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Low-Flow Assessment Methods for Ungauged Sub-Basins in the Upper Ping River Basin, Thailand

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Abstract

The assessment of low-flow in ungauged or poorly-gauged basins where the flow data are unavailable remains a challenge in many parts of the world. This study aims to address the low-flow assessment in the ungauged sub-basins in Thailand by regionalizing low flow indices including the base-flow index (BFI), 95th percentile-flow (Q95) and the annual minimum 7-day moving average flow with a 10-year recurrence interval (7Q10). The framework is demonstrated through the case study of 25 sub-basins of the Upper Ping River basin with available data from 1995-2014. Performance of two widely used regionalization methods, the regression and climate adjustment methods are tested and compared. The accuracy of the methods is assessed by comparing the predicted with the observed low-flow indices calculated in terms of R^2, NSE, and RMSE. The results of the regression method indicate that the method performs best for predicting 7Q10 compared to Q95 and BFI. The best R^2, RMSE, and NSE values obtained from the regression model for predicting 7Q10 are 0.95, 0.95, and 0.26 respectively. The results of the climate adjustment method show that the method with a comparatively long overlap period is found to improve over the regression method. The longest 15 overlap period tested in this study show that the R^2 and RMSE can be improved to almost 1.00 and NSE can be reduced to 0.09. While this study could offer a way forward improving low-flow estimation and water resources management in ungauged basins, further study on non-stationarity of the basin is recommended.

Keywords: Climate adjustment, Low-flow indices, Record augmentation, Regional regression, Upper Ping River Basin

1. INTRODUCTION

Water is vital for human living and essential for environmental, economic, and ecological management. Due to the growth of the global population, the water demand for food production and social development towards better living conditions have also been increasing (Kundzewicz, 1997). Since the amount of water is limited especially in the dry year while the demand has increased higher, this may lead some areas to face the problem of water scarcity. In order to cope with the problem, the management of water resources is necessary. In recent years, water resources management has become more focused on mid-term and long-term planning for water demand and conservation management, water transfer, and diversion (Karamouz et al., 2003). For riparian countries, monitoring of flow characteristics in the river basin is the principal for water resources management responding to the problem of water scarcity. One of the most essential indicators which are beneficial for flow characterization is known as "low-flow" which is defined as "flow of water in a stream during prolonged dry weather" (Smakhtin, 2001). During low-flow periods, most stream habitats are reduced in area and and may also affect biota. Low-flow characteristics information provides threshold values for different water-based activities and is required for some water resources management such as irrigation, water supply, and water quality and quantity estimations (Eslamian, 2018).

In Thailand, there are more flood studies than drought or low-flow. The method for low-flow estimation has been paid little attention. This study focuses on assessing the techniques for estimating low-flow in gauged and ungauged sub-basins of the Upper Ping River basin where the hydrological study is particularly challenging due to limited available data. A previous study by Visessri (2014) used BFI as a low-flow index to predict flow in the Upper Ping River basin. This study introduced other two low-flow indices (Q95 and 7Q10) that might be useful for the prediction in ungauged basins. The objective of this study is to define the applicable method for low-flow estimation in ungauged sub-basins of the Upper Ping River basin which is the headwater of the Chao Phraya basin. If the low-flow in the Upper Ping River basin can be monitored, it could also reduce the risk of water scarcity in the Chao Phraya basin.

2. DATA

2.1 Study Area

This study is conducted in the Upper Ping River basin which is in the northwestern part of Thailand. It stretches from latitude 17°00'N to 19°48'N and from longitude 98°05'E to 99°23'E and covers a total area of 26,674 km^2 with elevation ranges from 195 to 2577 m a.s.l (meter above mean sea level) as shown in Figure 1. The west of the basin is mainly mountainous while the central and the east of the basin are relatively flat. The major water resource is the Ping River flowing from the north to the south. The Bhumibol reservoir separates the upper and lower part of the Ping basin. The basin has a varied climate with a mean annual rainfall of 1,097 mm (Sharma & Babel, 2014).

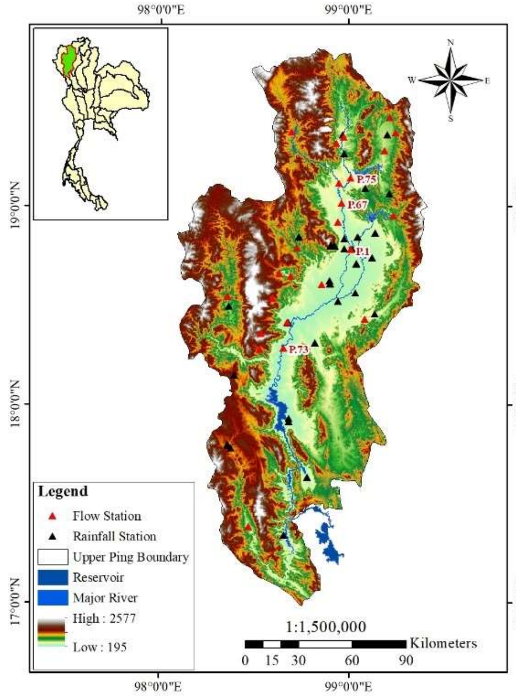

Figure 1 Elevation of the Upper Ping River basin

2.2 Flow Data and Rainfall Data

Flow data and rainfall data used in this study are daily series from 25 flow gauges obtained from the Royal Irrigation Department (RID) and the Department of Water Resources (DWR) and 43 rain gauges obtained from RID and the Thai Meteorological Department (TMD) which have been continuously monitored from 1995 to 2014, respectively. The study period from 1995 to 2014 was selected because it has a relatively small amount of missing data and sufficiently long records for low-flow assessment. The rainfall and streamflow time series from those stations are shown in Figure 2.

2.3 Land Use

Land use is classified into five main different types, such as Forest (F), Agriculture (A), Urban (U), Open water (W), and Mixed land-use (M). The major land use of the Upper Ping River basin is the forest which covers the area of 21,235 km^2 or equal to approximately 80% of the total area. The second majority is agriculture which covers another 14% of the total area while the urban, open water and mixed land-use areas show a minor proportion to the total area. The information mentioned above is obtained by overlapping the basin boundary with the land use data of year 2005 obtained from the Land Development Department (LDD), Thailand. The land use data of year 2000 are assumed to sufficiently represent the land use condition and have negligible change over the entire period of study. This assumption is supported by the study of Visessri & McIntyre (2015) which found that the land use change in the Upper Ping River basin was not significant enough to cause an impact on the regionalized flow indices (Visessri & McIntyre, 2015).

2.4 Soil Type

Based on the soil type data obtained from LDD, there are thirty-six soil types in the Upper Ping River basin. However, only four types among the total show the major value in terms of proportion to the total area. The first majority is Soil type group 62 which distributes about 70% and can be found almost everywhere in the basin. The second and third majorities are Soil type group 48 and Soil type group 20 which distribute about 9% and 3% to the basin, respectively. Another majority which distributes about 3% to the basin also is Soil type group 29. When considering the soil type of the 25 sub-basins used in this study, Soil type group 62 remains dominant; other soil types cover much smaller area.

A summary of the basin characteristics of the 25 sub-basins used in this study is given in Table 1.

2.5 Low-flow Characteristics

There are three commonly used low-flow indices (LFI) chosen in this study. They are ninety-five-percentile flow (Q95), baseflow index (BFI), and annual minimum 7-day moving average flow with a 10-year recurrence interval (7Q10).

2.5.1 Ninety-five-percentile Flow (Q95)

Q95 represents flow that is equaled or exceeded for 95 percent of the observation period and can be determined from the flow duration curve (WMO, 2008). It can be used for establishing low-flow criteria for stream standards. Furthermore, it can be used as a reference streamflow level to differentiate drought flows from nondroughted flows (Zelenhasić & Salvai, 1987). The value of Q95 is calculated for all 25 gauges from continuous daily flow data between 1995 and 2014 and is assumed to represent the long-term average of Q95.

2.5.2 Baseflow Index (BFI)

BFI is a non-dimensional index that is defined as the baseflow volume divided by the total streamflow volume. The values range between 0 and 1. The high index of baseflow indicates that the river flow can be sustained by the basin during a prolonged dry period (WMO, 2008). In this study, the BFI is determined using the method of local minimum as described in (White & Sloto, 1990) for all the 25 gauges.

2.5.3 Annual minimum 7-day moving Average Flow with a 10-year Recurrence Interval (7Q10)

7Q10 is determined from the annual series of minimum 7-day moving average flow at the selected 25 gauges. The average flow for each consecutive 7-day period is calculated from the daily records, and the lowest average value for each year represents that year in the annual series. The 7-day minimum average flows are fit to a log-Pearson Type III distribution to determine the recurrence interval for an individual 7-day minimum mean flow (Riggs, 1972).

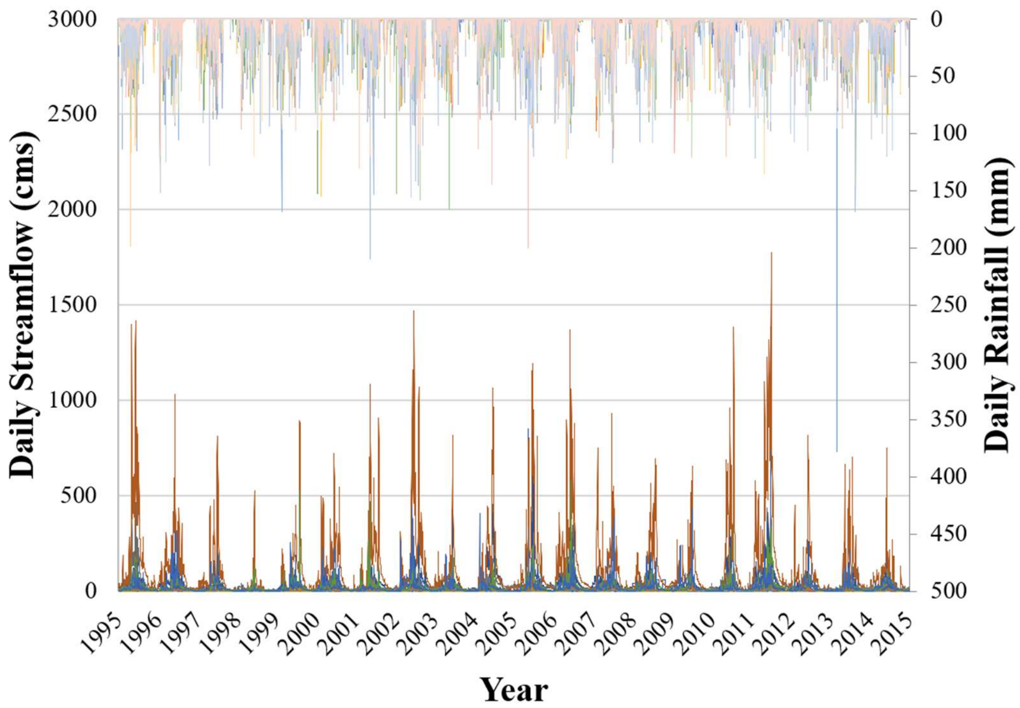

Figure 2 Daily rainfall and streamflow time series

Table 1 Statistical summary of the basin characteristics of the 25 sub-basins used in this study

Acronym	Variable description	Units	Minimum	Mean	Maximum
%A	Percentage of agriculture	%	0.01	14.43	31.17
%F	Percentage of forest	%	64.68	83.78	98.09
%G30	Percentage of soil type group 30	%	0.00	0.84	13.79
%G40	Percentage of soil type group 40	%	0.00	0.25	3.05
%G56	Percentage of soil type group 56	%	0.00	0.01	0.20
%G60	Percentage of soil type group 60	%	0.00	0.07	0.84
%G62	Percentage of soil type group 62	%	63.87	85.48	99.99
%M	Percentage of mixed-land use	%	0.00	0.42	3.37
%W	Percentage of open water	%	0.00	0.08	0.54
AMR	Annual mean rainfall	mm	912.90	1117.43	1305.40
Ar	Basin area	km^2	23.43	1638.54	14536.02
El_{max}	Maximum elevation	m	1251.00	1968.12	2577.00
El_{min}	Minimum elevation	m	195.00	436.44	1024.00
Sl_{max}	Maximum slope	%	116.25	236.32	441.30
Sl_{mean}	Mean slope	%	24.93	31.30	41.82

3. METHODOLOGY

There are two regionalization methods namely regional regression and climate adjustment used in this study because they performed reasonably well, and they require a few hydrological variables that allow us to test its applicability in the study area.

3.1 Regional Regression Method

Regional regression is a frequently used method to develop a relationship between LFI and an ‘optimal’ set of basin characteristics. The regression in this study is established using stepwise linear regression for homogeneous subregions to predict low-flow characteristics in ungauged sub-basins(Laaha et al., 2013). As stated in (Nathan & McMahon, 1992), a common form of prediction equations can be simplified as Eq. (1).

$$LFI = f(basin\ characteristics) \quad (1)$$

3.2 Climate Adjustment Method

The climate adjustment method is one of the methods to deal with the problem of low-flow estimation from a short streamflow record. The method consists of two steps which are the donor site selection and the record augmentation (Laaha & Blöschl, 2005). Unlike the regression method that is primarily based on the spatial relationship between the basin characteristics and LFI, the climate adjustment method is believed to be able to account for the influence of temporal variation of the climate on the prediction of LFI.

3.2.1 Donor Site Selection

In this study, the donor is selected based on the shortest Euclidean distance between the centroid of the donor (gauged) sub-basin and the centroid of the subject (ungauged) sub-basin or it is called the “Nearest basin method”.

3.2.2 Record Augmentation

Once the suitable donor has been selected, the predicted LFI at the subject site can be adjusted by transferring the information from the donor based on two record augmentation techniques.

In the first technique, the predicted low-flow characteristic at subject site (QS_{pred}) is adjusted by scaling LFI calculated from the overlap period of the subject site (QS_o) with the ratio of LFI calculated from the entire observations period and LFI calculated from the overlap period of the donor site (QD and QD_o). In this study, four overlap periods of 1-yr, 5-yr, 10-yr, and 15-yr are selected to test the predictive performance. The predicted LFI at the subject site can be extrapolated using Eq. (2).

$$QS_{pred} = QS_o \times \left(\frac{QD}{QD_o}\right) \quad (2)$$

The second technique applies the same principle, but a weighting coefficient M(r) is included to account for the robustness of correlation between subject and donor sites. The predicted LFI at the subject site can be extrapolated using Eq. (3).

$$QS_{pred} = QS_o \times \left(\frac{QD}{QD_o}\right)^{M(r)} \quad (3)$$

where M(r) considers the length of the overlap period in years (n_o), as well as the correlation coefficient (r) of annual low flows and, can be calculated using Eq. (4).

$$M(r) = \frac{(n_o-3).r^3}{(n_o-4).r^2+1} \quad (4)$$

3.3 Evaluation of Methods Performance

To define the most applicable method between the spatial regionalization and the temporal regionalization methods, the scatter plot between observed and predicted LFI for each method will be constructed and the statistical indicators including coefficient of determination (R^2), root-mean-square error (RMSE) and Nash-Sutcliffe efficiency (NSE) will be calculated to define which method is the most applicable for this study.

3.3.1 Nash-Sutcliffe Efficiency

The Nash-Sutcliffe efficiency is a normalized statistic that determines the relative magnitude of the residual variance compared to the measured data variance. NSE indicates how well the plot of observed versus predicted LFI fits the 1:1 line (Moriasi et al., 2007). NSE can be computed by using Eq. (5).

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n}(O_i-P_i)^2}{\sum_{i=1}^{n}(O_i-\bar{O})^2}\right] \quad (5)$$

where O_i is i^{th} observed low-flow indices, P_i is i^{th} predicted low-flow indices, $\bar{O}$ is mean of observed low-flow indices, and n is total number of observations.

3.3.2 Root-Mean-Square Error

The root-mean-square error is the square root of the mean of the square of all the errors. It is considered as an excellent general-purpose error metric for numerical predictions. RMSE is a good measure of accuracy, but only to compare prediction errors of different models or model configurations for a particular variable and not between variables, as it is scale-dependent (Neill & Hashemi, 2018). It can be computed by using Eq. (6).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2} \quad (6)$$

3.3.3 Coefficient of Determination

The coefficient of determination is the criterion generally used in the linear regression to test the adjustment of the model (Ait-Amir et al., 2020) and can be calculated by using Eq. (7).

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O_i-\bar{O})\times(P_i-\bar{P})}{\sqrt{\sum_{i=1}^{n}(O_i-\bar{O})^2}\times\sqrt{\sum_{i=1}^{n}(P_i-\bar{P})^2}}\right]^2 \quad (7)$$

where $\bar{P}$ is predicted low-flow indices

4. RESULTS AND DISCUSSIONS

The results are divided into three parts including the estimation of the observed and regionalized low-flow indices.

4.1 Low-flow Indices

4.1.1 Ninety-five-percentile Flow (Q95)

Figure 3 illustrates the flow duration curves (FDCs) of the 25 flow stations used in this study. It can be seen from Figure 3 that FDCs developed from the three located mainstream stations namely P.73, P.1, and P.67 indicate much higher flows for overall compared to the others. The Q95 of the 25 flow stations are then determined from the FDCs.

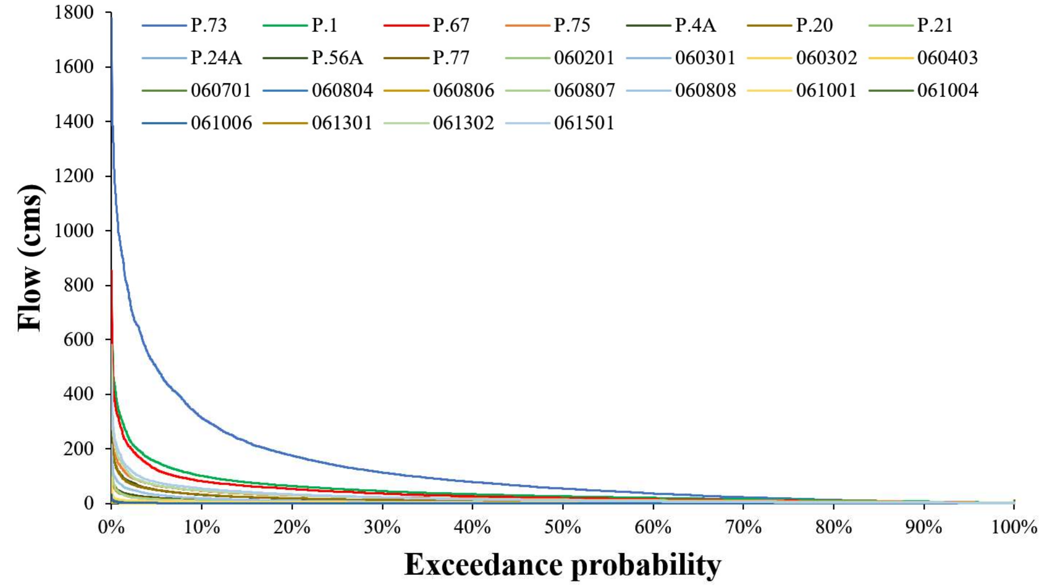

Figure 3 FDCs of the 25 selected flow stations

4.1.2 Baseflow Index

Figure 4 demonstrates the baseflow lines of the 25 selected flow stations. Similar to the FDC, the baseflow line developed from the three located mainstream stations namely P.73, P.1, and P.67 indicate much higher flows for overall comparing to the others. The plot also depicts that the daily baseflow in the 25 sub-basins has a similar pattern, but they are different in amount. The BFIs are then defined as the baseflow volume divided by the total streamflow volume.

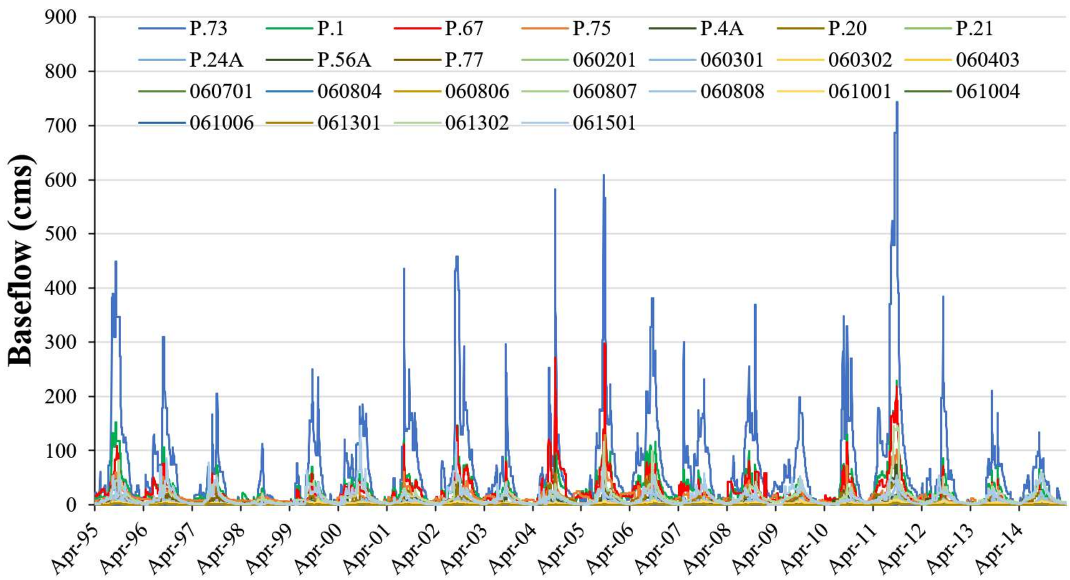

Figure 4 Baseflow hydrograph of the 25 flow stations

4.1.3 Annual Minimum 7-day Moving Average Flow with a 10-year Recurrence Interval

Figure 5 shows the 7-day moving average flow of the 25 selected flow stations. The plot is much similar to that of the baseflow hydrograph. However, they are different in terms of quantity. The 7-day minimum average flows determined from streamflow time series are fitted to a Log-Pearson Type III distribution to determine 7Q10. The result indicates that the three located mainstream stations (P.73, P.1, and P.67) mentioned above keep showing higher values. Moreover, station P.75 located upstream of the three stations is also found to present a significantly higher value of 7Q10 compared to the others.

The estimated LFI of all the 25 flow stations can be summarized as shown in Table 2

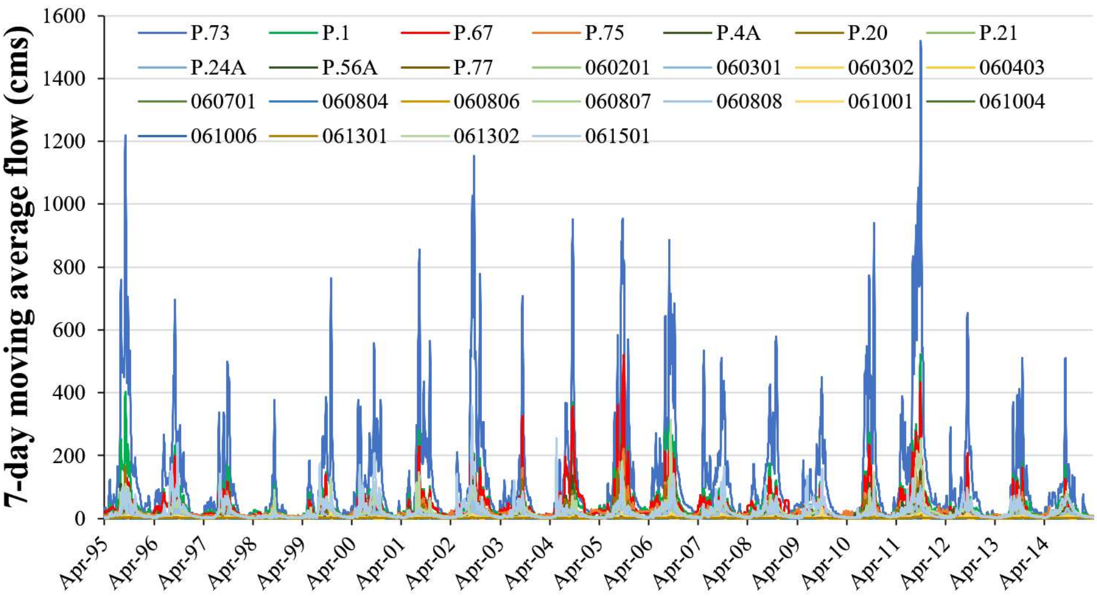

Figure 5 7-day moving average flow of the 25 stations

Table 2 The average LFI of the 25 sub-basins

No.	Station	Q95	BFI	7Q10	No.	Station	Q95	BFI	7Q10
1	P.1	4.60	0.58	10.21	14	060403	0.11	0.81	0.19
2	P.4A	0.12	0.41	0.50	15	060701	0.12	0.60	0.18
3	P.20	0.96	0.57	2.49	16	060804	0.06	0.51	0.12
4	P.21	0.15	0.48	0.41	17	060806	0.21	0.45	0.43
5	P.24A	0.21	0.45	0.52	18	060807	0.88	0.59	1.39
6	P.56A	0.31	0.49	0.83	19	060808	0.22	0.42	0.42
7	P.67	3.44	0.56	7.53	20	061001	0.70	0.73	0.93
8	P.73	0.96	0.53	12.98	21	061004	0.11	0.66	0.18
9	P.75	4.23	0.63	8.58	22	061006	0.10	0.58	0.16
10	P.77	0.01	0.52	1.53	23	061301	0.11	0.73	0.27
11	060201	0.11	0.67	0.23	24	061302	3.48	0.67	4.51
12	060301	0.26	0.65	0.45	25	061501	1.20	0.54	1.82
13	060302	0.11	0.65	0.15					

4.2 Regional Regression Method

4.2.1 Correlation between LFI and Each Independent Basin Characteristics

To investigate the possibility of using the regression to represent the relationship between the basin characteristics and the LFI, a matrix of scatter plots between each basin characteristic and each LFI was developed, and the correlation coefficient (r) is computed.

The results show that r of the Q95 ranges from -0.30 to 0.74. The %W and Sl_{max} are the descriptors with the highest r equal to 0.74 and 0.63, respectively. The r of the BFI ranges from -0.48 to 0.50. The El_{min} and Sl_{mean} seem to be most informative in predicting BFI with r equal to 0.50 and 0.49, respectively. For the 7Q10, r ranges from -0.57 to 0.91 where the Ar, %W, Sl_{max}, and %G62 are descriptors with relatively high r equal to 0.91, 0.90, 0.77, and -0.57, respectively. A few descriptors with high r values suggest the possibility of using the regression as the LFI can be explained by some of the informative basin characteristics.

4.2.2 Regression Equations

Based on the stepwise regression approach with the allowable p-value of 0.05, only three standardized basin characteristics namely proportions of agriculture (%A), forest (%F), and open water (%W) show a significant relationship for predicting the Q95. The regression equation which relates the three descriptors to the predicted Q95 is as shown in Eq. 8. The presence of the three sub-basin descriptors tends to increase the value of Q95 in each sub-basin. The result indicates that the regression equation yields a better R^2 and NSE of 0.78 with a moderate RMSE of 0.51 as shown in Figure 6(a).

$$Q95_{pred} = 2.20\%A + 2.63\%F + 1.18\%W \quad (8)$$

In the prediction of BFI, there are three standardized basin characteristics namely minimum elevation (El_{min}), mean slope (Sl_{mean}), and proportion of soil type group 60 (%G60) which share substantial contribution to the prediction. The regression equation which relates the three basin characteristics to the predicted BFI is as shown in Eq. 9. The presence of El_{min}, and Sl_{mean} tends to increase the amount of BFI while the presence of %G60 tends to decrease the amount of BFI in each sub-basin. The result shows that the equation yields a moderate R^2 and NSE of 0.58 with a high RMSE of 0.70 as shown in Figure 6(b).

$$BFI_{pred} = 0.43El_{min} + 0.37Sl_{mean} - 0.34\%G60 \quad (9)$$

The regression equation for predicting 7Q10 consists of four standardized basin characteristics namely area (Ar), proportions of agriculture (%A), forest (%F) and open water (%W) as shown in Eq. 10. The presence of the four descriptors tends to increase the amount of 7Q10 in each sub-basin. The result indicates that the equation yields a high R^2 and NSE of 0.95 with a low RMSE of 0.26 as shown in Figure 6(c).

$$7Q10_{pred} = 0.61Ar + 0.74\%A + 0.90\%F + 0.58\%W \quad (10)$$

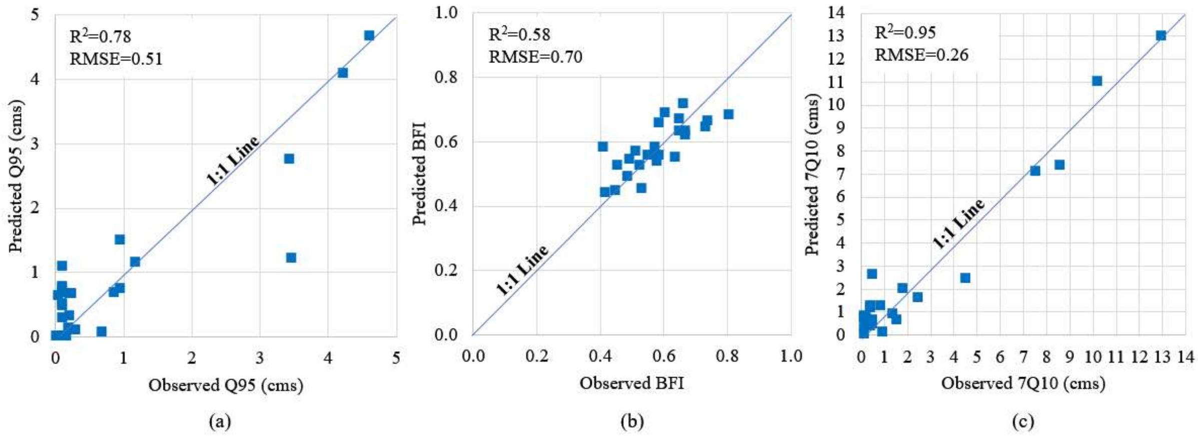

Figure 6 Predicted LFI estimated from regional regression method plotted versus Observed LFI estimated from overall 20-yr period: (a) Q95, (b) BFI, (c) 7Q10

To test the reliability of the regression model, the regression method was applied separately to calibration (2000-2014) and validation (1995-1999) periods. The regression method gives acceptable performance for Q95 and 7Q10 but not BFI. For Q95, the values of R^2, NSE, and RMSE are similar for both calibration and validation periods. When moving from calibration to validation period, a drop in performance of the 7Q10 is caused by an outlier. While further investigation of the outlier should have been done, it is beyond the scope of this study. The regression equation for BFI shows the worst performance for both calibration and validation periods. The results of reliability test are provided in Figure 7 and it can be concluded that the regression model is applicable for predicting low-flow indices but with variable performance.

4.3 Climate Adjustment Method

The climate adjustment method can be applied using different overlap periods. The effects of different overlap periods with different base years are investigated in the prediction. A sample of the Q95 which is predicted from various overlap periods of 1-yr, 5-yr, 10-yr, and 15-yr with the base year of 1995 is assessed using both augmentation techniques and can be plotted versus the observed Q95 estimated from the overall 20-yr period as shown in Figure 8. The results indicate that the appropriate length of overlap period is necessary for the prediction to obtain a reliable result. The figure clearly shows that for the overlap period of 1-yr, the prediction using the 1st technique performs better than the 2nd

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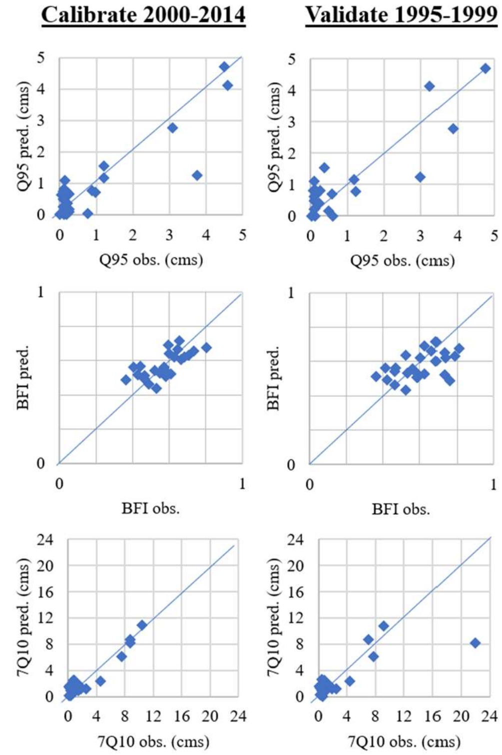
technique. However, for the overlap period of 5 years or more, the 2nd technique shows better performance overall.



Summary results

Q95	Calibrate	Validate
RMSE (cms)	0.65	0.66
R^2	0.78	0.76
NSE	0.78	0.75

BFI	Calibrate	Validate
RMSE	0.08	0.11
R^2	0.49	0.25
NSE	0.49	0.18

7Q10	Calibrate	Validate
RMSE (cms)	0.95	2.96
R^2	0.92	0.68
NSE	0.92	0.65

Figure 7 Performance of the regression model in calibration and validation periods

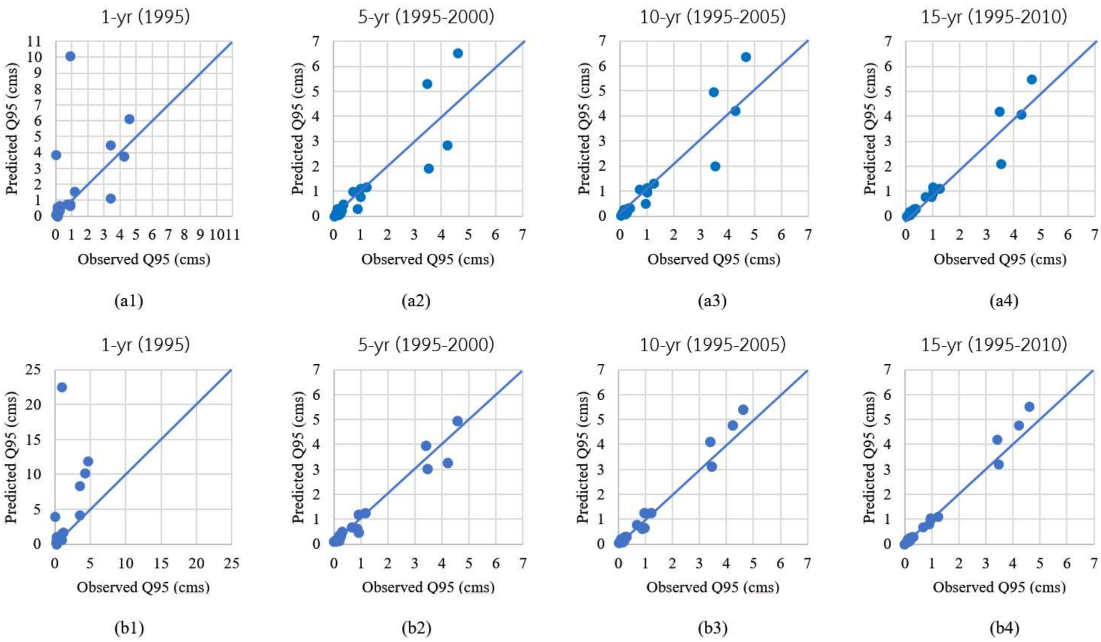


Figure 8 Adjusted $Q95_{pred}$ estimated from: (a1) 1-yr (1995), (a2) 5-yr (1995-2000), (a3) 10-yr (1995-2005), (a4) 15-yr (1995-2010) records using 1st technique plotted versus $Q95_{obs}$ estimated from overall 20-yr period; and Adjusted $Q95_{pred}$ estimated from: (b1) 1-yr (1995), (b2) 5-yr (1995-2000), (b3) 10-yr (1995-2005), (b4) 15-yr (1995-2010) records using 2nd technique plotted versus $Q95_{obs}$ estimated from overall 20-yr period

Figure 9 shows the summary of the method performance for the prediction of Q95 using both techniques with different overlap periods and base years. In the 1st technique, for 1-year overlap period, the method shows unsatisfied performance with very poor statistical indicators. For 5 years, the method yields R^2 range from 0.42 to 0.92, NSE range from -0.33 to 0.90, and RMSE range from 0.43 to 1.58. For 10 years, the method yields R^2 range from 0.72 to 0.97, NSE range from 0.69 to 0.96, and RMSE range from 0.28 to 0.77 while for 15 years, the method yields R^2 range from 0.89 to 1.00, NSE range from 0.89 to 0.99, and RMSE range from 0.25 to 0.62.

In the 2nd technique, for 5 years, the method yields R^2 range from 0.67 to 0.98, NSE range from -1.02 to 0.96, and RMSE range from 0.27 to 1.95. For 10 years, the method yields R^2 range from 0.90 to 0.98, NSE range from 0.79 to 0.97, and RMSE range from 0.25 to 0.62 while for 15 years, the method yields R^2 range from 0.98 to 1.00, NSE range from 0.96 to 1.00, and RMSE range from 0.09 to 0.27.

The summary of the BFI and 7Q10 is as shown in Figure 10 and Figure 11, respectively.

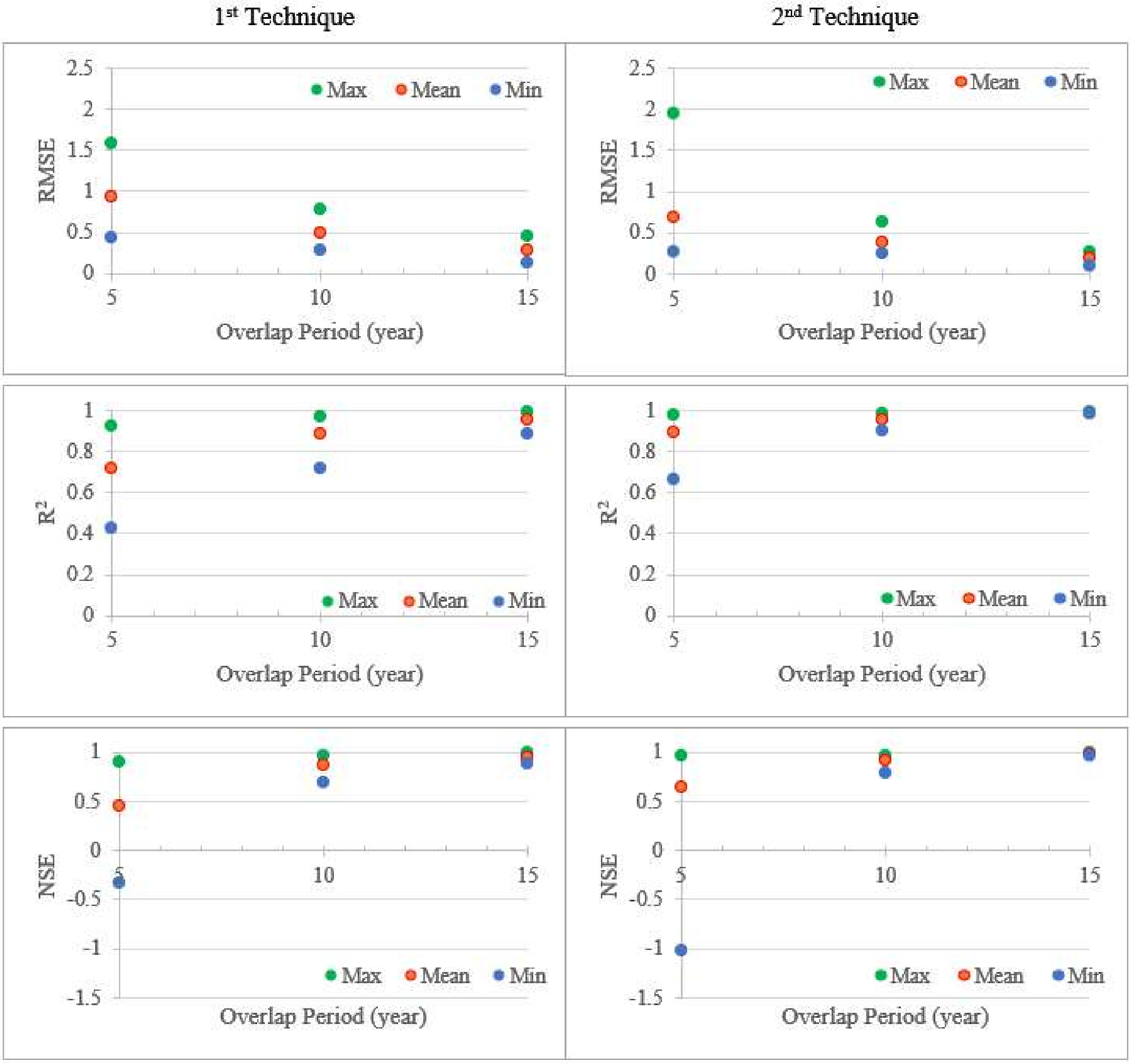


Figure 9 Summary of climate adjustment method performance of two augmentation techniques for Q95

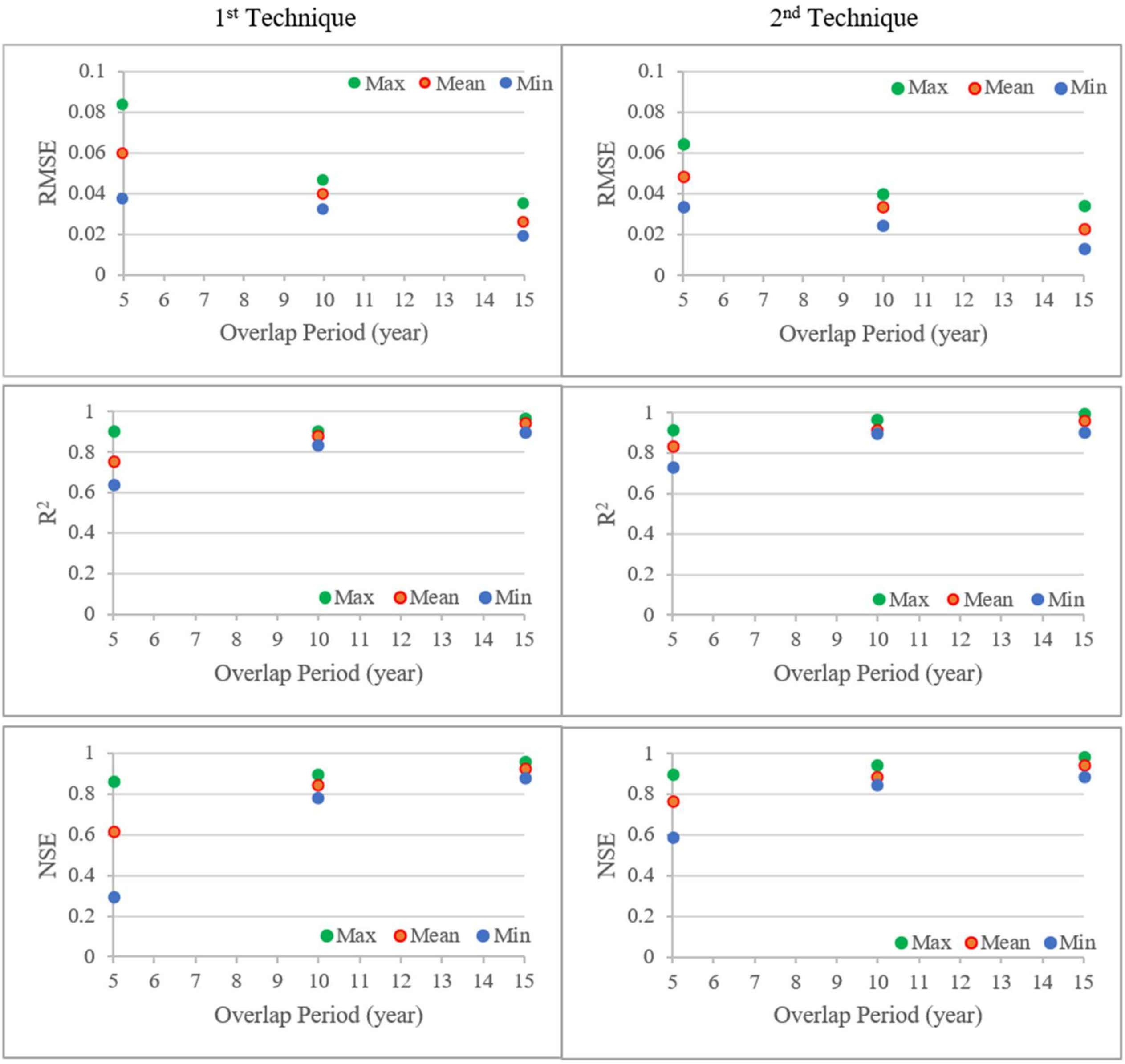


Figure 10 Summary of climate adjustment method performance of two augmentation techniques for BFI

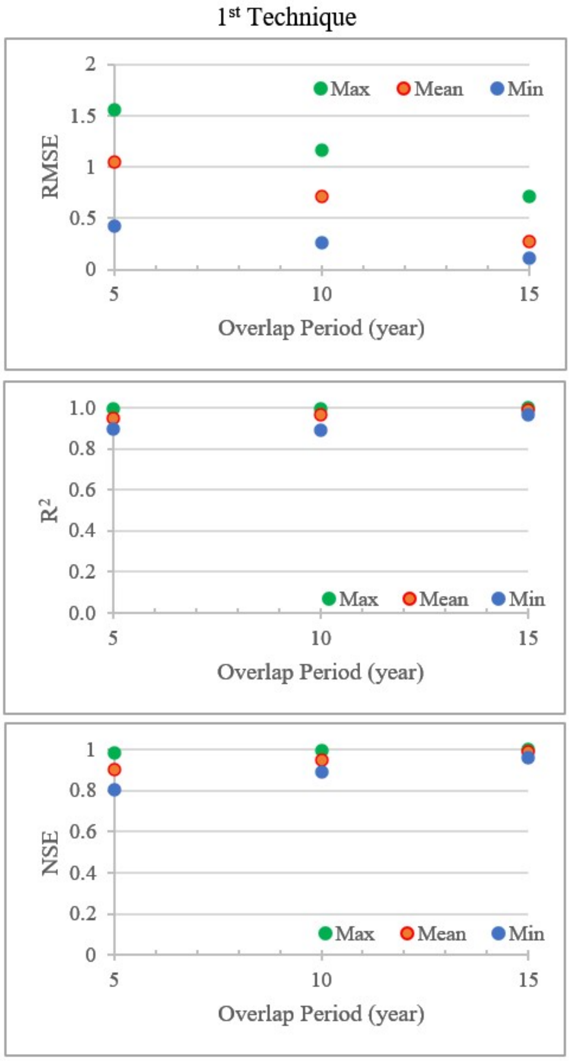
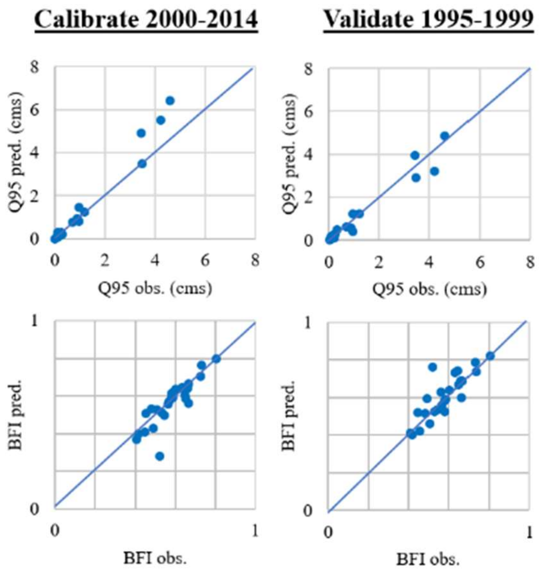


Figure 11 Summary of climate adjustment method performance using 1st techniques for 7Q10



Summary results

Q95	Calibrate	Validate
RMSE (cms)	0.55	0.30
R^2	0.98	0.92
NSE	0.84	0.95

BFI	Calibrate	Validate
RMSE	0.06	0.07
R^2	0.76	0.62
NSE	0.62	0.54

Figure 12 Performance of the 2nd technique of the climate adjustment method in calibration and validation periods

Figure 12 shows the results of reliability test when the 2nd technique of the climate adjustment method is used for calibration and validation period. The method can yield a reliable performance since the values of R^2, NSE, and RMSE in validation period are comparable to those of the calibration period. This supports the applicability of the climate adjustment method for estimating low-flow indices in ungauged basins.

5. CONCLUSIONS

The assessment of low-flow in ungauged basins remains a challenging issue especially for developing countries where the flow gauging network is limited. Regionalization using the regression and climate adjustment methods was found to be applicable to the prediction of low-flow in the Upper Ping River basin which is the study area. Generally, the climate adjustment method outperforms the regression method as it yielded better values for performance indices. The improved performance obtained from the climate adjustment method is probably due to being contribution from the consideration of the variation in climate over 20 years of the study period. The longer overlap period used for climate adjustment, the better the performance. However, the marginal increase in the performance is less seen when using the overlap period longer than 10 years. The 2nd technique of the climate adjustment method where the weighting coefficient was applied further improves the performance over its 1st technique. The framework demonstrated in this study could be used as a guideline to regionalize low-flow indices and estimate streamflow in other ungauged basins with similar climate regime and hydrological context. This would help address the issue of water scarcity and improve water resources management in ungauged basins.

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