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A Comparison of Fuzzy Logic Models for Breakup Forecasting of the Athabasca River

Wei Sun[1] and Bernard Trevor[2]
[1,2]River Forecast Section, Operations Infrastructure Branch,
Alberta Environment and Parks, Edmonton, Alberta, T5K 2J6
[1]Wei.Sun@gov.ab.ca, [2]Bernard.Trevor@gov.ab.ca

Fuzzy logic models are an effective tool for forecasting. However, few studies comparing different fuzzy logic models and their applications to river ice forecasting have been reported. This paper evaluates the application of two types of fuzzy logic models (a Qualitative Fuzzy Logic Model, QFLM and an Adaptive Neuro-fuzzy inference system, ANFIS) and an alternative model (Multiple Linear Regression, MLR) to predict the maximum water level during river ice breakup. The Athabasca River is the largest unregulated river in Alberta, Canada with ice jams frequently occurring in the vicinity of Fort McMurray. River ice breakup data for the Athabasca River at Fort McMurray, over the past 39 years (1977-2015), have been collected to facilitate the model comparisons. The results indicated that the QFLM can generate a qualitative evaluation and be treated as a pre-screening model for overall assessment of ice-caused flooding risk at breakup. As for quantitative prediction of deterministic values of maximum breakup water level, the fitting and predictive abilities of ANFIS are relatively better than those of MLR. In practice, both ANFIS and MLR can be used as forecast and backup tools, respectively. Further improvement of these models is still needed in terms of the selection of indicators and updating of datasets. These models lay the basis for effectively supporting spring breakup monitoring operations and emergency response to ice-related flooding.

1. Introduction

Each spring, some northern communities are at risk from ice-related flooding during river breakup. Sudden changes, with the formation and release of ice accumulations or ice jams, may cause dramatic water level increases within hours or even minutes. Rapidly changing river ice and flow conditions require timely mitigation measures and emergency response becomes a challenge (White et al., 2007). Thus, it is indispensable to develop effective tools to forecast the magnitude of water levels during the breakup period. Over the past few years, various river breakup forecasting tools have been developed, including threshold models, multiple regression models, discriminant analysis models, and artificial neural networks (Chen and Ji, 2005; Mahabir, 2006b; Wang et al., 2008; White, 1996; Zhao et al., 2010, 2011, 2012). However, due to the complicated interactions between hydro-meteorological effects and the mechanical properties of ice, as well as limited data availability, application of advanced forecasting tools to peak breakup water level prediction is still in progress (Beltaos 2007, 2008; Hicks, 2009; Morse and Hicks 2005; Shen, 2010; White, 2003).

As a soft computing method, fuzzy logic models can be used for nonlinear forecasting tools with wide applications (Fayek and Sun, 2001). Within the framework of fuzzy logic models: values for inputs and outputs can be represented by linguistic terms, the relationships between inputs and outputs can be defined as if-then rules, and the results of each rule can be combined and defuzzified to provide the final output (Jang, 1993; Jang and Sun, 1995). The primary advantage of fuzzy logic models over others is that the experiences of experts in understanding the historical cause and effect relationships can be naturally described (Mahabir et al., 2002, 2003a). However, there are no standard methods for transforming these experiences into the rule base and for fine-tuning of the membership functions to maximize the model's performance (Jang, 1993). To this end, the fuzzy logic model can be combined with artificial neural networks to form the adaptive neuro-fuzzy inference system (ANFIS). The ANFIS can not only represent highly nonlinear relationships, but can also generate the membership functions and other internal parameters automatically with certain learning algorithms. Fuzzy logic models including ANFIS have been applied to river ice jam flood forecasting (Mahabir et al., 2003b, 2005, 2006a, 2007). However, few studies comparing the different types of fuzzy logic models and their applications to river ice forecasting have been recently reported. Meanwhile, most of the previous ANFIS studies on river ice forecasting were based merely on training sets due to the limited data, which may have prevented the proposed models from keeping their generalization ability.

This study aims to evaluate the application of various fuzzy logic models to the prediction of the maximum water level during river ice breakup. In detail, two types of fuzzy logic models (a Qualitative Fuzzy Logic Model, and an ANFIS) and an alternative model (multiple linear regression) will be compared. The Athabasca River was selected as the study area since it is the largest unregulated river in Alberta, Canada, ice jams frequently occurring in the vicinity of Fort McMurray, and it has an ongoing spring breakup monitoring program. The available historical river ice breakup data for the Athabasca River at Fort McMurray for the past 39 years will be updated and enhanced to facilitate the comparison of these models. The advantages and limitations of these models in the prediction of the maximum breakup water level will be also discussed.

2. Fuzzy Logic Models

Qualitative Fuzzy Logic Model (QFLM)

A fuzzy logic model is a logical modeling system based on quantifying experts' experiences through fuzzy set theory. Its procedure usually comprises of three parts: fuzzification of the input variables, application of if-then rules, and defuzzification of the output. The main challenges in the development of a fuzzy logic model are: to establish membership functions and linguistic groupings for input and output variables, to define if-then rules to represent all corresponding relationships between inputs and outputs, to choose a aggregation method to combine the results of each rule, and to defuzzify the resultant set of output as a single crisp value. Those membership functions and rules are developed through expert knowledge and understanding the historical data. The number of if-then rules depends on the number of input variables and their linguistic terms (e.g. low, average and high). If there are m input variables and each of them is described by n linguistic terms, a complete rule base would include n^m rules. Many methods of aggregation and defuzzification have been designed and available for use. Selection of these methods is usually based on trial and error, which may have certain effects on the final crisp output (Mahabir et al., 2002). In this study, a qualitative fuzzy logic model (QFLM) is proposed which evaluates the output's level by removing the procedures of aggregation and defuzzification. Thus, the linguistic (qualitative) output of each if-then rule would be the final output of the entire model.

Adaptive Neuro-Fuzzy Inference Systems (ANFIS)

In order to automatically generate the rule base and accurately predict the crisp value of the output, an adaptive neuro-fuzzy inference system (ANFIS) can be developed through the combination of artificial neural network (ANN) and fuzzy logic modeling. The structure of an ANFIS is similar to that of a five-layered feed-forward neural network. These five layers usually include fuzzification of inputs, application of a multiplier, normalization, defuzzification of each rule's output, and aggregation of all the rules' outputs (Jang, 1993; Jang and Sun, 1995). The learning (training) algorithm of ANFIS include either back propagation or a combination of least squares estimation and back propagation. Based on these algorithms, the parameters associated with the membership functions of inputs and defuzzification functions of outputs are adjusted to minimize the error measure between predicted and observed outputs. Especially, the back propagation algorithm is used to adjust parameters in membership functions of inputs (i.e. the premise parameters of fuzzy rules); once the premise parameters are fixed, least squares estimation is used to optimize the defuzzification parameters (i.e. consequent parameters of fuzzy rules). Accordingly, the ANFIS relies on objective historical data instead of the subjective experiences of experts when developing a rule base and determining inherent parameters (Mahabir, 2007).

3. Alternative Models

As an alternative model, multiple linear regression (MLR) can be used for comparisons with and demonstration of the effectiveness of the proposed fuzzy logic models. MLR is a conventional statistical model used to build the relationship between the multiple inputs and the single output based on an assumed linear equation. Using a least-square estimation, the related parameters of

MLR are obtained to minimize the sum of squares of errors between each observed and predicted output samples. To obtain the unique parameters of the MLR, the number of selected inputs should be much less than that of the data samples and multi co-linearity between inputs should be avoided (Mahabir, 2007; Mahabir et al., 2006b).

4. Study Area

To compare the performance of fuzzy logic models in their application to the prediction of the maximum water level during river ice breakup, the Athabasca River at Fort McMurray was selected as the study area due to the frequent occurrence of ice jams and the availability of historical data. The Athabasca River is the largest, unregulated, northward flowing river in the province of Alberta, Canada (Andrishak and Hicks, 2011; Friesenhan, 2004) and the propensity for ice jamming in the vicinity of Fort McMurray is caused by a number of factors: the river's slope decreases by an order of magnitude, many sand bars and islands exist in a widened channel, and the Clearwater River discharges into the Athabasca River at this location (She et. al, 2009). For these reasons, when river breakup occurs in the southern portion of the basin first and progresses northwards each spring, there is a potential for ice-related flooding. For locations such as Fort McMurray, one of the largest communities along the Athabasca River, severe flooding can result in losses of millions of dollars in damage to residential and commercial properties. To prevent the economic loss and the threat to human lives, Alberta Environment and Parks has an ongoing annual river ice monitoring and observation program for the Athabasca River at Fort McMurray (Friesenhan et al., 2008; Kowalczyk and Hicks, 2003; Sun et al., 2015).

5. Datasets

The historical breakup data for the Athabasca River at Fort McMurray for the past 39 years (1977 to 2015) were collected to facilitate the comparison of fuzzy logic and alternative models. The candidate inputs (independent variables) of the models are those indicators which both can be calculated ahead of river ice breakup and have significant correlation relationships with maximum breakup water levels. The inputs include: accumulated summer precipitation at Fort McMurray measured from May 1 to October 31 in the previous year (X_1), degree-days of freezing from October 1 in the previous year to March 31 in the current year (X_2), ice thickness near the end of January (X_3), and average snow-water equivalent over the Athabasca River basin on March 1 in the current year (X_4). The max breakup water level at the confluence of the Athabasca and Clearwater Rivers is the output (Y).

A total of 39 samples were obtained based on on-site measurement or surveys from Environment Canada Water Survey of Canada, and Alberta Environment and Parks. All the dataset except 2015 were randomly divided into training (75%) and test sets (25%). The training set (1977 to 2014 excluding the years in the test set) was used for calibrating the fuzzy logic models and the test set (1979, 1984, 1986, 1992, 1995, 1997, 1999, 2004, 2008 and 2013) for verifying the developed model. The data of 2015 were selected for a separate verification. The correlation coefficient (R) and the root mean squared error (RMSE) were employed to evaluate the performance of the proposed models.

6. Results Analysis

Performance of QFLM

The QFLM was developed for prediction of maximum breakup water level. The inputs of the QFLM include all of the four candidate indicators (X_1 to X_4), each of which is fuzzified as three levels (low, average and high). Its output is three linguistic terms for the maximum breakup water level at the confluence of the Athabasca and Clearwater Rivers. Simplified membership functions for indicators and maximum breakup water level are listed in Table 1. The related eighty-one fuzzy logic rules embedded in the QFLM model are listed in Table 2. The procedures for QFLM mainly consists of two steps: in step 1, based on the ranges and criteria in Table 1, deterministic inputs can be classified into their corresponding linguistic (fuzzified) terms; in step 2, the fuzzified inputs would be compared with the condition in each rule to determine the linguistic terms of the output. For example, based on Table 1, the values in 2015 for freezing degree-days (1919^{o}C), ice thickness (0.59m), accumulated precipitation (337.7mm) and average snow-water equivalent (97.6mm) are evaluated as average, low, average, and high, respectively. Furthermore according to Rule 33 in Table 2, the evaluated flooding risk is average, which means the maximum breakup water level should be between 242m and 244.8m.

Table 3 presents the forecasts of maximum breakup water level from 1979 to 2015. The higher correction rate (89.74%) indicates that most of the predicted and observed values of the output are consistent with each other. Although QFLM can only generate a qualitative evaluation of the maximum breakup water levels, it can help emergency response managers and local communities to understand the overall ice-related river conditions. Since the maximum breakup water level is positively correlated with flooding risk, the QFLM can also be treated as a pre-screening model for assessment of ice-caused flooding risk at breakup.

Performance of ANFIS

The ANFIS models were developed for quantitative prediction of deterministic values of the maximum breakup water level. Different combinations of input variables were carefully selected for the ANFIS to enhance its predictive performance. Multiple combinations of inputs were checked by discarding one, two or three independent variables from all candidate ones and the selected input variables in the optimal ANFIS model are X_2 and X_4. Figure 1 shows the overall fitting and predictive performance of ANFIS. The small difference between the predicted and observed values in both the training and testing datasets indicates a good level of performance in the developed ANFIS model. Based on the calibrated and validated ANFIS, the predicted maximum breakup water level for 2015 would be 242.90 m. A maximum breakup water level (high water mark) at the confluence of Athabasca and Clearwater Rivers of 244.79m was surveyed during the on-site monitoring operations of 2015.

Performance of Alternative Models

As an alternative model, the MLR model was developed with the same datasets as those of the ANFIS, but different combinations of linear functions for inputs. The inputs selected to obtain the optimal performance of the MLR models are X_1, X_2 and X_4. Figure 2 shows the performance of the optimal MLR model. This difference between the predicted and observed values in both the training and testing datasets is small, which indicates that its performance is also acceptable, although MLR can only map the linear relationship. Based on the calibrated and validated MLR model, the predicted maximum breakup water level for 2015 would have been 243.05m.

Comparisons of models

Table 4 lists a comparison of the proposed forecasting models. QFLM can help evaluate the overall severity of the potential ice-caused flooding risk, which can be used as a pre-screening model before the spring breakup season. In comparison, ANFIS and MLR are able to provide crisp values of the maximum breakup water level. Accurate comparison between these quantitative forecasts and the flooding threshold level can determine both the flooding potential and the affected flood zones. The fitting and predictive abilities of ANFIS are relatively better than those of MLR when building nonlinear relationships between indicators and maximum breakup water level. The R for training and test sets of ANFIS (0.7793 and 0.6675) were much higher than those of MLR (0.5540 and 0.5529), whereas the RMSEs of ANFIS (1.0486 and 1.7294) were lower than those of MLR (1.3930 and 1.7821). However, due to its availability and simple implementation, the MLR can be treated as a good backup model for breakup forecasting. It is also noted that, the forecast of 2015 by MLR is even better than that by ANFIS.

7. Discussion

The combination of candidate input variables may have significant effects on the performance of fuzzy logic models. Also no unique combination of variables can be used for maximum water level prediction during spring breakup. The criteria for input variable selection rely on the correlation between inputs and the output, as well as the early availability of inputs. The correlation can be evaluated not only by the conventional correlation coefficients but also other indices. For breakup prediction of the Athabasca River at Fort McMurray, these inputs should be obtained and calculated no later than April 1 to provide sufficient lead time, since the earliest breakup date for this site in the historical record is April 6 and the average date is April 19 (Mahabir, 2007).

The proposed QFLM differs from previous studies as the QFLM is only used for a qualitative evaluation of the maximum breakup water level; conventional fuzzy logic models usually generate crisp values of the output based on the procedures of aggregation and defuzzification. The developed ANFIS is also unique since it is examined using separate training and test sets; in comparison, most of the previous ANFIS studies on river ice forecasting were built based on training sets due to limited data. Lack of validation using test set may prevent the proposed models from keeping their generalization ability since most of the nonlinear models can often encounter the over-fitting problem with the training set. Additionally, the selected inputs for the QFLM and the ANFIS, as well as the time range of investigated datasets are also different from those in previous river ice studies (Mahabir et al., 2003b, 2005, 2006a, 2007).

Validation of the QFLM needs further investigation since the number of years of breakup data (39) is much less than the number of if-then rules (81). Further performance improvement of the ANFIS models would also be desirable, since more accurate and deterministic forecasts of the maximum breakup water level will yield more effectively prepared ice monitoring operations and emergency response plans. Meanwhile, the relatively more complicated structure of the

ANFIS indicates that longer datasets should be collected and employed to calibrate the inherent parameters and validate the model performance.

8. Conclusions

Two types of fuzzy logic models (a qualitative fuzzy logic model, QFLM and an adaptive neuro-fuzzy inference system, ANFIS) and an alternative model (multiple linear regression, MLR) were developed and compared for the prediction of the maximum water level during river ice breakup. In Alberta, the Athabasca River jams frequently in the vicinity of Fort McMurray and this places the community at risk for ice-caused flooding. Accordingly, the past 39 years of spring breakup data for the site have been compiled and updated to facilitate the model comparisons.

The results indicate that the QFLM can generate a qualitative evaluation or be treated as a pre-screening model for assessment of ice-caused flooding risk at breakup. The QFLM can help emergency response managers and local communities to understand the overall breakup risk. As for the quantitative prediction of deterministic values of the maximum breakup water level, the fitting and predictive abilities of ANFIS are relatively better than those of MLR. In practice, both ANFIS and MLR can be used as forecast and backup tools, respectively. Further improvement of these models is still needed in terms of selection of indicators and updating of datasets. These models lay the basis for effectively supporting breakup monitoring operations and emergency response management.

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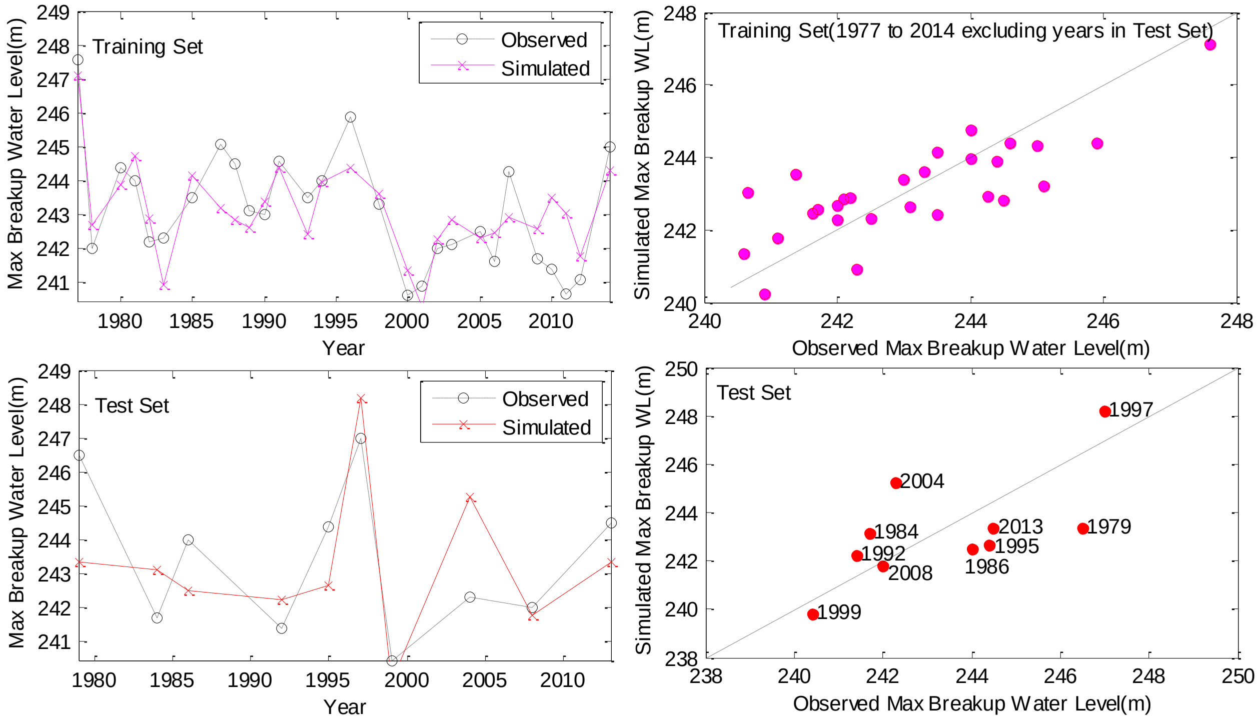

Figure 1. Performance of Adaptive Neuro Fuzzy Inference Systems.

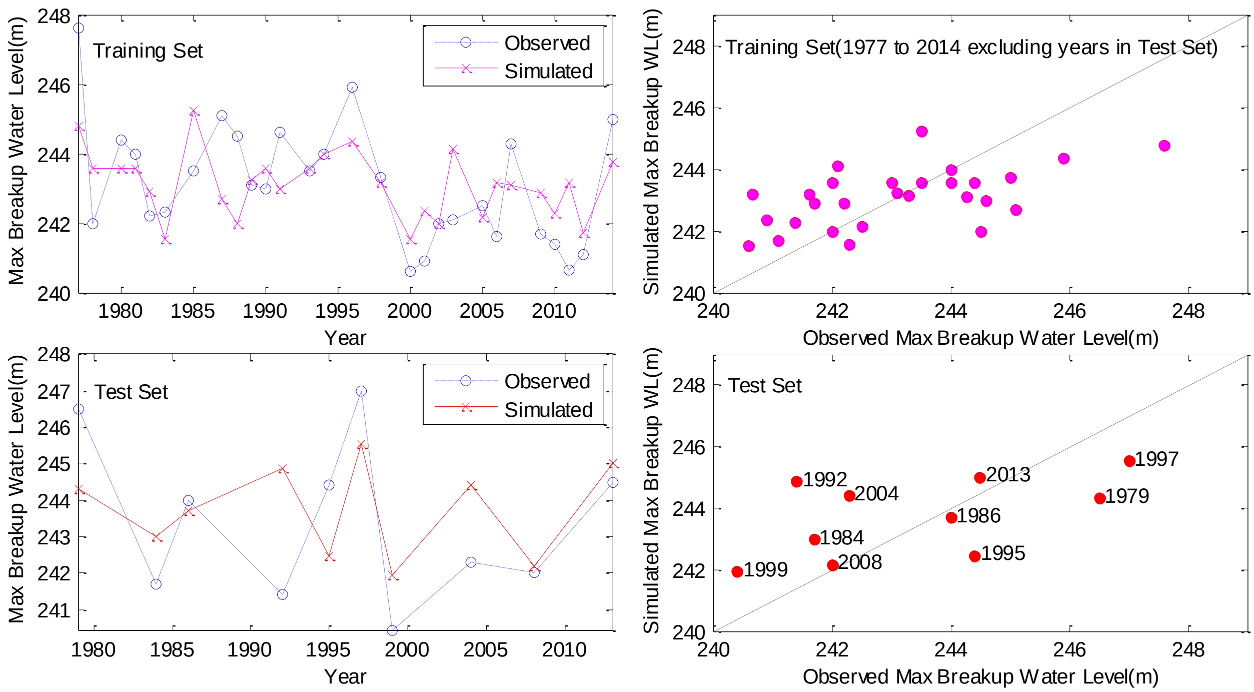

Figure 2. Performance of Multiple Linear Regression Models.

Table 1. Simplified membership functions for input and maximum breakup water level.

Variable	Meaning	Unit	Abbreviation	Membership Functions	Evaluation
X_1	Freezing Degree Days from Last October 1 to March 31 of the current year	℃	FDD	< 1800 1800⩽&⩽2100 > 2100	Low Average High
X_2	Ice Thickness near Fort McMurray	m	IT	< 0.6 0.6⩽& ⩽0.85 > 0.85	Low Average High
X_3	Accumulated Precipitation from May 1 to October 31 of last year	mm	AP	< 270 270⩽&⩽350 > 350	Low Average High
X_4	Average Snow-Water Equivalent over the basin on March 1	mm	SWE	< 19 19⩽&⩽84 > 84	Low Average High
Y	Maximum Breakup Water Level at the confluence of Athabasca and Clearwater Rivers	m	MBWL	< 242 242⩽&⩽244.8 > 244.8	Low Average High

Table 2. Rules within the Qualitative Fuzzy Logic Model (QFLM).

No.	FDD	IT	AP	SWE	MBWL
1	Low	Low	Low	Low	Low
2	Low	Low	Low	Average	Low
3	Low	Low	Low	High	Low
4	Low	Low	Average	Low	Low
5	Low	Low	Average	Average	Low
6	Low	Low	Average	High	Low
7	Low	Low	High	Low	Low
8	Low	Low	High	Average	Low
9	Low	Low	High	High	Average
10	Low	Average	Low	Low	Low
11	Low	Average	Low	Average	Average
12	Low	Average	Low	High	Low
13	Low	Average	Average	Low	Low
14	Low	Average	Average	Average	Low
15	Low	Average	Average	High	Low
16	Low	Average	High	Low	Low
17	Low	Average	High	Average	Average
18	Low	Average	High	High	Average
19	Low	High	Low	Low	Low
20	Low	High	Low	Average	High
21	Low	High	Low	High	Low
22	Low	High	Average	Low	Low
23	Low	High	Average	Average	Average
24	Low	High	Average	High	Low
25	Low	High	High	Low	Low
26	Low	High	High	Average	Average
27	Low	High	High	High	Low
28	Average	Low	Low	Low	Low
29	Average	Low	Low	Average	Average
30	Average	Low	Low	High	Low
31	Average	Low	Average	Low	Low
32	Average	Low	Average	Average	Low
33	Average	Low	Average	High	Average
34	Average	Low	High	Low	Low
35	Average	Low	High	Average	Average
36	Average	Low	High	High	High
37	Average	Average	Low	Low	Low
38	Average	Average	Low	Average	Average
39	Average	Average	Low	High	Average
40	Average	Average	Average	Low	Low
41	Average	Average	Average	Average	Low
42	Average	Average	Average	High	Low
43	Average	Average	High	Low	Average

44	Average	Average	High	Average	Average
45	Average	Average	High	High	High
46	Average	High	Low	Low	Low
47	Average	High	Low	Average	Average
48	Average	High	Low	High	Low
49	Average	High	Average	Low	Low
50	Average	High	Average	Average	Average
51	Average	High	Average	High	Average
52	Average	High	High	Low	Average
53	Average	High	High	Average	Average
54	Average	High	High	High	High
55	High	Low	Low	Low	Average
56	High	Low	Low	Average	Average
57	High	Low	Low	High	Average
58	High	Low	Average	Low	Average
59	High	Low	Average	Average	Average
60	High	Low	Average	High	low
61	High	Low	High	Low	High
62	High	Low	High	Average	High
63	High	Low	High	High	High
64	High	Average	Low	Low	Average
65	High	Average	Low	Average	Average
66	High	Average	Low	High	Average
67	High	Average	Average	Low	Average
68	High	Average	Average	Average	Average
69	High	Average	Average	High	High
70	High	Average	High	Low	High
71	High	Average	High	Average	Average
72	High	Average	High	High	High
73	High	High	Low	Low	Average
74	High	High	Low	Average	Average
75	High	High	Low	High	Low
76	High	High	Average	Low	Average
77	High	High	Average	Average	Average
78	High	High	Average	High	High
79	High	High	High	Low	High
80	High	High	High	Average	High
81	High	High	High	High	High

Table 3. Performance of QFLM for predicting maximum breakup water level.

Year	FDD	IT	AP	SWE	Predicted MBWL	Observed MBWL
1977*	Low	High	High	Average	Average	High
1978	High	High	Average	Average	Average	Average
1979	High	High	High	High	High	High
1980	Low	High	Average	Average	Average	Average
1981	Low	High	High	Average	Average	Average
1982	High	Average	Low	High	Average	Average
1983	Average	Low	Low	Average	Average	Average
1984	Low	High	Average	Average	Low	Low
1985*	High	High	High	High	High	Average
1986	Average	High	Average	Average	Average	Average
1987	Low	High	Low	Average	High	High
1988	Low	Average	Low	Average	Average	Average
1989	High	Average	High	Average	Average	Average
1990	High	Average	High	Average	Average	Average
1991	High	Average	Average	Average	Average	Average
1992	Low	High	High	High	Low	Low
1993	Average	High	Average	Average	Average	Average
1994	Average	High	Average	High	Average	Average
1995*	Low	High	Low	Average	High	Average
1996	High	High	High	High	High	High
1997	High	High	High	High	High	High
1998	Low	Average	High	Average	Average	Average
1999	Low	Average	Low	High	Low	Low
2000	Low	Average	Low	Average	Low	Low
2001	Low	Low	High	Average	Low	Low
2002	Average	Average	Low	Average	Average	Average
2003	Average	High	Average	Average	Average	Average
2004	Average	High	High	Average	Average	Average
2005	Average	High	Low	Average	Average	Average
2006	Low	High	Average	Average	Low	Low
2007	Average	Average	Low	High	Average	Average
2008	Average	High	Low	Average	Average	Average
2009	High	Low	Average	High	Low	Low
2010	Low	Average	Average	Average	Low	Low
2011	High	High	Low	High	Low	Low
2012	Low	Average	Low	Average	Low	Low
2013*	High	High	High	High	High	Average
2014	High	Average	Average	High	High	High
2015	Average	Low	Average	High	Average	Average

* indicates the predicted and observed values are not consistent with each other.

Table 4. Comparison of the forecasting models.

		QFLM	ANFIS	MLR
Coefficients		By experiences of experts	Calibration	Calibration
Correction rate:		89.74%	N/A	N/A
Training	R	N/A	0.7793	0.5540
	RMSE	N/A	1.0486	1.3930
Validation	R	N/A	0.6675	0.5529
	RMSE	N/A	1.7294	1.7821
Indicators		FDD, IT, AP, SWE	IT, AP	IT, AP, SWE
Predicted MBWL		Qualitative levels	Numbers	Numbers
Usage Purpose		Pre-screening and assessment	Forecast	Forecast (Backup)