographic region of Nepal and data were obtained from Department of Hydrology and Meteorology (DHM), Nepal, b) Catchments located in Japan, and data were obtained from Ministry of Land, Infrastructure and Transport (MLIT), Japan, c) catchments located in UK, and data were obtained from <http://www.ceh.ac.uk/data/nrfa/index.html>, d) catchments located in eastern Australia, and data were obtained from <http://www.stars.net.au/tdwg/?datasets> e) catchments located in France, and data were obtained from Model Parameter Estimation Experiment (MOPEX)-France.

Moreover, as the basins selected in the study are situated in different climate zones, a number of climate attributes were also considered and are as follow: (1) annual average rainfall (mm), (2) variance of monthly precipitation measured in mm, and (3) wetness index. In order to extract the landscape attributes for all basins, the land use data obtained from International Geosphere-Biosphere Programme (IGBP), soil data obtained from Food and Agricultural Organization (FAO), and The Shuttle Radar Topography Mission (SRTM) data that cover the entire globe with a 3-arc second (approx. 90m) digital elevation model were used.

## (2) Hydrological model

The TOPMODEL<sup>6)</sup>, which is a variable contributing area physically-conceived semi-distributed hydrological model, was selected. Based on a simple theory of hydrological similarity of points in a catchment, TOPMODEL makes distributed prediction of catchment response. These points of hydrological similarity are identified by an index that is derived from catchment topography. Flow is separated into surface runoff generated by rainfall on saturated contributing areas and subsurface downhill flow. TOPMODEL uses four basic assumptions to relate local down slope flow from a point to discharge at the catchment outlet: 1) The dynamics of the saturated zone are approximated by successive steady state representations, 2) The recharge entering the water table is spatially homogeneous, 3) The effective hydraulic gradient of the saturated zone is approximated by the local surface topographic gradient, 4) The distribution of down slope transmissivity  $To$  with depth is a function of storage deficit. The parameters requiring calibration are the

decay parameter (m) ( $m$ ), lateral transmissivity ( $To$ ) ( $m^2/h$ ), delay factor ( $Td$ ) (h/m), maximum root zone storage ( $Srmax$ ) (m), and parameters related to channel routing. As we focused on modeling flow in small to medium size basin at daily time scale, the routing of flow is not implemented. Moreover, the  $Srmax$  parameter was estimated from the root zone depth and soil properties<sup>6)</sup>. The inputs of the model are the land cover map, digital elevation model, soil map, daily precipitation, and potential evaporation data and daily streamflow data for calibration of parameters.

## (3) Model calibration

As multi-objective calibration eases in retrieving more information from the observed data and provides insight into parameter uncertainty and limitation of model structure, the multi-objective shuffle complex evolutionary algorithm<sup>7)</sup> (MOSCEM-UA) was used. The primary strength of MOSCEM-UA is the estimation of the PPD of CRR model parameters and is best suited for calibration of models that have small number of model parameters<sup>8)</sup>. For calibration the following goodness of fit criteria were used: (1) The Nash Sutcliffe efficiency (NSE), (2) NSE for the transformed flow to consider the heteroscedastic variance in flow, here the flow is transformed explicitly by using,  $z = [(y + 1)^\lambda - 1] / \lambda$ , where  $\lambda = 0.3$ ,  $z$  is the transformed flow, and  $y$  is the observed flow before evaluating the objective function, (3) NSE for low flow, and (4) NSE for peak flow. The result of model calibration i.e. the most probable value of MPs, the coefficient of variation (CV) of model parameters and correlation coefficient of MPs, for all basins is shown in Table 2. The variation in the CV of model parameters indicates that the degree of

**Table 2** Most probable parameters, coefficient of variation, and correlations among model parameters

Basin ID	Posterior mean			Coefficient of variation			Correlation coefficient		
	m(m)	To ( $m^2/h$ )	Td (h/m)	m	To	Td	(m,To)	(m,Td)	(To,Td)
1	0.115	10	0.4	0.059	0.522	0.818	0.296	-0.359	-0.699
2	0.05	6	0.5	0.380	0.082	0.421	-0.072	-0.811	0.021
3	0.09	5	1.5	0.171	0.065	1.004	0.047	-0.609	0.203
4	0.11	5	1	0.238	0.087	0.844	0.623	-0.459	-0.163
5	0.027	3.75	0.75	0.178	0.080	0.759	0.781	-0.710	-0.385
6	0.013	4.2	0.5	0.043	0.016	0.698	0.085	-0.014	-0.153
7	0.027	6	2.5	0.095	0.044	0.710	0.776	-0.171	-0.252
8	0.015	3.5	2	0.089	0.038	0.674	0.158	-0.204	0.012
9	0.011	4.85	4	0.108	0.042	0.646	-0.502	-0.106	-0.008
10	0.068	5.2	1.5	0.025	0.032	0.642	0.481	-0.039	-0.098
11	0.275	1.25	2.5	0.293	0.297	1.404	-0.831	0.324	-0.498
12	0.03	2.25	1	0.417	0.199	0.743	-0.282	-0.715	0.416
13	0.275	1.25	1.5	0.210	0.333	1.444	-0.340	0.110	-0.055
14	0.095	4.8	1	0.056	0.008	0.677	-0.050	-0.031	0.073
15	0.15	5.5	1.2	0.149	0.041	0.840	0.715	-0.188	-0.185
16	0.045	6.2	1.5	0.163	0.034	0.691	-0.515	-0.201	0.087
17	0.045	4.1	2.5	0.193	0.037	0.648	-0.571	-0.337	0.112
18	0.04	4.8	1.6	0.150	0.057	0.704	0.123	-0.222	-0.113
19	0.037	4.7	0.5	0.056	0.023	0.681	0.327	-0.053	-0.015
20	0.03	4.5	1.8	0.144	0.133	0.649	-0.491	0.866	-0.596
21	0.038	6.25	1	0.078	0.070	0.640	-0.279	-0.005	0.077

uncertainties in MPs varies from basin to basin depending on the basin attributes and data aspect. Moreover, the model parameter  $m$  and  $To$  were found comparatively sensitive than  $Td$ . Moreover, the correlation between the model parameters also varied among basins.

#### (4) Regionalisation of posterior probability distribution of model parameters

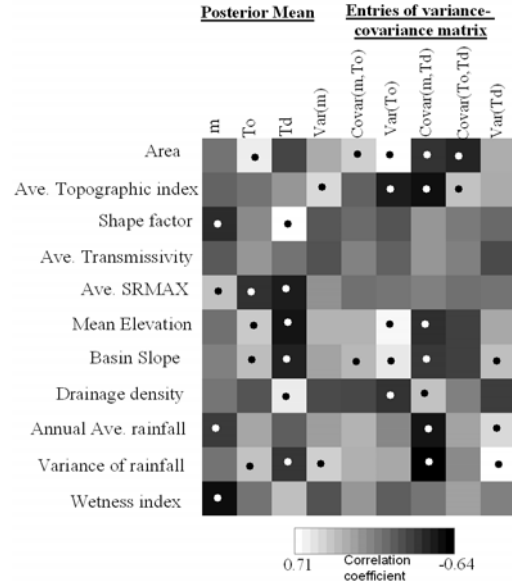
The posterior probability distribution can be entirely characterized by its mean, set of pair wise covariance and variances if it can be sufficiently approximated by multivariate normal distribution. For the structure of model use in this study, the number of characteristic parameters of PPD to be estimated via regional link function is nine i.e., three posterior mean and six entries of variance covariance matrix. The variance covariance matrix for the parameters of TOPMODEL used in this study can be expressed as following (Eq.2):

$$\sum_i = \begin{bmatrix} VAR(m)_i & COV(m, T_0)_i & COV(m, T_d)_i \\ COV(m, T_0)_i & VAR(T_0)_i & COV(T_0, T_d)_i \\ COV(m, T_d)_i & COV(T_0, T_d)_i & VAR(T_d)_i \end{bmatrix} \quad (2)$$

where  $\sum_i$  is the variance covariance matrix for the  $i^{th}$  basin,  $COV(m, T_0)_i$ , is the covariance between  $m$  and  $To$  (model parameter) for  $i^{th}$  basin, and  $Var(m)_i$  is the variance of the model parameter  $m$  for  $i^{th}$  basin. The linear correlation between the characteristics parameters of probability distribution of model parameters and catchment attributes (see Fig.1) apparently shows the prospect for developing the statistical relationship between the above mentioned dependent and independent variable (CAs). Moreover, some of the attributes were strongly correlated with each other. So to reduce the effect of multicollinearity, we combined various independent variables and selected only those combined variables for which the Variation Inflation Factors (VIF) is less than 10. The VIF expresses the degree to which collinearity among the predictors degrades the precision of an estimate.

The close look on the variance covariance matrix reveals that the interaction between MPs varied among basins. The linear correlation between the catchment attributes and covariance between model parameters reveals the following:

- 1) For basin with larger area and basin slope, the covariance between  $m$  and  $To$  is positive.
- 2) For basins with higher average topographic index and higher variability in monthly average rainfall, the covariance between  $m$  and  $Td$  is negative.
- 3) For larger basins, the covariance between  $To$  and  $Td$  is negative, whereas it is positive for basins characterized with lower average topographic index.



**Fig.1** Linear correlation calculated between catchment attributes and both posterior mean value of model parameters (MPs) and entries of variance covariance matrix of the posterior distribution of MPs approximated by multivariate normal distribution. The attributes that are significantly correlated with model parameters are marked with black and white marker

#### a) Regionalisation procedure

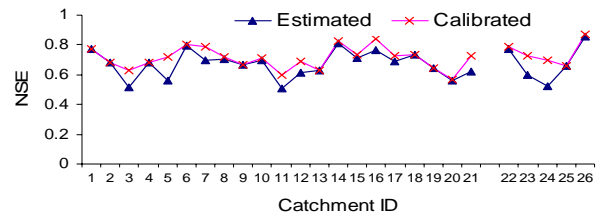
A close look into the work by Uhlenbrook *et al.* (1999) and Seibert (1997) reveals that the model parameter uncertainty depends on basins, forcing data and the structure of the hydrological model used. Moreover, Fig.1 also reveals that the entries of parameter variance covariance matrix are significantly correlated with few basin attributes. So, based on the assumption that basin with similar characteristics and data aspects will have similar PPD of model parameters, development of functional relation between characteristics parameters of PPD (i.e. posterior mean and entries of parameter variance covariance matrix) and catchment attributes is plausible. Assuming that the combinations of attributes are able to capture the exclusivity of each catchment, the method based on regional link function (i.e.  $\theta = H(\beta | \Phi) + e$ , where  $\theta$ ,  $\beta$  and  $\Phi$  are dependent variables (e.g. model parameters and entries of variance covariance matrix of MPs), regional parameters and catchment attributes respectively,  $H(.)$  is a functional relation between  $\theta$  and  $\beta$ , and  $e$  is the error term) was used as a regionalisation schemes. Here in this study, we used second order polynomial form to regionalize the value of posterior mean; however, for the coefficient of variance covariance matrix, we employed the generalized regression approach (i.e. artificial neural network). Artificial neural networks (ANNs) are more flexible model structures that can easily account for non-linearities. For the ANN-based schemes, the popular feed forward

neural network was used, consisting of three layers: the input layer, one hidden layer and output layer.

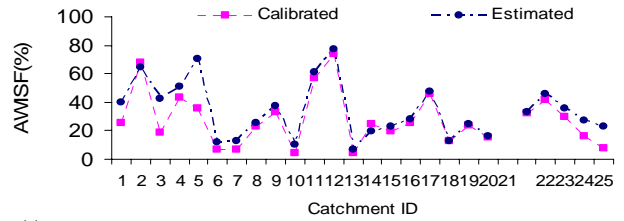
The regional link function estimates the posterior mean and variance covariance matrix from easily measurable catchment attributes. Subsequently numbers of model parameters that lie with in pre-specified confidence region can be sampled from the estimated PPD and fed into the model. Moreover, sampling the MPs from its regionalized posterior distribution will take into account the interdependency among MPs while estimating it for the target basin.

#### 4. RESULTS AND DISCUSSION

The parameter of the TOPMODEL was calibrated using 3 years of daily hydro-meteorological data utilizing MOSCEM-UA. As the calibrated parameters could not be uniquely identified, regionalisation is accomplished for all parameters simultaneously via a regional link function that links the posterior means to watershed characteristics. The simulated flow corresponding to posterior mean values explained much of the variability in observed runoff in basin considered for regionalisation. The performances of model evaluated in terms of NSE for posterior mean value of MPs varied from 0.52 to 0.86. The predictive model performance corresponding to MPs estimated from regional link function that links posterior mean with CAs for all basins is shown in Fig 2. The losses in model performance due to the use of regionalized value instead of calibrated value, and the spatial proximity of the estimated MPs were used for the evaluation of the predictive performance of regionalisation schemes. The spatial loss in the model performance is 7% for basins considered for calibration and 12% for basins presumed ungauged. The standard error in the estimated parameters is 0.009, 0.207, and 0.77 respectively for the model

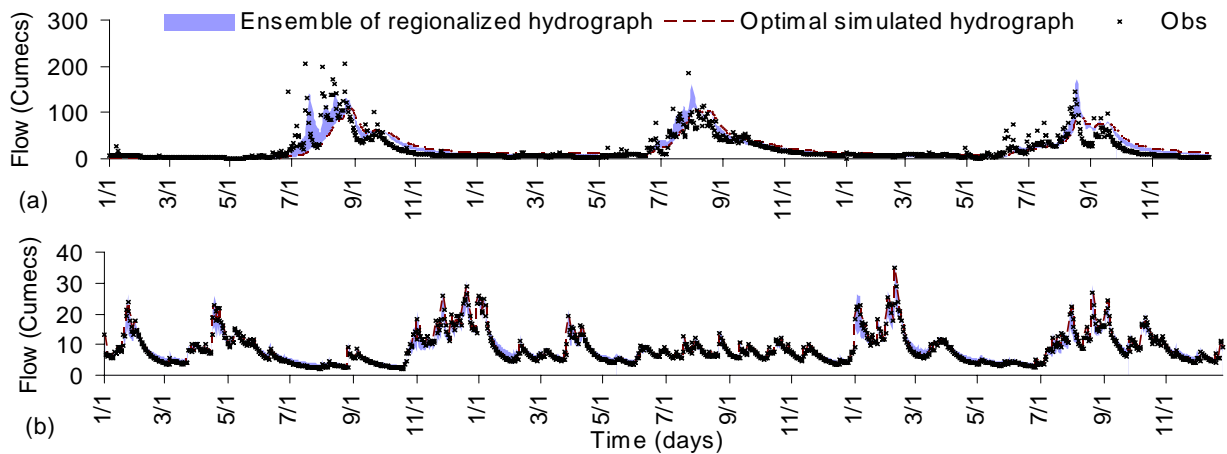


**Fig.2** Predictive performance of Regional model compared to the calibrated performance.



**Fig.3** Average Width of the Interval of Simulated Flow (AWISF) corresponding to model parameters (MPs) sampled from regionalized Posterior Probability Distribution (PPD) of MPs (Estimated) and PPD of MPs conditioned on observation (Calibrated).

parameter  $m$ ,  $To$  and  $Td$ . The PPD of model parameters provides insights into the uncertainty and the interaction among model parameters. The extent of interaction and uncertainty of MPs vary from basin to basin (Table 2) depending upon CAs. Uncertainties in the model parameter  $To$  was higher in larger basins, characterized with higher elevation, steeper slope and lower wetness index. Besides  $To$  and  $m$ , CV of  $Td$  was also significantly correlated with annual average rainfall and SD of monthly rainfall. The effect of model parameter uncertainty is approximately quantified here as the Average Width of the Interval of the ensemble of Simulated flow in % (AWISF) resulted from using numbers of MPs sampled (lying with in 90% confidence region) from the PPD of model parameters. The AWISF for all basins corresponding to MPs sampled from its PPD conditioned on observation and is referred to as calibrated PPD here after (see Fig. 3) is significantly correlated with CV of model parameters. A close



**Fig.4** Ensemble of simulated hydrograph obtained from the MPs sampled from regionalized posterior probability distribution of MPs for two basins presumed ungauged (a) 395.5 (Nepal), (b) 27035 (UK)

look into the prediction uncertainties and CAs reveals that higher prediction uncertainties are found to be associated with basins characterized with following attributes: Larger area, higher elevation, steeper slope, lowers wetness index, and higher variance in monthly rainfall. The prediction uncertainties were observed lower in French and English basins selected in this study compared to selected Nepalese and Japanese basin.

Once the PPD of MPs is estimated using the regional estimation equations, 500 various sets of MPs that satisfy equation 2 at 90% confidence level were sampled. The AWISF corresponding to the MPs sampled from estimated PPD was compared with the same obtained from MPs sampled from the calibrated PPD (Fig.3). The uncertainties in prediction measured in terms of AWISF for the MPs sampled from its regionalized and calibrated PPD were significantly similar to one another. The average value of AWISF obtained from the MPs sampled from its calibrated PPD were approximately 28% for basins considered for calibration and 25% in basin presumed ungauged, whereas the AWISF obtained from the MPs sampled from estimated PPD (referred to as estimated in Fig.3) were 34% and 33% in basins considered for calibration and validation respectively. Furthermore, the ensemble of simulated flow obtained from MPs sampled from regionalized PPD of MPs for two selected basin is shown in Fig.4. Even though the simulated ensemble of flow encapsulated the simulated flow corresponding to posterior mean value of MPs, it could not encapsulate completely the observed time series. The observed annual average flows for most of the basins were within the ensemble ranges except for Torinkyō (Japan), K0813020 (France) and Y5615030 (France) where it fell marginally outside the ranges of simulated annual average flow. This is more likely due to the insufficiency of model structure, because, even the ensemble of simulated flow corresponding to MPs sampled from the calibrated PPD of model parameters failed to encapsulate the annual average flow in these three basins.

## 5. CONCLUSIONS

Parameters of hydrological model can not be identified as a single value due to the interaction among model parameters. Close observation into the PPD of model parameters conditioned on observed streamflow revealed that despite using parsimonious model with only three parameters to be calibrated, the uncertainty in model prediction is apparent. Moreover, the variations in the PPD of model

parameters were apparent among basins, thereby suggesting that the uncertainties in MPs depend on the physical characteristics of basins and data aspects. Therefore an attempt to regionalize of PPD of model parameters is demonstrated through the case study involving number of small to medium size basins and TOPMODEL. The prediction uncertainties quantified from the model parameters sampled from regionalized PPD closely followed the same quantified from the MPs sampled from its probability distribution conditioned on observation indicating the prospect of the proposed method in dealing with model parameter uncertainty while doing regionalisation. Due to the assumption of TOPMODEL, the functional relationship developed in this study can be more accurately applied to catchments where the assumptions of the model are met, primarily wet catchments that have shallow, homogeneous soils, small to medium size.

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