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Towards a River Breakup Forecast System for the Athabasca River at Fort McMurray, AB

C. Mahabir, F. Hicks, C. Robichaud and A. Robinson Fayek
Dept. of Civil and Environmental Engineering
University of Alberta, Edmonton, AB, T6G 2G7
fehicks@civil.ualberta.ca

In Canada, ice jam events have frequently produced the most extreme and dangerous flood events on record, resulting in millions of dollars in associated damages. However, our ability to forecast such events remains quite limited. A good example of this is the Athabasca River at Fort McMurray, Alberta, where severe ice jam events have been documented for over 100 years, and where breakup has been monitored intensively for the past 25 years. Despite these efforts, no reliable flood forecast model is yet available for this site. Here, the use of Regression techniques and Fuzzy Expert Systems are explored to examine their potential for developing short and long lead time ice jam risk forecasts for this site. Model performance is assessed based on data obtained during breakup in 2003. While, both models performed well in 2003, issues regarding model sensitivity and parameter uncertainty require further investigation.

1. Introduction

Every year the spring breakup of the Athabasca River causes concern for the residents of Fort McMurray. In 1977 and again in 1997, severe flooding occurred as a result of ice jams during the river breakup and in 1997 alone, this ice jam related flooding caused millions of dollars in damages. Despite decades of observations of hydrometeorological parameters in this reach, there is still no ice jam flood forecasting model for this site. This can primarily be attributed to the complexity of the physical processes involved and the strong dependence of ice jam occurrence on meteorological parameters that are difficult to forecast more than a few days in advance, a situation that is common to sites affected by ice jam flooding.

Because of the complexity of processes involved in ice jam formation, and the general lack of quantitative data describing the details of these processes (e.g. discharge, accumulation thickness, flow velocity, etc.), a purely deterministic approach to the problem of ice jam occurrence is not yet practical. Consequently, numerous empirical approaches have been investigated for predicting the risk of ice jam formation. They include threshold methods, which explore the possibility of some critical value of a hydrometeorological factor (e.g. freeze-up level, breakup stage, cumulative heat input, discharge, etc.) beyond which an ice jam event tends to occur. Threshold models have proven to be of limited success, except in cases where multiple threshold conditions have been considered integrally (e.g. Wuebben *et al.* 1995). Other researchers have employed regression methods, particularly multiple regression techniques, in an attempt to rationalize a problem involving a multitude of complex variables. White (1996) employed the use of logistic regression, which has a discrete outcome of the multiple regression: 'jam' or 'no jam'. Massie *et al.* (2001) explored the viability of neural networks, black-box models that can be 'trained' to properly represent complex non-linear cause-effect relationships. For ice jam risk assessment, these latter two approaches have met with some success in terms of improved reliability over the traditional empirical and statistical approaches. One key problem with most models to date is that they continue to have a high level of false positive indications; that is, they predict jams when none occur. Also, most tend to provide only a relatively short lead-time for the risk forecast.

This paper reports on the progress of the authors to develop both short and long term forecasting models of the expected magnitude of maximum water levels during spring breakup at Fort McMurray. The first step in this research was to establish a comprehensive database of hydrometeorological data pertinent to river ice breakup which was used to identify which hydrometeorological variables influence the nature and rate of breakup at Fort McMurray. Threshold and regression models were then investigated. The use of fuzzy logic for the development of qualitative long range forecasts tools was then explored. The final objective was to assess the prototype models using data collected at Fort McMurray during breakup 2003.

2. Site Description

The Athabasca River is the largest unregulated river in Alberta. At Fort McMurray, the Athabasca River Basin is 133,000 km² comprised of mountain terrain, rolling foothills and boreal forest. From the Rocky Mountains the Athabasca River winds in a northeastern direction towards Fort McMurray (Figure 1). In the 80 km reach upstream of Fort McMurray, the river flows through an incised meandering channel, which is relatively steep (slope approximately

0.0010) and which contains numerous rapids sections. The Clearwater River joins the Athabasca River at the town of Fort McMurray, and there is significant development on the low floodplain located at this confluence (Figure 1). Downstream of this confluence, the slope of the Athabasca River is substantially reduced (to about 0.00014); here the channel is wide and contains numerous islands. Smith and Fisher (1993) proposed that the sudden change in physical characteristics of the Athabasca River is due to dominance of glacial melt water from the Clearwater River.

For the reach of interest, breakup is normally dynamic in nature and typically characterized by the formation of numerous small ice accumulations in the rapids upstream. Surges from upstream ice jam releases appear to be responsible for the lifting and release of these accumulations in a cascading fashion, resulting in ice runs down through Fort McMurray (e.g. see Kowalczyk and Hicks, 2003). The sudden changes in the physical characteristics of the Athabasca River in the vicinity of the Clearwater River confluence make this reach particularly prone to ice jams. Generally flooding results when such ice jams form downstream of the confluence and cause water to back up the channel of the Clearwater River.

3. Hydrometeorological Database

Hydraulic and meteorological data for the Athabasca River Basin has been collected for many years by numerous government agencies, private companies and other interest groups. For forecasting purposes, there are several sources of data available at varying time intervals. Robichaud (2003) compiled a database specifically for researching spring breakup on the Athabasca River at Fort McMurray. This historical hydrometeorological database was established starting from the 1972 breakup. The meteorological factors investigated were the air temperature, the solar radiation, and the basin snow water equivalent (SWE) in late winter. The hydraulic data considered were the ice thickness, and variables related to the water level during river ice freeze-up and breakup, such as the maximum freeze-up water level and the maximum breakup water level.

3.1.Meteorological Data

The Meteorological Survey of Canada (MSC) operates a station at the airport in Fort McMurray recording both air temperature and precipitation on 60 minute intervals. Also, as part of this research program, the University of Alberta (UA) has operated a near real time meteorological site in Fort McMurray since 2001, collecting solar radiation in addition to air temperature, precipitation, and barometric pressure data on 30 minute intervals. Details of the instrumentation selection and setup are provided by Robichaud and Hicks (2001).

A key parameter for ice event forecasting is the solar radiation. Environment Canada provided data on the hours of bright sunshine measured with a sunshine ball at the Fort McMurray Airport from November 1st, 1971 to March 31st, 1996. As indicated above, the UA meteorological station (which uses a pyranometer for measuring incoming solar radiation) became operational in 2001. To provide a complete record, overlap data was need for three reasons:

1. to fill the gap in the record, from 1996 to 2001;
2. to facilitate conversion of hours of bright sunshine to solar radiation and
3. to evaluate the potential effects of the difference in station location (the UA station is near, but not at, the airport).

Fortunately, solar radiation data were provided by Golder Associates from their Aurora station (located approximately 55 km north of Fort McMurray) for the years of 1988, 1989, and 1995 to 2001. This, together with data from the UA meteorological station from October 2000 to June 2001 allowed us to address the three issues above. Hours of bright sunshine were also measured with a sunshine ball at the UA meteorological station in 2001, to aid in the development of the complete record. Robichaud (2003) provides comprehensive details of this effort.

3.2. Snow Course Data

Alberta Environment provided the SWE for the years of 1972 to 2003 from 18 snow stations in the Athabasca River drainage basin upstream of Fort McMurray. Using the Thiessen polygon method, the 18 snow course sites were converted into a single basin average for the Athabasca Basin upstream of Fort McMurray. Data obtained in late February (March 1 record) and late March (April 1 record), were used in the forecasting models. March 15 and April 15 snow course records are available, but generally incomplete and therefore were not considered.

3.3. Hydraulic Data

Water Survey of Canada (WSC) stations measures water levels at two locations in the Fort McMurray area. The station 'Athabasca River below Fort McMurray' is located 5.6 km downstream of the town confluence with the Clearwater River. The 'Clearwater River at Draper' station is located approximately 13 kilometers upstream of the confluence with the Athabasca River.

The maximum water levels during breakup and the breakup dates at Fort McMurray were documented by various agencies over the years with the earliest breakup event documented in 1875. A summary of the documentation of historical breakup events is given in Robichaud (2003). WSC provided the freeze-up water level at the gauge below Fort McMurray associated with the 1973 to 2003 breakup years. Several years of breakup water levels at the WSC gauge below Fort McMurray were documented by Doyle (1987).

4. Empirical Models for Short Term Forecasting

Ice jam formation processes on the Athabasca River near Fort McMurray are very complex. Hydraulic and meteorological conditions can change rapidly throughout the breakup period making even basic monitoring a challenge. While the processes that control river breakup are not yet understood well enough to develop empirical process oriented models at this site, the influential factors have been identified, specifically ice thickness, and variables related to the water level during river ice freeze-up and breakup, such as the maximum freeze-up water level and the maximum breakup water level. The relevant meteorological factors have been identified to be air temperature, solar radiation, and basin snow water equivalent (SWE) in late winter. Using these parameters, various non-process oriented models were explored (Robichaud 2003). Because of the strong dependence of ice jam related flood levels on meteorological conditions in the few days just prior to occurrence, it was expected that such models would only be suitable for short term forecasting.

After compiling the hydrometeorological database, Robichaud (2003) investigated the relationship between individual variables and peak water levels during breakup using both threshold and linear regression models. As expected, given the complexity of processes involved, no practical relationships were found. Robichaud then explored multiple linear regression models and obtained very good correlations between the forecast peak water level at the Clearwater River confluence, and the actual observed peaks at the same site. Model results are shown in Figure 2, where it is seen that extreme water levels (> 246.0 m) predicted by the model were within 0.5 m of the observed values. The parameters that were identified as most significant in this relationship were: accumulated solar radiation, SWE measured in April, SWE measured in March, ice thickness, soil moisture (using an antecedent precipitation index) and the rate of rise in water levels on the Athabasca River (measured at the WSC gauge site).

Validation tests on this regression model were conducted using data obtained during spring breakup in 2003. The solar radiation and the rate of rise in water levels must be determined at the time of breakup; however, using solar radiation estimates based on meteorological forecasts, and assuming consistent rates of water level rise, the multiple linear regression equation can be used as a short term forecasting tool. The availability of meteorological forecasts limits the lead time of this model to approximately three days.

The date of initiation of the short term forecast model is dictated by the degree days of thaw, beginning with the first five consecutive days with average temperatures above zero. In 2003, this commenced on April 7th, so that by April 12th the short term model was operational, forecasting water levels of 243.9 m should breakup occur within the ensuing three days. The forecast water levels continued to rise until April 17th when a peak water level of 244.2 was forecast. At this point, the rate of rise in water level at the WSC gauge began to decrease (Figure 3), while the accumulated solar radiation continued to increase. Consequently, forecast water levels began slowly decreasing. Figure 4 illustrates these daily forecasts, along with the ±0.5 m error bands which were the target accuracy of the forecast model (based upon the performance indicated by Figure 2). On April 22, an ice run went through Fort McMurray and water levels at the Clearwater River confluence peaked at approximately 244.15 m. The forecast maximum water level for April 22 was 243.8 m, a low forecast by 0.4 m. The short term model is considered to have produced satisfactory results as this forecast was within the ± 0.5 m target range.

5. Fuzzy Expert System for Long Term Breakup Severity Forecasting

The strong dependence of ice jam related flood levels on meteorological conditions in the few days just prior to occurrence severely limits the advance warning capabilities of such models. Nevertheless it would be particularly useful, in terms of flood preparedness planning, to have some idea in late winter whether the oncoming spring breakup poses a low or high risk for ice jam related flooding. In this context, it is not essential to be able to quantitatively predict the anticipated peak water level; a reliable qualitative assessment of the risk severity would be just as useful.

In this study we explore the applicability of Fuzzy Expert Systems for providing such a long lead time risk assessment tool, in terms of predicting in late winter whether major ice jam flooding events might be expected at breakup. Fuzzy Logic was pioneered in the 1960s by Zadeh (1965);

it has been applied successfully in a variety of fields where the relationships between cause and effect (variables and results) are difficult to express numerically but are conceptually well defined. For example, See and Openshaw (1999) combined a Fuzzy Logic model with other methods of soft computing to enhance conventional flood forecasting techniques.

It is heuristically known that if the values of certain hydrometeorological variables are much lower than normal, the risk of ice jam flooding would be low. Conversely, if the values were much higher than normal, then a higher risk would exist. Fuzzy Expert Systems can incorporate heuristic knowledge from experts and can allow for overlapping ranges of values of variables when boundaries between classifications are not clearly defined. For example, an expert may be able to forecast the risk if all of the variables are "high", but may not be able to describe "high" as a single value.

Three of the variables identified as significant by the multiple regression equation are known in late winter, prior to breakup. These variables are: basin average soil moisture; basin average snow water equivalent for March 1 and April 1; and ice thickness. Fuzzy Experts Systems were explored to determine if they have the ability to recognize years with high potential risk of ice jam flooding from these antecedent parameters. The two remaining variables identified by the regression model as significant (total solar heat received and rate of rise in water level prior to breakup) can only be determined at the time of breakup, therefore they were not considered in this long term forecasting effort.

5.1. Fuzzy Expert Systems

Fuzzy Logic is a modeling technique that allows variables to be described in linguistic terms. Fuzzy Expert Systems produce a result based on logical linguistic rules rather than historical data, which allows this type of modeling to be less dependent upon the volume of historical data than many statistical methods. Fuzzy Expert Systems consist of four basic steps.

1. All variables (both dependent and independent) must be defined in terms of sets of linguistic classifiers. Membership functions are used to relate the degree to which a particular value of a variable is described by each linguistic term.
2. Membership functions of each independent (input) variable are related to the dependent (output) variable by defining statements or 'rules'. Normally rules are defined as a series of IF-THEN statements that relate the premise(s) to the conclusion.
3. The rules are mathematically evaluated and the results are combined through processes called implication and aggregation, respectively.
4. The resulting solution set of values is then transformed into a single number by a process called defuzzification.

In developing the Fuzzy Expert Systems, particularly the membership functions, extensive knowledge of the model subject is required. As a result, historical data and expert opinion are often combined in defining membership functions and rules.

5.1.1 Membership Functions

Each parameter in the model is generally described by a set of linguistic terms. For example, the value of the variable soil moisture could be described using the linguistic concepts of low, average and high. Membership functions are used to relate the degree, μ, to which a particular value of soil moisture is described by each of these linguistic term. The value of μ ranges from 0 (not part of the set) to 1 (perfectly represents the linguistic concept). A value of a variable may belong to more than one membership function, with varying degrees of membership. As an example, consider an ice thickness of 0.85 m measured by Water Survey of Canada (WSC) on the Athabasca River below Fort McMurray in late spring. While the ice is thicker than the average value of 0.75 m, it is not "thick" relative to the maximum ice thickness recorded (1.10m). Through the use of membership functions, Fuzzy Logic is able to define variables and/or results as belonging to linguistic groupings, such as thick or thin, to varying degrees. In this case, an ice thickness of 0.85 m might belong to "thick" to a degree of 0.8, but would also belong to "thin" to a much lesser degree.

One of the main challenges in developing a Fuzzy Expert System is establishing membership functions and the number of linguistic groupings for each variable. In cases such as this with small data sets, it is necessary to incorporate the judgment of experts to define membership functions based on experience, logic and physical bounds. Membership functions must be defined over the entire range of possible values of the variable they describe and can take on a variety of shapes, depending on the philosophy behind the concept of the linguistic term, as described by Mahabir *et al*. (2002).

5.1.2 Rule Definition

The Fuzzy Expert System consists of IF…THEN rules relating the linguistic terms of the input variables to the linguistic terms of the output variable. Operators such as AND can be used to relate the input variables to each other to define the result as a combination of the input variables. The AND operator is mathematically applied as an intersection operator by either the Minimum or Product function. Minimum is commonly used when the input data are independent of each other, and Product is often applied if input variables are interdependent.

In a rule-based model, the relationship between the input variables and the results is easily understood by simply reading the rule. For example, one rule could be: IF the ice thickness (premise) is high (linguistic term represented by a membership function) THEN the risk of an ice jam (conclusion) is high (linguistic term represented by a membership function).

Rules are influential in selecting the number of variables and the membership functions to be used within the Fuzzy Expert System, since the number of rules required increases if the number of membership functions increases, and increases exponentially with an increase in the number of input variables. To avoid undue complexity, a minimum number of parameters and membership functions should be considered for a Fuzzy Expert System.

Each rule also has an associated weight or certainty grade. A certainty grade can be used to weight rules between 0 and 1. As a starting point, certainty grades are normally set to one meaning all rules have equal weighting. Rule weights are often used to improve the model performance without modifying the membership functions of each linguistic term. Ishibuchi and Nakashima (2001) discuss the improvement of Fuzzy Rule-Based Systems by modification of certainty grades and contrast this method with modification of membership functions.

5.1.3 Implication and Aggregation

Implication is a process that evaluates the portion of the membership function that is active for a particular rule. Depending on the method of implication, the active set area can be considered to be all of the values in the membership function that belong to the membership function to an equal or lesser degree (known as the Minimum Operation), or the active set could be the entire membership function scaled by the degree to which the variable belongs (Product Operation). Implication results in one set of values for each rule evaluated.

The sets from Implication are combined into a single set in a process called Aggregation. If the sets from Implication are summed together, the method of Aggregation is called Summation. If Aggregation of the sets occurs by combining the maximum values obtained for each output membership function after Implication, then the Maximum method has been used. No firm guidelines have been developed for applying various methods of Implication and Aggregation. Typically, a sensitivity analysis is performed to determine which methods perform best for a particular Fuzzy Logic model.

5.1.4 Defuzzification

Defuzzification is the process by which a Fuzzy Logic solution set is converted into a single crisp value. The solution set is in the form of a function, relating the value of the result to the degree of membership. The Centre of Area (or Centre of Gravity) method is one of the most common of the Defuzzification methods. The Bisector method produces a value that will split the area of the solution set in half. Three other Defuzzification methods focus on the maximum membership value attained by the solution set. Frequently the maximum value of the solution set is a range of values rather than a point value. Smallest of Maxima selects the lowest value at which the highest membership value is attained. Similarly, Middle of Maxima and Largest of Maxima select the middle value of the maximum membership and the largest value at which the largest membership value occurs, respectively.

The method of Defuzzification is normally the most sensitive of the calculation parameters. For example, consider the case where a resultant set has a simple shape of 0.75 membership between A and C, otherwise 0 membership as shown in Figure 5. Smallest of Maxima will produce the lowest value where the highest membership occurs, which corresponds to value A on Figure 5. By contrast, the Bisector method will find the value that splits the resultant set in half by area and produce that value as the numerical result such as Value B in Figure 5. By selecting the Largest of Maxima, the largest parameter value for which the largest membership is achieved will be selected. This corresponds to point C on Figure 5. The objective of the model will influence the selection of the Defuzzification methods.

5.2.Fuzzy Expert System Design

A Fuzzy Expert System was created to evaluate the potential risk of ice jam flooding at Fort McMurray during spring breakup, based on antecedent conditions. Spring snowpack conditions in terms of basin averaged snow water equivalent (SWE), soil moisture conditions in terms of an antecedent precipitation index determined in late fall, and ice thickness were obtained from the historical database developed for the Athabasca at Fort McMurray. In terms of consequence, flood occurrence was assessed based on the peak water levels occurring on the Athabasca River at the Clearwater River confluence, as compared to the various thresholds for flooding concerns at the town. Where possible, the recorded water levels were used. For those years where the peak water level had not been documented, it was estimated using the regression model developed by Robichaud (2003). This created a data set consisting of 22 points, or 22 breakup events from 1977 to 1999.

5.2.1 Membership Functions

The ranges of each membership function were defined by the distribution of recorded values. Three membership functions were defined to describe Snowpack SWE and Antecedent Soil Moisture, namely, low, average, and high. In this study, "average" was considered to be the median value of the data set and was therefore a single point. A triangular membership function was defined by limiting the definition of average to values above the 25% quartile and below the 75% quartile. Values less than the 25% quartile were defined as belonging 100% to the definition of low, while data values between "low" and the median were defined as "low" to a lesser extent; this created a trapezoidal membership function. Similarly, data points above the 75% quartile to the maximum recorded value were defined as "high". Due to data limitations, it was not possible to define the transition from 100% membership to 0% membership based on physical evidence or inherent knowledge. For these reasons, straight lines have been used, following a similar approach to Mahabir *et al.*(2002).

Applying three linguistic terms to ice thickness generated a membership function for "average" that included a range of only 10 cm which, considering the natural variation of ice thickness, was too narrow a range to have any physical meaning. For this reason, it was decided that only two linguistic terms, thick and thin, would be used to describe the entire possible range of ice thickness.

The membership functions for the risk zones to be forecast were based on the known 'Alert' and 'Minor' flooding levels, specifically 244.0 m, and 246.0 m, respectively (Figure 6). If the forecast water level is higher than the Alert Level, then it belongs more to the Average membership function than the Low membership function. If the water level is greater than the level at which minor flooding occurs, then it belongs to the High membership function to a higher degree than to the Average membership function.

5.2.2 Rule Definition

The rule base of the Fuzzy Expert System was defined based on historical data and heuristic knowledge. Ideally, historical data would be available to define each of the rules. Since there are three input parameter with a total of 8 membership functions (3 for SWE, 3 for soil moisture and 2 for ice thickness), the required number of rules is 18 (3 x 3 x 2). The 22 years of data used to develop the Fuzzy Expert System did not include occurrences of all 18 possible combinations of variables, which means that historical records were not available to define each and every rule. Rules were determined based on the historical record wherever possible, and logical interpolation between rules was employed when no historical data were available to define particular rules.

5.2.3 Model Construction

The platform selected for the development of the Fuzzy Expert System was MatLab (Version 6.1.0.450, Release) and MatLab's Fuzzy Logic Toolbox (Version 2.1.1). The premises were combined using the concept of "AND" (minimum operator). Implication, aggregation and defuzzification were performed by the Minimum, Maximum and Centroid operators, respectively. A description of these operators and how they are applied are available in Klir *et al*. (1997). For the base model, all rules were weighted equally.

Using the base model configuration, two Fuzzy Expert Systems were created. The March Fuzzy Expert System includes the parameters that would be available on the first of March, specifically March 1 snowpack conditions (which are collected in late February), late fall soil moisture conditions and winter ice thickness. The April Fuzzy Expert System is identical except that it uses snow data collected during the last week of March (available on April 1).

5.3. Sensitivity Analysis on the Historical Record

While the Fuzzy Expert Systems were found to be less sensitive to the weightings of the rulebase, the results of the model were found to be highly sensitive to the method of defuzzification. From the data set, it was observed that if the soil moisture or the SWE was described as low, then the maximum water level attained at breakup was either low or average. If the ice thickness was low, the maximum water level could be any of the three possible linguistic descriptors. This led to the hypothesis that ice thickness may be less important than the other two parameters. Two models were created with weightings assigned to the rules. In the first model, rules for a premise with high ice membership functions were given half the weight of the other rules in the rule base. In the second model, rules regarding the low membership functions for Soil Moisture or SWE were given a higher weight than other rules. Neither of these models produced a significant change in the assessed water level risk compared to the base model. During the 2003 Breakup Event, all rules were weighted equally.

The method of defuzzification may hold the key for forecasting the occurrence of extremely high water levels at Fort McMurray caused by breakup ice jams. The Bisector method of Defuzzification produced similar, but slightly lower, forecasts of water levels compared to the base model, which applied the Centre of Gravity for Defuzzification. The performance of the base model was more accurate than that of Bisector Model. Smallest of Maxima, Mean of Maxima and Largest of Maxima produced forecasts similar to each other but very different from the base model. The Maxima models selected 1977 and 1997 as the only years with the risk of high water levels, and these are the only two years in the modeled period when major ice jam flooding occurred in Fort McMurray. These models did not, however, forecast the occurrence of high water for years when high water levels were caused by factors other than ice jams. For the four years that were forecast as lower risk years by the Maxima models, the actual water levels remained below the defined average water level of 245.0 m. This represents only four of the actual fifteen years of record where water levels were below average. However, it may be of value to identify any years that a lower risk exists.

5.4. Application to the 2003 Breakup Season

In early March of 2003, sufficient data were available from the various sources to produce an initial forecast of ice jam flood risk with the March Fuzzy Expert System. Slightly above normal precipitation was recorded at Fort McMurray from May to October and was used as an indicator of soil moisture for the Athabasca River basin. Snow surveys in late February confirmed that the SWE for the basin was above normal. As of March 1, the only ice thickness measurement available had been taken by WSC below Fort McMurray in mid January; it was 0.55 m. Comparison with historical measurements at this site indicated that ice thickness could either increase or decrease between January and March with a possible change of 12 cm in either direction. Based on a conservative estimate of ice thickness of 0.67 m, the 2003 river breakup was classified as a normal or medium risk year. At the same time, a sensitivity analysis was performed on the Fuzzy Expert System and the results showed that, for 2003, the model was extremely sensitive to ice thickness. If the ice thickness was estimated as 0.70 m then the risk would be high and if the ice thickness was estimated as 0.75 m, the risk would then be classified as extreme. This is not a typical scenario. For the 2002 March Forecast, analysis showed that an increase in ice thickness of more than 50 cm would have been required for the risk classification to change from normal to high. Given the sensitivity of the model in 2003, the risk of flooding during river ice breakup was classified as normal to high.

By mid March, ice thickness measurements were available from WSC. Detailed measurements showed that the average ice thickness was 0.75 m as of March 7. Basin SWE was calculated as 78 mm from snow surveys in late March. Based on this updated data, the April Fuzzy Expert System forecast an extremely high risk year for breakup 2003. Again the model results were found to be very sensitive to input ice thickness, with a reduction in ice thickness of 10 cm significantly reducing the perceived risk.

In the end, as Figure 4 indicates, peak water levels during the 2003 breakup did not get anywhere near flood levels. Therefore, the Fuzzy Expert System would be assessed as providing a false positive in 2003. However, it is significant to note that conditions (in terms of the size and extent of ice runs progressing down the river to Fort McMurray) were substantially greater than the average in 2003.

6. Discussion

One of the major problems in developing forecast models is the uncertainty contained in the variable that is being modeled, in this case, the peak water level on the Athabasca River at the Clearwater River confluence. As detailed in the database notes by Robichaud (2003), the water levels for ice jam events were measured at various locations throughout the river reach and later transposed to the confluence, sometimes by dubious methods. One of the key steps in reducing the error inherent in both short and long lead forecast models will be to thoroughly investigate the water levels at the confluence and improve the quality of those transposed values.

All of the models, particularly the long term forecast Fuzzy Expert System models, are very sensitive to ice thickness. For years such as 2003, the sensitivity of the model may limit its practical value. It may be possible to reduce the dependence of the models on ice thickness measurements by reintroducing variables that were removed because of covariance with ice thickness.

When forecasting parameters, it is vital to understand the potential for forecast error in an input parameter and the effect on the model result. The sensitivity of the model determines how precisely each parameter must be forecast. The potential range of values for the parameter usually influences how accurately a parameter can be forecast. For the multiple regression model, forecasting solar radiation accurately is less critical than forecasting the rate of rise in water level. For example, a poor forecast of solar radiation would be an underestimate or overestimate of about 200 W/m^2, resulting in an error of approximately 6 cm in the forecasted maximum water level at breakup. However, if the rate of water level rise is estimated incorrectly by 0.01 m/day, the result would be a one day error of 9 cm. While the maximum error for solar radiation is limited to approximately 450 W/m^2 (maximum possible daily value during April), the error in the rate of rise in the water level could be substantial since the possible range of values is anywhere from 1 cm/day to 50 cm/day.

Analysis of the 2003 event indicated that a two day moving average was sufficient to smooth diurnal effects while still capturing the general trend in the rate of increase in water levels. For reference purposes, the preliminary hydrograph for the Athabasca River at Fort McMurray is provided in Figure 3. Note that the two dominant rates of rise have been marked on the figure. While these values are easily distinguished after breakup, they are difficult to determine on a daily basis prior to breakup. Because the gradually rate of rise on the Athabasca represents a long wave rather than a local snowmelt phenomenon, it may be worthwhile to investigate the use of routing models to transpose the water levels from the gauge at the town of Athabasca (several hundreds of kilometers upstream), downstream to Fort McMurray. This additional information would assist the forecaster in anticipating a change in the rate of rise at Fort McMurray.

7. Conclusions

Preliminary results are promising for developing both short and long term forecasts for the maximum water levels attained at the Clearwater River Confluence with the Athabasca River. During the spring of 2003, the Fuzzy Expert Systems were able to generate reasonable forecasts. However, the sensitivity of the long term forecast model to ice thickness measurements limited its practical use. The linear multiple regression model was able to forecast the maximum water level at breakup to within the 0.40 m of the actual value, within the target range of ±0.5 m. While these initial results are promising, further study is required before these models can be considered operational forecasting tools.

8. Future Research

As the final stage in data collection, images and written accounts of breakup in the vicinity of Fort McMurray have been collected from provincial government archives. At this point, it is valuable to confirm water levels and breakup dates contained in the database. In addition, ice jam modeling is being undertaken to improve the estimates of Athabasca River water levels that must be transposed to the Clearwater River confluence. When the data has been finalized, a second evaluation of the short and long term models should be performed.

During the 2003 breakup season, both the multiple regression model and the Fuzzy Expert System models were deemed to be to sensitive to parameters that were are difficult to define precisely. Had more parameters been retained in these models, it may have been possible to reduce the dependence on the parameters with inherent uncertainties within the measured values. As a next step, it is proposed that Artificial Neural Networks be investigated as an addition to the current models as a means of retaining numerous variables related to river ice breakup.

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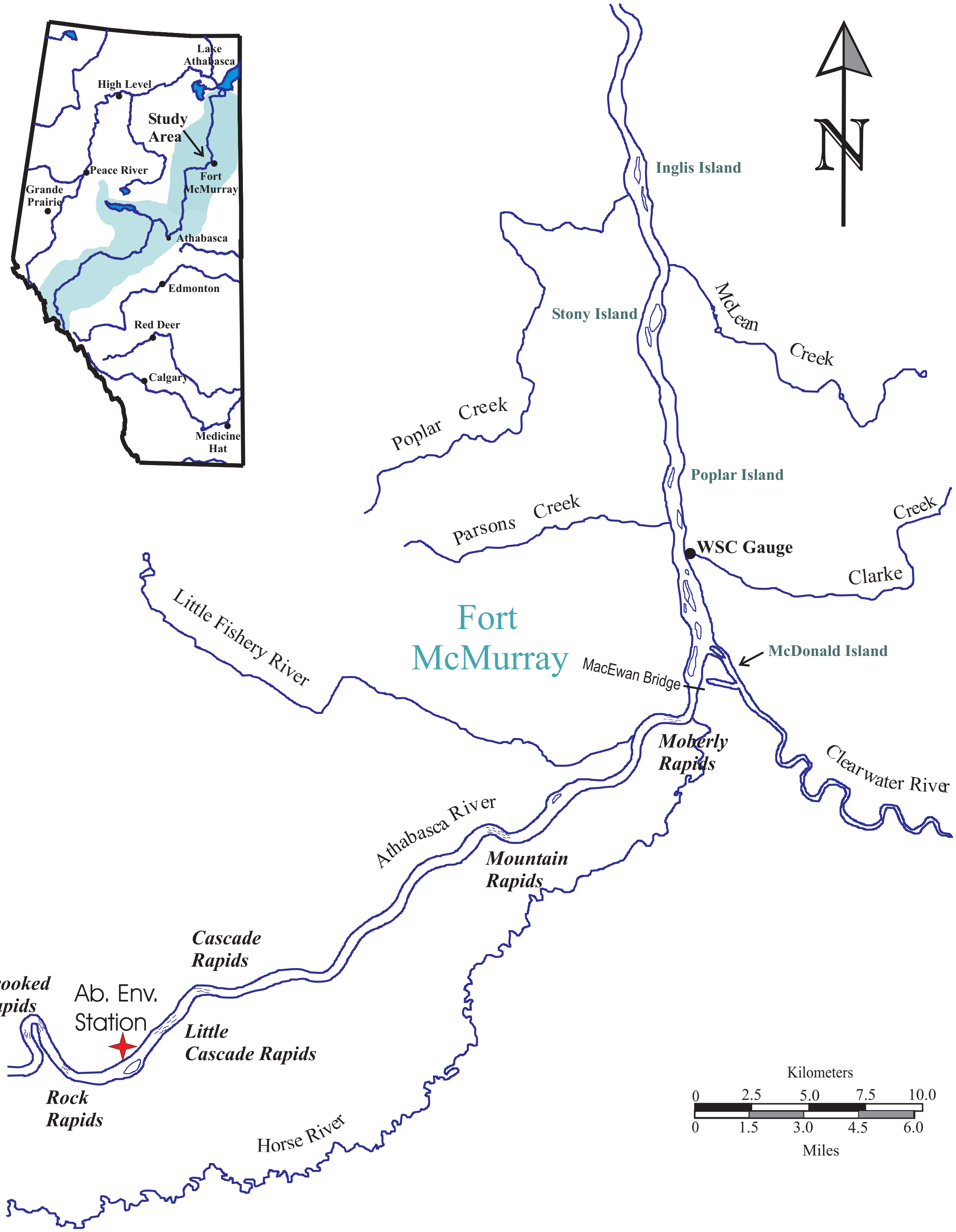

Figure 1. Athabasca River at Fort McMurray, AB (adapted from Robichaud, 2003)

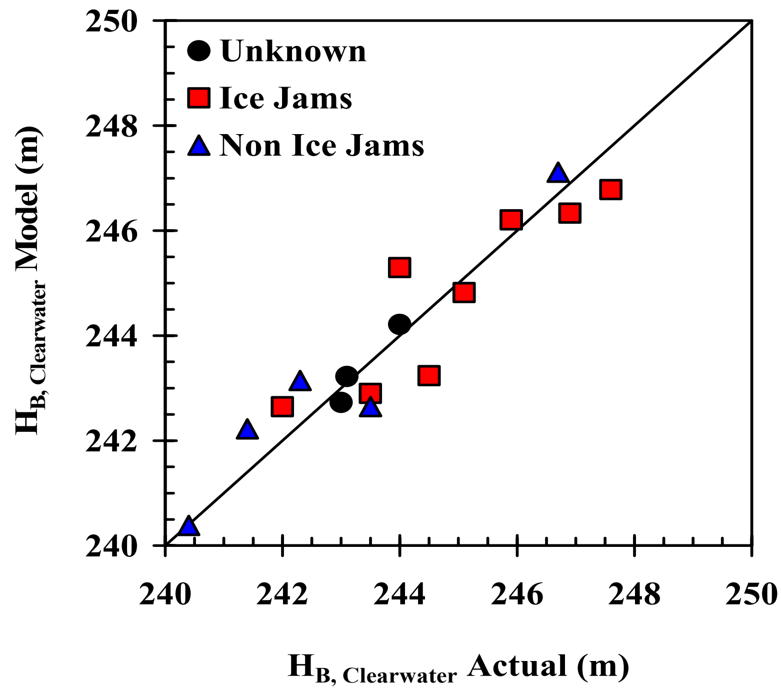

Figure 2. Linear multiple regression model forecasts for maximum breakup water level at the Clearwater River confluence (adapted from Robichaud, 2003).

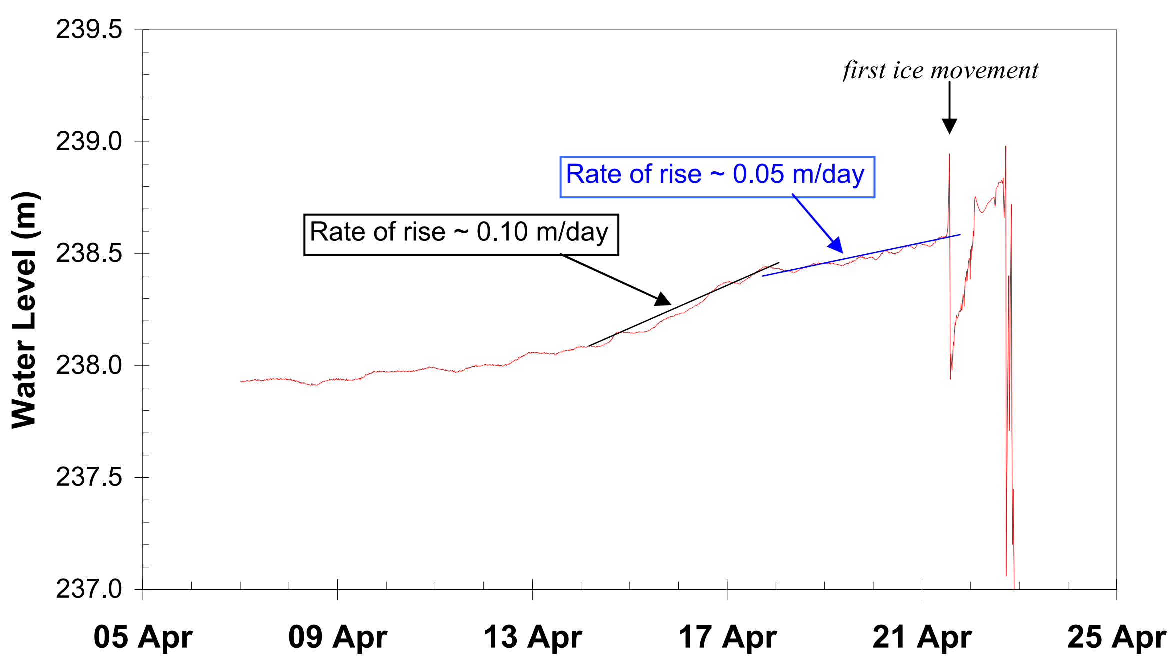

Figure 3. Estimation of rate of rise of water level prior to breakup from the Athabasca River below Fort McMurray gauging station.

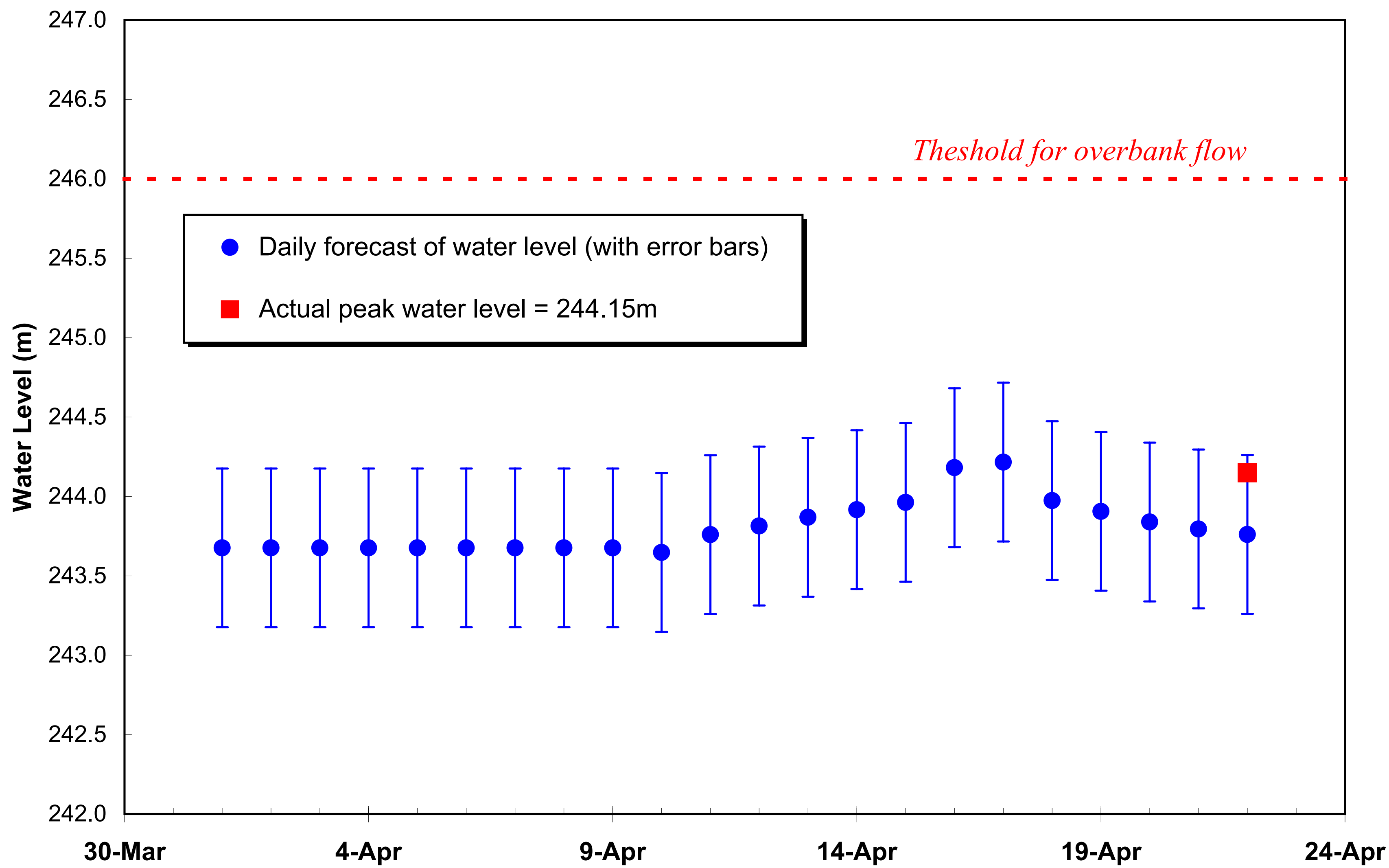

Figure 4. 2003 daily forecasts of peak breakup water level on the Athabasca River at the Clearwater River confluence.

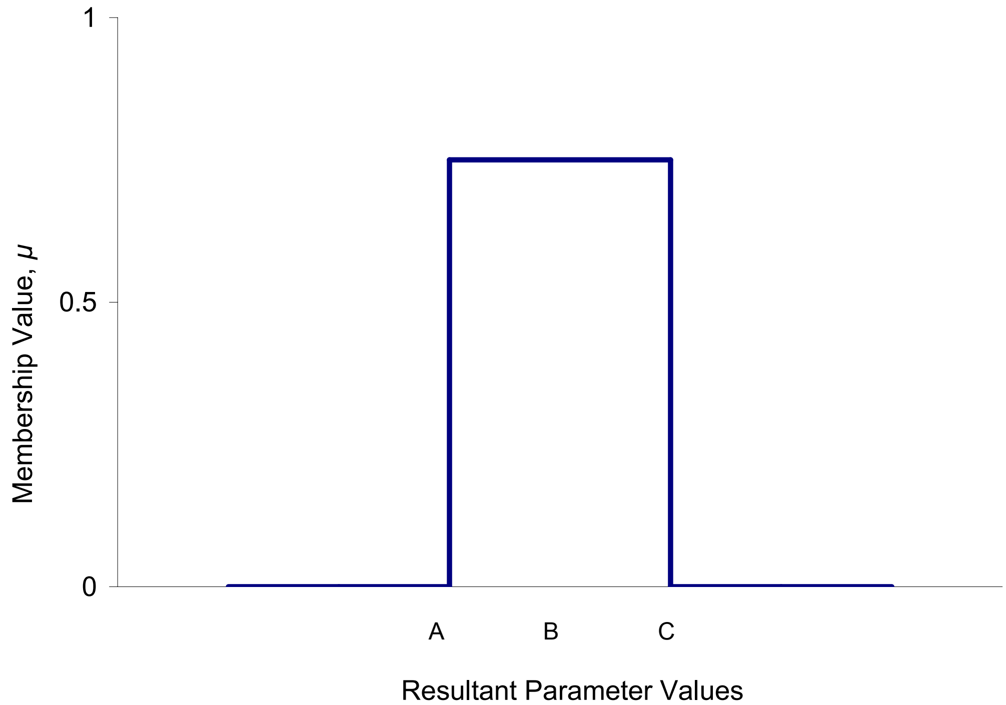

Figure 5. Defuzzification of Resultant Set where A represents result of Smallest of Maxima, B represents the result of Centroid and C represents the result of Largest of Maxima.

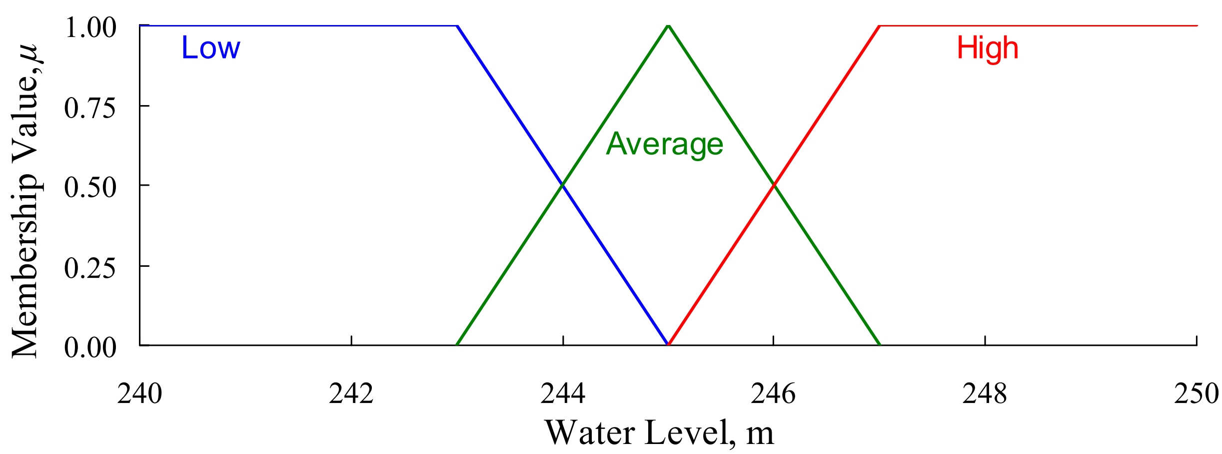

Figure 6. Membership functions for the flood risk levels.